UNIVERSITY OF SOUTHAMPTON

FACULTY OF SOCIAL SCIENCES

Department of Economics

Eating Disorders Studied over Online Social Networks

by

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Thesis for the degree of Doctor of Philosophy

May 2019

UNIVERSITY OF SOUTHAMPTON

ABSTRACT

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EATING DISORDERS STUDIED OVER ONLINE SOCIAL NETWORKS

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Eating disorders are complex mental disorders and responsible for the highest mortality rate among mental illnesses. Traditional research methods on these diseases mainly rely on personal interview and survey, which are often expensive and time-consuming to reach large populations. Recent studies show that user-generated content on social media provides useful information in understanding these disorders. However, most previous studies focus on analyzing content posted by people who discuss eating disorders on social media. Few studies have explored social interactions among individuals who suffer from these diseases over social media, while social networks play an important role in influencing and shape individual behavior and health.

This thesis aims to provide insights into eating disorders and their related communities from a network perspective, particularly to understand how individuals interact with one another, and the interplays between online social networks and individual behaviors. To this end, we first develop a snowball sampling method to automatically gather individuals who self-identify as eating disordered in their profile descriptions, as well as their social connections on Twitter, and verify the effectiveness of our sampling method by both computational analysis and manual validation. Second, we examine a large communication network of individuals suffering from eating disorders on Twitter to explore how social media shape community structures and facilitate interactions between communities with different health-related orientations. Third, we propose to use multilayer networks to model multiplex interactions among individuals and explore how activities of a set of actors in one type of communication correlate and influence activities of the actors in other types of communication. Finally, leveraging the longitudinal data on posting activities in our user samples spanning 1.5 year, we investigate characteristics of dropout behaviors among eating disordered individuals on Twitter and to estimate the causal effects of personal emotions and social networks on dropout behaviors. Our findings contribute to understanding of development and maintenance of healthy behaviors and cognition online, and have practical implications for designing network interventions that can promote organizational well-being in online health communities.

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Declaration of Authorship

I, Tao Wang , declare that the thesis entitled *Eating Disorders Studied over Online Social Networks* and the work presented in the thesis are both my own, and have been generated by me as the result of my own original research. I confirm that:

- this work was done wholly or mainly while in candidature for a research degree at this University;
- where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated;
- where I have consulted the published work of others, this is always clearly attributed;
- where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work;
- I have acknowledged all main sources of help;
- where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself;
- parts of this work have been published as: [Wang et al., 2017] (Chapter 3), [Wang et al., 2018a] (Chapter 4), [Wang et al., 2019] (Chapter 5)and [Wang et al., 2018b] (Chapter 6).

Signed:...

Date:..

Acknowledgements

First of all, I would like to thank my supervisors, Antonella Ianni, Markus Brede and Emmanouil Mentzakis, for giving me the opportunity to do this interesting project, but also for their continuous support, guidance and valuable feedback throughout my PhD. Special thanks to Dr. Robert Ackland, Prof. Leslie Carr, Dr. Jonathon Hare, Dr. Carmine Ornaghi and Dr. Hctor Calvo Pardo for their very helpful comments and suggestions. I would also like to thank the Alan Turing Institute for offering me a one-year placement, allowing me to continue my research in a multidisciplinary environment. Last but by no means least, I would like to thank my family for all their support and encouragement, especially my loving and supportive wife, Dandan Shi. Dandan has been my best friend and greatest companion, loved, supported, encouraged, inspired, entertained and helped me get through this agonizing period in the most positive way.

Chapter 1

Introduction

1.1 Motivation

Eating disorders (ED), such as anorexia nervosa and bulimia nervosa, are complex mental illnesses that are characterized by abnormal eating habits and excessive concerns about body weight and shape [Association et al., 2013]. These diseases can negatively affect people's physical and psychological health, with the highest mortality rate of any mental illness [Arcelus et al., 2011; National Institute of Mental Health, 2016]. Apart from serious health consequences, ED have become increasingly prevalent over recent years, particularly in adolescent populations [Abebe et al., 2012]. More than 725,000 people in the UK are reported to develop an ED at some stage in their lifetime, and the trend is indicated in increasing prevalence over time: approximately 7% increase each year since 2005-06 [Beat, 2015]. Given these negative impacts on both individuals and society, ED have been a major public health concern. While various treatments of ED have emerged over recent years [Corstorphine, 2006], individuals with ED often attempt to conceal their symptoms and many never seek support or treatment from professionals [Rich, 2006; Swanson et al., 2011], mainly because of the denial of illness, social stigma of being mentally ill and lack of health awareness [Guarda, 2008; Swan and Andrews, 2003]. This leads to a lack of quantifiable information on individuals' behaviors to identify the occurrences or severities of ED, and brings a significant challenge for health professionals to understand ED and develop effective treatment programs.

As the emergence of social media services such as Twitter, Facebook and Instagram over recent years, people are increasingly using social media to record details of everyday life, exchange information and seek social support, as well as to manage their chronic health conditions [Fergie et al., 2015]. This provides a new opportunity to study individuals' health-related behaviors, such as concerns, emotions, activities and socialization, by analyzing their data generated on social media. Recent studies have shown that user-generated data online can indeed reveal their mental health states, such as feelings of worthlessness, depression, helplessness, anxiety, self-hatred, suicidal ideation and concerns of body image [Chancellor et al., 2016a; Coppersmith et al., 2014; De Choudhury et al., 2013c; De Choudhury and Kıcıman, 2017; Juarascio et al., 2010]. Moreover, engagement in online ED communities is common among people with ED and has recently been suggested as a screening factor for ED [Campbell and Peebles, 2014]. Thus, a growing body of research has focused on using social media data to improve our understanding of disordered eating behaviors [Arseniev-Koehler et al., 2016; Chancellor et al., 2016a; Juarascio et al., 2010; Syed-Abdul et al., 2013; Yom-Tov et al., 2018].

Previous ED studies based on social media data are mainly carried out by psychologists and clinicians [Arseniev-Koehler et al., 2016; Branley and Covey, 2017; Juarascio et al., 2010; Wick and Harriger, 2018; Wilson et al., 2006; Wolf et al., 2013]. These studies often rely on surveys or interviews in data collection [Ransom et al., 2010; Wilson et al., 2006] and human coding in content analysis [Branley and Covey, 2017; Juarascio et al., 2010; Wick and Harriger, 2018]. Although in most cases these methods can provide reliable and valid measures, they often involve intensive manual labor, making previous studies be limited by small sample sizes. For example, Arseniev-Koehler et al. [2016] studied socialization of an ED community based on 45 users on Twitter and Wick and Harriger [2018] analyzed thinspiration content based on 222 images and text posts on Tumblr. Given the explosive growth of information online, there is therefore a need to develop more effective techniques to extend these efforts.

Recently, some computational methods have been proposed to study ED and other mental illnesses based on social media data [Chancellor et al., 2016a,c,d; Coppersmith et al., 2014; De Choudhury, 2015; De Choudhury et al., 2013b, 2014; Harman, 2014]. By leveraging users' content and behaviors generated online, researchers have explored to identify risks of individuals being affected by ED [Chancellor et al., 2016c; De Choudhury, 2015], depressions [De Choudhury et al., 2014, 2013c; Harman, 2014; Park et al., 2013; Schwartz et al., 2014; Tsugawa et al., 2015], addictions [MacLean et al., 2015; Murnane and Counts, 2014], suicidal ideation [De Choudhury and Kıcıman, 2017; De Choudhury et al., 2016a] and other health conditions [Coppersmith et al., 2015, 2014; Jamison-Powell et al., 2012; Mitchell et al., 2015]. However, previous studies have often focused on content analysis [Wongkoblap et al., 2017]. For example, in ED-related studies, De Choudhury [2015] compared the differences of pro-anorexia and pro-recovery posts, and Chancellor et al. [2016c] further explored to predict the likelihood of a user in recovery from ED based on users' posts on Tumblr. Other studies also examined the severity of ED based on tags posted by users [Chancellor et al., 2016a], characterisitics of removed ED-related tags [Chancellor et al., 2016b], and lexical variations of ED-related tags [Chancellor et al., 2017, 2016d] on Instagram. While most social media platforms offer multiple ways (such as "follow" on Twitter) for users to interact with one another, few studies have explored social ties and interactions among disordered peers online.

In fact, social dimension captured by social networks plays an important role in understanding lifestyle related conditions like ED [Chen, 2013], as our interests, concerns and behaviors are strongly influenced by the network of people with whom we interact [Fiori et al., 2006; Kawachi and Berkman, 2001; Paxton et al., 1999]. Previous studies on offline social networks have shown that various health-related attributes, such as obesity [Christakis and Fowler, 2007], happiness [Fowler and Christakis, 2008], and smoking [Christakis and Fowler, 2008], are affected by individuals' attributes but also by their social networks. Detailed records of individuals' interactivity on social media provide a great opportunity to extend these studies and explore the nature and extent of the person-to-person spread of disordered behaviors through online social networks. Moreover, unlike offline social networking data that is often collected via surveys, online social networking data is recorded in real time. The availability of such temporal data enables us to clarify the ordering of individuals' connections to different people and examine behavioral changes before and after the formation of a connection, which can help to extend our understanding on the relations (e.g., co-evolution) between social networks and individual behaviors. A deeper understanding of these relations can have practical implications in disease prevention and online intervention to improve organizational well-being over online social networks [Latkin and Knowlton, 2015; Valente, 2012].

1.2 Research Objectives

The main objective of this thesis is to **explore characteristics of social interactions in online ED communities from a network perspective and examine interplays between online social networks and individual health attributes**. Given this principal objective, we pursue the following subsidiary objectives:

- To develop a data collection method that can gather a large set of individuals affected by ED on social media (e.g., Twitter) and track their posting activities and social networking data online (Chapter 3).
- To characterize structural properties of online social interactions among individuals with ED by using network analysis methods (Chapter 3).
- To determine groups of individuals with a similar stance on ED (e.g., pro-recovery or anti-recovery) in an online ED community and how individuals with different stances interact with one another (Chapter 4).
- To establish the associations between individuals' positions in a social network and their behaviors online (Chapter 4).
- To analyze how different types of information (e.g., healthy and harmful content) flow through interpersonal communication networks in an online ED community and how these information flows correlate and influence one another (Chapter 5).

- To estimate the effects of social networks and individual attributes on behavioral change, e.g., dropout from a harmful online community (Chapter 6).

1.3 Thesis Structure

The remainder of this thesis is organized as follows.

In Chapter 2, we first introduce background on the research in this thesis and provide a comprehensive overview of related work. Then, we formulate our research questions by identifying research gaps in previous studies. Finally, we introduce key theories and methods that can be used to address these research questions.

In Chapter 3, our focus is to collect interaction **data** in online ED communities. We first present a snowball sampling method to sift ED individuals and their social networks on Twitter. We verify the effectiveness of this method by both computational algorithms and human annotations. Then, we characterize structural properties of social connections among ED individuals through various types of interactions (e.g., "follow", "retweet" and "mention") on Twitter and explore the presence of homophily in online ED communities. The main part of this chapter was published on [Wang et al., 2017].

In Chapter 4, our focus is to identify distinct subgroups of **actors** in an online ED community and examine how different subgroups of actors interact. We first present an automated approach that integrates topic modeling and clustering analysis to find groups of users sharing similar interests in online ED communities. Then, we use sentiment analysis techniques to identify the stances of each group of users towards ED and examine the differences of groups of users in social activities and psychometric properties. Finally, we explore the associations between individuals' positions in a social network and their behaviors by studying social norms [Parsons, 1937] in different groups. The main part of this chapter was published on [Wang et al., 2018a].

In Chapter 5, our focus is to identify distinct types of **content** spread through an online ED community and examine the correlations among different types of information flows. We first use topic modeling methods to detect the types of content shared in interpersonal conversations within an online ED community. Then, we propose a multilayer network representation [Boccaletti et al., 2014; Kivelä et al., 2014] to model individuals' interactions in communicating different types of content and demonstrate how this representation can facilitate analyzing the difference and correlations among different information flows. To better understand underlying processes that lead to the correlations of different information flows, we further investigate dynamics of the multilayer communication networks over time. The main part of this chapter was published on [Wang et al., 2019].

In Chapter 6, our focus is to explore how online social networks can lead to **behavioral changes**, particularly on discontinuation of engagement and dropout on Twitter. We first identify users' dropout behaviors by observing their posting activities on Twitter over 1.5 years. Then, we base the incentive theory [Kollock, 1999] and establish the causal effects of individual emotions and positions in social networks on their dropout behaviors (e.g., the probability of dropout and the time to dropout). The main part of this chapter was published on [Wang et al., 2018b].

In Chapter 7, we conclude the work in this thesis. We first summarize the main contributions in this thesis and discuss their implications for public health. Then, we propose several directions and open challenges for further research.

Chapter 2

Background

Social media facilitate access to social support and heath-related communication for people affected by health problems. User-generated data on social media, particularly health-related data, provides unprecedented opportunities to understand and prevent challenging health problems at a large scale. This thesis presents studies on eating disorders over social media. This section reviews four essential elements of background material for these studies, including (1) knowledge on eating disorders, (2) link between social media and health, (3) previous health-related research based on social media data, and (4) key theories and methods used in this thesis.

2.1 Eating Disorders

2.1.1 Clinical Knowledge

In standard medical manuals, such as Diagnostic and Statistical Manual of Mental Disorders (DSM-5) [Association et al., 2013] and International Statistical Classification of Diseases and Related Health Problems (ICD-10) [Organization, 1993], eating disorders (ED) are defined as mental illnesses characterized by abnormal attitudes towards food and unusual eating behaviors. The most common forms of ED are *anorexia nervosa* where sufferers restrict their eating to keep low weight, *binge ED* where sufferers ingest a large amount of food in a short period of time, and *bulimia nervosa* where sufferers repeat cycles of binge eating and purging [Association et al., 2013; Organization, 1993].

Exact causes of ED are still unclear; all biological (genetic effects), psychological (body image disturbance and personality traits), developmental (childhood sexual abuse), and sociocultural factors (idealization of thinness) can contribute to the development of these complex disorders [Rikani et al., 2013]. Symptoms of ED vary according to the nature and severities of disease [Strumia, 2005]. Common physical symptoms of ED include weakness, fatigue, weigh loss and growth failure [Association et al., 2013; Fairburn and Harrison, 2003; Pritts and Susman, 2003]. Also, due to the widespread use of starvation, vomiting, medicines (e.g., laxatives and diuretics) to lose weigh, ED sufferers often exhibit many complications like delayed puberty, dental enamel erosion [Pritts and Susman, 2003], neurologic and skin problems [Strumia, 2005]. Apart from these medical manifestations, people affected by ED often display abnormal behaviors, such as secret eating, strict rules on eating, repeated weighing, and highly driven, intense exercising of a compulsive nature [Fairburn and Harrison, 2003].

As a mental disease, ED are not only about eating behaviors and physical activity — psychological and emotional issues lie at the core of ED [Corstorphine, 2006; Harrison et al., 2009]. Difficulties in processing emotional states, particularly on negative emotions such as depression and anxiety, are implicated in the aetiology and maintenance of disordered eating behaviors [Hambrook et al., 2011]. Esplen et al. [2000] found that a lower level of soothing receptivity was correlated with a decreased capacity of evocative memory in bulimia nervosa patients, and highlighted the importance of understanding affect regulation and loneliness experience in developing treatment to ED. Swan and Andrews [2003] also evidenced that individuals with ED scored significantly higher than non-clinical controls on all shame areas; eating disordered women including those recovered scored higher than controls on shame around eating, bodily and characterological shame. A longitudinal study on 3,150 bulimic suffers followed for 11 years at three times further demonstrated that appearance satisfaction, and symptoms of anxiety and depression are associated with the development of bulimic symptoms in both males and females [Abebe et al., 2012]. In fact, learning how to recognize, regulate and healthfully express emotions is an essential step in ED recovery [Corstorphine, 2006; Hambrook et al., 2011].

Health care professionals use several methods to assess individuals with ED, where the primary methods include interviews, self-reported questionnaires, and physical assessment [Fairburn and Beglin, 1994]. Once diagnosed, treatment of ED can involve multiple formats of therapies [HALMI, 2005]. The widely used therapy approaches include family therapy which focuses on obtaining cooperation from family members, examining family attitudes on an individual's symptoms, and developing healthy eating patterns in family members [Johnston et al., 2015], and cognitive emotional behavioral therapy which aims to help individuals to evaluate the basis of their emotional distress and hence reduce the need for associated dysfunctional coping behaviors, such as binging, purging, restriction of food intake, and substance abuse [Corstorphine, 2006; Slyter, 2012].

2.1.2 Social Impacts

ED have serious impacts on individuals' health including the highest mortality rate of any mental illness, with 5.86 and 1.93 deaths per 1,000 per year for anorexia and bulimia respectively, and 20% of all deaths from anorexia are the result of suicide [Arcelus et al., 2011]. Despite the seriousness of these diseases, ED have become increasingly prevalent over recent years, particularly among adolescence and young people in western countries [Abebe et al., 2012]. As estimated by the National Institute of Mental Health, 2.7% of adolescents aged 13 to 18 years had manifested ED in the US [Merikangas et al., 2010]. More than 725,000 people in the UK are reported to develop ED at some stage in their lifetime, and the trend is indicated in increasing prevalence over time: approximately 7% increase per year since 2005-06 [Beat, 2015]. More than 85% of those suffering are below the age of 19 and 95% of sufferers are females. These widespread negative effects of ED on individuals further lead to a great burden on the society. As estimated by Beat in 2015, the UK's leading charity supporting people with ED, a direct financial burden was between £2.6 billion and £3.1 billion on sufferers per year, total treatment costs to the National Health Service (NHS) is between £3.9 billion and £4.6 billion and lost income to the economy is between £6.8 billion and £8 billion [Beat, 2015].

2.1.3 Challenges in ED Prevention

To reduce these negative impacts, clinicians have made ongoing efforts on preventing the occurrence of ED and delivering early interventions to ED sufferers [Council et al., 2009]. However, it remains several challenges in ED prevention.

- **Hard-to-reach population:** People affected by ED are often hard to reach via traditional health care services [Swanson et al., 2011]. Sufferers often conceal their symptoms and many never seek help or treatment from health care professionals [Rich, 2006; Swanson et al., 2011], likely due to social stigma of illness, shame or fear of stigmatization, and lack of awareness of ED [Guarda, 2008; Swan and Andrews, 2003]. In a survey conducted by Beat, over half of ED sufferers waited more than a year after recognizing symptoms of ED before seeking help [Beat, 2015]. This results in delays in receiving diagnosis and effective treatment, which further leads to a greater severity and long-term suffering of ED. Moreover, this hard-to-reach nature can lead to a big challenge for researchers to obtain quantifiable data that is representative for the whole population through traditional data collection methods such as interview and survey in ED research.

- **Social contagion:** Unhealthy eating behaviors and concerns are socially contagious and can spread from people with ED to those without ED through social contracts [Crandall, 1988; Page and Suwanteerangkul, 2007]. Since Crandall [1988] first evidenced social contagion of binge eating by showing that an individual's binge eating being predictable from the binge eating level of their friends, the effects of social contagion to eating behaviors have been observed across populations in different regions and cultures. Based on survey data from 31 middle and high schools in Minnesota, USA, Eisenberg et al. [2005] found that social norms in one's peer group could affect unhealthy weight-control behaviors, particularly for girls with average weight. In a sample of 2,519 Thai adolescents, Page and Suwanteerangkul [2007] found significant associations between friends' dieting behaviors and an ego's dieting behaviors, body mass index (BMI), weight satisfaction, and frequency of thinking about wanting to be thinner. While these findings emphasize the importance of social interactions in ED research, individuals' social network information is often absent in clinical data, making it difficult for clinicians to appropriately identify and track the transmission of ED in populations.

- **Uncertain outcomes of treatment:** Due to the complexity of ED, achieving full recovery from these diseases can take a long time period, with 57-79 months for anorexia [Strober et al., 1997]. This long period of treatment can in turn increase the chance of interruption of treatment and relapse. Indeed, dropout is common in the treatment of ED, with up to 70% of ED patients dropping out of outpatient treatment [Fassino et al., 2009], and relapse rates in ED patients are high, with 32.6% for anorexia and 37.4% for bulimia within 2.5 years [Richard et al., 2005]. Various factors such as high work stress, pressures from society and friendship, as well as other occurrences of negative stressful life events, can increase risk for relapse and weaken treatment outcomes [Grilo et al., 2012]. This indicates that, apart from clinical characteristics, information on individuals' feelings, thoughts, behaviors and social interactions may provide useful insights into how and why people choose a healthy or unhealthy lifestyle.

Over recent years, the widespread use (among the general population and discorded individuals) of social media services, such as Facebook and Twitter, to exchange thoughts and document details of daily life provides a new opportunity which can potentially complement traditional methods based on clinical data to address these challenges. Growing evidence has shown that user-generated data on social media provides rich, high-resolution records of people' feelings, thoughts, behaviors and social interactions that can help to understand complex mental disorders, such as depression, suicide and ED, at a large scale [De Choudhury et al., 2014, 2013c; Homan et al., 2014; Rice et al., 2016; Schwartz et al., 2014; Tsugawa et al., 2015; Yom-Tov et al., 2012]. Next, we introduce the research of human health based on social media data.

2.2 Social Media and Well-being

Social media are Internet-based services that allow people to express and exchange thoughts, develop social networks and relationships, and document details of daily life. [Buettner, 2016; Kaplan and Haenlein, 2010]. There are diverse forms of social media, including social networking (Facebook and LinkedIn), microblogging (Twitter and Tumblr), social search (Google and Ask.com), photo sharing (Flickr and Instagram), video sharing (YouTube), instant messaging (Skype and WhatsApp) and social gaming (World of Warcraft) [Aichner and Jacob, 2015]. Relying on mobile and Web-based technologies, these services have revolutionized the way people communicate and socialize in both the online and offline worlds [Kietzmann et al., 2011]. The popularity of social media has continued to increase steadily over recent years. According to statistics, more than 2.14 billion users, accounted for 64% of all Internet users, use social media services online in 2015 [Statista Inc, 2016b]. The number of social network users will continue to increase, estimated about 2.95 billion around the world in 2020 [Statista Inc, 2016a].

Given the pervasiveness of social media in modern life, using social media as key health information source and tool to manage chronic conditions has also increased steadily, particularly among young people [Fergie et al., 2015]. More than 30% of U.S. Internet users have participated in a medical or health-related community online [Johnson and Ambrose, 2006]. In a telephone survey of 1,745 adults, 31.58% of respondents reported using social media for seeking health-related information [Thackeray et al., 2013]. This provides new opportunities to learn more about challenging health problems on a large scale by studying people's thinking, emotions, concerns, activities and socialization based on user-generated data on social media [De Choudhury et al., 2014, 2013c; Homan et al., 2014; Schwartz et al., 2014; Tsugawa et al., 2015]. Next, we first introduce how social media can promote public well-being (particularly in risk detection and online intervention), and then discuss the strengths and challenges of using social media data in health care research.

2.2.1 Risk Detection

Social media have relevance to public health primarily through their functions on early risk detection, at both *individual* and *population* levels [De Choudhury et al., 2013c, 2016a; Homan et al., 2014; Schwartz et al., 2014; Tsugawa et al., 2015]. At the *individual* level, psychologists first observed the presence of abnormal language use in personal writing of students who scored highly on depression scales [Chung and Pennebaker, 2007; Rude et al., 2004]. They found that depressed people had more frequent usage of first person singular pronouns and more frequently expressed negative emotion words [Chung and Pennebaker, 2007; Rude et al., 2004]. Other studies further found that language people used online captured diagnostic information on a wide range of psychiatric disorders, such as depression and post traumatic stress disorder (PTSD), [Alvarez-Conrad et al., 2001; D'Andrea et al., 2012; He et al., 2012; Rude et al., 2004]. Recent work extended these studies by applying language-analysis methods to social media data and found differences of language use between disordered and control groups on social media, such as content discussed in chat rooms among individuals with bipolar disorders

[Kramer et al., 2004] and forum posts of depression [Ramirez-Esparza et al., 2008]. To date, researchers have shown the potential to learn about individuals' health and well-being through their linguistic and behavioral attributes online [De Choudhury et al., 2013c, 2016a; Harman, 2014; Homan et al., 2014; Schwartz et al., 2014; Tsugawa et al., 2015], such as identifying risk factors of harmful behaviors (like suicide) [De Choudhury et al., 2016a], onset of disease [De Choudhury et al., 2013c; Harman, 2014; Tsugawa et al., 2015], severity of illness [Chancellor et al., 2016a,c; Schwartz et al., 2014] and outcomes of treatment [Ernala et al., 2017].

On the other hand, social media have potential in *population*-level surveillance (or sentinel surveillance), an important task in public health that aims to continuously monitor the trends of common diseases in population [Paul and Dredze, 2011; Pfaller and Diekema, 2002]. Conventionally, monitoring data is collected from health care facilities or by using surveys, a well-known example being the Behavioral Risk Factor Surveillance System (BRFSS) administered by the Centers for Disease Control and Prevention (CDC) [CDC, 2014]. Every few years, this system conducts surveys via telephone to estimate the rates of some diseases among U.S. adults. Despite with a national-scale effort, many surveys have limited numbers of participant responses (often in the thousands). Moreover, the large temporal gaps between these measurements make it hard for professionals to timely track and identify disease-related risk factors, and to design effective prevention programs [De Choudhury et al., 2013b]. As an alternative, researchers have explored to use social media as a source of syndromic surveillance, providing data on a larger scale but at lower cost [Culotta, 2014; Ginsberg et al., 2009]. One well-known example is the Google Flu Trends (GFT) which detected the activity of influenza using query logs, with a reporting up to 7-10 days earlier than CDC's FluView [Carneiro and Mylonakis, 2009; Ginsberg et al., 2009], although other studies have shown that the validity and reliability of GFT are questionable [Lazer et al., 2014]. The trends analyses of influenza have also been explored based on Twitter temporal streams [Broniatowski et al., 2013; Smith et al., 2015]. Apart from influenza, Paul and Dredze [2011] employed topic modeling on health-related tweets to detect references of ailments such as allergies, obesity and insomnia. They also incorporated prior knowledge into this model for tracking illness activities over times, identifying behavioral risk factors, localizing geographic regions of illness occurring, and measuring symptoms. De Choudhury et al. [2013b] presented a population-level analysis of depression by leveraging signals of social activity, emotion, and language manifested on Twitter. Culotta [2014] performed a large-scale linguistic analysis on tweets posted from the top 100 most populous counties in the U.S., and found that Twitter information has a significant correlation with 6 of the 27 health statistics, including obesity, health insurance coverage, ingestion of healthy foods, and teen birth rates. Population-level food consumption and dietary choices have been investigated based on social media data as well [Abbar et al., 2015; De Choudhury et al., 2016b].

2.2.2 Online Intervention

In addition to identifying people at risk of diseases, social media also provide an opportunity to enhance individuals' health through online intervention [Dölemeyer et al., 2013; Hay and Claudino, 2015; Latkin and Knowlton, 2015; Rice et al., 2016; Valente, 2012; Wicks et al., 2010]. Online interventions can be delivered in a variety of different ways, from screening assessments to structured programs on managing health conditions, and from guided self-help to expert-system-based treatments [Dölemeyer et al., 2013; Latkin and Knowlton, 2015; Saddichha et al., 2014; ter Huurne et al., 2017]. To date, the most widely used approach is building online self-help (peer-to-peer) communities on general social media platforms like Twitter and Facebook, either by health care professionals/organizations or by sufferers. These online communities play a range of roles in improving ailment recovery and coping with health problems, e.g., sharing information that promotes a healthy lifestyle [De Choudhury, 2015; Johnson and Ambrose, 2006], facilitating communication among sufferers with similar health conditions (as well as health care professionals) in exchanging opinions on treatment options [Eysenbach et al., 2004; Hartzler and Pratt, 2011; Skeels et al., 2010], offering cognitive and affective support for sufferers to reduce sufferers' stress and isolation [Grimes et al., 2010; Johnson and Ambrose, 2006], enabling a management on chronic medical conditions [Fergie et al., 2015; Huh and Ackerman, 2012; Huh et al., 2014; Mankoff et al., 2011], collective sense-making and constructing health knowledge [Mamykina et al., 2015]. Also, there exist some expert-system-based interventions with targeted clients and structured programs, such as *Student Bodies* which uses cognitive-behavioral principle to educate individuals at risk of ED with tailored content and monitor individuals' behaviors, so as to improve their body image and reduce ED symptoms [Saekow et al., 2015].

Another potential use of social media for online interventions is to exploit social network data to promote behavior change at a community scale. Given the fact that social media facilitate social connections among disordered peers [Mabe et al., 2014; Syed-Abdul et al., 2013], and growing evidence on offline social networks showing that people can be influenced by their social networks to adopt new behaviors that effect their personal health [Christakis and Fowler, 2007, 2013], an area that has attracted increasing attention over recent years is community-oriented network interventions which exploit social networks among individuals to accelerate their behavior change and promote organizational well-being [Latkin and Knowlton, 2015; Valente, 2012]. A widely used approach in these network interventions is to identify community opinion leaders based on network attributes, such as those with a large number of ties or high centrality, and train these opinion leaders as change agents to promote behavior change in the whole community [Latkin and Knowlton, 2015; Valente and Pumpuang, 2007].

However, using online communities to develop and deliver successful interventions requires stability and frequency of interactions within these communities themselves [Cobb et al., 2010; Latkin and Knowlton, 2015]. For communities with a very high dropout rate, it is unlikely that members will have adequate opportunity to promote a target behavior change. Attrition (i.e. participants stopping usage or are lost in follow-ups) has been identified as a crucial issue in the efficacy of online interventions [Eysenbach, 2005; Laranjo et al., 2014; Williams et al., 2014], since cost-effectiveness is largely reduced for population-level interventions as the number of people reaping their benefits goes down [Vinkers et al., 2013]. A meta-analysis of 22 studies found that all studies suffered from decreased participation throughout the intervention period, with 12 studies reporting rates of more than 20% [Williams et al., 2014]. Despite such high attrition rates, characteristics that differentiate dropouts from completers at various time points in an online intervention are still unknown in the literature [Gow et al., 2010; Harvey-Berino et al., 2004], even under-explored in the research on traditional face-to-face interventions on various behavior-related conditions, such as obesity, smoking and alcohol misuse [Jiandani et al., 2016; Vinkers et al., 2013].

2.2.3 Strengths and Weaknesses

Social media data can potentially complement conventional data in health care studies through several strengths. First, data on social media is routinely recorded and preserved in general, and hence analysis based on such data alleviate the hindsight bias in retrospective analyses [De Choudhury et al., 2016a]. Second, a rich repository of social media data provides a large amount of finer-grained longitudinal features which are useful for identifying, tracking and predicting health risks for large populations [De Choudhury et al., 2013c]. Third, the (semi-)anonymous nature of social media platforms encourages people to naturally socialize and self-disclose [Bazarova and Choi, 2014], which allows professionals to study individuals' health problems by utilizing naturally occurring data in a non-reactive way. Finally, as fresh data is generating on social media in real time, automated processing on social media data can facilitate population-level health analysis in a cost-effective and time-saving way, while traditional methods for this purpose are often expensive, time-consuming and showing a significant delay [Harman, 2014].

Also, social media data has weaknesses in health care research. First, the use of social media to disclose individuals' health information may have the potential for negative repercussions due to the breaches of patients' confidentiality and privacy [Von Muhlen and Ohno-Machado, 2012]. Some users may leave social media platforms, enable a higher privacy setting or maliciously produce misleading information after they are aware of the risks of disclosing personal information. Second, due to a substantial amount of noise in user-generated content, health information collected from social media and other online sources often has quality concerns and a lack of reliability [Moorhead et al., 2013]. Third, given the virtual nature of social media, there often exists a challenge to verify how correctly the information found online reflects individuals' offline health states and how effectively social media tools influence users' behavioral changes and contagion in the real world. Finally, while anticipation in online health communities is increasingly common among people with health problems, the population of social media users with a health problem is likely to be a subset of the whole population affected by the health problem. Individuals with some attributes may be more likely to be observed and sampled by researchers, which can lead to selection bias and make a obtained sample not representative of the whole population. For example, people who are older, male and have lower socioeconomic status were less likely to use online resources for health care [Kontos et al., 2014]; those who were exposed to less emotional support were more likely to drop out from an online community [Wang et al., 2012].

2.3 ED Research over Social Media

It comes as no surprise that growing research has focused on using social media data to study ED, as researchers in this area have a long-standing interest in the effect of mass media (such as magazines, television shows, movies and Internet) on body image and eating behaviors [Hogan and Strasburger, 2008; Polivy and Herman, 2002; Reel, 2018]. Past studies have shown that the media play an outstanding role in shaping cultural stereotypes about the aesthetics of body image [Hogan and Strasburger, 2008; Perloff, 2014]. In particularly, advertising slim physical shape of celebrities (such as ultra-thin models) in the media motivates or even forces people to accept the thin-idealized body images as normative [Polivy and Herman, 2002]. Internalization of these distorted images can increase people's dissatisfaction with their bodies, and further drive them to adopt disordered eating behaviors [Perloff, 2014; Polivy and Herman, 2002]

As social media are emerging and replacing traditional mass media as a key source through which people seek information, the role of social media on the development of negative body image and disordered eating behaviors is becoming an increasing focus of research. Compared to traditional mass media, social media platforms have several distinctive attributes (such as interactivity, enhanced sense of presence of users, and visual content) that can lead to higher rates of image internalization and body dissatisfaction [Perloff, 2014; Reel, 2018]. In fact, people affected by ED have a high level of engagement in online ED communities on social media [Wilson et al., 2006]. Thus, active participation in pro-ED online communities has been suggested as a screening factor for ED recently [Campbell and Peebles, 2014]. Such evidence highlights the importance of understanding disordered individuals' engagement on social media.

To date, researchers have carried out studies of ED based on social media data. According to the methods in use, previous studies can be classified into *qualitative* studies and *quantitative* studies. Next, we discuss these studies in detail.

2.3.1 Qualitative Analysis

Psychologists and clinicians have long studied ED based on user-generated data online [Borzekowski et al., 2010; Chesley et al., 2003; Giles, 2006; Wilson et al., 2006]. The focus in this area has often been on pro-ED (e.g., pro-anorexia or pro-ana) communities which are featured by a stance to glorify ED (anorexia in particular) as a legitimate lifestyle choice rather than a dangerous illness [Mulveen and Hepworth, 2006; Overbeke, 2008; Wilson et al., 2006]. A systematic content analysis shown that members of these pro-ED communities actively engaged in sharing "thinspiration" (combined by "thin" and "inspiration", or short as "thinspo") materials that are designed to inspire people to lose weight and become unrealistically thin [Borzekowski et al., 2010]. Other studies extend such analysis on various social media platforms such as Facebook, Tumblr, YouTube and Twitter [Branley and Covey, 2017; Juarascio et al., 2010; Sowles et al., 2018; Syed-Abdul et al., 2013; Wick and Harriger, 2018], confirming the widespread presence of such content online. By interviewing individuals who engaged in an pro-ED community, researchers further established that exposure to thinspo content can exacerbate risk factors of ED [Overbeke, 2008; Ransom et al., 2010; Wilson et al., 2006] including reinforcement of individuals' identity on ED [Giles, 2006; Maloney, 2013], poor body image and thinness adoration [Bardone-Cone and Cass, 2006, 2007], learning and subsequently executing unhealthy methods for weight loss [Norris et al., 2006; Overbeke, 2008; Ransom et al., 2010; Wilson et al., 2006], and maintaining disordered eating [Mabe et al., 2014].

One might wonder why do ED sufferers often engage in pro-ED communities, even though knowing their serious harmfulness. This can be explained by *Goffmans' theory of stigma* [Goffman, 1959]. Unlike physical disabilities, there is a negative social stigma about mental illnesses. People affected by a mental illness are often perceived to have control of their disabilities and being responsible for causing them [Corrigan and Watson, 2002]. A majority of the general public did not sympathize those affected by a mental disorder, instead reacting to mental disability with anger and believing that help is not deserved [Socall and Holtgraves, 1992], though these attitudes have changed due to a better understanding of these disorders obtained over recent years. To minimize stigma, individuals often deny their illnesses and never seek help from health care professionals [Swanson et al., 2011]. As an alternative way, many sufferers seek social support and health-related information from anonymous online communities [Arseniev-Koehler et al., 2016; Gavin et al., 2008; Ransom et al., 2010; Swanson et al., 2011]. According to Goffmans' theory [Goffman, 1959], in groups of people who share the same social stigma, members tend to create a positive self-perception and normalize behaviors in spite of their harmful nature. Acceptance from peers can act as an extrinsic (external) motivation/reward to reinforce members continuously engaging in these groups [Kollock, 1999]. As more new members join, these groups can develop into larger communities and subcultures [Gailey, 2009].

One might also wonder how does exposure to thinspo content affect people's health. The negative effects of exposure to thinspo content often arise from the processes of *social comparison* [Levine and Murnen, 2009; Tiggemann and Zaccardo, 2015]. In social comparison theory [Festinger, 1954], there are two types of social comparisons: downward comparisons and upward comparisons. A downward comparison occurs when people compare to those who are less capable or fortunate than themselves, which can make people to feel better or relieved and thankful for their current states but can also lead to arrogance and selfishness [Wills, 1981]. In contrast, an upward comparison occurs when people compare to those who are more capable or superior than themselves, which can drive people to self-improve but can also lead to lower mood and self-esteem [Collins, 1996]. For most people, exposure to thinspo content can trigger an upward comparison, as people evaluate their appearances by comparing themselves to the cultural ideals of beauty and thinness in the media [Levine and Murnen, 2009]. This is confirmed by experimental evidence that viewing thin ideal images can promote body dissatisfaction and body-focused anxiety [Tiggemann and Polivy, 2010; Tiggemann and Zaccardo, 2015].

Social media can facilitate these social comparisons and reinforce poor body image for several reasons. First, most social media platforms provide a rich body of interfaces for people interact with one another, which largely increases the chance for ready and multiple comparisons [Tiggemann and Zaccardo, 2015]. Second, according to social comparison theory [Festinger, 1954], people tend to compare with those who are similar rather than dissimilar to themselves. Hence, peers appear to be more intended targets than celebrities or models for an appearance comparison [Heinberg and Thompson, 1995]. Past studies have shown that females exposed to photos of attractive peers has lower self-evaluations of their own attractiveness than those exposed to the same photos presented as professional models [Cash et al., 1983]. Social media platforms do not allow people to actively seek peer targets via a search engine, but also routinely recommend potential targets for people by recommendation algorithms. Finally, social media offer greater visibility to popular users and content that received more followers, likes and comments. Thus, people tend to overestimate the prevalence of a risky behavior based on the local observations of their social contacts while without global knowledge of the states of others, which can accelerate the spread of social contagions [Lerman et al., 2016].

In fact, online pro-ED communities have become a public concern and draw widespread criticism, particularly by so-called pro-recovery communities that aim to raise awareness of ED and offer support for people to recover [Branley and Covey, 2017; Lyons et al., 2006; Yom-Tov et al., 2012]. Under pressures from these pro-recovery communities and the general public, several social media platforms have adopted censorship-based interventions for pro-ED communities, e.g., banning pro-ED content and user accounts on Tumblr[1] and Instagram[2] [Casilli et al., 2013; Chancellor et al., 2017, 2016d].

[1] https://staff.tumblr.com/post/18563255291/follow-up-tumblrs-new-policy-against

[2] http://instagram.tumblr.com/post/21454597658/instagrams-new-guidelines-against-self-harm

Despite providing useful insights into online ED communities, these qualitative studies involve intensive manual labor in data collection and validation, e.g., manually coding online content and using surveys or interviews to assess individual behaviors. However, the volume of user-generated content online is explosively increasing, and this trend is likely to continue in the future. Thus, there is a need to devise more effective techniques to boost these analyses on the large and rapidly increasing amount of data. Next, we review prior studies on developing computational techniques to automatically detect and quantitatively analyze ED-related content online.

2.3.2 Quantitative Analysis

The research of ED using quantitative methods originates from the literature of psycholinguistics. Lyons et al. [2006] observed different linguistic markers in Internet self-presentation between self-identified pro-anorexics and self-identified anorexics in recovery. They found that pro-anorexia writers used more positive emotions, lower anxiety, a lower degree of cognitive reflection, and lower levels of self-directed attention than those in recovery. Despite the small sample sizes of the study and lack of a neutral control group, it provides preliminary evidence for distinctive language patterns used by people with different psychological conditions online. These differences were also observed in offline writing tasks. Wolf et al. [2007] implemented a journaling exercise in ED inpatients and found that inpatients used more self-related words, negative emotion words and less positive emotion words. By introducing a control group, Wolf et al. [2013] further confirmed that computerized quantitative text analysis can offer a novel and reliable tool to study people's psychological conditions.

Recently, researchers have extended these studies by using larger datasets and examining a wider range of behaviors on various social media sites. By using several keywords, De Choudhury [2015] collected several thousand of ED-related posts on Tumblr and characterized different patterns of language use between pro-anorexia and pro-recovery communities. Chancellor et al. [2016c] further explored to predict the likelihood of a user in the recovery from ED based on their posts on Tumblr. Yom-Tov and Boyd [2014] found an association between the Internet searching activities on celebrities suffering from anorexia and the searching activities of anorexic practices. Another study examined the differences between pro-ED communities in language use, search behaviors, self-reported weight statues and mood [Yom-Tov et al., 2016]. Very recently, the content of tags on Instagram has been widely used in ED research, e.g., Chancellor et al. [2016a] quantified the severity of ED among pro-ED users based on their usages of ED-related tags; Chancellor et al. [2017, 2016d] examined the content moderation and lexical variation in ED-related content; Chancellor et al. [2016b] measured the characteristics of removed content about ED on Instagram. Furthermore, a randomized controlled trial based on the Bing Ads system revealed that referring users interested in ED-related content to specific pro-ana communities might lessen their maladaptive online search behavior [Yom-Tov et al., 2018].

In addition to content analysis, researchers also explored interpersonal interactions among online ED communities. Oksanen et al. [2015] examined emotional reactions to pro-anorexia and anti-pro-anorexia online content on YouTube using sentiment analysis. They found that anti-pro-anorexia videos gained more positive feedback and comments than pro-anorexia videos. Yom-Tov et al. [2012] studied interactions between pro-anorexia and pro-recovery groups via photo sharing on Flickr. They found that pro-recovery groups tended to post comments on pro-ED content as an intervention for pro-ED groups. Moessner et al. [2018] demonstrated using topic modeling and network analysis methods to analyze communication patterns of a pro-ED community on Reddit, and Tiggemann et al. [2018] studied re-tweeting networks of pro-ED tweets on Twitter.

2.4 Research Gaps

While much progress has been made in ED research based on social media data, there are several research gaps that need to be filled in order to achieve a better understanding of ED and reduce the negative effects of harmful pro-ED content online.

Data Collection: Although recent studies have largely extended traditional data collection methods (e.g., surveys) to gather large samples, the mainstream approach of data collection in these studies is to filter users who post content containing a pre-defined set of keywords related to ED [Chancellor et al., 2016c; De Choudhury, 2015; Oksanen et al., 2015; Yom-Tov et al., 2012]. However, a relatively small set of keywords can hardly characterize the entire community, as people can use a wide range of lexical variants to express the same content online [Chancellor et al., 2017, 2016d; Stewart et al., 2017; Weng and Menczer, 2015]. Even in cases where a complete set of pattern matching rules can be obtained, people who talk about ED online may not suffer from the disease. Thus, these content-filtering based data collection methods often suffer from poor quality of data and can lead to misleading results. In this thesis, we explore an alternative approach to sample people affected by ED on social media.

Social Interactions: Prior studies largely focus on analysis of user-generated content online. Few studies have considered social interactions among individuals. However, social networks play an important role when interpreting health-related behaviors, as our concerns, behaviors and health states are influenced by the network of people with whom we interact [Fowler and Christakis, 2008]. In fact, an inherent nature of social media is interactivity, which allows users create content, conduct conversations with other, and build social relationships. Thus, studying social interactions is an important aspect of the research based on social media data. While recent studies have examined interactions in online ED communities [Moessner et al., 2018; Tiggemann et al., 2018;

Yom-Tov et al., 2012], what dictates the interactions of individuals having different stances on ED is still under-explored. In this thesis, we explore this question by examine social norms in different ED-related communities.

Community Structures: ED-related communities in prior work are confined to groups of users who post certain content that researchers are interested in [Chancellor et al., 2016c; De Choudhury, 2015; Oksanen et al., 2015; Yom-Tov et al., 2012]. This leads to a systematic exclusion of certain individuals who did not post such content from research. So far, the natural groupings among individuals affected by ED online remains unclear. In this thesis, we identify communities of users based on the similarity of users posting interests using unsupervised clustering algorithms, without assuming a priori that communities are featured by a certain posting pattern.

Multiplex Communication: Prior studies either focus solely on a single type of communication (e.g., sharing pro-ED content [Tiggemann et al., 2018]) or do not distinguish different types of information shared in online ED communities [Arseniev-Koehler et al., 2016; Moessner et al., 2018; Yom-Tov et al., 2012]. Yet, few studies have explored interdependencies among different types of communication. Insights into these patterns can help to understand how different information flows co-exist in a community (e.g., a competitive or cooperative co-existence) [Freilich et al., 2011]. This can further facilitate predictions of the community's responses to internal and external perturbations on an information flow [Connor et al., 2017], e.g., estimating if banning communication on a type of content would promote/suppress the communication on other content. In this thesis, we address this gap by characterizing multiplex and dynamic patterns of communication in online ED communities.

Community Attrition: Previous studies have largely focused on examining how people engage in and maintain an online health community, while little is known about how people drop out of such a community. As a dynamic process, people who join and actively engage in a community at earlier stages can have less participation and drop out of the community at later stages. Understanding what determines and accelerates the dropouts of individuals can enhance our knowledge of the dynamics in online communities and facilitate prediction of an community's growth or attrition. In fact, as explained in Chapter 6, studying the attrition process of a harmful or healthy community also has practical implications for disease prevention and online interventions [Eysenbach, 2005; ter Huurne et al., 2017]. In this thesis, we systematically characterize the determinants of dropout behaviors in online ED communities.

In the following, we introduce the theories and techniques that we used to address these research gaps.

2.5 Social Interaction Theories

2.5.1 Two-step Flow of Communication

The two-step flow of communication hypothesis is one of the most applied theories in the impact of social interactions on decision making, which has been rigorously verified in various empirical settings [Brosius and Weimann, 1996; Choi, 2015; Valente and Saba, 1998]. This hypothesis was first proposed by Lazarsfeld et al. [1944] in a voting study finding that personal influence, derived from people's social contacts and friendship networks, strongly affected their voting decisions. This finding led to the two-step flow of communication hypothesis, stating that people are indirectly influenced by mass media through the personal influence of opinion leaders. That is, ideas first flow from the media to opinion leaders and then spread from these leaders to a wider population. This is different from the traditionally one-step flow of the hypodermic needle model [Lasswell et al., 1927] in which people are assumed to be directly influenced by the media.

The original formulation of the two-step flow of communication hypothesis was then refined by Katz [1957]. By reviewing several empirical studies in communication research, Katz [1957] elaborated three aspects of this hypothesis. First, the impact of personal influence can be stronger than that of the mass media, particularly in the case of those who changed their minds during the process of decision-making. Second, opinion leaders are not fixed in a certain group of the population, e.g., opinion leadership in marketing often occurs among older women with larger families, while those in fashions and moviegoing were in young, unmarried girls. That is, opinion leaders differ across different social groups and a leader in one domain is unlikely to be influential in another unrelated domain, showing local leadership or domain-specific leadership. Finally, opinion leaders tend to be those who are more exposed to the mass media, and serve to guide their groups to relevant parts of the outside world.

A central concept in the two-step flow of communication is opinion leaders, a set of individuals influential in a specific domain [Katz et al., 2017; Liu et al., 2017b]. Identifying opinion leaders has attracted considerable interest over recent years [Aral and Walker, 2012; Valente and Pumpuang, 2007], often along with three lines formulated by Katz [1957]: *who one is*, individual personification of certain values, such as charisma, personality traits, or socioeconomic and demographic features; *what one knows*, professional competence of individuals, such as their knowledge, expertise, or ability to offer information or support on an issue; and *whom one knows*, attributes about an individual's position in the social network of a group. That is, individuals can be opinion leaders not only because they have certain characteristics but also because they locate in a proper network position that allows them to effectively spread information [Liu et al., 2017b]. Moreover, due to different interface settings on various social media platforms (e.g., whether friendships are directed or undirected), the characteristics of opinion leaders can be different across platforms, leading to more diverse measures of opinion leaders in online social networks than traditional offline social networks. Although individual characteristics related to opinion leadership can be measured in various ways [Aral and Walker, 2012; Matous and Wang, 2019; Rose and Kim, 2011], centrality measures, such as degree, closeness and betweenness [Freeman, 1978], have been particularly useful for identifying leaders based on their positions in social networks [Liu et al., 2017b; Valente and Pumpuang, 2007].

2.5.2 Incentive Theory

Incentive theory is a theory of motivation used to explain the reasons for people's needs, desires and actions in psychology [Ryan and Deci, 2000a,b]. In this theory, people's actions are driven by a desire for reinforcement or incentives. Such incentives can come from different sources and can be categorized in different ways. The most basic categorization is between *intrinsic incentives*, which refers to an action that is driven by personal interests and internal emotions of actors in doing the action itself, and *extrinsic incentives*, which refers to an action that is driven by external factors, such as a certain outcome, reward, recognition or avoiding punishment [Ryan and Deci, 2000a]. While the two types of incentives contradict each other, they often work together to motivate a person's actions, specifically in cases of continual actions being observed.

Incentive theory has been also widely used to explain people's participation in online communities, such as behaviors on commitment to an online community, coordination or interaction, and member recruitment [Kollock, 1999; Malinen, 2015]. Previous studies have shown that the decision of participation or dropout in online communities can be driven by factors, including personality traits [Orr et al., 2009], interests [Casaló et al., 2013], recognition in a community [Cook et al., 2009; Garcia et al., 2017; Tausczik and Pennebaker, 2012], informational [Xing et al., 2018] and emotional support [Budak and Agrawal, 2013; Wang et al., 2012] from other peers. Orr et al. [2009] performed online questionnaires among 103 students and found that shyness was significantly positively associated with the time spent on Facebook and significantly negatively correlated with the number of Facebook friends. Tausczik and Pennebaker [2012] combined responses to a survey and data on users' behaviors collected online. They found that users with more expertise had higher motivation to help others than those with less expertise, which [Cook et al., 2009] reported that professionals had lower incentives to contribute to a community than amateurs. By considering a user to drop out from a group if the user failed to post within 12 weeks, and measuring the amounts of exposure of the user to content on emotional (i.e., providing understanding, encouragement or caring) and informational support (i.e., providing advice, knowledge or referrals) respectively, Wang et al. [2012] found that users who had more exposure to emotional support were less likely to drop out while exposure to informational support did not show strong effects on dropout. Using a similar way, Xing et al. [2018] found that exchanging informational support with peers with different social roles effect individuals commitment in online health communities via different ways, e.g., requests from periphery users were related to higher community commitment while those from core users were not. Garcia et al. [2017] also suggested that periphery users are more likely to become inactive than core users in online communities.

2.5.3 Social Norms

In sociology, social norms play a critical role in understanding what dictates the interactions of people in social encounters and promotes the creation of roles in society so that people from different levels of social class structure function properly [Parsons, 1937; Scott and Marshall, 2009]. Social norms are often defined as informal rules that guide the behaviors of members in a society [Scott and Marshall, 2009]. In other words, norms are collective representations of acceptable group behavior and individual perceptions of particular group behavior [Lapinski and Rimal, 2005]. These rules can be cultural products such as values, customs and traditions [Sherif, 1936] that characterize individuals' basic understanding of what others do and think that they should do [Cialdini, 2003].

Norms can differ across different groups. Certain norms that run counter to the behaviors of the overarching society or culture may be developed and maintained within a particular subgroup of society. For example, Crandall [1988] found that groups like cheerleading squads, dance troupes, sports teams, sororities had a higher rate of bulimia than society as a whole. To characterize different patterns of norms, according to a psychological definition of social norms' behavioral component [Jackson, 1965], norms can be measured in two dimensions: how much a behavior is exhibited, and how much the group approves of that behavior. To explain social norms from a more theoretical respective, the return potential model (RPM), which plots the change of the amount of group acceptance or approval with the amount of behavior exhibited, has been widely used [Jackson, 1965]. However, the RPM is primarily a descriptive model; it can hardly assess the statistical significance of a acceptance pattern [Nolan, 2015]. Another general framework that can be used to study social norms is the repeated game of game theory [Voss, 2001; Zhang et al., 2010]. Relying on simulations, game-theory based modes provide a powerful and flexible way to test different and complex scenarios. A big challenge of these models is that their built-in assumptions and formulations may not provide an accurate description of the system and result in inaccurate conclusions [Law et al., 1991]. For example, players in a game are often treated as opponents [Martin, 1978; Rubinstein, 1991]. However, the situations in reality can be more complicated, e.g., some players with different interests and motivations may be opponents while others with similar interests may play cooperatively.

2.5.4 Social Influence

Social influence (or peer influence) is the effect of peers on people, particularly describing the impact on individuals who attempt to follow their peers by changing their emotions, opinions and behaviors to conform and gain acceptance or recognition from their peer groups [Brown et al., 1986; Kelman, 1958]. Impacts of peer influence in shaping individuals' behaviors have been examined in various real-world contexts, from academic achievement [Coleman, 1960], personal aspirations [Duncan et al., 1968], job attainment [Granovetter, 1973] to health-related behaviors and outcomes [An, 2015; Christakis and Fowler, 2007, 2008; Costa-Font and Jofre-Bonet, 2013; Fowler and Christakis, 2008].

Beyond in-person interactions, prior studies also suggested the presence of peer influence in online interactions on social media across various domains such as political voting [Bond et al., 2012], viral marketing [Bakshy et al., 2011; Cha et al., 2010], psychological and health outcomes [Jang et al., 2016; Kramer et al., 2014; Liu et al., 2017a]. Notably, Kramer et al. [2014] conducted a controlled experiment that manipulated the extent to which a sample of users were exposed to emotional expressions on Facebook. Their results shown a significantly positive correlation between emotions expressed by others and egos' emotions online, though this experiment raised ethical concerns. Rather than manipulating content exposed to users, Ferrara and Yang [2015] compared the differences of the average sentiments of tweets preceding a positive, negative or neutral tweet and used a null model which reshuffled the tweets that users were exposed to before posting their own tweets to determine the effect size of emotional contagion. Their findings also shown a positive correlation between average sentiments of tweets users were exposed to and those they produced. Other studies also proposed to use weather such as rainfall as an exogenous instrument to people's behaviors such as expressing emotional content and outdoor exercise, and used instrumental variable estimation (which will be introduced below) to quantify the strength of effect of friends' behaviors on an ego's behavior [Aral and Nicolaides, 2017; Coviello et al., 2014].

Also, a large number of studies of peer influence on social media have focused on quantifying influence and identifying influentials [Cha et al., 2010; Garcia et al., 2017; Kwak et al., 2010; Tang et al., 2009], often with a hypothesis that individuals who are more popular or more likely to affect others to adopt certain behaviors have higher social influence. Cha et al. [2010] compared three measures of influence by using the numbers of followers, retweets, and mentions respectively. Results of these measures shown little overlap in top influentials, suggesting that different measures captured different aspects of social influence. Their findings also suggested that influence was not gained spontaneously or accidentally, but through long-term efforts in building reputation focusing on a single topic. Apart from measuring individuals' positions in social networks [Cha et al., 2010; Garcia et al., 2017; Kwak et al., 2010; Suh et al., 2010], prior studies have proposed to identify influential individuals through other dimensions, such as seeding large cascades [Bakshy et al., 2011; Kitsak et al., 2010], information forwarding activity [Romero et al., 2011], and topical interests [Tang et al., 2009; Weng and Menczer, 2015]. For example, Bakshy et al. [2011] defined social influence as a user's ability to post new content that can produce large cascades of reposts, precisely quantified as the number of users who subsequently repost such content. Then, future influence of a user was predicted according to individual features and her/his past influence. They found that it is hard to predict which user and content would produce large cascades. Weng et al. [2010] suggested that social influence is topic-sensitive and proposed a PageRank-based algorithm, TwitterRank, to incorporate both the topical similarity and the link structure between users. Other studies found that people had different levels of influence on different topics [Tang et al., 2009], and highly topical diversity helped a hashtag grow popular but did not help an individual to gain social influence on Twitter [Weng and Menczer, 2015].

2.5.5 Homophily

While the theory of social influence (or contagion) argues that social connections lead to similarity among friends, there is another theory claiming that similarity breeds connections [McPherson et al., 2001]. This theory is known as homophily (also known as selection in sociology and assortative mixing in network science [Newman, 2002]), which refers to the tendency of individuals to connect with others who share similar characteristics [McPherson et al., 2001]. In this theory, people tend to interact and form social relationships with others who have already shared common attributes, such as geographical locations, demographics, interests, attitudes and values, with them. The presence of homophily in social networks has been discovered in a range of observational and experimental studies [Aiello et al., 2012; Aral et al., 2009; Fiore and Donath, 2005; Gallos et al., 2012; Maldeniya et al., 2017; McPherson et al., 2001; Şimşek and Jensen, 2008; Zhou et al., 2018]. As identified by Manski [1993], influence and homophily are two common hypotheses explaining that individuals belonging to the same group tend to behave similarly[3].

However, fully distinguishing homophily and influence is hard in social network studies, as both two processes are often mixed together [Aral et al., 2009; Crandall et al., 2008; Lewis et al., 2012; Shalizi and Thomas, 2011]. To separate the effects of homophily from those of influence, Aral et al. [2009] used the propensity score estimation [Rosenbaum and Rubin, 1983] based on a large set of an individual's personal and network attributes to match pairs of users who shared similar attributes. Then, the difference of paired individuals in adoption of a produce was assumed to solely associate to the presence

[3] Manski [1993] categorized homophily effects into two sub-types: correlated effects which appear when individuals in the same group behave similarly because they share similar individuals characteristics, and contextual effects which appear when individuals behave similarly because their groups share similar characteristics. We here do not distinguish these sub-types for simplicity.

of an individual being exposed to their friends' adoption behaviors, which allows for an estimate of the proportion of association that is caused by influence, but excluding the proportions attributable to homophily. Although the authors included a large set of observed covariates to control the effects of homophily, their efforts may be inadequate if any unobserved factors can influence both tie formation and produce adoption. Another notable work [Lewis et al., 2012] employed an stochastic actor-based model [Snijders et al., 2010] to examine the effects of homophily and influence on the Facebook activity among college students over 4 years, while this method is applicable in principle to small networks with a relatively small number of nodes (about 1,000) [Snijders et al., 2010].

2.6 Content Analysis

2.6.1 Topic Detection

Understanding what people talk about on social media is a first step to assess the effects of online information on people's health. By meking personal contacts with several pro-anorexia groups on Facebook and MySpace to obtain access to analyze the content generated in these groups, Juarascio et al. [2010] found that social support and ED specific content were two main themes emerged from the content analysis. Wolf et al. [2013] analyzed pro-ED, recovery and control blogs relying, finding that ED-related blogs have a stronger occupation with food, weight, and body shape, but with less references to other areas of life, e.g., school. Recent studies [Sowles et al., 2018; Wick and Harriger, 2018] further shown that concerns on eating and body shape were the most prevalent topics in the content of online pro-ED community and such content often displayed guilt about eating, secretive eating and feeling fat. These methods however often involve intensive manual labor to code the themes of content, which can hardly deal with a large body of data and obtain a large-scale view on the content shared in online ED communities. In this thesis, we explore using computational methods to automatically extract topic structures from online content.

A common approach for detecting topics in texts is topic modeling, a statistical technique to extract latent topics from a collection of documents [Blei, 2012]. The oldest topic modeling approach is the Latent Semantic Analysis (LSA) which decomposes document-term matrix X into a product of two low rank matrices $X = U \times V$using singular value decomposition (SVD) [Dumais, 2004]. A major limitation of this approach is that the generated topics are not interpretable, e.g., decomposed components might be negative. To track the problem, the Probabilistic Latent Semantic Analysis (PLSA) uses a probabilistic model to characterize the relations among words, topics and documents [Hofmann, 2017]. Unlike LSA that downsizes the occurrence tables based on linear algebra, PLSA models the probability of each co-occurrence (w, d) between words w and document (d) as a mixture of conditionally independent multinomial distributions:

$P(w, d) = \sum_c P(c)P(d|c)P(w|c) = P(d) \sum_x P(c|d)P(w|c)$, where c denotes the topic of word w. For each document d, a latent topic is chosen according to $P(c|d)$ and a word is then generated from the topic according to $P(w|c)$. These probabilities can be learned using the Expectation-Maximization (EM) algorithm [Dempster et al., 1977]. However, PLSA is not a generative model of new documents, as the prior probability of a document $P(d)$ is pre-determined in a dataset. To address this limitation, Latent Dirichlet allocation (LDA) uses a Dirichlet prior on the document-topic and word-topic distributions, which enable this model to have better generalization, particularly on generating new documents [Blei et al., 2003]. LDA is a flexible model and can be easily extended, e.g., including a correlation structure of topics [Blei and Lafferty, 2006], modeling topics in a hierarchy way [Shu et al., 2009], and nonparametric extensions of LDA [Paisley et al., 2015]. Despite the wide use in text mining, most topic models are proposed for processing documents that are sufficiently long to extract robust contextual statistics. Prior studies [Alvarez-Melis and Saveski, 2016; Hong and Davison, 2010; Steinskog et al., 2017] have shown that topic models lead to topics that are uninformative and hard to interpret when applied on short documents.

A second method for topic detection is document clustering [DeMasi et al., 2016; Ferrara et al., 2013; Ifrim et al., 2014; Petrović et al., 2010], in which a document is represented as a vector of features (such as the frequency of a term in a document [Petrović et al., 2010], n-grams [Aiello et al., 2013], metadata like hashtags [Ferrara et al., 2013]) and documents with similar features are grouped into a topic by clustering algorithms such as k-means [DeMasi et al., 2016; Ferrara et al., 2013]. Conventionally, each term is represented as a unique one-hot vector and each document is represented as a bag-of-words (BOW). However, this method often suffers from the problems of data sparsity, and it fails to capture the semantic relatedness between words, such as polysemy and synonymy. Text embedding methods have been shown to be effective to address these problems by learning low-dimensional representations for words and documents, such that semantically similar words and documents have similar representations [Le and Mikolov, 2014; Mikolov et al., 2013b]. Moreover, embedding models leverage the word co-occurrences within small sliding windows for representation learning, which further enables these models to (at least partially) capture the information on word orders, in the same way as n-gram models. Currently, continuous bag-of-words and skip-gram are two widely used embedding models, where CBOW predicts a target word from a window of surrounding context words while SG uses the target word to predict context words [Mikolov et al., 2013b]. Due to the unsupervised learning manner, embedding methods are generic and have boosted the performance of many natural language processing tasks, such as latent semantic analysis [Mikolov et al., 2013a], syntactic parsing [Socher et al., 2013] and machine translation [Zhao et al., 2015]. The word embedding models have been extended to go beyond word level and learn sentence-level or document-level representations [Le and Mikolov, 2014; Socher et al., 2013]. Also, some supervised embedding methods that incorporate the label information of training data have been proposed [Kuang and Davison, 2017; Li et al., 2016; Nam et al., 2016; Tang et al., 2015].

Another approach identifies topics by detecting densely connected clusters in a graph of correlated keywords that are extracted from documents [Agarwal et al., 2012; Tang et al., 2009; Weng and Menczer, 2015]. This approach builds on the topic locality (or topicality) assumption which refers to the phenomenon that most Web pages are likely to link with related content in the Web context [Davison, 2000]. The effect of topic locality is used in collaborative filtering [Goldberg et al., 1992], topical/focused crawlers [Menczer and Belew, 1998], Web page classification and tagging [Qi and Davison, 2009; Schifanella et al., 2010]. In the context of social media like Twitter, topic locality describes the hypothesis that semantically similar tags tend to be used in the same posts and hence to be close to one another in the tag co-occurrence network [Weng and Menczer, 2015].

2.6.2 Sentiment Analysis

Past work on anorexia-related misinformation propagated through YouTube videos found that pro-anorexia videos were less common than informative videos, while pro-anorexia content was highly favored and rated by its viewers [Syed-Abdul et al., 2013]. This finding highlighted the effects of audience' attitudes on the diffusion of health-related information. To quantify people's attitudes, a common approach is sentiment analysis (also known as opinion mining) which applies natural language processing (NLP), text analysis and computational linguistics to identify opinionated information from user-generated content and determine the opinion or sentiment polarity of a author towards some topics [Pang and Lee, 2008]. Sentiment analysis within social media can capture the public attitudes on political issues like election [Tumasjan et al., 2010] and public health issues like adverse drug reactions [Korkontzelos et al., 2016], even though handling negations, jokes, exaggerations, and sarcasm are still challenging in such a analysis.

Existing methods for sentiment analysis on social media can be classified into four classes, i.e., *machine learning*, *lexicon-based*, *hybrid* (machine learning and lexicon based), and *graph-based* methods [Giachanou and Crestani, 2016]. Most machine learning methods built supervised classifiers that predict the polarity of a given text based on a set of features extracted from the textual content [Aston et al., 2014; Da Silva et al., 2014; Go et al., 2009; Hassan et al., 2013; Kiritchenko et al., 2014]. These classifiers are often trained via a training dataset in which each textual document is labeled with a polarity on a multi-way scale (such as positive and negative, or rating scales). Recently, researchers have intensively exploited deep learning techniques which use a deep neural network with multiple processing layers to model high-level abstractions of data [LeCun et al., 2015], so as to enhance the performance of opinion mining tasks [Tang et al., 2014; Vo and Zhang, 2015]. The lexicon-based methods infer the polarity of sentiment based on a manually or automatically built dictionary of positive and negative words [Ding et al., 2008; Thelwall et al., 2010; Turney, 2002]. Some widely used sentiment lexicons include SentiStrength [Thelwall et al., 2010], SentiWordNet [Baccianella et al., 2010], AFINN [Nielsen, 2011] and MPQA [Wiebe et al., 2005]. Hybrid approaches combine machine learning and lexicon-based methods [Ghiassi et al., 2013; Khan et al., 2014; Kumar and Sebastian, 2012]. For example, Ghiassi et al. [2013] used a n-grams model to develop a Twitter-specific lexicon and then incorporated this lexicon into a dynamic artificial neural network to perform sentiment classification. Khan et al. [2014] presented a hybrid method combining emoticon and lexicon-based classifier.

Rather than exploiting textual data, the graph-based methods exploit social relations to perform sentiment analysis, based on the assumption that people influence one another [Cui et al., 2011; Speriosu et al., 2011; Tan et al., 2011]. A representative work in this line [Speriosu et al., 2011] leveraged label propagation over a graph that model users, tweets, word unigrams, word bigrams, hashtags, and emoticons as nodes, in which users are connected based on the Twitter follower graph, users are also connected to the tweets they created, and tweets are connected to the unigrams, bigrams, hashtags and emoticons they contain. Before label propagation, the graph is seeded with several sources of prior information, including the polarity values in the OpinionFinder system [Wilson et al., 2005], the known polarity of emoticons, and automatically assigned labels that are trained by a maximum entropy classifier. Tan et al. [2011] used graphical models incorporating social network information and demonstrated that information of social relationships can be used to improve user-level sentiment analysis, compared with a method only using textual information.

2.6.3 Language and Psychology

Language is one of the most common ways for people to translate their internal thoughts and emotions into a form that others can understand [Tausczik and Pennebaker, 2010]. That is, the usage of language in people's talks and writings provides a window into their emotional and cognitive worlds [Pennebaker et al., 2007]. Over the last several decades, researchers have shown that the language people use is strongly correlated with their physical and mental health [Gottschalk and Gleser, 1969; Stone et al., 1966]. More recently, a rich body of research has provides useful insights into human psychology by examining language use [Pennebaker et al., 2003; Schwartz et al., 2013; Tausczik and Pennebaker, 2010]. A typical approach to measure psychological attributes based on language involves counting word usage over pre-defined categories of language [Schwartz et al., 2013]. For example, we can categorize "dish", "eat", and "pizza" into a *ingestion* lexicon, and count how often words in the lexicon are used by two different individuals in order to examine who talks more about the *ingestion*. The most widely used lexicon is Linguistic Inquiry and Word Count or LIWC, developed by human judges designing categories for common words over decades [Tausczik and Pennebaker, 2010]. The 2007 version of LIWC (used in this thesis) contains 80 output variables including 4 general descriptor categories (total count of words, number of words per sentence, percentage of words captured by the lexicon, and percent of words longer than six letters), 22 standard linguistic dimensions (e.g., percentage of words that are pronouns, articles, auxiliary verbs, etc.), 32 word categories tapping psychological constructs (e.g., affect, cognition, and biological processes), 7 personal concern categories (e.g., work, home, and leisure activities), 3 paralinguistic dimensions (assents, fillers, and nonfluencies), and 12 punctuation categories (periods, commas, etc.) [Pennebaker et al., 2007].

Pennebaker and King [1999] performed one of the first applications of LIWC by examining words in a variety of contexts including diaries, writing assignments, and journal abstracts. Their results shown good internal consistency across these contexts, revealing patterns such as neurotic people using more negative emotion words and agreeable individuals using more articles. By examining essays written by students with different levels of depression, Rude et al. [2004] found similar results to Pennebaker and King [1999] and that depressed people used more first-person singular and more negative emotion words than non-depressed individuals. Recently, the emergence of social media has provided a rich body of personal discourse on everyday concerns [Schwartz et al., 2013], which allows the applications of LIWC to go beyond laboratory studies. Researchers have applied LIWC to examining personality traits based on people's language use in online blogs [Yarkoni, 2010], text messages [Holtgraves, 2011] and posts on Facebook [Sumner et al., 2011]. Findings of these studies largely confirmed past results of LIWC over offline writing data, but also shown new results such as neurotic individuals using more acronyms online [Holtgraves, 2011]. Other studies further demonstrated that LIWC outputs capture diagnostic information about a range of psychological states such as psychiatric disorders [De Choudhury et al., 2013b, 2014; Harman and Dredze, 2014] and suicidal ideation [De Choudhury and Kıcıman, 2017].

2.7 Network Analysis

2.7.1 Graph Representation

A social network is a social structure comprising a set of social actors (e.g., individuals and organizations), and sets of dyadic ties or social interactions among actors [Wasserman, 1994]. Generally, social networks are represented as a graph $G = (V, E)$, where V denotes a set of nodes and E denotes a set of edges [Newman, 2010]. Each node in V denotes an object of interest, such as an individual in a social network. Each edge in $E = \{e_{i,j} | i, j \in V\}$ denotes a relation that node i connects to node j, such as individual i befriending individual j in a social network (and hence $E \subseteq V \times V$). A graph is undirected if its edges have no orientation, while a graph is directed if each of its edges is associated with a direction. For an efficient computation, graphs are typically represented by an adjacency matrix A, where each entry $A_{i,j}$ (row i, column j) annotates the number of edges from node i to node j. For special cases where $A_{i,j} \in \{0, 1\}$, a graph is called unweighed graph, and weighted graph otherwise. In undirected graphs, $A_{i,j} = A_{j,i}$, while $A_{i,j} \neq A_{j,i}$ in directed graphs. Basic concepts in network analysis are introduced in Appendix A.

2.7.2 Null Models

In network analysis, null models are in particular important as they are useful to evaluate non-trivial network properties that cannot be quantified directly because of the complexity of a system in question [Karrer and Newman, 2011; Maslov and Sneppen, 2002; Newman et al., 2001; Zhai et al., 2018]. A widely used null model of a network is the configuration model, which generates random networks by keeping the same degree of all nodes in the original network, while rewiring the edges among nodes at totally random [Maslov and Sneppen, 2002]. Measuring a particular property of these randomized networks allows to obtain the average expectation and the standard deviation for the property. Then, the relevance of this network property can be quantified by comparing the difference between the quantity observed in the original network and those observed in the randomized networks. This null model has been widely used in quantifying complex network characteristics such as community structure [Newman, 2006a], assortativity [Newman, 2003], and motif detection [Schlauch and Zweig, 2015].

The concept of null model has been generalized to be a randomized version of a network that matches the original network in some of its structure features, while that is otherwise taken to be an instance of a random network [Newman and Girvan, 2004]. Various null models have been proposed to evaluate different network properties of interest. For example, Opsahl et al. [2008] proposed several null models for weighted networks to quantify the tendency of prominent elements to form clubs with exclusive control over the majority of a system's resources. Croft et al. [2011] used a node-label permutation model to test whether some individuals were more likely to occupy some specific positions in a network than expected. A generalization of random geometric graphs was proposed to model disease propagation on populations [Estrada et al., 2016]. Thus, null models have been a powerful tool in analyzing the structures and dynamics of complex networks.

2.7.3 Multilayer Networks

As big and multidimensional data sets become growingly available in recent years, partly because they are increasingly collected through cheap and numerous information-sensing devices such as mobile devices and Internet-service logs, there are increasingly attempts to use more complicated but more realistic network frameworks (beyond a single graph) to model information in different dimensions and represent real-world systems [Kivelä et al., 2014; Mondragon et al., 2018]. One of the most popular frameworks is so-called multilayer networks, in which a set of nodes are connected in different layers by links denotes interactions of different types [Boccaletti et al., 2014; Kivelä et al., 2014].

Unlike traditional monolayer networks in which actors are connected by a single type of ties [Newman, 2010], multilayer networks explicitly incorporate multiple channels of connectivity and provide a natural way to describe systems interconnected through different types of ties [Boccaletti et al., 2014]. For example, in social networks, two individuals know each other because they are friends, while two other individuals know each other because they co-work in the same octogenarian. To fully represent the complexity of this social network, we can categorize ties based on the nature of the relationships and represent each type of relationships in a different layer [Kivelä et al., 2014]. In contrast, ignoring the difference of relationships and aggregating all types of relationships into a single-layer network can lead to a substantial loss of information [De Domenico et al., 2015]. This multilayer network framework has been provides useful insights into systems such as social [Nicosia and Latora, 2015], biological [Bentley et al., 2016], infrastructure [Buldyrev et al., 2010] and transportation [De Domenico et al., 2014] networks.

Following Nicosia and Latora [2015]'s notation, a multilayer network consists of N nodes and M layers, which can be described by a set of M adjacency matrices (i.e., a tensor), one for each layer, $G = [A^{[1]}, A^{[2]}, ..., A^{[M]}] \in \mathbb{R}^{N \times N \times M}$. Each layer $A^{[\alpha]}$ is a directed or undirected, weighted or unweighted network, in which a link $a_{ij}^{[\alpha]}$ runs from node i to node j if i connects with j at layer α and a node is said to be active at a layer if it connects with at least one other node at this layer. Based on this notation, traditional metrics that are used to characterize the structural properties of a monolayer network can be extended to the context of multilayer networks. For example, the degree of a node i in a multilayer networks is the vector $k_i = (k_i^{[1]}, ..., k_i^{[M]})$ [Battiston et al., 2014; De Domenico et al., 2013]. By aggregating the vector-type degree of a node, we obtain the overlapping degree of node i, as $o_i = \sum_{\alpha=1}^{M} k_i^{[\alpha]}$ [Battiston et al., 2014]. Similar to a monolayer network, a geodesic between two nodes i and j in a multilayer network is one of the shortest path that connects i and j, while a path in multilayer networks can contain two types of links, namely interlayer and interlayer links [Berlingerio et al., 2011]. De Domenico et al. [2013] introduced a definition of modularity for multilayer networks in which a null model is obtained by randomly rewiring connections in a tensor.

One of the most important tasks in multilayer-network analysis is to measure correlations of structural properties of networks across different layers. These correlations make multilayer networks encode more information than single layers taken in isolation [Boccaletti et al., 2014]. As not all nodes are active in all layers, a first correlation is the pairwise multiplexity [Nicosia and Latora, 2015] which quantifies the correlations of activities of nodes across layers by the fraction of nodes that are active at pairwise layers in all nodes of a multilayer network. A second type of correlations that are widely considered is inter-layer degree correlations. These correlations are used to identify whether hubs in one layer are also the hubs, or low-degree nodes, in another layer, which can be quantified by the Pearson, the Spearman or the Kendalls correlation coefficients between the degree sequences $\{k_i^{[\alpha]}\}$ and $\{k_i^{[\beta]}\}$ in two layers α and β [Nicosia and Latora, 2015]. A third correlation is link overlap which is to capture whether the connectivity patterns in different layers are correlated. For example, we may have a number of friends with which we communicate through several channels such as emails and phones, which indicates that the email social network has a overlap with the phone network [Boccaletti et al., 2014]. The link overlap can be quantified by several ways, such as the absolute number of links present at the same time in two different layers [Bianconi, 2013] and the Jaccard index of links in two layers [Szell et al., 2010]. In weighted multilayer networks, the weights of links in different layers can also be correlated with one anther [Menichetti et al., 2014; Mollgaard et al., 2016]. These correlations can be measured by the pairwise Pearson correlation coefficients of links weights at two layers [Mollgaard et al., 2016] or the distribution of strengths that a node has in different layers [Menichetti et al., 2014].

2.8 Statistical Techniques

2.8.1 Classification Analysis

In statistics and machine learning, classification is a task of automatically categorizing new objects, on the basis of a training set of objects with known category memberships. As a supervised learning approach, classification requires a set of pre-defined categories and labeled observations beforehand to train a classification model or classifier. For example, given a set of users belonging to two classes, either disordered or healthy, predicting if a new user is disordered or healthy lays out a classification task. Common classifiers include Support Vector Machines [Cortes and Vapnik, 1995], Naive Bayes [Russell et al., 2003], Maximum Entropy [Malouf, 2002], k-Nearest Neighbors [Altman, 1992], etc. To obtain a generalizable evaluation, a classifier often runs with k-fold cross validation. The training data is randomly divided into k fold and each fold contains approximately the same percentage of observations in each class. At each run, the classifier is trained on k-1 folds and tested on the rest one. Repeating this process k times until each fold has been tested, the final evaluation is the average results of k runs.

Given a collection of objects with observed class labels $C \in \{c_1, c_2, ..., c_n\}$ and corresponding predicted labels $P \in \{p_1, p_2, ..., p_n\}$. Accuracy is the ratio of correctly predicted objects in all tested objects.

$$accuracy = \frac{1}{n}|\{c_i|c_i = p_i, 1 \leq i \leq n\}| \tag{2.1}$$

Table 2.1: Contingency table of inputs and outputs in binary classification.

	Observed positive	Observed negative
Predicted positive	True positive (TP)	False positive (FP)
Predicted negative	False negative (FN)	True negative (TN)

For binary classification (with two classes of positive and negative classes), we can construct a contingency table between inputs and outputs, as shown in Table 2.1. TP, FP, FN and TN are the numbers of intersections between objects from a corresponding row and objects from a correspoding column respectively. Based on these indexes, we can compute precision and recall, two most common evaluating measures for classification.

$$precision = \frac{TP}{TP + FP} \tag{2.2}$$

$$recall = \frac{TP}{TP + FN} \tag{2.3}$$

Typically, high precision is often achieved at cost of low recall. F_1 score is the harmonic mean to combine precision and recall.

$$F_1 = 2 \times \frac{precision \times recall}{precision + recall} \tag{2.4}$$

When the discrimination threshold of a classifier is not determined, we can obtain a set of model outcomes at various threshold settings and use the receiver-operating-characteristic (ROC) analysis to select an optimal model. The ROC curve illustrates the discriminative ability of a classifier by plotting the true positive rate ($TPR = \frac{TP}{TP+FN}$) against the false positive rate ($FPR = \frac{FP}{FP+TN}$). A curve closer to the top left indicates better performance of classification. The ROC plot can be summarized by the area under the ROC curve (AUC) into a single number from 0 (worst) to 1 (best).

2.8.2 Clustering Analysis

Clustering is a task of grouping a set of objects into several clusters such that objects in the same cluster are more similar to one another than those in different clusters [Anderberg, 1973]. As an unsupervised learning approach, clustering does not require pre-defined classes and labeled data for training models. Common clustering algorithms can be categorized into *content-based methods*, such as hierarchical clustering, k-means, PCA and the expectation-maximization algorithm [Bishop, 2006], and *link-based models* such as communication detection methods discussed in Section A.2. The content-based methods often represent an object as a vector of features and group objects based on the similarities of vectors. In these methods, objects sharing similar trails are grouped in the same cluster, and the relationships among different objects are often unknown before the clustering algorithms execute. By contrast, the link-based methods often represent objects as nodes in a graph and cluster nodes based on the structural connections (representing known relationships beforehand) of nodes, although the content-based clustering algorithms can be also used for such purposes. For instance, in a link community detection method, a content-based hierarchical clustering algorithm is used after similarities between pairs of edges in a network are computed [Ahn et al., 2009].

The results of clustering algorithms can be evaluated in two ways: internal evaluation and external evaluation [Pfitzner et al., 2009]. The internal evaluation quantifies a clustering result based on the data that was clustered itself. Methods for such evaluation often assign the best score to the algorithm that generate clusters with high similarity in a cluster and low similarity between clusters, such as the DaviesBouldin index [Davies and Bouldin, 1979], Dunn index [Dunn, 1973] and silhouette coefficient [Rousseeuw, 1987]. Take the widely used silhouette coefficient for example. Given a set of data points $\{x_1, x_2, ..., x_n\}$, the average silhouette coefficient is:

$$s = \frac{1}{n} \sum_i \frac{b_i - a_i}{\max\{b_i, a_i\}}, \tag{2.5}$$

where a_i is the mean distance between a sample x_i and all other points in the same cluster. b_i is the mean distance between x_i and all other points in the next nearest cluster. This coefficient measures how appropriately the data have been clustered by computing how similar an object is to its own cluster compared to other clusters. The score ranges between -1 and 1, where a high value indicates a better clustering.

In external evaluation, clustering results are assessed based on data that was not used in clustering, such as pre-classified observations or benchmark classes created by human. Clustering algorithms are assigned with a high score if they can produce similar clustering structures to these benchmark classes. Common measures for external evaluation include purity [Liu, 2012], F-measure, Dice index [Schütze et al., 2008] and Rand index [Hubert and Arabie, 1985]. Take the Rand index for example. This measure computers how similar the clusters (obtained by a clustering algorithm) are to the benchmark classes, defined as:

$$RI = \frac{TP + TN}{TP + FP + FN + TN}, \tag{2.6}$$

where TP, FP, FN and TN are elements in a contingency table between clusters and benchmark classes, as shown in Table 2.1 but replacing predicted results with clustered results. The adjusted Rand index is the corrected-for-chance version for the Rand index.

2.8.3 Instrumental Variables Estimation

In statistics and econometrics, instrumental variables (IV) approach is widely used to achieve consistent estimates in a causal model containing endogenous variables, where an variable is said to be endogenous if it is correlated with the error term in a regression model [An, 2015; Angrist and Imbens, 1995; Cawley and Meyerhoefer, 2012]. Such correlation can appear when (i) a change in the dependent variable can change the value of any independent variable (simultaneous causality); (ii) there are omitted (or confounding) variables that affect both the dependent and independent variables; or (iii) an accurate measure of one of the independent variables is unavailable (measurement error) [Wooldridge, 2015]. In any of these situations, ordinary least squares (OLS) produces biased and inconsistent estimates [Angrist and Imbens, 1995]. However, achieving consistent estimates may be possible if one has an instrumental variable (or instrument for short) that does not itself belong in the explanatory equation but is correlated with the endogenous explanatory variables, conditional on other covariates. Given a linear model, $Y = \beta_1 E + \beta_2 X + U$ for example, a valid instrument Z must satisfy two conditions:

- **Relevance Condition:** Z must be correlated with the endogenous explanatory variables E, conditional on the other covariates X, e.g., $cov(Z, E) \neq 0$. If this correlation is highly statistically significant, then Z is said to be a strong instrument.
- **Exclusion Condition:** Z cannot be correlated with the error U in the explanatory equation, conditional on the other covariates, i.e., $cov(Z, U) = 0$. In other words, Z cannot suffer from the same problem as the original predictors.

A common method to compute IV estimates is two-stage least squares (2SLS or TSLS). In the first step, an auxiliary linear regression of the instruments and exogenous variables on the endogenous variables runs.

$$E = \gamma_0 + \gamma_1 Z + \gamma_2 X + V, \tag{2.7}$$

where Z denotes the instruments, γs are estimable parameters and V is an error term. In the second step, predicted values for E are obtained (i.e. $\widehat{E} = \widehat{\gamma_0} + \widehat{\gamma_1} Z + \widehat{\gamma_2} X$) and are used to replace the original endogeneous variables E.

$$Y = \beta_0^{'} + \beta_1^{'} \widehat{E} + \beta_2^{'} X + U, \tag{2.8}$$

Intuitively, $\widehat{E}$ capturers the variation of Y due to the shifts of E only induced by Z, not accounted for confounding bias. Since $cov(Z, U) = 0$, we yield $cov(\widehat{E}, U) = cov(\widehat{\gamma_0} + \widehat{\gamma_1} Z + \widehat{\gamma_2} X, U) = 0$. In words, there is no endogeneity issue when estimating the effect of $\widehat{E}$ on Y. Thus, $\beta_1^{'}$, for sufficiently large samples, delivers consistent estimates of the effects of interest. IV approach has been widely used to estimate causal effects when it is unfeasible to conduct a randomized controlled trial in which treatments are randomly assigned by investigators and undertaking an treatment or not is the only thing that differs among different individuals or groups (mainly because of ethical and practical issues) [Chalmers et al., 1981], such as estimating peer effects [An, 2015; Aral and Nicolaides, 2017; Coviello et al., 2014] and medical care costs of health problems [Cawley and Meyerhoefer, 2012].

2.8.4 Survival Analysis

Survival analysis methods are often used to analyze the expected duration of time until an event of interest occurs, such death or failure [Machin et al., 2006; Miller Jr, 2011; Richards, 2008]. A key component in performing such analysis is defining duration or survival time. Taking death as an "event" for example, the survival time of a sample is considered to be the duration from the beginning of an observation to the occurrence of death. However, samples might not experience death during the entire observation period, or samples are lost to follow up during the study [Machin et al., 2006; Richards, 2008]. In these cases, we know that the event of death did not happen when a sample is under observation, while we do not know her/his exact survival time. The survival time of such sample is said to be censored.

To model such information, survival analysis often involves two-variable outcomes $(\delta_i, \tilde{t}_i)$ for each sample, where δ_i is the censoring variable denoting whether the event of interest occurs and $\tilde{t}_i$ is the survival time denoting the length of time until the occurrence of an event. To quantify the proportion of a population that will survive after a certain time, we can define a survival function $S(\tilde{t})$ characterizing the probability that a sample will survive (i.e., not experience a "death event") beyond any give specified time $P(\tilde{T} > \tilde{t})$, i.e., $S(\tilde{t}) = P(\tilde{T} > \tilde{t}) = 1 - F(\tilde{t})$, where $\tilde{T} \in [0, \infty)$ is a random variable on the survival time with cumulative distribution function $F(\tilde{T})$. The nonparametric Kaplan-Meier estimator [Kaplan and Meier, 1958] is often used to estimate and graph the survival function. This estimator gives univariate descriptive statistics for survival data, including survival curves and the median survival time at which one half of the entire cohort experiences an event. To assess overall differences between the estimated survival curves for different groups of samples, the log-rank test can be used [Peto and Peto, 1972].

Apart from descriptive statistics, survival analysis can be also used for predictive analysis, i.e., exploring what and how particular characteristics can increase and decrease the probability of survival [Aalen, 1989; Cox, 1992]. One of the most popular techniques for such purpose is the Cox proportional hazards regression model [Cox, 1992] which relates individual characteristics to a hazard function. A hazard function (or hazard rate) is the instantaneous risk per unit time for an event to occur, given an object has survived up to time $\tilde{t}$, i.e., $h(\tilde{t}) = \lim_{\Delta\tilde{t}\to 0} \frac{S(\tilde{t}) - S(\tilde{t}+\Delta\tilde{t})}{\Delta\tilde{t} S(\tilde{t})}$. The validity of this model however largely relies on the proportional hazards assumption that the ratios of hazard functions (i.e., hazard ratios) for different strata are constant over time. One data does not satisfy this assumption, the proportional hazards model may give misleading results.

The Aalens additive hazards model offers a flexible alternative for modeling associations on the hazard scale [Aalen et al., 2008; Aalen, 1989]. Unlike the proportional hazards model that estimates the hazard ratio, the additive model estimates hazard differences, i.e., the change in hazards due to the change of values for an explanatory variable. The hazards difference is measured in an additive way, which leads to two notable advantages. First, covariates act in additive manner on an unknown baseline hazard function, which can recover a marginal additive hazards model under fairly reasonable assumptions and lend the regression results to a natural interpretation as the excess hazards due to the effect of a covariate. Second, the computational methods for fitting additive hazards regression make it relatively easy to model effects of covariates over time [Aalen et al., 2008]. The additive hazards model has gained increasing attention and has been widely used in survival analysis across different fields [Kim et al., 2016; Tchetgen et al., 2015; Yin, 2007]. Suppose that one has observed independent and identically distributed data on $(\tilde{T}, E, X)$ for n users, where E is the endogenous variables, X is the control variables, and $\tilde{T}$ is the time to event outcome. Let U denote the unobserved error terms. Then, an additive hazards model that estimates the effect of E on $\tilde{T}$ is:

$$h(\tilde{t}|E, X, U) = \beta_0(\tilde{t}) + \beta_e(\tilde{t})E + \beta_x(\tilde{t})X + \beta_u(U|E, X, \tilde{t}), \tag{2.9}$$

where $h(\tilde{t}|E, X, U)$ is the hazard function of $\tilde{T}$ evaluated at $\tilde{t}$, conditional on E, X and U. $\beta_0(\tilde{t})$ is the unknown baseline hazard function, while $\beta_e(\tilde{t})$, $\beta_x(\tilde{t})$ and $\beta_u(U|E, X, \tilde{t})$ are regression functions that measure the effects of their corresponding covariates. All of these functions are allowed to vary freely over time. The model posits that conditional on X and U, the effect of E on $\tilde{T}$ is linear in E for each $\tilde{t}$, although, the effect size $\beta_e(\tilde{t})$ may vary with $\tilde{t}$. A sub-model is the partially-constant hazards model which can be obtained by setting $\beta_e(\tilde{t}) = \beta_e$, where β_e is an unknown constant. However, similar to general regression models, the endogeneity problems can also bias the estimates of an additive hazards model [Chan, 2016; Li et al., 2015; Tchetgen et al., 2015]. To obtain consistent estimates, Tchetgen et al. Tchetgen et al. [2015] proposed a method that incorporates IV estimation in the survival context.

2.9 Summary

In this chapter, we have reviewed previous studied related to this thesis, including the background of ED research, applications of social media in health care research, and the state-of-the-art studies on online ED communities. Generally, most previous studies focus on examining individuals' behaviors in isolation, and largely ignore their social interactions. However, both theoretical analysis and empirical evidence suggested that social interactions are important in understanding people's behavior and health statuses, but also can have practical implications in effective interventions. This thesis attempts to fill in such research gap by performing the following technical tasks.

- Developing an effective data collection method to anatomically sample individuals with ED on social media (e.g., Twitter), as well as their social networking data.
- Characterizing community structures in ED populations on social media and social norms in each community.
- Exploring interdependencies of different types of communication in online ED communities.
- Investigating how personal attributes and social networks can influence individuals' participation in online ED communities.

In the next chapter, we shall introduce our methods for collecting and characterizing ED communities on social media.

Chapter 3

Data Collection

Eating disorders are complex mental disorders and responsible for the highest mortality rate among mental illnesses. Recent studies reveal that user-generated content on social media provides useful information in understanding these disorders. Most previous studies focus on studying communities of people who discuss eating disorders on social media, while few studies have explored community structures and interactions among individuals who suffer from this disease over social media. In this chapter, we first develop a snowball sampling method to automatically gather individuals who self-identify as eating disordered in their profile descriptions, as well as their social network connections with one another on Twitter. Then, we verify the effectiveness of our sampling method by: 1. quantifying differences between the sampled eating disordered users and two sets of reference data collected for non-disordered users in social status, behavioral patterns and psychometric properties; 2. building predictive models to classify eating disordered and non-disordered users based on the assumption that the predictive models could achieve good performance if disordered and non-disordered users display much different attributes on Twitter. Finally, leveraging the data of social connections between eating disordered individuals on Twitter, we present the first homophily study among eating-disorder communities on social media, showing a potential to leverage online social networks to reach eating disordered populations that are often hard to reach via traditional health care services. Our findings shed new light on how an eating-disorder community develops on social media.

3.1 Introduction

Eating disorders (ED) are mental disorders characterized by abnormal attitudes towards food and unusual eating habits [Association et al., 2013; National Institute of Mental Health, 2016]. The most common ED are anorexia nervosa where sufferers restrict their eating to keep low weight, and bulimia nervosa where people repeat cycles of binge eating and purging [Association et al., 2013]. ED can negatively affect a person's physical, psychological and social health. Symptoms of ED include self-starvation, laxative abuse, anxiety, depression, or other extreme behavioral and emotional responses to eating food and gaining weight [National Institute of Mental Health, 2016]. Specifically, ED exhibit the highest mortality rate of any mental illness and 20% of all deaths from anorexia are the result of suicide [Arcelus et al., 2011]. Recently, prevalence of ED has significantly grown, with a 2015 report from the ED charity Beat estimating more than 725,000 people in the UK are eating disordered (ED), in a trend that is increasing over time [Beat, 2015]. More than 85% of those suffering are below the age of 19 and 95% of sufferers are females.

To date, numerous studies in psychiatry, psychology and medicine have been carried out to identify and understand ED [Abebe et al., 2012; Esplen et al., 2000; Swan and Andrews, 2003]. However, these clinical studies are typically carried out by means of surveys and interviews, and these methods are known to present several limitations. First, the denial of illness, ambivalence towards treatment and high drop-out rates make ED populations hard to detect and reach [Guarda, 2008]. Even in cases where data can be collected, participants may conceal their condition and/or its extent, largely reducing the response accuracy and reliability of the data. Second, most of these surveys and interviews are conducted within small groups of individuals in a temporal granularity, which may not be representative of large populations and miss finer-grained longitudinal data [De Choudhury et al., 2013c]. Finally, pre-defined questionnaires alone may be insufficient to reveal the physical and psychological states of individuals.

The usage of social media services, such as Twitter, Facebook and Instagram, to express and exchange thoughts or to document details of daily life has increased steadily over recent years, particularly in young populations. Previous studies have shown that people's behaviors and content generated on social media can indeed be used to infer their mental health states [Chancellor et al., 2016a; Coppersmith et al., 2014; Juarascio et al., 2010]. In this chapter, we show that using analyses based on social media data can help to overcome the limitations of traditional surveys in ED studies, by providing finer-grained features of ED with a large number of samples. Besides, the (semi-)anonymous nature of social media encourages people to naturally socialize and self-disclose [Bazarova and Choi, 2014], and this allows us to study ED by utilizing naturally occurring data in a non-reactive way. Thus, social media data may complement conventional data and help estimating the offline occurrences of ED.

Some computational methods have been proposed to study ED and other mental illnesses over social media recently [Chancellor et al., 2016a,c,d; Coppersmith et al., 2014; De Choudhury, 2015; De Choudhury et al., 2013b, 2014; Harman, 2014]. Most previous studies focus on identifying signs of a mental illness from user-generated content on social media. However, few studies have explored social ties and interactions between mentally ill peers over social media. A rich body of psychological literature shows that people's concerns and behaviors can be influenced by peer pressure [Paxton et al., 1999]. Evidence suggests that the social dimension captured by social networks plays an important role in the studies of life-style related conditions, such as ED and other mental disorders [Kawachi and Berkman, 2001]. In this chapter, we explore an alternative and complementary method to detect ED communities and characterize social interactions among ED peers on social media, focusing on Twitter.

3.2 Related Work

Most previous studies of ED based on social media data come from the psychological and medical communities. Juarascio et al. [Juarascio et al., 2010] make personal contacts with several pro-ED groups on Facebook and MySpace to get access to observe and analyze the groups' content. Wolf et al. [Wolf et al., 2013] analyze pro-ED, recovery and control blogs relying on quantitative text analyses. Syed-Abdul et al. [Syed-Abdul et al., 2013] study anorexia-related misinformation propagated through YouTube videos. Arseniev-Koehler et al. [Arseniev-Koehler et al., 2016] find that many followers of pro-ED users also self-identify with ED by studying 45 pro-ED users on Twitter. Most of these studies use qualitative methods and involve intensive manual labor in data collection and validation. This work contributes to this literature by developing computational techniques to automatically detect and quantitatively analyze ED communities on social media platforms.

In the social computing community, research on ED over social media is limited, especially on Twitter. Twitter, which was created in 2006 and is used by more than 33% of US teens [Arseniev-Koehler et al., 2016], provides *rich* and *public* information of users' social and behavioral context. Analyzing such information can offer a deep insight into ED individuals. Moreover, while many sites such as Facebook and Instagram have taken steps to counteract the diffusion of pro-ED content [Chancellor et al., 2016d], Twitter has taken no actions to limit such content [Arseniev-Koehler et al., 2016]. The latter feature makes Twitter a unique online social media platform to study ED. A recent work measures the psychological features in a "pro-anorexia" community on Twitter [Wood, 2015]. However, the community studied in this work is a group of users who talk about ED in their tweets, and this typically includes not only people who are really affected by the condition, but also a large number of people who casually discuss the disease on a one-off basis. By contrast, in what follows, we study the community of people who self-identify with ED in their profile descriptions, and we show that such information is more reliable to filter users affected by ED on Twitter.

Research on ED has also been carried out on social media platforms other than Twitter. The differences of pro-anorexia and pro-recovery posts on Tumblr are studied in [De Choudhury, 2015]. Another work further explores to predict the likelihood of a user in the recovery from ED on Tumblr [Chancellor et al., 2016c]. Very recently, researchers study ED from the content of tags on Instagram: [Chancellor et al., 2016a] quantifies the severity of ED for a collection of users who post ED-related tags; [Chancellor et al., 2016d] examines the content moderation and lexical variation in ED-related users; [Chancellor et al., 2016b] measures the characteristics of removed content about ED. While the findings in these studies are insightful, they are mostly confined to the study on individuals' behavioral patterns in isolation, without their mutual interactions. This work extends prior work by studying social interactions in ED groups on social media. The work of [Yom-Tov et al., 2012] is the most closely related to ours, as the authors examine the interactions between pro-anorexia and pro-recovery communities on Flickr. We extend this research by exploring individuals' attributes that can facilitate the social interactions in ED communities on social media.

3.3 Data

Our study protocol was approved by the Ethics Committee at the University of Southampton. All data we gathered is *public* information on Twitter, and available via the official Twitter API. Any data that has been set as *private* is not included in our study.

3.3.1 Collecting ED Data

A big challenge faced by research on ED and on other mental illnesses from social media is how to gather a sufficient number of reliable sample individuals with an illness (i.e., positive samples). To date, researchers seek positive samples mainly relying on users' self-reported diagnoses [Chancellor et al., 2016a; Coppersmith et al., 2014; De Choudhury, 2015; De Choudhury et al., 2013b]. The methods of collecting self-reports are broadly classified into two categories. One category is *survey* based methods, in which self-reports are gathered by surveys (via personal contacts or crowd-sourcing) [De Choudhury et al., 2013b, 2014; Juarascio et al., 2010]. Typically, survey based methods are time-consuming and expensive to create a large sample set, and often suffer from small sample sizes. This feature may in fact undermine the statistical significance of the results obtained by these methods. Although some approaches have been proposed to address small sample problems [McNeish, 2016], most surveys have a reactive element which can cause a reaction on some individuals being studied in such a way that the data are affected [Bailey, 2008]. The other category is *information filtering* based methods, in which self-reports are filtered from public information available online by using computational techniques [Chancellor et al., 2016a,b; Coppersmith et al., 2014; De Choudhury, 2015; Harman, 2014]. Most filtering methods use a set of keywords as search queries to filter users whose posts on social media (e.g., tweets on Twitter) contain these keywords. Due to pervasive noise in online information, these methods often suffer from low quality of data. Moreover, existing data collection methods mainly focus on gathering positive individuals, but missing the data of social network connections between individuals.

3.3.1.1 Filtering Self-reported ED Diagnoses

To retrieve reliable ED samples, we draw self-reported diagnoses from users' profile descriptions on Twitter, i.e., the user-defined texts describing their accounts below profile images. This is based on two observations. First, a profile description is often regarded as the biography of a user, while many statements in tweets are less trustworthy. Second, users' personal profiles always pertain to themselves, while people often comment on (or refer to) others in tweets. Thus, the information in profiles can be more indicative of the most genuine aspect of a user than that in tweets [Culotta, 2014]. Table 3.1 shows some examples of diagnostic statements in tweets and profile descriptions. We see that people who talk about ED in tweets may not be affected by ED. It may be difficult to identify a user as ED positive based on one of their posts.

Table 3.1: Examples of self-reported ED diagnoses.

Diagnostic Statements in Tweets	
Joke	My mom and brother thinks I have a **eating disorder** cause I don't eat a lot and when I do eat my mom tells me 'good girl'.
Reference	If you're saying @USER has an **eating disorder**, please unfollow me.
Diagnostic Statements in Profile Descriptions	
ED-related User	Project HEAL Toronto Chapter! Promoting **Eating Disorder** Awareness, Positive Body Image, & Scholarships for Those Battling ED.
ED User	16 years old. **Ednos**. Not skinny enough for **anorexia**. 128 **lbs** 5 foot 7 inch / Yes i look and feel like a wale. I will reach my **UGW**; 99 **lbs**.

Based on the above considerations, we assume that users self-identify as being diagnosed with ED, for the purposes of our study, if their profile descriptions display any ED-diagnosis keyword listed in Table 3.2. These keywords are initialized with the semantically related words of "eating disorder" in the Urban Dictionary[1]. Urban Dictionary is a crowd-sourced online dictionary of slang words and phrases, which is useful to find the words that are currently popular on the Internet. Then, we finalize the ED-diagnosis keywords with the following processing.

1. Remove words that are generic to use in various non-ED contexts, such as "food", "fat" and "self-harm".
2. Remove words that are the abbreviations of ED and ED-related symptoms but have ambiguity, such as "ed" (may denote the past-tense suffix of verbs), "ana" and "mia" (may be a person's name).
3. Track the tweet stream with the keywords after the above refinements via the Twitter Public API, and add words, which have high co-occurrences with the refined keywords

[1] http://www.urbandictionary.com, retrieved January 2016.

in the crawled tweets and can directly map to ED, into the ED-diagnosis keyword set.

However, users whose profile descriptions display ED-related keywords may be therapists, institutes or other organizations related to ED rather than genuine ED sufferers (see Table 3.1 for example). To filter out these ED-related but non-ED users and obtain higher-quality samples, we further add another filtering constraint by requiring that users' profile descriptions should also contain some personal biological information (bio-information), such as body weight. As organizations have no such bio-information and ED therapists are unlikely to disclose bio-information in their profiles, this constraint can help to refine our ED samples. Since ED sufferers generally focus excessively on their body weight [Association et al., 2013; National Institute of Mental Health, 2016], most bio-information keywords we used are weight-related words. Table 3.2 lists the bio-information keywords we used and their descriptions. Some of these words are the acronyms of ED glossary[2] and the remainder are the units of weight (e.g., lbs and kg). Profile descriptions are considered to disclose bio-information if they contain any of these bio-information keywords. We identify a user as ED positive if their Twitter profile descriptions contain both ED-diagnosis information and personal bio-information.

Table 3.2: Keywords of ED diagnoses and bio-information used for filtering ED users.

Category	Keywords
ED diagnosis	eating disorder, eatingdisorder, anorexia, anorexic, anorexia nervosa, bulimia, bulimic, bulemia, bulimia nervosa, ednos, edprob, proana, promia, anamia, askanamia, purge, binge, thinspo, bonespo, legspo.
Bio-information	BMI (Body Mass Index), CW (Current Weight), UGW (Ultimate Goal Weight), GW (Goal Weight), HW (Highest Weight), LW (Lowest Weight), lbs, kg.

3.3.1.2 Snowball Sampling ED Communities

To obtain a larger number of ED users and their social connections, we develop a user collection method based on snowball sampling. In brief, we start from a small set of seed users and expand the user set by a snowball sampling method based on users' following networks on Twitter. Both seed users and users collected in snowball sampling procedures are those who self-identified as disordered in their Twitter profile descriptions. Algorithm 1 shows the detailed steps of this method. The sampling is carried out via breadth-first search. Line 1 to line 5 show the initialization of seed users. Line 6 to line 13 show the snowball sampling to collect ED communities. $Publishers(T)$ denotes the set of unique users who published the set of initial tweets T. Function $ED\_check(u_i, K_d, K_b)$ returns true if the profile description of user u_i contains at least

[2] http://glossary.feast-ed.org/

one ED-diagnosis keyword in K_d and one bio-information keyword in K_b. $V^{(l)}$ denotes the subset of users sampled at level l. $Friends(u_i)$ denotes u_i's friends on Twitter, including followers and followees. In the updates of edges E (line 12), add $e(u_i, u_j)$ if u_j is one of u_i's followers, and add $e(u_j, u_i)$ if u_j is one of u_i's followees. Our crawler implemented based on Algorithm 1 stops after six rounds of snowballing in February 2016. At each sampling stage, we filter out non-English speaking accounts and finally obtain 3,380 unique users.

Algorithm 1: Snowball sampling framework for collecting ED communities on Twitter.

```
   Input: Community graph $G = (V, E)$ with user set $V$ and directed follow edge set $E$; set
          of ED-diagnosis keywords $K_d$; set of bio-information keywords $K_b$.
   Output: $G$.
 1 $(V, E) \leftarrow (\emptyset, \emptyset)$;
 2 Track initial tweet stream $T$ with $K_d$;
 3 for $u_i \in Publishers(T)$ do
 4     if $ED\_check(u_i, K_d, K_b)$ then
 5         $V^{(0)} \leftarrow V^{(0)} + \{u_i\}$;
 6 $l \leftarrow 0$;
 7 while $V^{(l)} \neq \emptyset$ do
 8     for $u_i \in V_l$ do
 9         for $u_j \in Friends(u_i)$ do
10             if $ED\_check(u_j, K_d, K_b)$ and $u_j \notin V$ then
11                 $V^{(l+1)} \leftarrow V^{(l+1)} + \{u_j\}$;
12                 $E \leftarrow E + \{e(u_i, u_j) | e(u_j, u_i)\}$ ;
13     $l \leftarrow l + 1$;
14 return $G$;
```

To inspect the quality of our collected ED data, we develop a labeling system by which the Twitter homepage of each user is automatically downloaded for inspectors. Inspectors annotate each user as to whether a user is suspected of having ED according to their posted tweets, images and friends' profiles. Our annotation results on 1,000 samples randomly selected from our entire user set (N = 3,380) show that almost all of the checked samples are suspected of having ED and 95.2% of the samples are labeled as being highly likely to have ED. This illustrates that the proposed data collection method provides a set of relatively high-quality ED positive samples. Moreover, in the following section, we further use classifiers to verify the reliability of our data collection method.

All the 3,380 users are used as ED-positive samples. For each ED user, we download up to 3,200 (the limit returned from Twitter official API) of their most recent tweets.

3.3.2 Collecting Reference Data

To validate our sampled ED data, we collect two sets of reference data as negative samples. The first set of data is used to compare the differences between ED users and the general population on Twitter, which is built by selecting a set of users at random, labeled as *Random* data. The second set of data is used to compare the differences between ED users and young females, labeled as *Younger* data. As ED develop predominantly in young females [Abebe et al., 2012; Association et al., 2013], the effects of demographics (i.e., age and gender) can be further controlled in comparing ED and Younger users, which helps to explore the key differences between ED and non-ED users.

Random Data. We construct Random data as follows. First, 252,970 initial tweets are randomly sampled via the Twitter Public API. To avoid biases of sampling tweets about specific topics or from specific communities, we collect these tweets in three phases over two weeks. In each phase, only tweets written in English are collected. Second, from the unique users who posted these initial tweets, 3,380 (the same number of ED users) users are randomly selected. Third, to avoid another bias of preferentially sampling users that are very active on Twitter, we further crawl the friends (including followees and followers) of the 3,380 seed users, resulting in 11,102,079 users. Finally, we retrieve historical tweets for these users. Due to the huge number of tweets, we stop this collection process after one-month running, yielding 60,774,175 tweets of 30,684 users.

Younger Data. To target young female populations on Twitter, we use the names of 14 popular artists, ranked by Billboard[3] in 2016, as keywords to track an initial tweet stream of candidate users. This is motivated by the observation that popular music is always a hot topic discussed among young people on Twitter. The initial tweets are also filtered in three phases. Then, we refine the candidate users by filtering female users. To this end, we follow the widely used method in previous work [De Choudhury et al., 2013a; Rao et al., 2010], i.e., 1. select the candidate users that have given a full name in their profiles; 2. perform a lexicon-based method that identifies matches of the first name of each selected user to a dictionary of first names. Our name dictionary is built with the top 200 most popular first names for girls born in 2000s, obtained from the US Social Security Administration[4]. Also, we filter out the accounts that have been verified to exclude celebrity friends of the listed artists. Next, we select 3,380 refined users as seed users and crawl their friends (only the non-verified users with a female name are collected). Finally, we randomly select 37,983 users and download their most recent tweets to finalize Younger data (also collected in one-month running of crawler).

Table 3.3: Statistics of numbers of users, numbers of tweets, and average numbers of tweets per user.

Dataset	#Users	#Tweets	#T/U
ED	3,380	1,797,239	531.73
Random	30,684	60,774,175	1,980.65
Younger	37,983	57,253,947	1,507.36

[3] http://www.billboard.com/artists/top-100/2016

[4] https://www.ssa.gov/oact/babynames/decades/names2000s.html

Table 3.3 lists the statistics on the three sets of data. There are no pairwise intersections between all of the user sets.

3.4 User Characterization

3.4.1 Measures

We first present three types of measures to characterize differences between ED and non-ED users on Twitter.

3.4.1.1 Social Status

Engagement. We define three engagement measures based on the overall volumes of users' followees, tweets and followers respectively, to assess users' states of being engaged on Twitter. However, previous studies report that many statistics of users on Twitter obey power-law distributions [Lerman et al., 2015; Myers et al., 2014]; some Twitter users have posts and social connections that greatly exceed the average. To reduce the skewness towards large values, we employ logarithmic scales and define the engagement degree of user u in terms of statistic s as:

$$Engagement(u, s) = \log\left(1 + \#s_u\right), \tag{3.1}$$

where $s \in \{Followees, Tweets, Followers\}$, and $\#s_u$ denotes the count of s that u has. The constant 1 is added to avoid infinite values in logarithmic scales.

Activity. Similarly, we use the average normalized numbers of followees, tweets and followers per day to measure the activity of a user on Twitter. The activity degree of user u in terms of statistics s is defined as:

$$Activity(u, s) = \log\left(1 + \frac{\#s_u}{t_u}\right), \tag{3.2}$$

where t_u denotes the number of days from the date of u joining Twitter to the date of u's last post.

3.4.1.2 Behavioral Patterns

Tweeting Preference. We use the proportions of tweets that involve different types of behaviors in a user' most recent tweets to measure users' tweeting preferences. The behaviors of interest are: three manners of publishing posts (i.e., originally tweet, re-tweet and quote[5]); two forms of interacting with others (i.e., mention and reply); following the discussions of public topics (i.e., use hashtags); and sharing external links (i.e., append URLs). Note that we only count the mentions that are directly made by users. Any mentions in the original tweets that users re-tweeted are ignored.

Interaction Diversity. We also quantify the ways in which users interact with the external world, specifically on examining whether a user tends to follow a variety of topics or a specific set of topics; whether she/he prefers to interact with various individuals or certain specific individuals. For this purpose, we employ entropy, which is widely used in previous studies [Eagle et al., 2010; Weng and Menczer, 2015], as a diversity measure. Given a user u, we track the sequence of targets of interest to u (e.g., hashtags u used or other users u re-tweeted in the past), denoted as T_u. The interest diversity of u in terms of a type of interactions I is computed by calculating the entropy of such interactions with different targets $v \in T_u$:

$$H(u, I) = -\sum_{v \in T_u} p(I_v) \log p(I_v), \tag{3.3}$$

where $I \in \{Hashtag, Re\text{-}tweet, Mention, Reply\}$, and $p(I_v) = \frac{\#I_v}{\sum_{j \in T_u} \#I_j}$. $\#I_v$ is the number of interactions I with target v, e.g., using hashtag v or re-tweeting user v. Larger entropy values indicate a higher diversity of interests that a user has.

3.4.1.3 Psychometric Properties

We use the Linguistic Inquiry and Word Count (LIWC) lexicon [Tausczik and Pennebaker, 2010] to distill a set of variables that relate to health statistics from users' posts on Twitter. LIWC is composed of 80 psychologically-relevant categories and about 4,500 word patterns[6]. Each word pattern is associated with one or more categories, corresponding to different emotions, linguistic styles, personal concerns, etc. Given a text file, LIWC computes the percentage of words that match each of these built-in categories, and hence produces a quantitative summary of 80 dimensions for the textual data. This lexicon has been widely used to capture people's psychological and health states from the words they use [Coppersmith et al., 2014; Culotta, 2014; De Choudhury et al., 2014].

To facilitate this analysis, we combine the collection of posts generated by each user together as a document. Users' re-tweets are also used in this analysis, as the content users re-tweeted can indicate their interests as well [Metaxas et al., 2015]. Then, we remove mentions, hashtags, URLs and the prefixes of re-tweets (i.e., "RT"). Finally, the pruned documents are split into tokens by white-space characters and the documents

[5] Add comments before re-tweeting to make it a quote tweet.
[6] The version used in this work is LIWC2007.

that have more than 50 tokens are processed with LIWC, resulting in a vector of category percentages for each user.

3.4.2 Classification Framework

Next, we follow prior studies [Coppersmith et al., 2014; Harman, 2014] that use classifiers to further verify the reliability of data sampling method. If the labels of ED users are reliable (i.e., largely different from non-ED users), we expect that the performance of classifying ED and non-ED users would be better than that of classifying two sets of non-ED users.

We build separate binary classifiers to predict the classes of ED, Random and Younger users. Each user is represented as a vector of 97 features obtained from the above measures (6 social-status features; 11 behavioral features; 80 psychometric features). To boost the performance of classification, we standardize the values of each feature by subtracting the corresponding mean and dividing by the corresponding standard deviation. To determine the optimal classification algorithm, we compare several different parametric classifiers and non-parametric classifiers, such as Naive Bayes, Support Vector Machine (SVM) with linear, RBF, Sigmoid and Polynomial (degree=3) kernels and k-Nearest Neighbors with different settings on number of neighbors and distance functions, in our preliminary experiments. The best performing classifier we found is the linear SVM with the default settings in Scikit-learn 0.17 package[7]. As the samples are unbalanced across positive and negative classes, we adjust the regularization constants of different classes with the weights that are inversely proportional to class sizes in the training data [Raskutti and Kowalczyk, 2004]. To obtain more generalizable evaluations, all results are obtained with 5-fold cross validation. Each fold contains approximately the same percentage of users of each class.

3.5 Community Characterization

Individuals connect/interact with others and form communities on Twitter primarily by four ways: “follow”, “re-tweet”, “reply” and “mention”. According to follow, re-tweet, reply and mention ties between users (e.g., who-follows-whom ties), we build four types of weighted and directed networks among ED users, i.e., follow, re-tweet, reply and mention networks, respectively. The re-tweet, reply and mention ties are extracted from users’ most recent posts we retrieved. Typically, users establish different types of relational ties for different purposes, e.g., follow others to maintain a long-term friendship; re-tweet someone to diffuse information; mention and reply to a user for creating temporary conversations. Hence, different types of networks can have different

[7] http://scikit-learn.org/stable/index.html#

topologies and reflect the features of a community from different perspectives [Conover et al., 2011]. Next, we investigate the characteristics of ED communities based on these networks.

3.5.1 Network Characterization

We first examine the topological features of different types of networks built above. We measure networks by using nine widely used metrics: 1. total number of nodes (i.e., users); 2. total number of edges; 3. edge density (the ratio of number of edges to maximum possible number of edges); 4. average shortest path length of connected node pairs; 5. total number of weakly connected components; 6. fraction of nodes in the giant weak component; 7. global clustering coefficient (the probability that two neighbors of a node are connected); 8. reciprocity (the likelihood of nodes with mutual links); 9. assortativity coefficient of degree (the preference for nodes to link to others with similar degree values) [Newman, 2003]. Note that directed networks are considered as undirected ones in measuring global clustering coefficient, and the degree assortativity measured here are the correlations between source in-degree and destination out-degree [Myers et al., 2014].

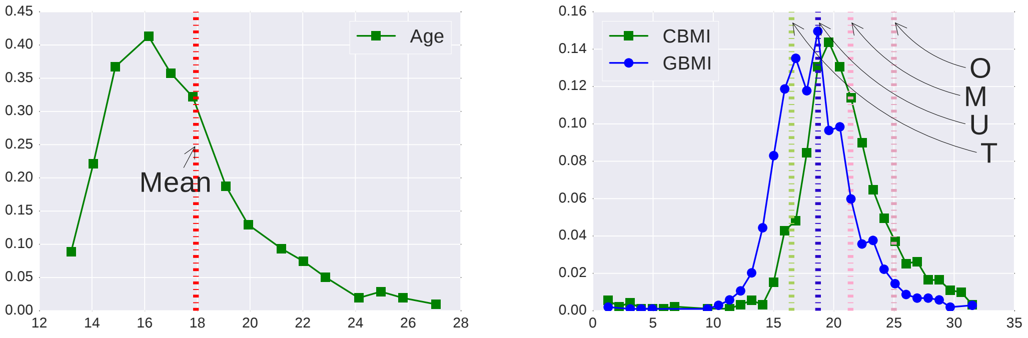
3.5.2 Homophily Analysis

Homophily (known as assortative mixing in network science) is the tendency of individuals to connect with others who share similar characteristics [McPherson et al., 2001]. The properties of homophily can help understand the way a community develops.

To explore homophily in ED communities, we study assortative mixing in their networks built above, focusing on mixing according to social-status, behavioral and psychometric features measured in Section 3.4.1. We quantify the assortativity coefficients of different types of networks by each of these features [Newman, 2003]. To further test the statistical significance of these assortativity outcomes, for each feature, we randomly shuffle users' feature values and re-measure assortativity coefficients based on the shuffled values. We repeat this procedure 3,000 times to yield the simulated distributions of assortativity coefficients for each feature. Finally, we use two-tailed hypothesis tests to assess how significantly the assortativity outcomes differ from the simulated distributions.

Table 3.4: Statistics of bio-information in ED users.

Category	Indicator	#Users	%Users
Observed Information	Age	1,030	30.47%
	Height	1,401	41.45%
	GW	2,781	82.28%
	CW	2,238	66.21%
	LW	466	13.79%
	HW	1,296	38.34%
Inferred Information	GBMI	1,168	34.56%
	CBMI	1,025	30.33%



(a) Age

(b) BMIs

Figure 3.1: Probability density functions of ages and BMIs. "T", "U", "M" and "O" mark thinness, underweight, median and overweight cut-offs from WHO.

3.6 Results

3.6.1 ED Validation with Bio-information

We first validate our ED data from users' bio-information. We build several regular expressions to extract ED users' bio-information, such as age, height, GW, CW, LW and HW (see Table 3.2 for notations), from their profile descriptions. According to the values of CW, GW and height, we further infer users' goal BMI (GBMI) and current BMI (CBMI) values respectively. Table 3.4 shows the number and percentage of users that have information related to each indicator. We see that the proposed data collection method has harvested a large amount of bio-information for ED users.

Next, we discuss these indicators in detail. Figure 3.1 shows the distributions of age and BMIs values of ED users. Consistent with the findings in clinical studies [Abebe et al., 2012; Association et al., 2013], most targeted ED users are teenage, concentrated in the age range of [14, 20], and the average age is 18. Comparing the curves of BMIs, we see that the GBMI values of this group of users are smaller than their CBMI values. This indicates that most of these users wish to lose weight, an important signal of ED

[Association et al., 2013]. Also, we obtain the reference figures of BMI for 18-year-old girls from WHO[8]. The dotted lines in Figure D.3 mark the reference cut-offs of thinness, underweight, median and overweight. We see that most ED users have CBMI values lower than normal and their GBMI values are around the clinically underweight cut-off. These evidences demonstrate the effectiveness of our method in targeting ED populations on Twitter.

3.6.2 Comparisons of User Features

We now present some descriptive analyses on the differences of ED and non-ED users, based on the measures we used in user characterization. Table 3.5 lists the mean and standard deviation values of some representative measures. We use the Kolmogorov-Smirnov (KS) test [Lilliefors, 1967] to evaluate the statistical significance of differences between two sets of users, and use the Bonferroni correction to counteract the problem of multiple comparisons [Frane, 2015]. We see that most measures can distinguish well between ED and non-ED users. Comparing the KS statistics of different sets of users, the differences of ED and non-ED users are generally larger than those of Random and Younger users. This indicates that the sampled ED users are significantly different from the general population on Twitter.

For social status, ED users show the least social engagement, indicating that they have smaller #followees, #tweets and #followers than non-ED users (see Eq. 3.1). However, ED users do not show the least activity in the three sets of users. Basically, activity measures are the ratios of #followees, #tweets or #followers to active-period lengths (see Eq. 3.2). We thus conclude that ED users are generally active on Twitter over a relatively shorter time period. For behavioral patterns, we find that ED users prefer to post original tweets (i.e., %tweet) rather than re-tweeting others' tweets (i.e., %re-tweet and %quote). Besides, ED users have less interactions with other users (e.g., %mention and %reply) and follow fewer public topics (e.g., %hashtag and %URL); their interactions with the external world are less diverse than those of non-ED users. These results align with evidence that individuals affected by ED tend to suffer from social anxiety and they are likely to shy to interact with others [Juarascio et al., 2010]. For psychometric properties, we see that ED users use more of the 1st person singular (i.e., "I") and less of the 1st person plural (i.e., "we"), reflecting ED users' loneliness, self-focused attention and psychologically distancing from others [De Choudhury et al., 2013b]. Also, ED users express less positive emotion but more negative emotion (e.g., anger and sadness) in their posts, which may reflect their tendencies for depression, mental instability and irritability. Most of these indications are the common symptoms of ED [Juarascio et al., 2010]. Finally, we see that ED users are more concerned about body image and ingestion, which is another important signal of ED [Abebe et al., 2012;

[8] http://www.who.int/growthref/who2007_bmi_for_age/en/

Table 3.5: Statistics of measures characterizing differences of ED, Random and Younger users. Results of Kolmogorov-Smirnov tests comparing each pair of user sets (significance levels with Bonferroni correction: * $p < 0.01/m$; ** $p < 0.001/m$; *** $p < 0.0001/m$ where $m = 97$). Maximum values of each row are shown in bold.

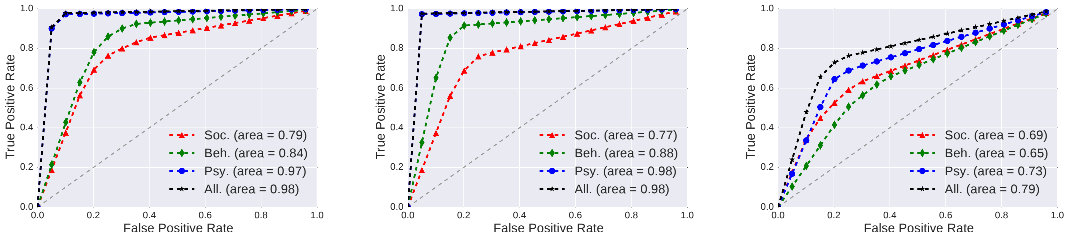
Category	**Measure**	**ED (c_1)**	**Random (c_2)**	**Younger (c_3)**	$ks(c_1, c_2)$	$ks(c_1, c_3)$	$ks(c_2, c_3)$
Characteristics of Social Status							
Engagement	#Followees	4.86(σ=1.29)	**6.56**(σ=2.03)	6.17(σ=1.36)	$\mathbf{0.42}^{***}$	0.41^{***}	0.14^{***}
	#Tweets	5.20(σ=1.85)	**7.95**(σ=2.43)	6.72(σ=2.44)	$\mathbf{0.53}^{***}$	0.37^{***}	0.24^{***}
	#Followers	4.53(σ=1.52)	**7.54**(σ=2.82)	5.76(σ=1.83)	$\mathbf{0.53}^{***}$	0.33^{***}	0.28^{***}
Activity	#Followees/day	**1.11**(σ=1.02)	**1.11**(σ=1.29)	0.76(σ=1.02)	0.12^{***}	$\mathbf{0.25}^{***}$	0.15^{***}
	#Tweets/day	1.22(σ=0.84)	**1.92**(σ=1.36)	1.05(σ=0.93)	0.26^{***}	0.13^{***}	$\mathbf{0.31}^{***}$
	#Followers/day	0.91(σ=0.86)	**1.80**(σ=1.92)	0.60(σ=0.81)	0.23^{***}	0.25^{***}	$\mathbf{0.32}^{***}$
Characteristics of Behavioral Patterns							
Tweeting Preference	%Tweet	**0.74**(σ=0.21)	0.66(σ=0.29)	0.69(σ=0.27)	$\mathbf{0.15}^{***}$	0.09^{***}	0.06^{***}
	%Re-tweet	0.26(σ=0.21)	**0.34**(σ=0.29)	0.31(σ=0.27)	$\mathbf{0.15}^{***}$	0.09^{***}	0.06^{***}
	%Quote	0.00(σ=0.01)	**0.03**(σ=0.07)	0.01(σ=0.04)	$\mathbf{0.54}^{***}$	0.47^{***}	0.10^{***}
	%Mention	0.27(σ=0.19)	0.42(σ=0.28)	**0.44**(σ=0.26)	0.29^{***}	$\mathbf{0.33}^{***}$	0.07^{***}
	%Reply	0.08(σ=0.09)	0.13(σ=0.16)	**0.18**(σ=0.16)	0.17^{***}	$\mathbf{0.35}^{***}$	0.19^{***}
	%Hashtag	0.14(σ=0.15)	**0.23**(σ=0.27)	**0.23**(σ=0.21)	0.19^{***}	$\mathbf{0.24}^{***}$	0.11^{***}
	%URL	0.03(σ=0.09)	**0.26**(σ=0.28)	0.25(σ=0.26)	$\mathbf{0.64}^{***}$	0.63^{***}	0.02^{***}
Interaction Diversity	ΔRe-tweet	2.90(σ=1.47)	**4.39**(σ=1.58)	3.91(σ=1.51)	$\mathbf{0.41}^{***}$	0.31^{***}	0.17^{***}
	ΔMention	2.06(σ=1.24)	**3.37**(σ=1.46)	3.35(σ=1.44)	$\mathbf{0.41}^{***}$	$\mathbf{0.41}^{***}$	0.01
	ΔReply	1.94(σ=1.27)	**3.33**(σ=1.53)	3.14(σ=1.41)	$\mathbf{0.40}^{***}$	0.37^{***}	0.06^{***}
	ΔHashtag	2.65(σ=1.31)	3.85(σ=1.51)	**4.16**(σ=1.64)	0.38^{***}	$\mathbf{0.46}^{***}$	0.12^{***}
Characteristics of Psychometric Properties							
Linguistic Styles	1st pers singular	**0.10**(σ=0.03)	0.04(σ=0.03)	0.05(σ=0.03)	$\mathbf{0.76}^{***}$	0.74^{***}	0.21^{***}
	1st pers plural	0.00(σ=0.00)	**0.01**(σ=0.01)	**0.01**(σ=0.01)	0.61^{***}	$\mathbf{0.62}^{***}$	0.08^{***}
Affective Processes	Positive emotion	0.04(σ=0.01)	0.05(σ=0.02)	**0.06**(σ=0.02)	0.35^{***}	$\mathbf{0.49}^{***}$	0.14^{***}
	Negative emotion	**0.04**(σ=0.02)	0.02(σ=0.01)	0.02(σ=0.01)	0.54^{***}	$\mathbf{0.64}^{***}$	0.11^{***}
	Anger	**0.02**(σ=0.01)	0.01(σ=0.01)	0.01(σ=0.01)	0.38^{***}	$\mathbf{0.53}^{***}$	0.15^{***}
	Sadness	**0.01**(σ=0.01)	0.00(σ=0.00)	0.00(σ=0.00)	$\mathbf{0.64}^{***}$	0.62^{***}	0.06^{***}
Biological Processes	Biological processes	**0.07**(σ=0.02)	0.03(σ=0.02)	0.03(σ=0.01)	0.79^{***}	$\mathbf{0.84}^{***}$	0.09^{***}
	Body	**0.02**(σ=0.01)	0.01(σ=0.01)	0.01(σ=0.01)	0.62^{***}	$\mathbf{0.68}^{***}$	0.07^{***}
	Health	**0.02**(σ=0.01)	0.01(σ=0.01)	0.01(σ=0.01)	0.73^{***}	$\mathbf{0.81}^{***}$	0.14^{***}
	Ingestion	**0.04**(σ=0.02)	0.00(σ=0.01)	0.01(σ=0.01)	$\mathbf{0.86}^{***}$	0.85^{***}	0.15^{***}
Personal Concerns	Work	0.01(σ=0.01)	**0.02**(σ=0.01)	**0.02**(σ=0.01)	0.41^{***}	$\mathbf{0.55}^{***}$	0.14^{***}
	Leisure	0.01(σ=0.01)	**0.02**(σ=0.02)	**0.02**(σ=0.01)	0.39^{***}	$\mathbf{0.62}^{***}$	0.26^{***}

Table 3.6: Performance of predicting the classes of ED, Random (RD) and Younger (YG) users.

Measure	ED-RD	ED-YG	RD-YG
Accuracy	.972(σ=.036)	.982(σ=.011)	.793(σ=.029)
Precision	.982(σ=.017)	.986(σ=.007)	.797(σ=.028)
Recall	.972(σ=.036)	.982(σ=.011)	.793(σ=.029)
F1	.975(σ=.031)	.983(σ=.010)	.791(σ=.029)

Association et al., 2013]. In contrast, non-ED users care more about work and leisure than ED users.

3.6.3 Classification Performance



(a) ED-Random Classification (b) ED-Younger Classification (c) Random-Younger Classification

Figure 3.2: ROC curves of classifications with different types of features. The larger area under the curve (AUC) indicates the better performance. Gray dotted lines denote chance performance.

Next, we assess the ability of using the above features to classify ED and non-ED users. Table 3.6 lists the mean and standard deviation values of four metrics for classification evaluations. We see that ED users are clearly distinguishable from non-ED users. Notably, the classification accuracy is above 97%, significantly higher than those in prior studies (e.g., 72% in predicting depression [De Choudhury et al., 2013c]). There are two main reasons for such enhanced accuracy. First, self-reported diagnoses in users' profiles are more useful to accurately target positive users than identification on the basis of posts in prior studies [Coppersmith et al., 2014]. Second, our sampling method enabled us to construct significantly more training samples than prior methods (e.g., 171 positive users in [De Choudhury et al., 2013c]). These results further confirm the effectiveness of our method in sampling ED users on Twitter. Due to different sampling methods in use, we see that Random and Younger users can also be classified well, but with an accuracy lower than those in classifying ED and non-ED users. Another finding is that the differences of ED and Younger users (with classification accuracy of 98%) are a bit larger than those of ED and Random users (with classification accuracy of 97%), which is against our expectation. We conjecture the reason is because we gather Younger users by starting from popular artists. This may cause sampling biases and hence collect a set of users from some specific communities that are more different from ED users than Random users.

We further examine the importance of each type of features in predicting ED users. We train one classifier each using: 1. social status; 2. behavioral patterns; 3. psychometric properties; 4. all features. Figure 3.2 shows the Receiver Operating Characteristic (ROC) curves generated by classifiers with different types of features. Comparing different classifications, we see that the differences between ED and non-ED users are consistently larger than those between Random and Younger users measured by each type of features. Comparing different types of features, although the best performance in each classification is achieved by using all features, psychometric properties alone are the best to distinguish different classes of users, particularly, achieving almost the same performance as using all features in classifying ED and non-ED users. This illustrates that: 1. the words people used in tweets are effective to reflect their mental health states; 2. we have sampled ED users that are easily distinguishable from non-ED users, so that using fewer features seems good enough to classify them well.

3.6.4 Characteristics of Networks

We now discuss the characteristics of different networks in ED users. Table 3.7 lists the statistics of follow, re-tweet, reply and mention networks among ED users. Each network is constructed by ED users who have at least one corresponding link to other ED users in our dataset, e.g., at least one who-follows-whom link in the follow network. All loop edges are ignored. Note that, due to the settings of Twitter API, all re-tweeters of a tweet in each cascade are directly linked to the tweet's author in the re-tweet network. For example, if Bob re-tweets Andy and then Cole re-tweets Bob, both Bob and Cole are linked to Andy, even though Cole has not re-tweeted Andy directly. As most re-tweeting cascades are fairly shallow [Bakshy et al., 2011], all re-tweeters of a tweet can be regarded as direct re-tweeters approximately [Weng and Menczer, 2015].

Table 3.7: Statistics of networks between ED users.

Measure	Follow	Re-tweet	Reply	Mention
#Nodes	3,143	2,128	1,403	941
#Edges	52,982	11,338	4,344	1,408
Density	0.005	0.003	0.002	0.002
Avg. Path	3.156	4.398	5.030	5.258
#Components	2	10	22	37
%Giant Comp.	99.9	99.1	96.9	91.9
Clustering Coef.	0.122	0.089	0.052	0.029
Reciprocity	0.556	0.098	0.570	0.091
Degree Ass.	-0.105	0.002	-0.017	-0.199

Since Twitter follow networks have been intensively studied in the previous work [Bild et al., 2015; Kwak et al., 2010; Myers et al., 2014], we first compare our feature statistics on the follow network with those in the literature. The average shortest path lengths in the ED follow network is 3.156 which is smaller than 4.05 and 4.8, the reference average shortest path lengths in the Twitter follow network reported in [Myers et al., 2014] and [Bild et al., 2015] respectively. This may indicate that ED users connect one another through a relatively short path. As reported in [Kwak et al., 2010], the reciprocity in the Twitter follow network is low at 0.221. In contrast, the reciprocity in the ED follow network is 0.556, significantly higher than the reference reciprocity. This illustrates that ED users have a relatively high density of social ties and have formed a tightly linked community. From the values of degree assortativity, we see that the follow network is disassortative by degree, i.e., users who have many followees are unlikely to be followed by others who have many followers, which aligns with the results in prior studies [Bild et al., 2015; Myers et al., 2014]. Moreover, the degree assortativity in ED users (i.e., -0.105) is smaller than that in the general population (e.g., -0.0089 in [Bild et al., 2015]). This means that the more people an ED user follows, the less popular the user tends to be.

We then explore the features of other ED networks. From the reciprocity of the reply network, we find that frequent mutual communications occur in tightly knit groups. These findings indicate that ED users tend to engage in socializing and communicating with other ED users on Twitter. In conjunction with our previous findings that ED users like to express negative emotions and discuss about body image and ingestion, we conjecture that ED users may use Twitter to seek social support from other ED peers and exchange ED-specific information [Juarascio et al., 2010]. Similar to the follow network, the reply and mention networks are also disassortative by degree. However, we find that the re-tweet network is assortative, i.e., users who have been re-tweeted a lot tend to re-tweet others who often re-tweet, which is in line with the results in [Bild et al., 2015]. That is, popular re-tweeters often seek information from other active re-tweeters. This sounds reasonable, as we can easily understand why information could propagate through Twitter by re-tweeting based on this [Taxidou and Fischer, 2014]. Note that the statistics discussed above are potentially biased due to the bias of the data we collected via the snowball sampling methods [Illenberger and Flötteröd, 2012; Lee et al., 2006] and hence may not be generalized to all other online ED communities.

3.6.5 Patterns of Homophily

Next, we present the results of homophily analysis in these networks. According to the significance test results of assortativity by each of 97 features, we list the percentages of features by which networks are assortatively mixed at different significance levels in Table 3.8. We see that various networks of ED users are significantly assortative by most features, especially in the follow, re-tweet and reply networks. For example, for 85.6% of features, users with high feature values significantly tend to be connected to others with high feature values in the follow network, at significance level of 0.05. This indicates the presence of homophily in ED communities. This, in turn, illustrates the feasibility of our snowball sampling ED users through their follow networks.

Table 3.8: Percentages of assortatively mixed features at different significance levels.

Sig. Level	Follow	Re-tweet	Reply	Mention
$p < 0.05$	85.6%	83.5%	75.3%	46.4%
$p < 0.01$	79.4%	78.4%	58.8%	30.9%
$p < 0.001$	68.0%	69.1%	47.4%	17.5%

For a more detailed discussion, we rank these features by their values of z-score: $z = (r - \mu)/\sigma$, where r is the assortativity coefficient of networks by a feature, and μ and σ are the mean and standard deviation of the randomly simulated assortativity coefficients by the feature respectively. Table 3.9 shows the statistics of features ranked in the top 5 for each network. An interesting finding is that the feature "parenth", which denotes the percentage of using parentheses (e.g., '(', ')'), is ranked very highly across different networks. To investigate this, we go through the posts of some users. We find that most parentheses are used to represent emoticons, such as ":))", ":((". That is, users who like to use emoticons tend to connect with others who also like to use emoticons. This means that ED users have similar habits in using language. Other significantly assortative features include tweeting preferences (e.g., %tweet and %quote), diversities of using hashtags, concerns of death, and emotion (e.g., sad).

Moreover, we employ a similar method to investigate the homophily of ED users in terms of their bio-information indicators (in Table 3.4). The results are listed in the bottom of Table 3.9. We find that ED users tend to follow others who have similar HW or LW, and tend to reply to others who have similar CW. In other words, ED users often seek acquaintances with others who have similar experiences on weight management, while they communicate with others who are in a similar situation at present. Thus, we suppose that ED users follow others to seek a sense of community identity and peer support, and reply to others perhaps to discuss weight loss or other contingent information.

3.7 Conclusion

In this chapter, we study to detect and characterize ED communities on social media. We first present a snowball sampling method to automatically sift ED individuals and their community structures from Twitter data. We then compare ED and two sets of non-ED users in social status, behavioral patterns and psychometric properties, and find that ED users show young ages, prevailing urges to lose weight even if being clinically underweight, high social anxiety, intensive self-focused attention, deep negative emotion,

Table 3.9: Examples of assortative mixing by features, ranked by the absolute values of z-score. Statistical significance tests are based on two-tailed hypothesis tests (* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$).

Network	Feature	r	μ	σ	z	p
User Characteristics						
Follow	Parenth	.13	.00	.005	24.87	.0***
	%Quote	.12	.00	.005	24.63	.0***
	Death	.11	.00	.005	20.71	.0***
	%Tweet	.10	.00	.005	19.88	.0***
	%Re-tweet	.10	.00	.005	19.85	.0***
Re-tweet	ΔHashtag	.20	.00	.009	20.81	.0***
	%Quote	.16	.00	.009	18.29	.0***
	Parenth	.17	.00	.010	17.50	.0***
	Sad	.17	.00	.010	17.29	.0***
	SemiC	.13	.00	.009	14.25	.0***
Reply	%Quote	.21	.00	.016	13.42	.0***
	Parenth	.24	.00	.019	13.10	.0***
	%Tweet	.18	.00	.019	9.61	.0***
	%Re-tweet	.18	.00	.019	9.52	.0***
	Death	.15	.00	.019	8.02	.0***
Mention	Parenth	.25	.00	.028	8.84	.0***
	%Re-tweet	.22	.00	.028	7.94	.0***
	%Tweet	.22	.00	.028	7.89	.0***
	%Quote	.16	.00	.023	6.67	.002**
	%Reply	.16	.00	.028	5.66	.0***
Bio-indicators						
Follow	HW	.05	.00	.013	4.00	.001***
	LW	.09	-.01	.038	2.66	.021*
Reply	CW	.06	.00	.029	2.21	.038*

increased mental instability, and excessive concerns of body image and ingestion on Twitter. We further build classifiers to classify ED and non-ED users, and show that Twitter data can help estimating the occurrence of ED. Finally, we leverage the social networking data among ED users, and present the first empirical homophily analysis of ED communities on social media. We find that: 1. ED users have significant assortative mixing patterns in tweeting preferences, language use, concerns of death and emotions etc.; 2. ED users tend to follow and reply to other ED users having similar body weight. Our findings indicate that ED individuals primarily use social media for a sense of community identity and mutual social support online. Moreover, the presence of homophily in ED communities and the accuracy of more than 97% in predicting ED users show the feasibility of develop computational methods to detect larger ED communities on Twitter, beyond those that have self-identified. For example, we can reach larger ED communities through users' social networks online and identify users potentially at risk of ED using predictive models trained based on users' tweeting patterns as we used in this chapter, even if these users did not self-identify as disordered online.

The results presented in this chapter show that we are highly likely to have detected a set of individuals affected by ED on Twitter. As reported in previous qualitative studies, a notable characteristic of online ED communities is that their members differ widely in their stances on ED, where some of them treat ED as an illness and help one another to recover while some others instead promote ED as a legitimate lifestyle [Bardone-Cone and Cass, 2006; Harper et al., 2008; Mabe et al., 2014; Overbeke, 2008; Wilson et al., 2006]. To learn more about social structures of these communities, in the next chapter, we explore to use computational methods to distinguish individuals' stances on ED and examine how groups of users with a different stance interact.

Chapter 4

Social Structures

Online health communities facilitate communication among people with health problems. Most prior studies focus on examining characteristics of these communities in sharing content, while limited work has explored social interactions between communities with different stances on a health problem. In this chapter, we analyze a large communication network of individuals affected by eating disorders on Twitter and explore how communities of individuals with different stances on the disease interact online. Based on a large set of tweets posted by individuals who self-identify with eating disorders online, we establish the existence of two communities: a large community reinforcing disordered eating behaviors and a second, smaller community supporting efforts to recover from the disease. We find that individuals tend to mainly interact with others within the same community, with limited interactions across communities and inter-community interactions characterized by more negative emotions than intra-community interactions. Moreover, by studying the associations between individuals' behavioral characteristics and interpersonal connections in the communication network, we present the first large-scale investigation of social norms in online eating disorder communities, particularly on how a community approves of individuals' behaviors. Our findings shed new light on how people form online health communities and can have broad clinical implications on disease prevention and online intervention.

4.1 Introduction

As discussed in Chapter 2, not all the online communities offer healthy advice and recovery-oriented support. Some communities in fact promote harmful content and health-threatening behaviors, which has been a public health concern [Oksanen et al., 2015; Overbeke, 2008; Wilson et al., 2006; Yom-Tov et al., 2012]. One area that is receiving increasing attention in public health research is identifying the characteristics and relationships of online communities with different stances on health problems, which has many applications in enhancing positive and reducing negative impacts of these communities, disease prevention, and online intervention [Latkin and Knowlton, 2015; Valente, 2012; Valente and Pumpuang, 2007].

Psychologists and clinicians have long studied online eating disorder (ED) communities [Borzekowski et al., 2010; Chesley et al., 2003; Giles, 2006; Wilson et al., 2006]. The focus in this area has often been on pro-ED (e.g., pro-anorexia or pro-ana) communities which are featured by a stance to glorify ED (anorexia in particular) as a legitimate lifestyle choice rather than an illness [Mulveen and Hepworth, 2006; Overbeke, 2008; Wilson et al., 2006]. These communities engage in disseminating content that encourages an unrealistic ideal of thinness and inspires people to lose weight, as well as tips on how to become and stay extremely thin [Borzekowski et al., 2010; Giles, 2006; Juarascio et al., 2010; Overbeke, 2008; Wilson et al., 2006]. Members of these communities display a more negative perception of body image, a higher drive for losing weight, and an increased likelihood to adopt disordered eating behaviors and maintain ED, which has become a major public health concern [Bardone-Cone and Cass, 2006; Harper et al., 2008; Mabe et al., 2014; Overbeke, 2008; Rodgers et al., 2012; Wilson et al., 2006]. More recently, attention has been turned from pro-ED communities to others that treat ED simply as an illness online, one typical example being so-called pro-recovery communities where members share treatment advice and provide support for people moving towards recovery [Chancellor et al., 2016c; De Choudhury, 2015; Lyons et al., 2006]. The focus in this research has often been on the characterization and comparison of content posted by different communities online, e.g., demonstrating that pro-ED and pro-recovery individuals have distinct linguistic styles and language usages in online self-presentation [De Choudhury, 2015; Lyons et al., 2006], pro-recovery content received more positive comments than pro-ED content on YouTube [Oksanen et al., 2015], individuals' language use provides useful diagnostic information (e.g., emotional states and thoughts) for their severities of ED [Chancellor et al., 2016a; Wolf et al., 2007] and indicates signs of recovery [Chancellor et al., 2016c].

Despite providing useful insights, previous studies have several limitations. First, most previous studies focus on analysis of user-generated content online; few studies have considered social interactions among individuals. However, social networks play an important role when interpreting health-related behaviors, as our concerns, behaviors and health states are influenced by the network of people with whom we interact [Fowler and Christakis, 2008], although there is still considerable dispute concerning the causal effects of social networks on human health [Cohen-Cole and Fletcher, 2008]. One pioneering study has examined interactions between 491 pro-ED and pro-recovery users via photo sharing on Flickr [Yom-Tov et al., 2012]. Yet, what dictates the interactions of individuals having different stances on ED is still under-explored. Second, a common approach for collecting data in previous studies is filtering users who post content containing a pre-defined set of keywords that relate to ED [Chancellor et al., 2016c;

De Choudhury, 2015; Oksanen et al., 2015; Yom-Tov et al., 2012]. However, a relatively small set of keywords can hardly characterize the entire community, as people can use a wide range of lexical variants to express the same content online [Chancellor et al., 2017, 2016d; Stewart et al., 2017; Weng and Menczer, 2015]. Even in cases where a complete set of pattern matching rules can be obtained, people who talk about ED online may not suffer from the disease. Thus, these content-filtering based data collection methods often suffer from poor quality of data and can lead to misleading results. Finally, online ED communities studied in prior work are confined to groups of users who post certain content that researchers are interested in [Chancellor et al., 2016c; De Choudhury, 2015; Oksanen et al., 2015; Yom-Tov et al., 2012]. This leads to a systematic exclusion of certain individuals from research. So far, the natural groupings among individuals affected by ED online remains unclear.

In this chapter, we explore how individuals with different stances on ED interact and associate with different communities online. Studying the interactions among different communities of individuals can enhance our understanding of the affiliations of individuals in communities through the characteristics of relations between and within communities, instead of the characteristics of each community in isolation. To this end, we collect a large set of individuals who self-identified with ED in their Twitter profile descriptions using a snowball sampling method [Wang et al., 2017] and study individuals' direct conversations through "reply" and "mention" interactions on Twitter. We focus on the Twitter platform due to its anonymous and pervasive nature, along with its very limited attempts to censor content on ED [Arseniev-Koehler et al., 2016]. This allows us to study online ED communities in a non-reactive way.

4.2 Methods

To analyze social interactions in online ED communities, we have gathered a large set of conversations between individuals who self-identified with ED in their Twitter profile descriptions and their Twitter friends (including followees and followers). Each Twitter conversation comprises a sequence of tweets, where each tweet is a message used by a user to reply to or mention others. In this work, we focus on studying users' conversations around ED. By projecting these conversations onto the users who send and receive a message, we build a directed, weighted social network connecting 6,169 users with 11,056 edges. An edge $e_{i,j}$ runs from a node representing user i to a node representing user j if i mentions or replies to j in a tweet, indicating that information propagates from i to j. The interaction strength of an edge $e_{i,j}$ is weighted by the count of mentions and replies from user i to user j.

Data Collection. We collect a set of users who have self-identified with ED in their Twitter profile descriptions and their Twitter friends ($n = 208,065$) using a snowball sampling approach [Wang et al., 2017]. For each user, we collect up to 3,200 (the limit returned from Twitter APIs) historical tweets, resulting in a corpus of tweets ($n = 241,243,043$) in March 2016. From this corpus, we extract 633,492 ED-related tweets posted by 41,456 unique users by checking the occurrences of ED-related hashtags (e.g., "#thinspo" and "#edproblems") in tweets. The ED-related hashtags we used are obtained by: (i) applying Infomap [Rosvall and Bergstrom, 2008], an established method for community detection, to the co-occurrence networks of hashtags posted by self-identified ED users, resulting in topic clusters of semantically related hashtags; (ii) selecting ED-related topics based on prior evidence of ED-related content on social media [Chancellor et al., 2016c; De Choudhury, 2015; Juarascio et al., 2010]; (iii) removing generic hashtags (e.g., "#skinny" and "#food") from the selected topics.

Based on users' mentioning and replying relationships in these ED-related tweets, we build a communication network comprising 13,139 non-isolated nodes and 21,761 edges to represent users' interactions in ED-related conversations. All mentions in re-tweets are excluded, as these mentions are used by the original author of a re-tweet, not by the users who re-tweeted this tweet. To filter out noise, e.g., users who occasionally mention ED, we exclude users who have less than three distinct ED-related tweets. The resulting network contains 6,775 nodes and 11,405 edges, where the largest weakly connected component has 6,169 nodes and 11,056 edges, with 7 nodes in the second-largest component. We focus on analyzing the largest component due to its dominance (see *Appendix B*, Sect. 1).

User Profiling and Clustering. We profile each user by their interests in posting different ED-related hashtags, as the social signal of posting specific tags on social media has been shown to strongly indicate the tendency of an individual for a healthy or unhealthy lifestyle [Arseniev-Koehler et al., 2016; Chancellor et al., 2016c; De Choudhury, 2015; Oksanen et al., 2015; Syed-Abdul et al., 2013; Yom-Tov et al., 2012]. Since multiple duplicate hashtags can represent the same event, theme or object, we shift attention from single tags, as widely used in prior work [Chancellor et al., 2017, 2016c; De Choudhury, 2015; Yom-Tov et al., 2012], to more general categories, i.e., topics of semantically related tags. We identify the topics of hashtags by constructing a co-occurrence network of hashtags in the ED-related tweets, and detecting dense clusters in the network using the Infomap algorithm. Then, we track the sequence of hashtags that a user used in the ED-related tweets, and profile the user by a vector that consists of proportions of usage of these hashtags across the topics found above. Finally, we apply the k-means clustering algorithm on these vectors to group users who have similar posting interests into the same community. To identify the natural number of communities in data, we run k-means with different values of k and select the value of k that maximizes the average Silhouette coefficient over all samples [Rousseeuw, 1987]. To ensure the robustness of the results, we repeat these analyses 100 times with $k \in [2, 20]$ and observe high consistency in the results (see *Appendix B*, Sect. 2).

Sentiment Analysis. To examine users' attitudes to pro-ED and pro-recovery content, we measure their sentiments expressed in pro-ED and pro-recovery tweets. We categorize pro-ED and pro-recovery tweets based on the occurrence of a pro-ED or pro-recovery hashtag in a tweet. The pro-ED and pro-recovery hashtags we used are obtained by (i) identifying pro-ED and pro-recovery topics from the topics of hashtags found in the ED-related tweets, based on previous studies on the language use in online pro-ED and pro-recovery communities [Chancellor et al., 2016c; De Choudhury, 2015; Oksanen et al., 2015; Yom-Tov et al., 2012]; (ii) removing generic hashtags such as "#ana" and "#ed" (*Appendix B*, Sect. 3).

SentiStrength [Thelwall et al., 2010] is used to measure sentiments as: (i) it is designed for short informal texts with abbreviations and slang, and thus suitable to process tweets; (ii) it accounts for linguistic rules of negations, amplifications, booster words, emoticons, spelling corrections, showing good performance in sentiment analysis [Ferrara and Yang, 2015; Thelwall et al., 2010]. This tool assigns two values to each tweet: S_p which measures positive sentiment, ranging from 1 (not positive) to 5 (extremely positive), and S_n which measures negative sentiment, ranging from -1 (not negative) to -5 (extremely negative). Due to the paucity of information conveyed in short texts (up to 140 characters in tweets), previous studies suggest that measuring the overall sentiment is more accurate than measuring the two dimensions of sentiment separately [Ferrara and Yang, 2015; Thelwall et al., 2010]. Following this research, we capture the sentiment polarity of each tweet with one single measure, i.e., $S = S_p + S_n$, in the range of $[-4, 4]$ where 0 indicates a neutral opinion. All hashtags, URLs, re-tweet and mention marks are removed before sentiment analysis. The same pre-processing is used in measuring the sentiments of tweets that are associated with intra- and inter-community interactions (see *Appendix B*, Sects. 3 and 4).

Null Model. We use a null model [Newman and Girvan, 2004] to evaluate the normalized modularity (or assortativity coefficient) [Newman, 2003] of the communication network by users' community labels that are assigned by the clustering algorithm based on users' posting interests. We randomly shuffle users' community labels and re-measure assortativity by the shuffled labels. Repeating this procedure 3,000 times, we obtain an empirical distribution of assortativity by users' community labels, with the mean value of assortativity coefficients $\mu = 0$ and the standard deviation $\sigma = 0.01$. Using this distribution as a baseline, we measure the deviation of the actual assortativity A from randomness via a z-score: $z = (A - \mu)/\sigma$. The result is $z = 90.88$, showing that the actual value of assortativity is larger than the random values of assortativity, significantly at $p \ll 0.001$ in a two-tailed test.

Characterizing Language Use. We adopt the psycholinguistic lexicon LIWC [Tausczik and Pennebaker, 2010] to characterize content and language use in tweets. This tool reads a given text and counts the percentages of words that reflect different emotions, thinking styles, and social concerns; it has been widely used to capture people's psychological and health states from the words they used [Chancellor et al., 2017, 2016c; De Choudhury, 2015]. For a more reliable evaluation, we combine all historical tweets of each user as a document. All re-tweets are excluded, since they reflect cognitive attributes of their original authors rather than those of re-tweeters. After removing mention marks, hashtags and URLs, each document is split into tokens by white-space characters. Only documents containing more than 50 tokens are processed with LIWC for more trustworthy results (see *Appendix B*, Sect. 5).

Characterizing Social Norms. We measure the two dimensions of social norms by (i) the amounts of language reflecting different psychological attributes (e.g., concerns and emotions) in a user's tweets and (ii) the centrality of the user in the social network within a community. We measure the PageRank centrality [Page et al., 1999] due to its several advantages over other centralities (e.g., degree and eigenvector centrality): (i) it accounts for the centralities of a node's neighbours, and (ii) it is insensitive to spammers with a large number of out-links. Due to the dominance of the giant weakly connected component in the intra-community networks and incomparable PageRank values of nodes across disconnected components, we focus on users within the giant components in the analysis of social norms. For validation, we perform the same analyses using other centrality metrics for directed, weighted networks — hubs and authorities [Kleinberg, 1999]. The results are similar (see *Appendix B*, Sect. 6.1).

To explain social norms from a more theoretical respective, a common method is the RPM, which plots the change of the amount of group acceptance with the amount of an attribute exhibited [Jackson, 1965]. However, the RPM is primarily a descriptive model; it can hardly quantify the strength of a relation between two dimensions of social norms. Here, we follow the framework of RPM and build linear regression models to quantify these relations. Each model predicts a user's centrality in a network based on an attribute of the user (such as concern on body or positive emotions) and covariates including the numbers of followers, tweets, followers that the user has, the fractions of tweets mentioning and replying to others, and the number of the historical tweets that the user has in our data. Given the long tailed distributions of centrality values, we use robust linear regression models, which are less sensitive to outliers or influential observations [Andersen, 2008], to achieve robust estimations on the relations between individuals' psychological attributes and centralities in social networks (see *Appendix B*, Sect. 6.2).

4.3 Results

Based on the dataset collected above, we have performed the following analyses. First, we explore natural groupings of users who engage in ED-related conversations on Twitter and identify the stances of different groups/communities of users on ED. Second, we characterize interactions of these communities by measuring structures of communication networks among users within the same community and across communities. Third, to obtain a more in-depth analysis of these interaction patterns, we measure individuals' behavioral characteristics online. Finally, we explore the associations between individuals' behavioral attributes and the organizational structure of a community by explicitly characterizing social norms within the community, focusing on how a community approves of individuals' behavioral attributes [Jackson, 1965]. Below, we present our findings in detail.

4.3.1 User Groupings

We profile each user by a vector that characterizes their preferences in posting content on different ED-related topics, and perform the k-means clustering algorithm on these vectors to find the natural groupings of users that share similar posting interests (see *Methods*). Fig. 4.1(a) shows results of k-means with different values of k. The algorithm consistently produces the highest Silhouette scores [Rousseeuw, 1987] at $k = 2$ (with $\mu = 0.803$ and $\sigma = 0.001$), revealing that two natural groups of users with similar characteristics are present in the sample. By inspecting content discussed in each group, we further find that these groups show two distinctive perspectives on ED. Users in group A ($n = 5,708$) focus on posting "thinspirational" content such as "#thinspo", "#weightloss" and "#proana" (Fig. 4.1(b)). Such content has been well-known to promote unhealthy ideals of thinness and encourage people to maintain ED as a lifestyle choice [Juarascio et al., 2010; Norris et al., 2006; Overbeke, 2008]. In contrast, users in group B ($n = 461$) often discuss mental health problems and post recovery-oriented content like "#mentalhealth" and "#edrecovery" (Fig. 4.1(c)), indicating their intentions in promoting recovery from ED [Chancellor et al., 2016c; De Choudhury, 2015; Yom-Tov et al., 2012]. These results show that users involved in the ED-related discussions on Twitter can be divided into two natural groups that are likely to have a pro-ED and pro-recovery tendency respectively.

To verify whether a group indeed has pro-ED or pro-recovery stance, we measure sentiments expressed by each group of users in commenting on pro-ED and pro-recovery content (see *Methods*). Fig. 4.1(d) shows the average sentiments of the two groups of users towards content on different themes, where the results are normalized based on the mean sentiment and standard deviation of a whole group expressed in all the ED-related tweets (so called *relative sentiments*, see *Appendix B*). The two groups of users

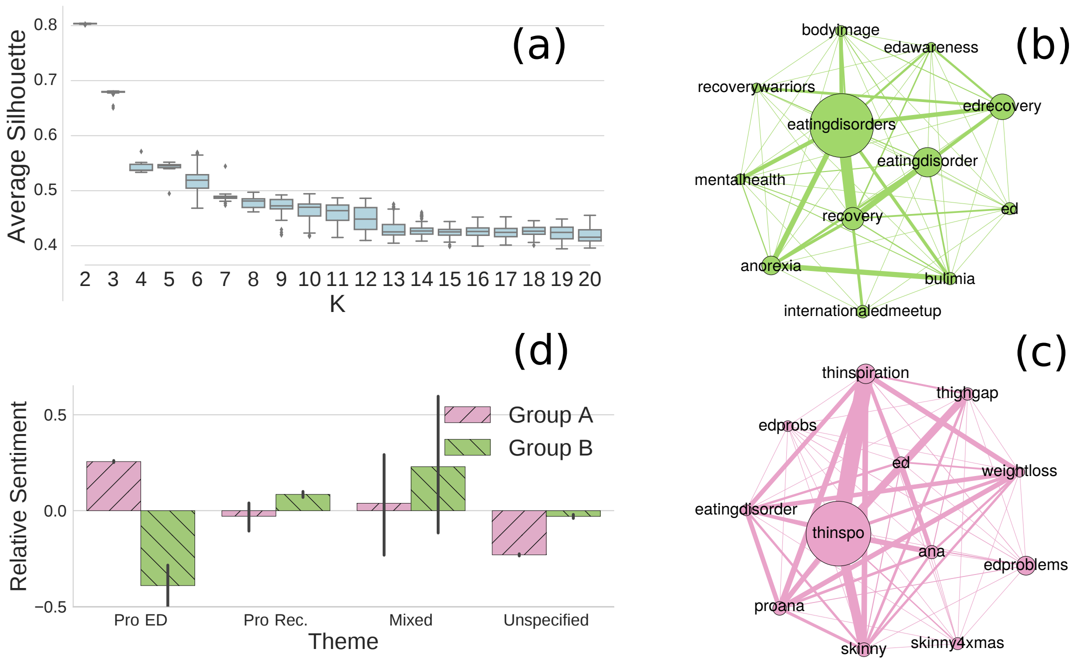


Figure 4.1: (a) Distributions of average Silhouette scores with different k values in k-means. Each box shows the quartiles of the scores obtained in 100 rounds running, and the whiskers show the rest of a distribution. (b) and (c) The most frequent hashtags and their co-occurrence networks used by two groups of users in ED-related tweets respectively. Each node is a hashtag and its size is proportional to the frequency of the tag used in a group. Edge width is proportional to the number of co-occurrences of two hashtags in tweets. (d) Average relative sentiments of two groups on different themes: *"pro-ED"* where each tweet contains a pro-ED hashtag without pro-recovery tags; *"pro-recovery"* where each tweet has a pro-recovery hashtag without pro-ED tags; *"mixed"* where a tweet has both pro-ED and pro-recovery tags; and *"unspecified"* where a tweet has neither a pro-ED nor a pro-recovery tag. Error bars denote 95% CI. Mann-Whitney U tests are used to assess the differences of sentiments between two groups on each theme. All p-values for "pro-ED", "pro-recovery" and "unspecified" themes are $p < 0.001$, while no significant difference occurs for the "mixed" theme (see *Appendix B*).

show clearly different stances on ED. Users in group A have positive comments (i.e., using words containing positive sentiment) on *"pro-ED"* content and relatively negative comments (i.e., using words containing negative sentiment) on *"pro-recovery"* content, revealing that these users typically promote negative body image and disordered eating behaviors. In contrast, users in group B have a negative view on *"pro-ED"* content and a positive view on *"pro-recovery"* content, showing that these users oppose pro-ED behaviors and encourage people to recover from ED. These results confirm that group A can be identified as a pro-ED community while group B can be identified as a pro-recovery community. To ensure the reliability of our results, we also manually annotate the presence of a pro-ED or pro-recovery tendency for a random set of users. Our annotations show very good agreement with the assignments produced by the algorithms (Cohen's $\kappa = 0.85$, see *Appendix B*).

4.3.2 Network Structures

Based on users' community memberships identified above and their direct communication, we visualize the communication network between pro-ED and pro-recovery communities in Fig. 4.2(a). One clear feature shown in this figure is a division of the network into two densely connected sub-graphs, where each sub-graph consists primarily of users belonging to the same community. We measure the strength of division of the communication network into the pro-ED and pro-recovery communities (as assigned based only on users' posting interests without considering their structural connections in the previous section) by Newman's normalized modularity [Newman, 2003]. We find that the communication network is highly segregated by users' community identities, with the normalized modularity $r = 0.88$ ($z = 90.88$, $p \ll 0.001$ compared to a null model, see *Methods*). The segregated social circles are likely associated with the disagreement or conflict between these communities. We illustrate this in Fig. 4.2(b) which compares average sentiments expressed in intra- and inter-community messages, $S_{\circlearrowright}$ and $S_{\curvearrowright}$. All results are normalized based on the mean sentiment and standard deviation of all messages sourced from a whole community (see *Appendix B*). In both pro-ED and pro-recovery communities, inter-community interactions $S_{\curvearrowright}$ carry more negative emotions than intra-community interactions $S_{\circlearrowright}$, strongly demonstrating the disagreement between the two communities.

Table 4.1: Statistics of the communication networks among pro-ED and pro-recovery communities. Total number of nodes (N); number of edges (E); average degree per node ($\langle k \rangle$); average shortest path length of connected node pairs (L); number of weakly connected components ($\#Comp.$); ratio of nodes in the giant connected component (GCR); reciprocity measuring the likelihood of nodes with mutual links (R); global clustering coefficient (or transitivity) measuring the probability that two neighbours of a node are connected (C); assortativity coefficient of degree measuring the preference for nodes to link to others with similar degree values (A). Degree assortativity measured here are the correlations between source out-degree and destination in-degree [Newman, 2003], and z_X denotes the z-score of a property X observed in an empirical network compared to those observed in null models, i.e., randomized networks by preserving the degrees of the empirical network [Newman and Girvan, 2004].

Network	N	E	$\langle k \rangle$	L	$\#Comp.$	GCR	R	C	A	z_R	z_C	z_A
Pro-ED	5,708	9,023	1.58	10.76	114	97.8%	0.03	0.01	-0.13	90.45	0.33	-12.16
Pro-Rec.	461	1,666	3.61	3.95	62	84.2%	0.16	0.19	-0.13	20.12	10.62	-5.57
Entire	6,169	11,056	1.79	10.20	1	100.0%	0.05	0.03	-0.14	113.41	32.14	-14.45

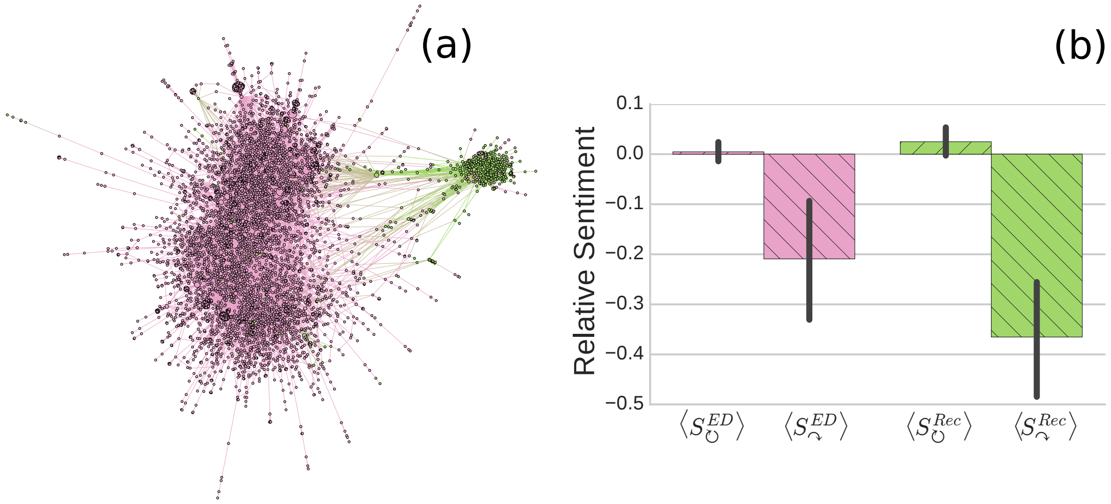


Figure 4.2: (a) The communication network of users in pro-ED and pro-recovery communities, laid out by ForceAtlas2 [Jacomy et al., 2014]. Each node represents a user and edges represent mentioning or replying relationships. Red nodes (on the left side) denote pro-ED users and blue nodes (on the right side) denote pro-recovery users. Node size is proportional to in-degree. (b) Average relative sentiments of intra- and inter-community messages $\langle S_{\circlearrowright}\rangle$ and $\langle S_{\curvearrowright}\rangle$ sourced from pro-ED (ED) and pro-recovery (Rec) communities respectively. Error bars denote 95% CI. Differences between $S_{\circlearrowright}$ and $S_{\curvearrowright}$ are significant ($p < 0.01$) in U tests in both two communities.

We next examine the network structures of pro-recovery and pro-ED communities in more detail. Table 4.1 shows the statistical properties of intra- and inter-community networks among pro-ED and pro-recovery users. The size of the network among pro-ED users (accounting for 93% of the whole user sample in our data) is larger than that among pro-recovery users. However, pro-recovery users have more dense connections (see $\langle k\rangle$), as compared to pro-ED users. The smaller value of average path length (see L) in the pro-recovery network implies that pro-recovery users are more closely connected with one another. While the two communities have several disconnected components (see $\#Comp.$), most users (97.8% pro-ED users and 84.2% pro-recovery users) are connected in the giant components (see GCR). The results of reciprocity R and clustering coefficient C indicate that pro-recovery users are more likely to reciprocate the interactions they have received from others and cluster together. Both reciprocity and transitivity occur more than expected by chance in each community (see z_R and z_C). Aligning with evidence on most online social networks [Hu and Wang, 2009], both communities show disassortative mixing by degree, i.e., high-degree nodes or hubs tend to be attached to low-degree or peripheral nodes. Compared to random networks, the pro-ED network shows stronger dissortativity than the pro-recovery network (see z_A), indicating that the pro-ED community has a more pronounced core-periphery network organization. Due to the dominant number of pro-ED users in the user sample, the inter-community (i.e., *entire*) network show similar topological characteristics to the intra-community network of pro-ED users. These comparisons of network properties emphasize that pro-ED and pro-recovery users have different interaction patterns online and have formed communities with different organizational structures.

4.3.3 Behavioral Characteristics

To understand users' interaction patterns, we conduct a detailed analysis and comparison of behaviors of the pro-ED and pro-recovery users on Twitter. We focus on characterizing users' behaviors on social activities and language use in tweets which have been well examined in previous studies [Chancellor et al., 2016c; De Choudhury, 2015; Yom-Tov et al., 2012]. A summary of behavioral characteristics of users in each community is reported in Table 4.2. We see that pro-ED and pro-recovery individuals display clearly distinctive behaviors online. Compared to pro-recovery users, pro-ED users are less active in socializing (see #followees) and generating content (see #tweets); posts of pro-ED users receive less audience (see #followers) on Twitter. Similar findings have been reported for other platforms like Tumblr [De Choudhury, 2015]. The results on average activities per day show that pro-ED users are more active in following and tweeting per day, while pro-recovery users tend to attract more audience per day. Further, pro-ED users prefer to re-tweet others (see %re-tweet) and interact less with others by mentions and replies (see %mention and %reply); they tend to re-tweet content from a wider variety of people (see H(re-tweet)) but mention and reply to only a specific set of users (see H(mention) and H(reply)). As re-tweeting is a key part of the process of community formation and information diffusion on Twitter [Boyd et al., 2010], these results show that pro-ED users use Twitter as a community engagement tool rather than a communication tool.

From the psychometric properties reflected by users' language use in tweets, we find that pro-ED users are more concerned about body image (see *body* in Table 4.2) and ingestion (see *ingest*), which is an important signal of ED [Abebe et al., 2012]. Also, pro-ED users typically use the 1st person singular (see I), reflecting their loneliness, self-focused attention and psychological distancing from others [De Choudhury et al., 2013b]. In contrast, pro-recovery users often use the 1st person plural (see *we*), showing their social embedding within the group. These results are confirmed by that pro-ED users have less social concerns (see *social*). This can be due to feelings of social isolation and rejection, or due to the lack of social support for those suffering from mental illness [De Choudhury, 2015; Lyons et al., 2006]. Further, pro-ED users use more swear (see *swear*) and negation words (see *negate*) in their discourse on Twitter, reflecting their aggression and refusal/contradiction [Tausczik and Pennebaker, 2010]. Pro-ED users also manifest less positive emotions (see *posemo*) but more negative emotions (e.g., sadness, anxiety and anger, see *negemo*), indicating their tendencies for depression, mental instability and irritability. The typically negative tone of pro-ED users also reflects a lowered sense of

Table 4.2: Comparing communities in social activities and language use, where measures on language use count the percentages of words that reflect different psychometric properties, such as concerns, emotions and thinking styles, in a user's historical tweets. Two-sided Mann-Whitney U tests evaluate differences between groups, significance levels with Bonferroni correction: * $p < 0.05/m$; ** $p < 0.01/m$; *** $p < 0.001/m$ where $m = 22$.

Measure	*Description*	*Pro-ED* ($\mu \pm \sigma$)	*Pro-Rec.*($\mu \pm \sigma$)	z	p
Social Activities					
#Followees	Number of total followees	543.70 ± 1,096.09	1,561.58 ± 4,022.53	-14.82	0.000 ***
#Tweets	Number of total tweets	2,573.03 ± 6,515.83	5,485.02 ± 10,166.14	-9.24	0.000 ***
#Followers	Number of total followers	1,339.11 ± 27,384.37	16,299.21 ± 128,844.20	-17.52	0.000 ***
#Followees/day	Average number of followees per day	2.22 ± 7.23	1.72 ± 6.18	3.36	0.001 *
#Tweets/day	Average number of tweets per day	5.48 ± 9.01	4.13 ± 8.73	7.69	0.000 ***
#Followers/day	Average number of followers per day	2.41 ± 12.36	7.51 ± 46.21	-3.81	0.000 **
%Re-tweet	Ratio of re-tweets in historical posts	0.30 ± 0.20	0.21 ± 0.18	9.76	0.000 ***
%Mention	Ratio of posts with mentions	0.31 ± 0.17	0.36 ± 0.20	-5.08	0.000 ***
%Reply	Ratio of posts with replies	0.10 ± 0.09	0.15 ± 0.13	-7.10	0.000 ***
H(Re-tweet)	Entropy of re-tweeting others	4.28 ± 1.20	3.36 ± 1.08	16.97	0.000 ***
H(Mention)	Entropy of mentioning others	2.33 ± 1.09	2.91 ± 1.04	-11.76	0.000 ***
H(Reply)	Entropy of replying others	2.71 ± 1.21	2.87 ± 1.05	-3.09	0.002 *
Language Use					
Body	Concerns of body image	0.02 ± 0.01	0.01 ± 0.01	25.68	0.000 ***
Ingest	Concerns of ingestion	0.03 ± 0.02	0.02 ± 0.02	13.41	0.000 ***
Health	Concerns of health	0.02 ± 0.01	0.02 ± 0.01	0.97	0.334
I	1st personal singular use	0.11 ± 0.03	0.04 ± 0.03	30.94	0.000 ***
We	1st personal plural use	0.00 ± 0.00	0.01 ± 0.01	-25.52	0.000 ***
Social	Social concerns	0.08 ± 0.02	0.11 ± 0.03	-19.78	0.000 ***
Swear	Abusive language	0.01 ± 0.01	0.00 ± 0.00	28.84	0.000 ***
Negate	Negation use	0.03 ± 0.01	0.02 ± 0.01	25.86	0.000 ***
Posemo	Positive emotions	0.05 ± 0.01	0.06 ± 0.02	-18.34	0.000 ***
Negemo	Negative emotions	0.04 ± 0.01	0.02 ± 0.01	26.14	0.000 ***

self-esteem, likely due to normative dissatisfaction with one's body weight and shape [Wolf et al., 2007]. Moreover, these results hint that users' psychological properties are likely to shape their social networks online, e.g., less social concern and more refusal of others among pro-ED users may explain their fewer interconnections, less likelihood to cluster together and a lower reciprocity in the communication network (see Table 4.1).

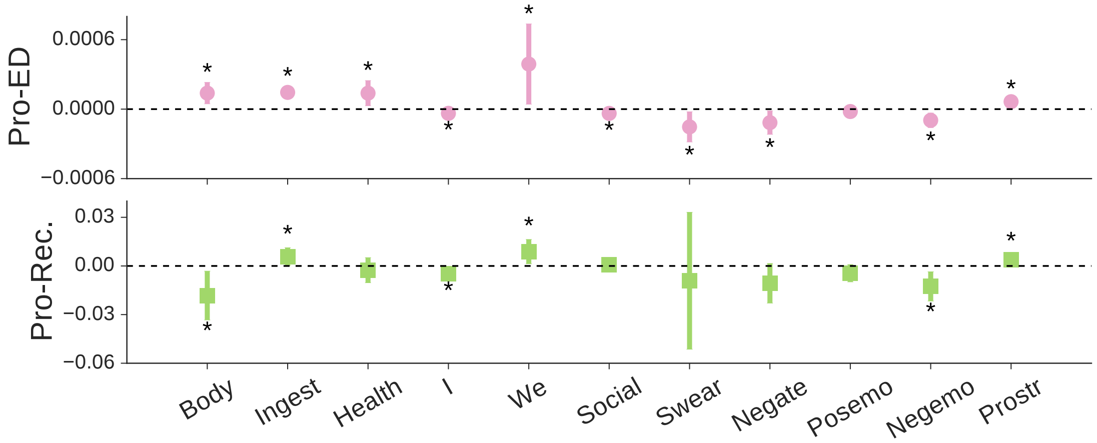


Figure 4.3: Parameters estimates β and 95% confidence intervals for effects of an attribute on PageRank centralities in pro-ED and pro-recovery communities, estimated using robust linear models with controls on social capital covariates (see *Methods*). Coefficients at significance level $p < 0.05$ are labelled with an asterisk. (*Prostr*) is the strength that a user promotes a pro-ED or pro-recovery tendency, measured by the average sentiment of the user on pro-ED or pro-recovery content in tweets (see *Appendix B*).

4.3.4 Community Norms

Next, we present a more systematic exploration of the associations between individuals' behavioral characteristics and the collective network structure of a community. We establish the links between individual characteristics and organizational structures from a sociological perspective and situate our analysis in the context of social norms, i.e., how a group approves of individuals' behavioral attributes. According to the classic definition of social norms in psychological studies [Jackson, 1965], we assume that social norms have two dimensions: (i) how much an attribute of an individual is exhibited, and (ii) how much the group approves of that attribute. We focus on users' psychological attributes (e.g., concerns and emotions) reflected by their behaviors in language use, as these attributes are more related to psychometric indexes of ED than others [Association et al., 2013]. We measure the amount of an attribute exhibited by the percentage of words related to the attribute in a user's tweets (i.e., in the same way as measured in Table 4.2) and measure the amount of group acceptance by the user's PageRank centrality [Page et al., 1999] in an intra-community network. PageRank centrality quantifies how focal or popular an individual is in a network by considering all connections in the network;

people who receive a greater amount of attention (e.g., in-links) have a higher centrality. Compared to other centrality measures (e.g., degree centrality), PageRank centrality can capture the heterogeneity of links, i.e., people who are connected by many well connected peers are more central than those who are connected by the same number of poorly connected peers. In other words, individuals who receive attention/links from popular people will tend to be more central than those who receive attention from the unpopular. In this light, the centrality metric can effectively capture the structural properties of a network, but can also be interpreted as a good measure of acceptance of an individual in a group. Then, we use the classic Return Potential Model (RPM) [Jackson, 1965] to explain social norms, and build regression models which use the amount of an attribute exhibited to predict the amount of group acceptance to evaluate the strength of a norm (see *Methods*).

Fig. 4.3 shows estimated correlations between psychological attributes and network centralities of individuals in different communities. We find that users with more concerns about body image tend to be located more centrally in the pro-ED community. In contrast, users with more concerns about body image tend to be more peripheral in the pro-recovery community. Users who talk more about ingestion tend to be more central in both two communities. Interestingly, pro-ED users who share more information on medication and health-related materials tend to be more focal (see *health* in Fig. 4.3); a cause may be that pro-ED individuals often share/seek advice on using medications (e.g., diuretics, enemas and laxatives) to lose weight or inhibit appetite in online communities [Campbell and Peebles, 2014]. Consistent with studies in social psychology [Pope and Bierman, 1999], people who exhibit less self-focused attention (using less *I* and more *we*) are more popular in a social community. Also, people with more negative emotions tend to be located in the periphery of their communities. This finding aligns with previous findings in offline social networks that happy people are likely to be located in the center of their local social networks [Fowler and Christakis, 2008], and also confirms the positive role of optimism in social network development [Brissette et al., 2002]. Finally, users who show a stronger pro-ED or pro-recovery tendency tend to be more popular in the corresponding communities, emphasizing their roles as opinion leaders [Katz and Lazarsfeld, 1966; Valente and Pumpuang, 2007].

4.4 Discussion

In this chapter, we have explored ED-related communities on Twitter and their interactions via Twitter conversations. We have shown that participants in ED-related conversations on Twitter can be divided into two main communities: a pro-ED community which promotes disordered eating behaviors; and a pro-recovery community which encourages people to recover from the disease. Consistent with prior studies of these communities on other platforms like Flickr and YouTube [Oksanen et al., 2015; Yom-Tov et al., 2012], we find that people tend to interact almost exclusively with others in the same community, with extremely limited interactions between communities on Twitter. That is, people sharing similar interests and stances on ED tend to be connected within the communication network on Twitter, expressed by the presence of strong homophily [McPherson et al., 2001]. This is of particular importance in reaching larger populations affected by ED through online social networks. Beyond that, our findings shed new light on the role of emotional interactions in the segregation between the two communities in social networks, i.e., more negative emotions in inter-community interactions can intensify the split in affiliation between different communities [Oberschall, 2007; Yardi and Boyd, 2010], whereas more positive emotions in intra-community interactions can enforce social ties and strengthen pre-existing identities of members within the same community [Chmiel et al., 2011; Oksanen et al., 2015].

We find that users in the two communities display distinctive social behaviors and psychological properties on Twitter. Compared to pro-recovery users, pro-ED users exhibit an excessive focus on body image and food ingestion, increased feelings of social isolation and self-occupation, heightened aggression and refusal, more negative emotions and less positive emotions, showing greater risk of ED and poorer mental health. These results are compatible with prior evidence that pro-ED communities exacerbate risk of ED [Overbeke, 2008; Wilson et al., 2006] through an unrealistically thin ideal [Bardone-Cone and Cass, 2006; Mabe et al., 2014], reinforcement of an ED identity [Giles, 2006; Maloney, 2013], or exposing and adopting harmful weight loss practices [Overbeke, 2008; Wilson et al., 2006]. Also, our results show that the negative impact of pro-ED communities tends to self-reinforce through very active Twitter engagement (e.g., actively following, tweeting and re-tweeting behaviors). Similar findings that pro-ED groups are more active than pro-recovery groups have been reported for other platforms like Facebook [Teufel et al., 2013].

We further find that individuals' psychological characteristics can shape their social networks on Twitter. Characteristics that benefit community development (e.g., less self-focused attention and lowered negative tones) and behaviors that strongly indicate a community identity (e.g., actively sharing content on body image and making positive comments on pro-ED or pro-recovery content) tend to attract more attention and help actors to be more central in a social network. While our data do not allow us to identify the actual causal mechanisms of network dynamics, our results provide new insights into how people maintain order in these online communities. Our findings also indicate that central individuals in a social community are likely to act as opinion leaders in the community [Katz and Lazarsfeld, 1966; Winter and Neubaum, 2016]. These individuals actively promote information on a specific lifestyle (e.g., pro-ED or pro-recovery) and their central positions can further make them a credible, easily-assessable source of information. In this light, these central individuals can be more influential than others to shape health-related opinions in a community.

In summary, this chapter presents a first study of online ED communities that analyses their social interactions and norms based on a large sample of data. It provides a new perspective to understand how people form and maintain online health communities. Notably, we have observed that pro-ED and pro-recovery communities are connected within the same social network, although this network is a highly segregated by community identity. A natural question is whether individuals change their participation from a community to the other and how individuals' activities in one community affect their engagement in the other. This will be further discussed in the next chapter.

Chapter 5

Information Flows

Recent studies have shown that social media facilitate diffusion of both pro-recovery and anti-recovery information among people affected by mental health problems, while little is known about the associations of people's activities in sharing different types of information. Our work explores this question by analyzing a large set of Twitter conversations among users who self-identified as eating disordered. We use clustering algorithms to identify topics shared in online conversations and represent interpersonal interactions by a multilayer network in which each layer represents user-to-user communication on a different topic. By measuring structural properties of the multilayer network, we find that (i) the same set of users form social networks with different structures in communicating different types of information and (ii) exposure to content on body image can reinforce individual engagement in anti-recovery communication and weaken engagement in pro-recovery communication. By measuring structural changes in a sequence of temporal, multilayer networks built based on users' conversations over time, we further find that (i) actors previously engaged in pro-recovery communication are likely to engage in anti-recovery communication in the future and (ii) actors in anti-recovery communication have frequent entries into and exits from such communication system. Our results shed light on the organization and evolution of communication in online eating disorder communities.

5.1 Introduction

As a public concern, pro-ED (or pro-eating disorder) communities draw widespread criticism, particularly by so-called pro-recovery communities that aim to raise awareness of ED and offer support for people to recover [Chancellor et al., 2016c; De Choudhury, 2015; Lyons et al., 2006; Oksanen et al., 2015; Wang et al., 2018a]. Under pressures from these pro-recovery communities and the general public, several social media platforms have adopted censorship-based interventions for pro-ED communities, e.g., banning pro-ED content and user accounts on Tumblr[1] and Instagram[2] [Casilli et al., 2013; Chancellor et al., 2017, 2016d]. However, the efficacy of these interventions is still uncertain. Concerns about this are heightened by recent findings that censoring pro-ED content leads to a wide spread of more harmful alternatives to such content (e.g., content sharing self-harm) [Chancellor et al., 2017, 2016d], and banning pro-ED users makes these individuals more "invisible", less reachable by health care providers and recovery-oriented information [Casilli et al., 2013]. These findings highlight the importance of understanding how different types of information (not only pro-ED content but also ED-related content more generally) flow through an online ED community and how these information flows correlate with one another, before introducing interventions.

However, our understanding of information flows in online ED communities is limited, as prior studies in this field have often focused on content analysis and largely ignored interaction patterns. Examples of these analyses are examining the types of content shared in online ED communities [Borzekowski et al., 2010; Branley and Covey, 2017; Juarascio et al., 2010; Sowles et al., 2018; Teufel et al., 2013; Wick and Harriger, 2018], characterizing linguistic styles of individuals in online self-presentation [De Choudhury, 2015; Lyons et al., 2006], identifying diagnostic information from language use in pro-ED content [Chancellor et al., 2016a,c], detecting lexical variation of pro-ED content [Chancellor et al., 2017, 2016d], and measuring people's attitudes on pro-ED and pro-recovery information based users' emotional expressions in online comments [Oksanen et al., 2015; Syed-Abdul et al., 2013]. Yet, social interactions in information exchange and the resulting communication networks have been largely under-explored. As a result, little is known about the organizational structure of communication in online ED communities and the functional roles of individuals in communicating different types of information.

Although recent studies have turned attention from content analysis to network analysis [Arseniev-Koehler et al., 2016; Moessner et al., 2018; Tiggemann et al., 2018; Yom-Tov et al., 2012], they either focus solely on a single type of communication (e.g., sharing pro-ED content [Tiggemann et al., 2018]) or do not distinguish different types of information shared in online ED communities [Arseniev-Koehler et al., 2016; Moessner et al., 2018; Yom-Tov et al., 2012]. It remains unclear how different types of communication correlate with one another in these communities. Insights into the correlations among different types of communication can facilitate predictions of an community's responses to interventions. For example, if users' activities in two types of communication have a highly positive correlation, blocking one type of communication is likely to promote the other type of communication.

In this chapter, we address these research gaps by using a multilayer network approach to systematically characterizing communication networks for a broad range of types of

[1] https://staff.tumblr.com/post/18563255291/follow-up-tumblrs-new-policy-against

[2] http://instagram.tumblr.com/post/21454597658/instagrams-new-guidelines-against-self-harm

content in an online ED community. We analyze a large set of Twitter conversations (i.e., tweets with a "mention" or "reply") among individuals who self-identified by having ED in their Twitter profile descriptions and their online friends, involving 2,206,919 tweets posted by 55,164 users over 7 years (from March 2009 and March 2016). Three major research questions guide our analysis: (i) what types of content are often discussed in an online ED community? (ii) how do different types of content flow through interpersonal communication networks? and (iii) whether and how do different types of communication correlate with one another?

5.2 Data

Our dataset is collected from Twitter, a microblogging platform that allows millions of people to interact by exchanging short tweet messages. Whereas many social media sites restrict pro-ED content [Chancellor et al., 2016d], Twitter has not yet enforced any restrictions [Arseniev-Koehler et al., 2016]. This makes Twitter a unique platform to examine communication naturally happening within online ED communities in a non-reactive way. All data used in this chapter is publicly accessible information on Twitter; no personally identifiable information is used. Next, we provide details about the dataset we used.

5.2.1 Collecting user sample

We use a snowball sampling method [Wang et al., 2017] to gather data about individuals affected by ED on Twitter. We first search for ED-related tweets by a set of keywords (e.g., "eating disorder", "anorexia" and "bulimia") via the Twitter APIs. From authors of 1,169 ED-related tweets, we identified 33 users who self-reported both ED-diagnosis information (e.g., "eating disorder", "edprob" and "proana") and personal bio-information (e.g., height and weight) in their Twitter profile descriptions. Starting with these seed users, we use a snowball sampling procedure through users' who-follows-whom networks to expand the user set. This results in 3,380 *ED users* who self-identified as disordered in their profile descriptions. Our data validations show that 95.2% of the ED users are likely to be affected by ED (i.e., a high precision, see [Wang et al., 2017] for more details). However, the above process does not ensure a high recall, as we miss users who did not disclose their disorders in Twitter profile descriptions.

To obtain a more representative sample of online ED communities (i.e., including those who did not disclose their disorders in Twitter profile descriptions), we further collect ED users' Twitter friends (including followees and followers) who posted ED-related content in tweets. To this end, we first crawl all friends of each ED user on Twitter, yielding 208,065 users (including the 3,380 ED users). For each user, we retrieve up to

3,200 (the limit returned from the Twitter APIs) of their most recent tweets, resulting in 241,243,043 tweets. This collection process finished on March 2, 2016. Then, we search for users who posted an ED-related hashtag in their historical tweets (see Appendix C, Section 1 for details), resulting in 41,456 ED-related users.

5.2.2 Tracking interpersonal conversations

The other task of our data collection is to track interpersonal communication of ED-related users. We focus on users' communication via the *"mention"* and *"reply"* interactions as these interactions are the two main ways to conduct direct communication on Twitter. Also, as users can discuss a topic by sending and replying to tweets over several rounds, a single tweet message often cannot provide complete context to understand human communication. For example, it may be hard to recognize that user A might dissuade user B from committing suicide based on a single tweet *"@XXX please don't do it, I love you so much!"*, without considering that this tweet is user A's reply to user B's tweet *"9 30pm on the 8th of July 2012 I will hopefully die, so n/r going to write my suicide note"*. Thus, to obtain a relatively complete context in a discussion, we shift attention from single tweets to conversations, i.e., aggregations of successive tweets in a discussion [Alvarez-Melis and Saveski, 2016].

Specifically, for each user, we search for their tweets that contain a mention or reply. Then, we aggregate tweets into conversations based on the *"in_reply_to_status_id"* field returned by the Twitter APIs. Each conversation consists of a seed tweet, all tweets in reply to it, and replies to the replies, which can involve several tweets and users. Mentions that do not receive any replies are considered as individual conversations. We obtain 1,044,573 conversations consisting of 2,206,919 tweets. All re-tweets are excluded, since the mentions or replies in a re-tweet are conducted by the original author of the re-tweet, not by users who re-tweet it. Detailed statistics of these conversations are presented in Appendix C, Section 2.

5.3 Analyses

In this section, we present our analyses of Twitter conversations in online ED communities. These analyses involve three steps: (i) characterizing the types of content in users' conversations; (ii) examining how different types of content flow through interpersonal interactions and measuring structural correlations among different types of communication; and (iii) exploring how different types of communication correlate by analyzing temporal information.

5.3.1 Content analysis

Common methods for characterizing the types of textual content are topic modeling (e.g., latent Dirichlet allocation models [Alvarez-Melis and Saveski, 2016; Blei et al., 2003]) and content-based clustering methods (e.g., bag-of-words and word/document embeddings [Le and Mikolov, 2014; Mikolov et al., 2013a]). However, these methods generated topics that were hard to interpret in our preliminary experiments. Previous studies have shown that these methods perform poorly when applied to short and noisy tweets [Alvarez-Melis and Saveski, 2016]. Although we aggregate short tweets into a conversation, most conversations are still short (on average 21.9 words in each conversation) and they are often dominated by general chats (e.g., "why do you follow me?"). Inspired by prior work [Weng and Menczer, 2015], we here characterize the types of users' conversations by identifying topics of hashtags used in these conversations. As hashtags are often used to annotate the theme of a tweet, these clusters of hashtags have been shown to effectively indicate the underlying topics in tweets [Steinskog et al., 2017; Wang et al., 2014; Weng and Menczer, 2015].

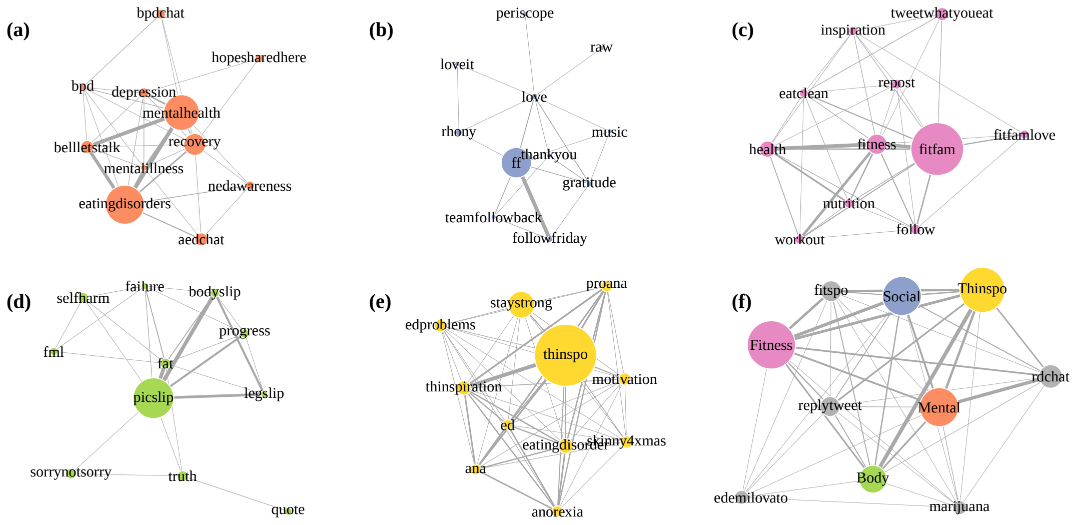


Figure 5.1: Topics in hashtag co-occurrence networks. (a-e) Co-occurrence networks of the most frequent hashtags in each of the five popular topics, where each node denotes a hashtag. The size of a node is proportional to the number of tweets with a hashtag and edge width is proportional to the number of co-occurrences between tags. (f) Co-occurrences of popular topics involving more than 1,000 users, where each node denotes a topic as labeled. The node size is proportional to the number of tweets mentioning a topic and edge width is proportional to the ratio of the number of tweets mentioning both topics over the number of tweets mentioning at least one topic.

We detect topics of hashtags by performing community detection in co-occurrence networks of hashtags. We build an undirected, weighted hashtag network based on the co-occurrences of hashtags in the tweets of users' conversations, where an edge is weighted by the co-occurrence count of hashtags. To filter out noise, only tags used by more than three distinct users and used in more than three tweets are considered. The resulting network contains 65,756 nodes and 109,663 edges, partitioned in 672 connected components, where 5,791 nodes are in the giant component and 4 in the second largest component. Due to the dominance, we focus on analyzing the giant component and obtain 26 topic clusters of hashtags by applying the Louvain method [Blondel et al., 2008] to this network[3]. The resulting modularity is $Q = 0.51$ ($z = 6.63$ compared to a random configuration model [Newman and Girvan, 2004], $p < 0.001$ in a two-tailed test), indicating a clustered topic structure in the hashtag co-occurrence network. By examining the numbers of tweets and users related to each of the 26 topics identified above, we find that users have consistently high levels of engagement in five topics with IDs 2, 4, 8, 16 and 22 respectively, whereas other topics are much less popular (see Appendix C, Section 3). To avoid analyzing topics of interest to a specific subgroup of online ED communities, we focus on the five popular topics in this chapter.

Figures 5.1(a-e) show the most frequent hashtags and their co-occurrence networks for each of the five popular topics. As shown in Figure 5.1(a), topic 2 is dominated by "#eatingdisorders", "#mentalhealth", "#recovery" and "#bellletstalk"[4], showing a clear tendency to support recovery from ED and promote mental health [Chancellor et al., 2016c; Yom-Tov et al., 2012]. We label this topic *mental*. In contrast, topic 4 (Figure 5.1(b)) is dominated by a single tag "#ff" which is likely to be an abbreviation of "#followfriday", given frequent co-occurrences between the two tags. These tags are often used in a weekly social events where people recommend their followers to follow more people on Twitter[5]. We thus label this topic *social*. Figure 5.1(c) shows that topic 8 is mainly concerned with fitness activities and diet (thus labeled *fitness*). Topic 16 (Figure 5.1(d)) is about "#picslip" which is often used by users to post a picture of themselves[6]. Other tags that highly co-occur with "#picslip" are "#bodyslip", "#fat", "#selfharm" and "#failure", indicating a theme of body image and body dissatisfaction, thereby labeled *body*. As shown in Figure 5.1(e), topic 22 is mainly about thinspiration (or pro-ED) content (e.g., "#thinspo" and "#proana") which is designed to inspire people to lose weight and stay extremely thin [Borzekowski et al., 2010; Juarascio et al., 2010]. We label this topic *thinspo*. Moreover, to illustrate the relationships of these popular topics, we visualize a co-occurrence network of popular topics in Figure 5.1(f).

To ensure the validity of our results, we check the reliability of the topic structure found in users' conversations. First, we check if the relationships of topics aligns with findings

[3] We also tried other well-established methods for community detection in networks, e.g., the Infomap algorithm [Rosvall and Bergstrom, 2008]. These methods produced comparable results in our preliminary analysis. In this chapter, we use the Louvain method due to its efficiency of processing large-scale networks [Blondel et al., 2008].

[4] An annual campaign on social media to break the silence around mental illness and support mental health: https://letstalk.bell.ca/en/

[5] https://www.urbandictionary.com/define.php?term=followfriday

[6] https://www.urbandictionary.com/define.php?term=picslip

in prior qualitative studies on online ED content [Borzekowski et al., 2010; Juarascio et al., 2010]. To this end, we project hashtags to their associated topics and measure the relatedness of topics based on the co-occurrences of topics in tweets, where topics often co-occurring in the same tweets tend to correlate [Weng and Menczer, 2015]. To avoid bias that popular topics tend to have frequent co-occurrences, we quantify the relatedness of pairwise topics using the Jaccard coefficient, i.e., the ratio of the number of tweets mentioning both topics over the number of tweets mentioning at least one topic, rather than the absolute numbers of co-occurrences. Figure 1(f) of the main text shows relatedness of topics, where we notice that the *thinspo* topic is highly related to the *body* and *fitness* topics. This confirms prior qualitative studies showing that pro-ED content often contains graphic material inspiring the adoration of a thin body, and exercising or dieting tips on losing weight [Borzekowski et al., 2010; Juarascio et al., 2010]. In contrast, the *mental* topic is less related to *body* and more related to *rdchat* which is about online charting on nutrition with registered dietitians[7]. This confirms the recovery-oriented feature of *mental*, as a shift of focus from physical appearance to healthy diet is an important movement into ED recovery [Shapiro et al., 2007] and talking to professionals is a useful way to cope with the disease [Linville et al., 2012].

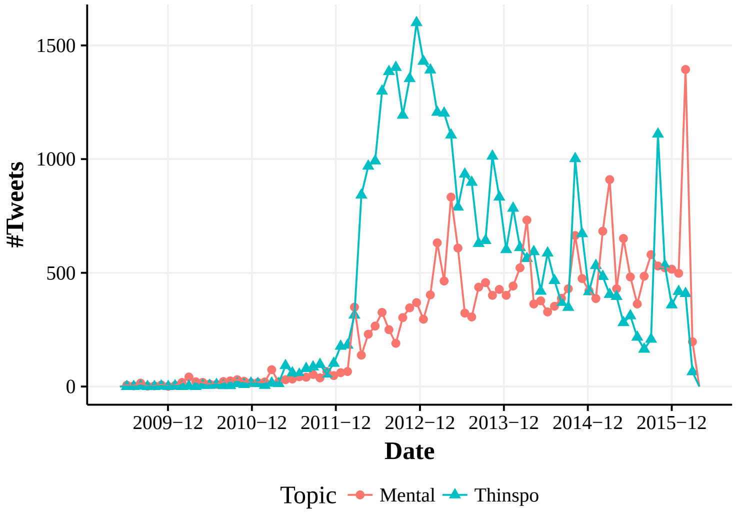


Figure 5.2: Numbers of tweets on *mental* and *thinspo* per month.

Second, we check if these topics cover real world events in ED communities. Two well-known events are "Eating Disorders Awareness Week (EDAW)", a campaign run by pro-recovery communities to raise awareness of risks of ED from February to March[8], and the "Skinny4Xmas" challenge which is run by pro-ED communities to achieve a net calorie goal (i.e., the total number of calories consumed minus that burned by exercises) from October to December[9]. Inspecting the numbers of tweets on *mental* and *thinspo*

[7] https://www.symplur.com/healthcare-hashtags/rdchat/

[8] https://www.beateatingdisorders.org.uk/edaw

[9] http://letters-from-ana.blogspot.co.uk/2013/10/skinny4xmas.html

topics over time (Figure 5.2), we find that our identified topics indeed relate to these two events, as a large number of tweets on *mental* appear around March (i.e., the time period of “EDAW”) and many tweets on *thinspo* appear around October (i.e., the period of “Skinny4Xmas”). This further confirms that the topics found by the clustering algorithms give a reliable picture on the types of content discussed in online ED communities.

5.3.2 Network analysis

We proceed to explore how different types of content flow through interpersonal interactions using network analysis methods. To do this, we first categorize users’ conversations based on the topics of hashtags found above. Given a conversation document, we track the sequence of hashtags used in the conversation and annotate the topics of this conversation with the topic labels of these hashtags. To avoid ambiguous annotations, we only consider conversations that are labeled with only one unique topic; those with multiple topics or without a hashtag are excluded in our analysis[10]. This results in 102,554 conversations consisting of 201,155 unique tweets. Then, we represent information about who interacts with whom and on which topic in users’ conversations via a multilayer network with $N = 55,164$ nodes representing users and $M = 5$ layers representing topics. The multilayer network can be described by a set of M adjacency matrices, one for each layer, $G = [A^{[1]}, A^{[2]}, ..., A^{[M]}] \in \mathbb{R}^{N \times N \times M}$. As shown in Figure 5.3, each layer $A^{[\alpha]}$ is a directed, weighted network, in which a link $a_{ij}^{[\alpha]}$ runs from a node representing user i to a node representing user j if i mentions or replies to j in the conversations on topic $\alpha = 1, 2, ..., M$, weighted by the frequency of these mentions and replies.

Based on this multilayer representation, we characterize communication patterns in online ED communities by quantifying structural properties of the multilayer network. First, we measure structural properties of single-layer networks (i.e., each layer is considered as a separated network) to examine organizational features of each type of communication. Second, we measure inter-layer dependencies in the multilayer network (i.e., structural correlations between inter-layer networks) to explore associations of different types of communication.

5.3.2.1 Structures of single-layer networks

We first examine structures of single-layer networks to explore the organization of an online ED community in a type of communication. Figure 5.4 shows cumulative in- and

[10] While this process reduces the size of our raw data, it can avoid biased results. For example, one could build classifiers based on content features (e.g., bag-of-words [Sriram et al., 2010]) in conversations labeled with a single topic to predict the most likely topic for conversations labeled with multiple topics and conversations without a hashtag. This however can introduce classification errors and noise data.

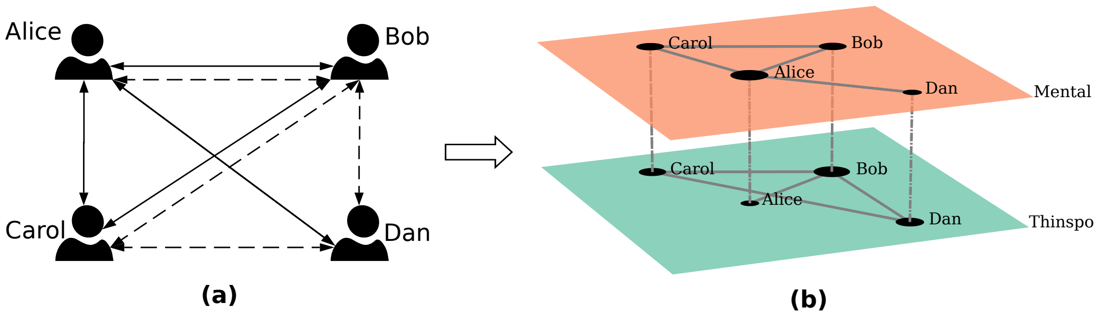


Figure 5.3: Multilayer communication network. (a) The information flows of exchanging content on *mental* health (solid lines) and *thinspo* (dotted lines) within four users. (b) Representation of different types of communication in a multilayer network, where each node denotes a user and each layer denotes a topic as labeled. Links in the same layer are the communication connections of the corresponding topic and links across layers align users.

out-strength distributions of each single-layer network, and Table 5.1 gives details about structural properties of these networks. The key results are as follows.

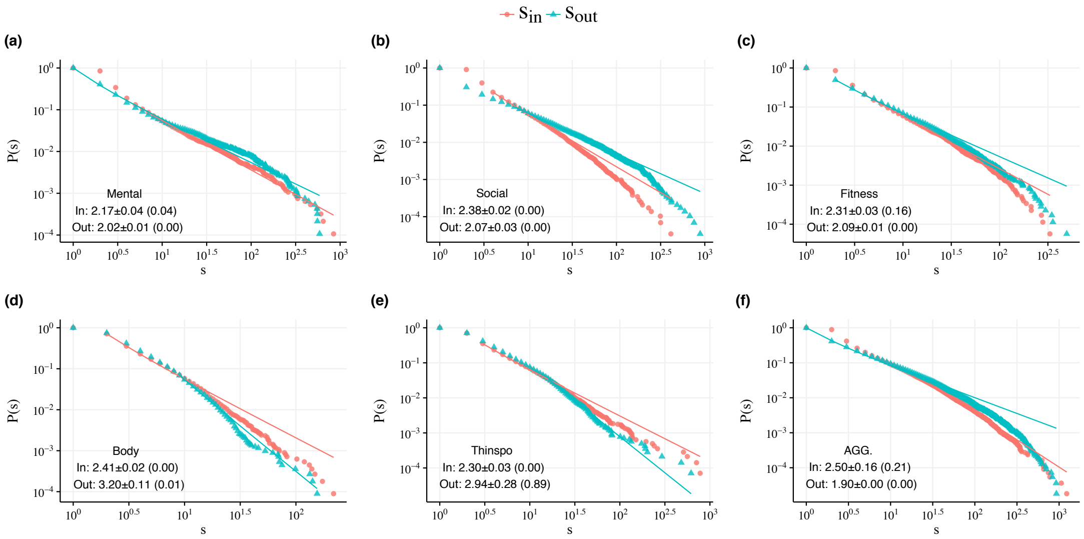


Figure 5.4: Distributions of in-/out-strength (s_{in}/s_{out}) at each layer and the full aggregated network (AGG.). All values of s are shifted by 1 to account for nodes with zero values on the log-log plots. Lines fit a power-law distribution $P(s) = s^{-\lambda}$ using the maximum likelihood estimator and a p-value for the goodness of fit is obtained using a bootstrapping procedure [Clauset et al., 2009]. The mean values and standard deviations of exponents λ are shown in the legends, and p-values obtained via 1,000 bootstrap replications are reported in parenthesis.

Users' engagement levels in posting harmful content have skewed distributions. Figures 5.4(a-e) show two distinct behaviors in in- and out-strength (s_{in} and s_{out}) distributions of single-layer networks. Specifically, the distributions of s_{in} are more

Table 5.1: Statistics of single-layer networks and the aggregated (AGG.) network, including 1. the number of active nodes $N^{[\alpha]}$, i.e., nodes that are connected by at least one in-/out-link [Nicosia and Latora, 2015]; 2. the total number of edges $E^{[\alpha]}$; 3. the average strength $\langle s^{[\alpha]}\rangle$; 4. density $D^{[\alpha]}$ measuring the ratio of the number of edges to maximum possible number of edges; 5. fraction of nodes in the giant weakly connected component $\%G^{[\alpha]}$; 6. reciprocity $r^{[\alpha]}$ quantifying the likelihood of nodes with mutual links; 7. the Kendall's τ correlation between in- and out-strengths $\tau(s_{in}^{[\alpha]}, s_{out}^{[\alpha]})$. 8. global clustering coefficient $C^{[\alpha]}$ which measures the extent that two neighbors of a node are connected; 9. assortativity coefficient by strength $A_s^{[\alpha]}$, i.e., the correlation between the out-strengths of source nodes and the in-strengths of destination nodes [Newman, 2003]. Values of $z(x)$ are z-scores for the empirical results based on null models. For each property x of a network, we generate 1,000 randomized networks via the configuration model [Newman and Girvan, 2004] and measure the property in these randomized networks. Then, the deviation of x from randomness is quantified by a z-score: $z(x) = (x - \langle x\rangle)/\sigma_x$, where $\langle x\rangle$ is the mean value of the property in randomized networks and σ_x is the standard deviation.

Network	Mental	Social	Fitness	Body	Thinspo	AGG. (all αs)
$N^{[\alpha]}$	9,381	28,959	17,689	11,199	14,156	55,164
$E^{[\alpha]}$	17,306	54,609	34,040	17,881	27,807	140,330
$\langle s^{[\alpha]}\rangle$	3.55	2.89	2.94	2.46	2.96	4.32
$D^{[\alpha]}$	1.97×10^{-4}	6.51×10^{-5}	1.09×10^{-4}	1.43×10^{-4}	1.39×10^{-4}	4.61×10^{-5}
$\%G^{[\alpha]}$	76.55%	89.17%	83.84%	73.87%	88.87%	95.67%
$r^{[\alpha]}$	0.24	0.19	0.36	0.45	0.33	0.29
$\tau(s_{in}^{[\alpha]}, s_{out}^{[\alpha]})$	-0.06	-0.04	0.09	0.21	0.13	0.11
$C^{[\alpha]}$	0.06	0.04	0.03	0.03	0.01	0.03
$z(C^{[\alpha]})$	40.70	198.96	61.25	109.21	6.29	160.67
$A_s^{[\alpha]}$	-0.08	-0.07	-0.1	-0.02	-0.08	-0.1
$z(A_s^{[\alpha]})$	-10.64	-17.24	-19.05	-4.60	-14.04	-37.80

skewed than those of s_{out} in the *mental*, *social* and *fitness* layers, while the distributions of s_{out} are more skewed in the *body* and *thinspo* layers. These behaviors can be quantified by fitting a power-law function $P(s) = s^{-\lambda}$. We find that all networks have comparable values of λ in s_{in} distributions, indicating similar patterns of popularity ranking for actors in different interactions. However, the s_{out} distributions in the *body* and *thinspo* layers ($\lambda \approx 3$) have a larger value of λ than those in the *mental*, *social* and *fitness* layers ($\lambda \approx 2$). As exposure to thin-ideal content (*thinspo* and *body*) is associated with higher risks of ED [Hargreaves and Tiggemann, 2003; Yu, 2014], this implies that the fractions of users who actively post harmful content are relatively small.

Private communication takes place in small groups. As shown in Table 5.1, *mental* and *body* layers have lower fractions of nodes in the giant weakly connected component $\%G^{[\alpha]}$ than other layers, revealing that users tend to form smaller communities when discussing mental health and body image. This may be related to the private nature of these topics—due to fear of rejection and feelings of shame [Becker et al., 2010; Swanson et al., 2011], people are more likely to talk about their illnesses and body image to someone they can trust rather than any friends online.

Interactions related to body image are reciprocal. Table 5.1 shows that interactions on body image and appearance management (*fitness*, *body* and *thinspo*) have higher degrees of reciprocity $r^{[\alpha]}$ than those on other types of content (*mental* and *social*). A strong tendency to reciprocate the interactions received from others can reward and reinforce these interactions [Fehr and Gächter, 2000]. The high degrees of reciprocity of interactions in the *fitness*, *body* and *thinspo* layers are confirmed by positive correlations between in- and out-strengths ($\tau > 0$), while $\tau < 0$ implies a suppression of reciprocity in the *mental* and *social* layers. These results imply that online ED communities tend to mutually exchange information about body image, which align with psychological evidence that body image issues (including both positive and negative ones) are at the core of ED [Thompson et al., 1999].

Users in general communication cluster. While the clustering coefficients $C^{[\alpha]}$ are low in each network (Table 5.1), the value of $z(C^{[\alpha]})$ in general communication (*social*) is larger than those in communication on specific topics (*thinspo* and *mental*). Higher values of $z(C^{[\alpha]})$ indicate that users are more likely to cluster together, compared to a baseline of random clustering. Such high value of $z(C^{[\alpha]})$ in general communication may be due to the fact that more general topics tend to be of interest to a wider variety of individuals, and a higher level of individuals sharing common interests leads to a more cohesive social community [Lim and Datta, 2013].

Private communication forms a weakly disassortative network. As Table 5.1 shows, all networks are characterized by disassortative mixing by strength ($A_s^{[\alpha]} < 0$), i.e., hubs tend to be attached to peripheral nodes, which aligns with prior evidence on online social networks [Hu and Wang, 2009]. Compared to null models, the disassortative strengths in private communication (*body* and *mental*) are relatively weaker than those in other communication (*social*, *fitness* and *thinspo*). This implies that people tend to discuss private topics with others who have similar social-status characteristics in a community, aligning with the social penetration theory [Altman and Taylor, 1973] which argues that similar individuals are more likely to self-disclose more widely (i.e., a wider range of topics in discussion) and deeply (i.e., a higher degree to which the information revealed is private or personal).

The independent analysis of single-layer networks described above shows different organizational structures in different types of communication, highlighting the multiplex nature of human interactions [Lewis et al., 2012; Szell et al., 2010]. To demonstrate the disadvantage of not distinguishing types of communication, we include the statistics for the aggregated network (i.e., aggregating all single-layer networks in a single network) in

Figure 5.4 and Table 5.1. We see that ignoring the differences of interactions can lead to the loss of essential information and a misrepresentation of the system, e.g., losing information on differential network structures between harmful and healthy communication (as shown in Figure 5.4).

5.3.2.2 Dependencies of inter-layer networks

We next extend the independent analysis of single-layer networks to analysis of interdependencies between these networks. The aim of this interdependency analysis is to examine the correlations of individuals' activities and their functional roles in different types of communication. We consider the following measures.

Activity correlation: the tendency of users to be involved in one type of communication if they are involved in another type of communication. This can be measured by multiplexity, namely the fraction of nodes that are active (i.e., having at least one connection with other nodes) at both layers α and β in all nodes of a multilayer network [Nicosia and Latora, 2015].

Role correlation: the extent to which hubs (e.g., those users who have high popularity or active engagement) in one type of communication are also hubs in another type of communication. We measure this by the Kendall's τ rank correlations of nodes' in-/out-strengths between two layers of the multilayer communication network. To avoid bias due to a low degree of multiplexity in real-world networks [Nicosia and Latora, 2015], we only consider nodes that are active in both layers.

Link overlap: the tendency that user i connects to user j in both types of communication. This can be measured by the Jaccard coefficient between two sets of links (binary links) at two layers [Szell et al., 2010].

Link-strength correlation: the extent to which user i has frequent interactions with user j in two types of communication. We measure this by Kendall's τ correlation of link strengths between two layers. Due to the sparseness of connections in real-world networks (see Table 5.1), we only consider links between two nodes that are present in the two layers.

These measures alone, however, are not adequate for evaluating inter-layer correlations. This is because the values of these measures are influenced by the size and connectivity of each single-layer network, which can be related to the processes of data collection and content categorization discussed in the previous sections. For a reliable evaluation, we need to assess the statistical significance of a correlation result. A standard statistical approach for distinguishing patterns of networks from those generated by chance is null models [Connor et al., 2017; Newman and Girvan, 2004]. A null model generates patterns by randomizing an observed network many times under proper constraints; an observed pattern that differs from the distribution of randomly generated patterns is potentially derived from meaningful processes rather than chance [Gotelli and Ulrich, 2012; Paul and Chen, 2016]. According to the null hypothesis in question, null models can have different constraints and randomization processes, such that randomized networks preserve structural features of an original network but have a random distribution for a property of interest, e.g., interactions. Here, we consider four null models for testing hypotheses of interest (see Table 5.2). In each model, randomized networks in each layer have the same sizes (i.e., the numbers of active nodes and edges) as the original ones, so as to control for the effects of data collection and content categorization on inter-layer correlations. Details of these null models are introduced in Appendix C, Section 5.

Table 5.2: Null hypotheses on correlations of individuals' activities and roles in types of communication.

Correlation	Null hypothesis	Null model
Activity correlation	The activities of users in a type of communication are unrelated to those in other types of communication.	Hypergeometric model [Nicosia and Latora, 2015]
Role correlation	The roles of users in a type of communication (i.e., their positions in a type of communication network) are unrelated to those in other communication.	Independent multilayer node-permutation model [Croft et al., 2011]
Link overlap	Users' interconnections in one type of communication are unrelated to those in other communication.	Independent multilayer configuration model [Paul and Chen, 2016]
Link-strength correlation	The strength/frequency of interactions between two users in one type of communication is unrelated to those in other communication.	Independent directed-weight reshuffling model [Opsahl et al., 2008]

We generate 1,000 randomized multilayer networks for each null model, and measure a z-score for the empirical value of an inter-layer correlation measured in the original network x as $z(x) = (x - \langle x \rangle)/\sigma_x$, where $\langle x \rangle$ and σ_x are the mean and standard deviation of the values of x measured in randomized networks respectively. The results are shown in Figure 5.5, which can be summarized as follows.

Activity correlation: social networks in the *body* layer bridge those in the *mental* and *thinspo* layers. Figure 5.5(a) shows z-scores of inter-layer multiplexity compared to a hypergeometric model [Nicosia and Latora, 2015]. The largest z-score occurs between *body* and *thinspo* layers, indicating that the correlation of users' activities in sharing *thinspo* and *body* topics is much stronger than expected at random. On the other hand, while the overlap of actors in *mental* and *thinspo* layers is not significantly different from randomness, actors in the *mental* layer have a pronounced overlap with those in the *body* layer. These results imply that the group of users who engage in sharing *body* may bridge two groups who engage in sharing *mental* health and *thinspo* content. This may not be surprise because body image issues are at the core of both

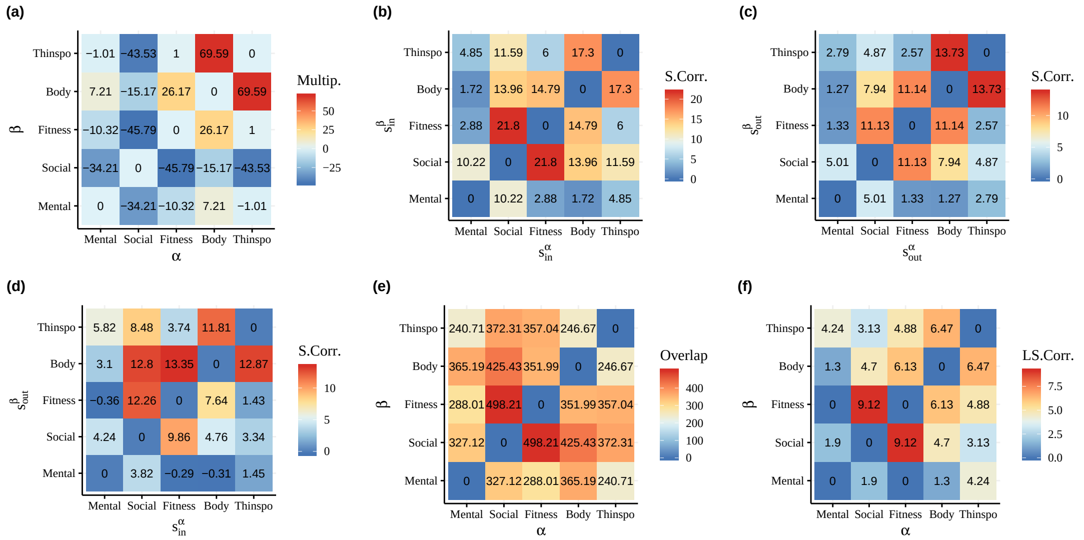


Figure 5.5: Deviations of empirical pairwise correlations of inter-layer networks to null models. (a) Multiplexity, (b-d) in-/out-strength correlations, (e) link overlaps and (f) correlations of link strengths, where $p < 0.05$ when $z < -1.96$ or $z > 1.96$ with assumptions of normality.

the development and recovery of ED, where negative body image contributes to the development of ED while positive body image can be helpful for ED recovery [Thompson et al., 1999].

Role correlations: actors play different roles in healthy and harmful communication. Figures 5.5(b-d) show z-scores for in- and out-strength correlations of nodes in pairwise layers, as compared to an independent multilayer node-permutation model [Croft et al., 2011]. In most pairwise layers, nodes with higher in-/out-strengths in a layer tend to have higher in-/out-strengths in the other layer (Figures 5.5(b-c)), which indicates that popular/active users in a field are likely to be popular/active in the other field. However, nodes' positions in the *mental* layer are not significantly correlated with those in the *body* layer, implying that actors may play a different role in these types of communication. Surprisingly, this pattern is absent between the *mental* and *thinspo* layers, i.e., nodes' positions in these layers are significantly correlated. A possible reason for such correlations is that pro-recovery users who actively post *mental* health may send healthy information to pro-ED users who post *thinspo* content as interventions [Yom-Tov et al., 2012]. This can be illustrated by the results in Figure 5.5(d) that nodes with higher out-strengths in the *thinspo* layer are likely to have higher in-strengths in the *mental* layer. That is, users who post more *thinspo* content tend to receive more content on *mental* health. Figure 5.5(d) also reveals users' responses when receiving different content. For example, nodes with higher in-strengths in the *fitness* and *body* layers tend to have higher out-strengths in the *thinspo* layer and lower out-strengths in the *mental* layer. This indicates that receiving more *fitness* and *body* content may reinforce users' engagement in posting *thinspo* content and reduce their engagement in posting *mental* health. A possible explanation is that exposure to *fitness* and *body* content may trigger body comparison which can promote body dissatisfaction and body-focused anxiety [Tiggemann and Polivy, 2010; Tiggemann and Zaccardo, 2015]. Such dissatisfaction and anxiety can further motivate people engage more in pro-ED conversations and less in pro-recovery conversations.

Link overlap: people often connect to the same friends in different types of communication. Figure 5.5(e) shows z-scores for overlaps of links in pairwise layers, as compared to an independent multilayer configuration model [Paul and Chen, 2016]. We see that high z-scores show in each pair of layers, indicating that users generally tend to connect to the same friends when discussing different topics. This aligns with prior evidence that people are often surrounded by a relatively stable social network [Viswanath et al., 2009].

Link-strength correlation: strengths of interactions on *mental* health generally have no significant correlations with those on other content. Figure 5.5(f) shows z-scores for correlations of link strengths, compared to an independent directed-weight reshuffling model [Opsahl et al., 2008]. A notable pattern is that users who often exchange content of *mental* health have no significant tendencies to frequently discuss other topics such as *social*, *fitness* and *body*. This can arise from two different processes: (i) actors in the *mental* layer exclusively focus on discussing *mental* health, while largely ignoring interactions on other topics; and (ii) actors who previously engaged in other topics are less likely to engage in discussing *mental* health later. Distinguishing the two processes requires detailed time information on different interactions, which will be discussed in the next section.

5.3.3 Dynamic analysis

To better understand the relationships among different types of communication, we consider the time dimension of Twitter conversations and examine the dynamics of communication networks over time. Compared to the above analysis on static networks, dynamic analysis on temporal networks allows to explore how users start/stop to engage in a topic and change interests from one topic to others, yielding further insights into the correlation patterns of different types of communication.

To this aim, we represent temporal information about who interacts with whom on which topic and when in Twitter conversations using temporal multilayer networks. Specifically, we divide users' conversations into multiple sub-sets over time periods $1, ..., T$,

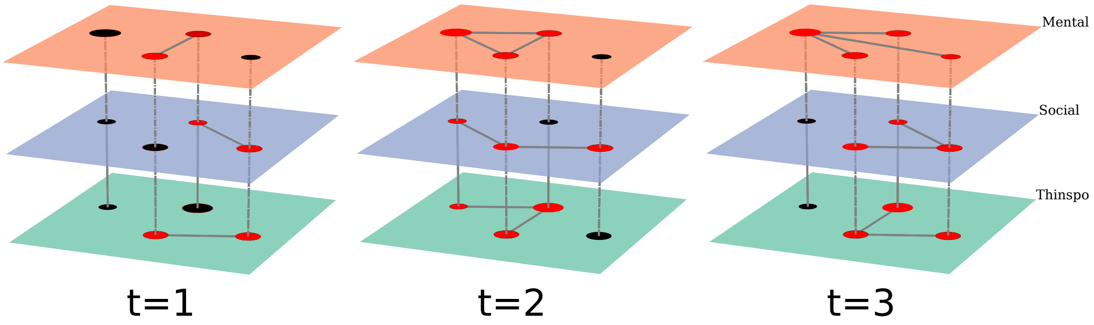


Figure 5.6: Temporal multilayer communication networks. Each node denotes a user and each layer denotes a topic as labeled. Links in the same layer are the communication connections on the corresponding topic and links across layers align the same users. The red color marks active nodes in each layer α at time t.

based on the posting timestamp of a tweet. To reduce potential bias due to intermittent posting activities of users and temporal popularity of topics online[11], we build temporal networks by a fixed number of tweets instead of a fixed time interval. We rank all tweets by a chronological ordering and partition the tweets into subsets with a fixed number of tweets. The number of subsets is estimated by the Freedman-Diaconis rule which is widely used to select the width of the bins in a histogram [Freedman and Diaconis, 1981], resulting in 55 subsets. As shown in Figure 5.6, for conversations in a subset at period $t \in [1, ..., T]$, we build a temporal multilayer network $G_t = [A_t^{[1]}, A_t^{[2]}, ..., A_t^{[M]}] \in \mathbb{R}^{N \times N \times M}$ in the same way that we build the static multilayer network, where M layers representing M topics and N nodes representing N users are fixed over time. Detailed statistics for these temporal multilayer networks are reported in Appendix C, Section 6.

Based on these temporal networks, we study the dynamics for users' communication in two ways. First, we measure the likelihood of users engaging in a type of communication given that they have engaged in other types of communication. Clarifying such likelihood is not only useful to understand how the above correlation patterns appear among different types of communication, but also helps to identify signs suggestive of engagement in a type of communication, e.g., risk factors for engaging in harmful communication. Second, we examine the stability of a community of users who engage in a type of communication over time, particularly on investigating the presence of hardcore actors who have long-standing involvement in a type of communication. Evidence from this investigation can give clues about what strategies are likely to achieve quality, cost-effective outcomes in interventions. For example, if a type of communication is mainly carried out by a fixed set of hardcore actors, banning a small number of these actors can lead to serious damage to the connectivity of the communication network [Kirman and

[11] As shown in Figure C.2(d), users are highly active in posting tweets at some time periods, e.g., in 2013. This can be related to several factors, e.g., users in our sample might have high levels of engagement at these periods (i.e., sampling bias), or some topics were highly popular online at these periods (i.e., environmental factors).

Lawson, 2009] and reduce the efficacy of the network in shaping individual cognition and behavior [Kilduff et al., 2006], while banning a larger number of actors at random may have limited influence on the network [Albert et al., 2000].

5.3.3.1 Transition of engagement activities

We first examine how users change their engagement between types of communication by measuring transitions of nodes' activities across layers in temporal multilayer networks. As users can engage in discussing multiple topics at the same time period, following prior work [Nicosia and Latora, 2015], we represent the activity state of node i across layers at time t by a node-activity vector $b_{i,t} = (b_{i,t}^{[1]}, ..., b_{i,t}^{[M]})$, where $b_{i,t}^{[\alpha]} = 1$ if node i is active at layer α of G_t (i.e., user i engages in topic α at time t) and $b_{i,t}^{[\alpha]} = 0$ otherwise. For computational efficiency, each binary vector $b_{i,t} = (b_{i,t}^{[1]}, ..., b_{i,t}^{[M]})$ is encoded as a decimal integer $R_{i,t} = \sum_{m=1}^{M} b_{i,t}^{[m]} \cdot 2^{M-m}$, where $R_{i,t} = 0$ indicates that node i has no interaction with others at time t and $R_{i,t} = 2^M - 1$ indicates that node i interacts with others in discussing all topics at time t. Then, we measure the transitions of users' engagement from a set of topics to another set by the period-to-period transition probability of node i from state $R_t = x$ to state $R_{t+1} = y$[12] as:

$$P(R_{t+1} = y | R_t = x) = \frac{\sum_{t=1}^{T-1} \sum_{i=1}^{N} I(R_{i,t} = x, R_{i,t+1} = y)}{\sum_{t=1}^{T-1} \sum_{i=1}^{N} I(R_{i,t} = x)}. \tag{5.1}$$

where $I(R_{i,t} = x, R_{i,t+1} = y)$ is an indicator function denoting whether node i has both an activity state $R_{i,t} = x$ at time t and a state $R_{i,t+1} = y$ at $t + 1$, defined as:

$$I(R_{i,t} = x, R_{i,t+1} = y) = \begin{cases} 1 & \text{if } R_{i,t} = x \text{ and } R_{i,t+1} = y \\ 0 & \text{otherwise.} \end{cases} \tag{5.2}$$

Similarly, $I(R_{i,t} = x) = 1$ if node i has an activity state $R_{i,t} = x$ at time t and $I(R_{i,t} = x) = 0$ otherwise.

Figure 5.7(a) shows results of transition probabilities $P(R_{t+1}|R_t)$ in our data, where we only consider nodes that are active in at least one of the two successive periods, i.e., $R_{i,t} + R_{i,t+1} > 0$. These results reveal the following patterns.

Users tend to shift engagement from healthy communication to other communication. One notable pattern in Figure 5.7(a) is that the probability values in region I, namely $P(R_{t+1} > 16 | R_t < 16)$, are smaller than those in other regions. Since $R_t \geq 16$ and $R_t < 16$ denote whether nodes are active in the *mental* layer or not respectively[13], this result indicates that users who previously engaged in other topics are less likely to discuss *mental* health subsequently. In contrast, the values of

[12] For simplicity, we assume that the conditional probability for engagement at the next period depends only on the current state of engagement and not on the states of engagement at previous periods.

[13] If $R_t \geq 16$, $b_t^{[1]} = 1$. In contrast, $b_t^{[1]} = 0$ if $R_t < 16$.

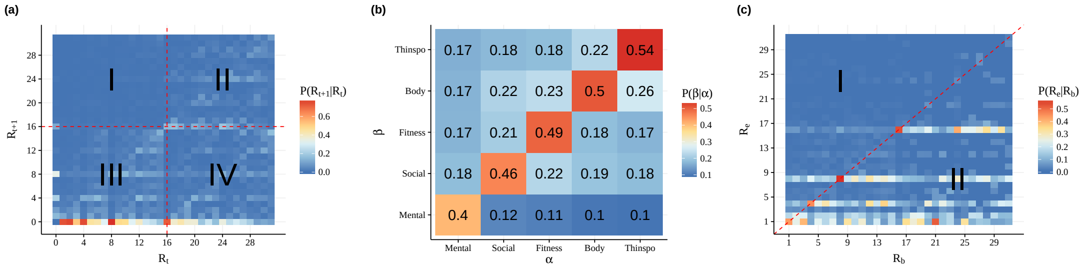


Figure 5.7: Transitions of engagement in different topics. (a) Transition probabilities of topic engagement in two subsequent observations R_t and R_{t+1}; (b) Fractions of users who posted content on topic α earlier will post β later (note that $\sum_\beta P(\beta|\alpha)$ is not necessarily equal to 1 as a user can post multiple different topics β after posting α); (c) Transition probabilities of topic engagement at the beginning R_b and the end R_e of participation.

$P(R_{t+1} < 16|R_t > 16)$ in region IV are relatively high, showing that users who previously talked about *mental* health tend to change to talk about other topics like *thinspo* (i.e., $R_{t+1} = 1$). Together, these results imply that users are more likely to shift engagement from pro-recovery to pro-ED communication than vice versa.

To reinforce the above argument on users' engagement between pro-recovery and pro-ED communication, we inspect users' historical tweets and compute the probability that users post content on topic β after posting content on topic α. The results are shown in Figure 5.7(b). We see that 17% of users who posted *mental* earlier will post *thinspo* later, while only 10% of users who posted *thinspo* earlier will post *mental* later, which confirms that users are more likely to shift engagement from pro-recovery to pro-ED communication. Also, the probabilities in the last row of Figure 5.7(b) are relatively low, indicating that users previously engaged in posting other content are less likely to engage in posting *mental* health. This explains why the link strengths in the *mental* layer are less correlated with those at other layers (Figure 5.5(f)). Moreover, the highest probability occurs when users post *body* content after posting *thinspo*. This explains the significant inter-layer correlations between *body* and *thinspo* (Section 5.3.2.2), and also confirms that individuals are likely to engage in comparison of body image after viewing thinspo content [Bardone-Cone and Cass, 2007].

Users interested in a specific topic earlier tend to engage in the same topic later. Another notable pattern in Figure 5.7(a) is the relatively high values of $P(R_{t+1}|R_t = 0)$ at $R_{t+1} = 1, 2, 4, 8, 16$. Since $R_t = 0$ denotes users having no engagement in the communication system at time t and $R_{t+1} = 1, 2, 4, 8, 16$ denotes users engaging in a single topic at $t + 1$, this result suggests that new users (and those who restore to active state after an inactive period) often join the communication system by discussing a single topic. Similarly, the results of $P(R_{t+1} = 0|R_t)$ show the statues of users' engagement in topics before they leave the system. We see that the values of $P(R_{t+1} = 0|R_t)$ at

$R_t = 1, 2, 4, 8, 16$ are generally high, indicating that users have high dropout rates when discussing only a single topic. Thus, a natural question is whether users have constant interests in the same topics at the beginning and the end of participation in the communication system.

To explore this question, we use the same method described above to measure the beginning-to-end transition probabilities $P(R_e|R_b)$, where R_b and R_e are nodes' activities across layers at the beginning and the end of participation, respectively. To avoid overestimation of $P(R_e|R_b)$ for users who are observed only in one time period[14], we only consider nodes that are active at least in two different temporal networks (i.e., $1 \leq b < e \leq T$). The results are shown in Figure 5.7(c). As expected, high probabilities of $P(R_e|R_b)$ appear when $R_e = R_b$ (highlighted in a red line) and $R_b = 1, 2, 4, 8, 16$, indicating that users who engage in a single topic earlier are more likely to engage in the same topic later. However, this pattern is absent when users engage in more than one topic at an early stage, i.e., $R_e = R_b$ but $R_b \neq 1, 2, 4, 8, 16$. Measuring Cohen's κ between $R_{i,b}$ and $R_{i,e}$ for each user i confirms that the consistency between the beginning and end of participation for users with $R_{i,b} = 1, 2, 4, 8, 16$ ($\kappa = 0.34$) is higher than that with $R_{i,b} \neq 1, 2, 4, 8, 16$ ($\kappa = 0.01$).

The diversity of users' interests decreases over time. We also notice that the probabilities in region II of Figure 5.7(c) are higher than those in region I. In region II, $R_b > R_e$, meaning that users who engage in a wide range of topics at the beginning of participation tend to focus on a small number of specific topics at the end of participation. To verify this pattern, we measure the diversity of users' interests in tweets over sliding windows. Again, we set sliding windows by a fixed number of tweets rather than a fixed time interval. This is to avoid bias from intermittent activities of users, e.g., as a user becomes less active in posting content, the number of tweets posted in a fixed time interval decreases and the diversity of topics in these tweets will also decrease over time. Given user u posting n distinct tweets on topics $T_1, ..., T_n$ (with repetition), the diversity of posting interests of u in window $i \in [1, n-k+1]$ is measured by the entropy of topics $T_i, ..., T_{i+k}$:

$$H_i(u) = -\sum_{T_j \in \mathbb{T}_{u,i}} P(T_j) \log P(T_j), \tag{5.3}$$

where $\mathbb{T}_{u,i}$ is the set of distinct topics among $T_i, ..., T_{i+k}$. $P(T_j) = C(T_j)/k$ in which $C(T_j)$ counts the frequency of T_j in $T_i, ..., T_{i+k}$. A larger value of $H_i(u)$ indicates a higher degree of diversity in users' interests. In a similar way, we also measure the diversity of user interests based on tweets that are received from other users.

Figure 5.8 shows the mean entropy $\langle H_i \rangle$ and 95% confidence intervals (CI) of topics in tweets posted and received by users over sliding windows, where a window size of $k = 10$ is used. Inactive users who have posted or received less than 20 tweets are excluded

[14] For a user i who is observed once, the initial state of participation $R_{i,b}$ and the final state of participation $R_{i,e}$ are the same, leading to $P(R_{i,e}|R_{i,b}) = 1$.

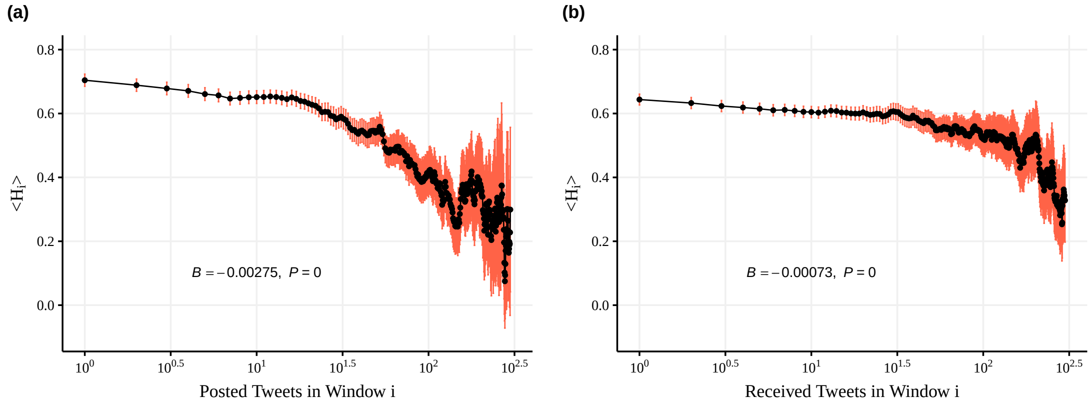


Figure 5.8: Mean entropy $\langle H_i \rangle$ and 95% CI of topics in (a) posted and (b) received tweets over sliding windows with a size of $k = 10$. CI become wider due to the decreased sample sizes of users having a large number of tweets. Legends report estimated coefficients B and p-values in a linear regression model: $\langle H_i \rangle = Bi + \epsilon$, where estimations are based on windows over $i \in [1, 150]$ due to relatively small mean errors in this range.

to avoid noise. Both plots show that the diversity of user interests has a decreasing trend over time. Results of linear regression models that relate $\langle H_i \rangle$ to a function of i confirm negative correlations between $\langle H_i \rangle$ and i, with $p < 0.001$ in both models. Robustness checks using other window sizes and thresholds for excluding inactive users produce similar results. These findings strongly support the hypothesis that users tend to focus on a small number of specific topics as they engage more online. Moreover, the diversity of interests in received tweets declines more slowly, as compared to that in posted tweets. This hints a time-lag between the two trends, likely because a user might continue to receive information on a topic from other users even when the user loses interests in posting the topic.

5.3.3.2 Stability of communities

We now turn our focus from analyzing changes in topics of conversations to studying stability of a community of users involved in a type of communication. We measure the stability of a community by overlaps of users who engage in the same type of communication over time, i.e., the overlaps of active nodes in the same layer α in different pairs of temporal multilayer networks G_t and $G_{t+\Delta t}$. This can be computed by the Jaccard similarity of nodes that are active in $G_t^{[\alpha]}$ and $G_{t+\Delta t}^{[\alpha]}$ as:

$$J^{[\alpha]}(t, t+\Delta t) = \frac{N_{11}^{[\alpha]}}{N_{01}^{[\alpha]} + N_{11}^{[\alpha]} + N_{10}^{[\alpha]}}, \tag{5.4}$$

where $\Delta t \in [1, T-1]$ is the time interval between two networks G_t and $G_{t+\Delta t}$. $N_{11}^{[\alpha]}$ is the number of nodes that are active at both $G_t^{[\alpha]}$ and $G_{t+\Delta t}^{[\alpha]}$, $N_{01}^{[\alpha]}$ is the number of nodes that are active at $G^{[\alpha]}_{t+\Delta t}$ but not in $G^{[\alpha]}_{t}$, and $N^{[\alpha]}_{10}$ is the number of nodes that are active at $G^{[\alpha]}_{t}$ but not in $G^{[\alpha]}_{t+\Delta t}$. Then, we calculate the mean similarity across intervals Δt, and can obtain the overlaps of actors as a function of Δt:

$$O^{[\alpha]}(\Delta t) = \frac{1}{T - \Delta t} \sum_{t=1}^{T-\Delta t} J^{[\alpha]}(t, t + \Delta t). \tag{5.5}$$

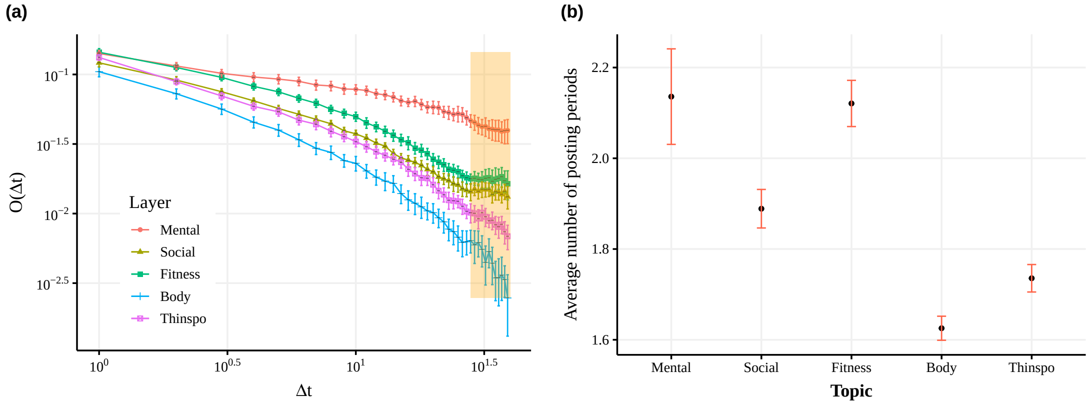


Figure 5.9: (a) Mean overlaps of active users in temporal networks across interval Δt. Error bars give 95% CI and yellow region highlights the stable stages in the *mental*, *social* and *fitness* layers. (b) Average numbers of periods that users post content on each topic. Error bars show 95% CI.

Figure 5.9(a) shows results of $O^{[\alpha]}(\Delta t)$ in each layer of temporal networks. As only a small number of observations are available for large values of Δt, we only consider results of $\Delta t \in [1, 40]$ to reduce noise. The key findings are summarized as follows.

Limited numbers of hardcore members engage in harmful communication. As shown in Figure 5.9(a), users engaged in discussing *mental* health have the largest overlaps over time, indicating strong stability of pro-recovery communities. Moreover, the overlaps of actors in the *mental*, *social* and *fitness* layers tend to be relatively stable (see the highlighted region in Figure 5.9(a)), suggesting the presence of a large set of hardcore users who have a constantly high level of engagement in exchanging these types of content. In contrast, the overlaps in the *thinspo* and *body* layers continue to decline as the interval Δt increases. This indicates that members of pro-ED communities have frequent entries into and exits from the system, revealing a high level of fluctuation in these communities.

Individuals engage in harmful communication while organizations engage in healthy communication. To better understand the results in Figure 5.9(a), we examine users' posting activities in more detail and compute the number of time periods that a user posts a topic. Figure 5.9(b) shows the average number of posting time periods of users on each topic. We see that users on average share *body* and *thinspo* content in 1.63 and 1.74 time periods respectively, less frequently than sharing other content.

This aligns with our results that active nodes in the *body* and *thinspo* layers are highly fluctuating in Figure 5.9(a). Inspecting the most active users in sharing each topic, we find that active users in sharing *mental* health are often charities and organizations that devote to preventing ED and mental illnesses, such as *@HealingFromBPD*, *@beatED* and *@NEDAstaff*. Similarly, active users in sharing *social* and *fitness* often show a brand-promoting or marketing purpose, e.g., *@WWE* for *social* and *@Reebok* for *fitness*. In contrast, most active users in sharing *thinspo* and *body* content tend to be personal users. Compared to professional organizations and marketing accounts, personal users are less likely to keep continuously active engagement online due to their limited time and attention. Thus, it is not surprising that the *thinspo* and *body* layers have less overlaps of active nodes over time than other layers. This may also explain why the *thinspo* and *body* layers have a more skewed distribution of nodes' out-strengths than other layers in Figures 5.4(d-e).

5.4 Discussion

In this chapter, we have investigated patterns of communication revolved around topics in online ED communities through a large set of conversations among users who self-identified with ED and their friends on Twitter. Applying clustering algorithms to textual content of these Twitter conversations, we find that members of online ED communities are interested in discussing specific topics. By projecting interpersonal interactions in exchanging different topics into a multilayer communication network, we show that different types of communication have distinct network structures and people play different roles in different types of communication. We further incorporate an additional dimension, namely time, into the multilayer network and reveal dynamic characteristics of multiplex communication in online ED communities.

We show that online ED communities largely focus on discussing mental health, general social activities, fitness, body image and thinspo content, which aligns with previous qualitative studies on the content in these communities [Borzekowski et al., 2010; Juarascio et al., 2010; Tiggemann et al., 2018]. Beyond such content analysis, we further find that different types of content are diffused in different ways, e.g., conversations on private content often take place within small groups and actors in sharing general topics tend to cluster. This multiplex feature of communication cannot be observed through a single-layer network obtained by aggregating all different types of communication, highlighting the importance of considering multiplex patterns in studying human interactions [Nicosia and Latora, 2015; Szell et al., 2010].

In line with evidence on other social media platforms [Borzekowski et al., 2010; Chancellor et al., 2016c; De Choudhury, 2015; Yom-Tov et al., 2012], we find the presence of two communities with distinct stances on Twitter: (i) a pro-recovery community in which members discuss their health problems and support sufferers to recover from ED and (ii) a pro-ED community in which members often encourage people to lose weight and stay thin. We observe that a small number of users engage in exchanging both pro-ED and pro-recovery content, as indicated by the low value of multiplexity between *mental* and *thinspo* layers. This aligns with prior evidence that social networks of pro-ED communities have small overlaps with those of pro-recovery communities on Flickr [Yom-Tov et al., 2012] and YouTube [Oksanen et al., 2015]. Despite these small direct overlaps, our results suggest that both pro-ED and pro-recovery communities have pronounced overlaps with communities of users who engage in exchanging content on *body* image, reveling an indirect connection of social networks between pro-ED and pro-recovery communities. Moreover, we find that users who receive more content on *body* image are likely to post more *thinspo* content and less content on *mental* health. This confirms a conceptual model based on social comparison theory [Yu, 2014] where people who are exposed to images of others' bodies tend to compare their appearance with others, which can lead to a negative view of their own bodies and social pressures to have a thin body that can promote the development of ED.

Our results show that users are more likely to engage in pro-ED communication after pro-recovery communication than vice versa. A possible reason for this is that pro-recovery communities tend to post comments on pro-ED content as an intervention for pro-ED communities [Yom-Tov et al., 2012]. We also find that people tend to focus their communication on narrow, specific topics over time. This can be explained as follows: an individual's time and attention are finite resources, and hence each individual must make a choice about how best to use them given the priority of personal preferences, interests and needs [Gonçalves et al., 2011]. Prior studies have shown that focusing on a single topic and posting creative or insightful content on the topic can help people to gain influence online [Cha et al., 2010], and the perception of being valued and respected by others can further motivate people to do so [Ryan and Deci, 2000a]. The settings on social media platforms, such as recommendation systems on Twitter, could also filter topics that less interest a user and reinforce the user to engage in a small set of topics. Moreover, our results suggest that pro-ED communities have a limited number of hardcore actors, with strongly fluctuating membership in the periphery of the communities. This unstable community structure aligns with views of the pro-ED communities as hidden, secretive groups with frequent migrations [Casilli et al., 2013], which can make it hard to monitor and track the positions/roles of individuals (e.g., influential cores) in these communities [Sekara et al., 2016]. Such fluctuating characteristics is likely to be reinforced by the banning actions of pro-ED content [Casilli et al., 2013; Tiggemann et al., 2018], making pro-ED communities less reachable by health care professionals on social media sites.

In conclusion, our investigation of communication behaviors in online ED communities has uncovered distinct patterns in different types of communication on Twitter. The rich information in our data allows us to explore the effects of multi-dimensional interactions on the structure and evolution of a large-scale social network, thereby establishing the first empirical basis for modeling multiplex and dynamic communication in online health communities. Moreover, the findings in this chapter suggest that individuals vary in levels of engagement in online ED communities. In the next chapter, we will investigate characteristics of individuals' online engagement in detail.

Chapter 6

Behavioral Change

The use of social media as key health-information source has increased steadily among people affected by eating disorders. Intensive research has examined characteristics of individuals engaging in online communities, while little is known about discontinuation of engagement and the phenomenon of participants dropping out of these communities. This chapter aims to investigate characteristics of dropout behaviors among eating disordered individuals on Twitter and to estimate the causal effects of personal emotions and social networks on dropout behaviors. Using a snowball sampling method, we collected a set of individuals who self-identified with eating disorders in their Twitter profile descriptions, as well as their tweets and social networks, leading to 241,243,043 tweets from 208,063 users. Individuals' emotions are measured from their language use in tweets using an automatic sentiment analysis tool, and network centralities are measured from users' following networks. Dropout statuses of users are observed in a follow-up period 1.5 years later (from Feb. 11, 2016 to Aug. 17, 2017). Linear and survival regression instrumental variables models are used to estimate the effects of emotions and network centrality on dropout behaviors. The average levels of attributes among an individual's followees (i.e., people who are followed by the individual) are used as instruments for the individual's attributes.

We find that eating disordered users have relatively short periods of activity on Twitter, with one half of our sample dropping out at 6 months after account creation. Active users show more negative emotions and higher network centralities than dropped-out users. Active users tend to connect to other active users, while dropped-out users tend to cluster together. Estimation results suggest that users' emotions and network centralities have causal effects on their dropout behaviors on Twitter. More specifically, users with positive emotions are more likely to drop out and have shorter-lasting periods of activity online than users with negative emotions, while central users in a social network have longer-lasting participation than peripheral users. Findings on users' tweeting interests further show that users who attempt to recover from eating disorders are more likely to drop out than those who promote eating disorders as a lifestyle choice. Thus, presence in online communities is strongly determined by individual's emotions and social networks, suggesting that studies analyzing and trying to draw condition and population characteristics through online health communities are likely to be biased. For example, users with positive emotions in online ED communities tend to drop out of Twitter and these users, as well as their characteristics, are less likely to be observed by researchers. Future research needs to examine in more detail the links between individual characteristics and participation patterns if better understanding of the entire population is to be achieved. At the same time, such attrition dynamics need to be acknowledged and controlled for when designing online interventions so as to accurately capture their intended populations.

6.1 Introduction

As discussed in Chapter 4, one notable characteristic of online eating disorder (ED) communities is their participants having widely different stances on ED [Lyons et al., 2006; Wilson et al., 2006; Yom-Tov et al., 2012]. Some communities encourage members to discuss their struggles with ED, share treatment options and offer support towards recovery from ED, so called *pro-recovery* communities [Lyons et al., 2006; Wolf et al., 2013; Yom-Tov et al., 2012]. There are also many anti-recovery or pro-ED communities in which members often deny ED being a disorder and instead promote ED as a healthy lifestyle choice [Borzekowski et al., 2010; Wilson et al., 2006]. These pro-ED communities can negatively affect health and quality of life among people with and without ED, through reinforcing an individual's identity around ED [Maloney, 2013], promoting thin ideals [Bardone-Cone and Cass, 2006], and disseminating harmful practices for weight loss [Wilson et al., 2006]. Recent studies have shown that individuals' language use online strongly indicate their pro-ED or pro-recovery stances [Chancellor et al., 2016c; De Choudhury, 2015; Lyons et al., 2006], as well as emotions of depression, helplessness and anxiety that reflect their mental disorders [Chancellor et al., 2016a]. Other studies have also examined interactions between pro-ED and pro-recovery communities on Flickr [Yom-Tov et al., 2012], anorexia-related misinformation [Syed-Abdul et al., 2013], sentiments of comments on ED-related videos on YouTube [Oksanen et al., 2015], characteristics of removed pro-ED content [Chancellor et al., 2016b] and lexical variation of pro-ED tags on Instagram [Chancellor et al., 2017, 2016d]. Yet, prior studies have largely focused on examining how people engage in and maintain an online ED community, while little is known about how people drop out of such a community. As a dynamic process, people who join and actively engage in a community at earlier stages can have less participation and leave the community at later stages. Understanding the attrition processes of online communities can enhance our knowledge of the dynamics in these communities.

Studying the attrition process of an online community can also have practical implications for disease prevention and health interventions. Given the ease of accessibility of social media for many individuals (e.g., via mobile devices), increasing attention has focused on using online communities to deliver health interventions [Casilli et al., 2013; Laranjo et al., 2014; Latkin and Knowlton, 2015; Maher et al., 2014; McLean et al., 2017; Stapleton et al., 2018; Williams et al., 2014]. One of the most popular approaches is to deliver health lessons and behavior-change instructions via an online community [Laranjo et al., 2014; Latkin and Knowlton, 2015; Maher et al., 2014; McLean et al., 2017; Stapleton et al., 2018; Williams et al., 2014]. Although pilot studies based on small samples have demonstrated the effectiveness of this approach in reducing body dissatisfaction and disordered eating [McLean et al., 2017; Stapleton et al., 2018], evidence from interventions for a variety of health behaviors (e.g., smoking, diet, exercise and sexual health) suggests that attrition (i.e., participant loss) is one of the most common challenges in online interventions [Laranjo et al., 2014; Williams et al., 2014]. This is known as the "law of attrition" of online interventions [Eysenbach, 2005]. A recent study has shown a high attrition rate in an online intervention for ED [ter Huurne et al., 2017], though this intervention is delivered via a purposely designed website rather than a general social media site. Thus, an important goal in conducting successful interventions via online communities is to improve members' retention, as members who remain longer are more likely to receive these interventions and have more opportunities to promote a target behavior change. To achieve this goal, a critical first step is to understand what factors influence members' retention in an online community.

Prior studies have shown that people's decisions of retention or dropout in online communities are associated with a variety of factors [Kollock, 1999; Malinen, 2015], including personality traits (e.g., shyness and the Big-Five traits) [Hughes et al., 2012; Orr et al., 2009], interests [Casaló et al., 2013], recognition in a community [Chiu et al., 2006; Cook et al., 2009; Lai and Chen, 2014; Nahapiet and Ghoshal, 2000] and support from others [Wang et al., 2012; Xing et al., 2018]. However, such an association is not adequate to establish a relationship that changing an individual's attribute affects her/his online participation, i.e., casual relationships [Angrist et al., 1996; Stovitz et al., 2017]. This is because an association can arise from non-causal relationships. For example, most prior studies focus on the use of self-reported surveys and rely on participants' reports of their own personality, concerns and behaviors [Chiu et al., 2006; Orr et al., 2009; Tausczik and Pennebaker, 2012]. This can introduce considerable retrospective bias and measurement errors, leading to a coincidental association between two unrelated variables. Even if variables are measured rather than self-reported [Wu, 2018; Xing et al., 2018], participation in an online community is inherently self-selected (e.g., sharing common interests) and members can drop out for many different reasons (e.g., effect of an online or offline event). Thus, unobservable factors (i.e., confounding variables) may affect both a main predictor and participation outcomes, causing a spurious association. Moreover, in some cases reverse causality can lead to an association, e.g., prior studies suggest that feelings of social isolation are linked to frequent social media use [Orr et al., 2009; Sheeks and Birchmeier, 2007] whereas recent studies indicate that social media use is linked to increased feelings of social isolation [Primack et al., 2017]. Technically speaking, the issues of measurement errors, confounding variables and reverse causality can cause endogeneity which refers to an explanatory variable of interest being correlated with the error term in a regression model [Angrist et al., 1996]. In these cases, traditional methods such as ordinary least squares (OLS) give biased and inconsistent estimates of the effect of interest. It is therefore not surprising that mixed results exist in prior studies, e.g., a positive association between individuals' expertise and online participation was found in [Tausczik and Pennebaker, 2012] while a negative association was found in [Cook et al., 2009].

This chapter aims to estimate determinants of dropout in an online ED community, while addressing the endogeneity issues by using an instrumental variables (IV) approach [Angrist et al., 1996]. Specifically, we analyze tweeting activities of a large set of individuals who self-identified with ED on Twitter over 1.5 years and identify the presence of dropout if a user ceased to post tweets in the observation period. We explore determinants of a user's dropout based on incentive theory [Kollock, 1999; Ryan and Deci, 2000a] which argues that people's engagement in an activity can be driven by (i) intrinsic motivation which refers to doing something because it is interesting or enjoyable, and (ii) extrinsic motivation which refers to doing something because it earns an external reward. We here focus on the intrinsic motivation captured by personal emotions and the extrinsic motivation captured by sociometric status in an online peer-to-peer community. Rather than using self-reports [Chiu et al., 2006; Orr et al., 2009; Tausczik and Pennebaker, 2012], we measure users' emotions based on their emotional expressions in tweets using sentiment analysis techniques [Thelwall et al., 2010] and quantify users' sociometric statuses by network centrality [Friedkin, 1991] in the social network of an ED community on Twitter. Based on these measured variables, IV estimators both for the decision to drop out and for the time to dropout are implemented to achieve consistent estimates of the effects of personal emotions and network centrality on dropout in an online ED community. To better understand the estimation results, we further examine the relations of posting interests among users who have different values of independent and dependent variables respectively. To our knowledge, this study is the first to systematically characterize the determinants of dropout behaviors in online ED communities. Three research questions are examined: (i) what are the general characteristics of the attrition process in an online ED community, (ii) how do intrinsic (i.e., personal emotions) and extrinsic factors (i.e., social networks) affect the decision of an individual to drop out of the community, (iii) how do these factors affect the duration of time until the occurrence of dropout?

6.2 Methods

6.2.1 Data Collection

Our data is collected from Twitter, a microblogging platform that allows millions of users to self-disclose and socialize. As many social media platforms like Facebook and Instagram have taken moderation actions to counteract pro-ED content and user accounts [Chancellor et al., 2016d], Twitter has not yet enforced actions to limit such content until the period of our data collection [Arseniev-Koehler et al., 2016]. This makes Twitter a unique platform to study the attrition process naturally happening in an online ED community and allows us to examine individuals behaviors in a non-reactive way. Our study protocol was approved by the Ethics Committee at the University of Southampton. All data used in our study is *public* information on Twitter and available through the Twitter APIs (application programming interfaces). No personally identifiable information is used in this study. Our data collection process includes three phases.

- First, we collect a set of individuals who self-identified with ED on Twitter using a snowball sampling approach. Specifically, we track the public tweet stream using “eating disorder”, “anorexia”, “bulimia” and “EDNOS” from Jan. 8 to 15, 2016. This results in 1,169 tweets that mention ED. From the authors of these tweets, we identify 33 users who self-reported both ED-related keywords (e.g., “eating disorder”, “anorexia” and “bulimia”) and personal bio-information (e.g., body weight and height) in her profile descriptions (i.e., a sequence of user-generated text describing their accounts below profile images). Starting from these seed users, we expand the user set using snowball sampling through their social networks of followees/followers. At each sampling stage, we filter out non-English speaking accounts and finally obtain 3,380 unique ED users who self-report ED-related keywords and bio-information in their profile descriptions. Note that our focus in this work is studying individuals who are affected by ED rather than those who are related to ED. The inclusion of bio-information in user sampling allows us to filter out ED-related therapists, institutes or organizations, as these users often display ED-related keywords but do not show bio-information in their Twitter profile descriptions. Details about the data collection of ED users can be found in our prior work [Wang et al., 2017].
- Then, we collect all friends (including followees and followers) of each ED user, leading to a large social network consisting of 208,063 users. For each user, we retrieve up to 3,200 (the limit returned from Twitter APIs) of their most recent tweets and obtain 241,243,043 tweets in total. The data collection process finished on Feb. 11, 2016.

- Finally, we open a follow-up observation period for all users on Aug. 17, 2017 to obtain measurements on users' activities online. In the second observation, we only collect users' profile information which includes users' last posted statuses.

To verify the quality of our collected sample, two members of the research team classified a random sample of 1,000 users on whether they were likely to be a true ED user based on their posted tweets, images and friends' profiles. Users are classified as "disordered" if they frequently and intensively post their body weights, details of their dietary regimen (e.g., calories), struggles with eating (e.g., "I want to eat but cannot"), pictures of themselves, self-reports of being disordered or in recovery in tweets and follow ED-related friends (e.g., user profiles with ED-related keywords). The process revealed a 95.2% match between the identified ED individuals in the data collection stage and those classified as ED during inspection. Although it is impossible to diagnose individuals' disorders based on their online behaviors, this inspection provides a strong indication that the collected users are likely to be affected by ED rather than those who merely talk about ED online. See [Wang et al., 2017] for details of data validation.

6.2.2 Estimation Framework

Two different models are specified to estimate the effects of emotions and network centrality on dropout. First, we specify a linear probability model on the whole sample to estimate the effects of individuals' characteristics observed in the first-observation period on the probability of dropping-out in the second-observation period. Second, we estimate survival models to explore the effects of individuals' characteristics observed in the first observation on the time to dropout in the second observation (i.e., the duration from our first observation to the dropout in our second observation). However, like all social media studies, only a limited number of individuals' characteristics are available for our estimations and these are mostly observed through user-generated data online. This leads to confounding variable bias, since unobservable factors can be correlated with both the main explanatory variables (i.e., emotions and network centrality) and dropout outcomes. For example, undergoing hospital treatment which may not be able to be observed via social media data can simultaneously affect a person's emotional state and the use of social media. Further, prior studies have shown that social media use is associated with increased depression [Lin et al., 2016], social anxiety [Primack et al., 2017] and body dissatisfaction [de Vries et al., 2016; Mabe et al., 2014], implying an effect of online participation on individuals' emotions (i.e., reverse causality). Both confounding variables and reverse causality result in biased and inconsistent estimates of the effects of emotions and network centrality on dropout. This problem can be addressed by using a randomized controlled trial, where emotions or network centralities are randomly assigned to users by researchers [Kramer et al., 2014]. Such a trial, however, is not always feasible, due to ethical and practical limitations [Coviello et al., 2014].

Here, we propose an alternative approach for estimating the effects of interest that is based on instrumental variables (IV) regression, an econometric technique to infer causal relations from observational data [Angrist et al., 1996]. This technique has been applied to a variety of contexts, from identifying the causal effect of education on earning [Card, 1999], the effect of a health treatment [Tchetgen et al., 2015], to estimating social contagion effects on both online [Coviello et al., 2014] and offline behaviors [Aral and Nicolaides, 2017]. Formally, consider a model $Y = \beta_1 X_1 + \beta_2 X_2 + u$, where X_1 is endogenous, X_2 is exogenous, u is a random error term and βs are effects to be estimated. IV methodology uses an instrument Z (which is (i) not contained in the explanatory equation, (ii) correlated with X_1, i.e., $cov(Z, X_1) \neq 0$, and (iii) uncorrelated with u, i.e., $cov(Z, u) = 0$, conditional on the other covariates such as X_2) and runs a first stage reduced-form regression $X_1 = \gamma_1 Z + \gamma_2 X_2 + v$, where v is a random error. The causal effect of X_1 on Y is then given in a second stage regression $Y = \beta_1 \widehat{X_1} + \beta_2 X_2 + u$, where $\widehat{X_1}$ is the predicted values of X_1 from the first stage. For more details please see [Angrist et al., 1996].

6.2.3 Measures

A number of variables are needed for estimations. All independent variables and IV are measured in the first-observation period (unless otherwise stated), while dependent variables are measured in the second-observation period.

6.2.3.1 Dropout Outcomes as Dependent Variables

Following previous studies [Wang et al., 2012; Xing et al., 2018], we identify the presence of dropout if a user ceases to post tweets. Specifically, in the linear probability models, we encode the dropout status of a user as 0 (denoting *non-dropout*) if the user has updated posts in our second observation, and 1 (denoting *dropout*) otherwise.

In the survival models, each user has a two-variable outcome: (i) a censoring variable denoting whether the event of dropout occurs, and (ii) a variable of survival time denoting the duration of time until the occurrence of dropout. We censor the occurrence of a "dropout event" in two ways. First, users are said to drop out if they have not posted tweets for more than a fixed threshold interval π before our second observation (so called *identical-interval censoring*). As people use social media platforms with different activity levels, e.g., some users post every several hours while other users only post once every couple of days, our second censoring method further accounts for personalized posting activities of individuals (called *personalized-interval censoring*). In this method, users are said to drop out if they have not posted tweets for more than a variate threshold interval $\lambda\pi + (1 - \lambda)I_i$ before our second observation, where π is a fixed threshold, I_i is the average posting interval of individual i in our first observation period, and λ is a tunable parameter to control the effects of individual activities. We tune the parameters by maximizing the agreement between the estimated dropout states based on users' activities in our first observation and the observed states in our second observation. See *Appendix D* for details. For users who are censored as dropped-out, we set their survival times as the durations from our first observation to their last postings in our second observation. For those who are censored as non-dropped-out, we set their survival times as the whole time period between our two observations.

6.2.3.2 Emotions and Network Centrality as Main Explanatory Variables

Individuals' emotions are measured through their language used in tweets. There is a variety of sentiment analysis algorithms to measure emotional expressions in texts [Gonçalves et al., 2013; Thelwall et al., 2010]. In this study, we use SentiStrength [Thelwall et al., 2010] as (i) it has been used to measure the emotional content in online ED communities and shown good inter-rater reliability [Oksanen et al., 2015]; (ii) it is designed for short informal texts with abbreviations and slang, and thus suitable to process tweets [Thelwall et al., 2010]. After removing mention marks, hashtags and URLs, each tweet is assigned a scaled value in $[-4, 4]$ by SentiStrength, where negative/positive scores indicate the strength of negative/positive emotions respectively, and 0 denotes neutral emotions. We quantify a users emotional state by the average score of all tweets posted by the user. All re-tweets are excluded, as re-tweets reflect more the emotions of their original authors than those of their re-tweeters. For robust results from the language processing algorithms, we only consider users who have more than 10 tweets and post more than 50 words.

Network centrality measures the importance of a person in a social network; people well-recognized by their peers often have high centralities in a group [Friedkin, 1991]. To measure a user's centrality in the ED community, we build a who-follows-whom network among ED users and their friends, where a directed edge runs from node A representing user A to node B representing user B if A follows B on Twitter. While there are various measures of network centrality, we focus on coreness centrality [Seidman, 1983] as it has been shown to outperform other measures such as degree and betweenness centrality [Friedkin, 1991] in detecting influential nodes in complex networks [Kitsak et al., 2010] and cascades of users leaving an online community [Garcia et al., 2017, 2013]. We measure the sociometric status of a user in the ED community by the in-coreness centrality [Giatsidis et al., 2013] of a node in the generated network using the package igraph 0.7.0 [Csardi and Nepusz, 2006].

6.2.3.3 Aggregated Emotions and Network Centrality of Friends as Instrumental Variables

As IV for a user's attributes, we use average emotions and network centrality over all followees of the user, i.e., people who are followed by the user. The choice of these IV are based on the following considerations. First, we consider the relevance assumption of our instruments requiring that the characteristics of followees are correlated to the user's characteristics, i.e., $cov(Z, X_1) \neq 0$. We expect that followees' updates act as information sources for a user, and followees' behaviors as well as emotions manifested in their tweets can influence the user. Prior work [Wang et al., 2017] has shown the presence of homophily among ED users on Twitter suggesting that users who share similar emotional and network attributes tend to follow one another. Further, the empirical existence and strength of the relevance property are tested in a first stage regression and presented along with the structural estimates of the models. This reduces the possibility that our IVs affect directly on a user's drop-out while have no effects on the user's emotions and centrality.

Second, we examine the exogeneity requirement (i.e., $cov(Z, u) = 0$), where followees' emotions and centrality must not be have a direct effect on the drop-out decision of the user other than through their effect on the user's emotions. While we take such assumption to be reasonable, we identify a pathway through which direct links could arise. Followees' attributes (e.g., emotions) could affect a user's dropout through their effects on followees' own dropouts, e.g., followees' emotional states may affect their own dropouts, and a feeling of loneliness due to friends' leaving may then drive the target user to drop out. To control for this channel, we measure the proportion and durations of followees that remain active in our second observation (regardless of whether the target user drops out or not). Further, we change the definition of followees (that are used to create the instruments) to those who are followed by a user but do not follow the user back (called *single-way followees*). Since users' dropouts are less likely be observed by single-way followees, the reverse causality of a user's dropout on followees' attributes is nullified in this setting, which strengthens the exogeneity assumption on IV and controls.

6.2.3.4 Estimation Covariates

Our estimates control for several covariates that may affect users' tweeting activities. Details of these covariates are shown in Table 6.1. We first measure users' social capital on Twitter (e.g., the numbers of social connections and the levels of engagement in sharing content) to capture effects that people with different levels of popularity may have different tendencies to share content online [Wasko and Faraj, 2005]. Note that, although the numbers of followees and followers can regarded as the in- and out-degree centralities of a user in the whole social network on Twitter (i.e., the "global" social capital), we are interesting in the "local" network centrality that is measured from the social

Table 6.1: Control variables used in estimations.

Control effect	Covariate	Description
Social capital		
	#Followees #Posts #Followers	Number of total followees Number of total posts, including tweets and re-tweets Number of total followers
Activity level		
	Active days #Followee/day #Posts/day #Followers/day	Number of days from account creation to last posting Average number of followees per day Average number of posts per day Average number of followers per day
Observational bias		
	#Tweets in use #Followees in use	Number of tweets in use to measure emotions Number of followees whose attributes are used as instruments
Alternative causal channel		
	%Active followees ⟨Followee durations⟩	Proportion of followees being active between two observations Average days of followees being active between two observations

networks within the ED-specific communities. Second, previous studies have shown that social media use is significantly associated with increased depression [Lin et al., 2016]. We thus measure historical activity levels of users (i.e., active days) to capture effects that previous engagement may relate to both users' emotions and their future engagement. We also measure users' activity frequencies (e.g., posting frequency) to capture their patterns of Twitter usage. Third, the covariates on observational bias are used to control for effects caused by incomplete observations, e.g., a limited number of tweets are retrieved and used to measure emotions for a user. All variables on social capital, activity level and observational bias are measured from users' profile information and tweets collected in our first observation. Moreover, as discussed above, we include the proportion and average durations of followees that are active in our second observation to capture the channel that followees' emotions affect a user's dropout through their effects on followees' own dropouts.

6.2.4 Model Estimations

6.2.4.1 IV Estimation in Linear Regression Model

We use standard two-stage least squares (2SLS) estimators for linear probability models (LPM). We here use LPM rather than non-linear models such as logistic regression because the IV estimating procedure cannot be simply extended to non-linear models [Foster, 1997], making it hard to consistently estimate the effects of interest. In the first stage, we run an auxiliary regression and predict the endogenous variables (i.e., an individual's emotional state and network centrality) based on IV and exogenous covariates. In the second stage regression, we substitute the endogenous variables of interest with their predicted values from the first stage. Estimation is conducted through the AER package [Kleiber and Zeileis, 2008] and robust standard errors are computed.

6.2.4.2 IV Estimation in Survival Model

We use a Kaplan-Meier estimator [Kaplan and Meier, 1958] to estimate the survival function from data. Aalen's additive hazards model [Aalen et al., 2008] is used to estimate the effects of users' attributes on the time to dropout. Compared to the proportional hazards models in which the ratios of hazard functions (i.e., hazard ratios) for different strata are assumed to be constant over time [Cox, 1992], the additive model is more flexible and applies under less restrictive assumptions. To compute an IV estimator in an additive hazards model, we use a control-function based approach which is proposed by Tchetgen et al. [Tchetgen et al., 2015]. The TIMEREG package [Scheike and Zhang, 2011] is used for the implementation of the estimation algorithm. Standard errors are obtained through non-parametric bootstrap.

6.3 Results

6.3.1 Descriptive Statistics

We obtain 2,906 users who posted more than 10 tweets (excluding re-tweets) and 50 words in our data, where 2,459 (85%) users had no posting activities during our two observation periods. Based on the timestamps of account creation and last posting, we use the Kaplan-Meier estimator to estimate the "lifetime" of a user on Twitter, i.e., the duration from account creation to the last posting. The estimated median lifetime of these users on Twitter is 6 months, i.e., one half of the entire cohort drops out at 6 months after creating an account. Figure 6.1 visualizes the social network between dropouts and non-dropouts among ED users. We note that users with the same dropout states tend to cluster together. Computing Newman's homophily coefficient r [Newman, 2003] of this network by users' dropout states, we find $r = 0.09$ ($z = 16.84$ and $P < .001$ compared to a null model, see *Appendix D*), suggesting that users with the same dropout states tend to befriend one another. See *Appendix D* for details of data statistics.

6.3.2 Estimation Results of Linear Probability Models

Table 6.2 shows estimated results in the linear models with two different IV specifications. In the first specification, we use all followees of a user to create IV for the user's attributes. The results are given in columns 2-3, in which both OLS and IV estimators show that positive emotions are associated with a higher probability of dropout

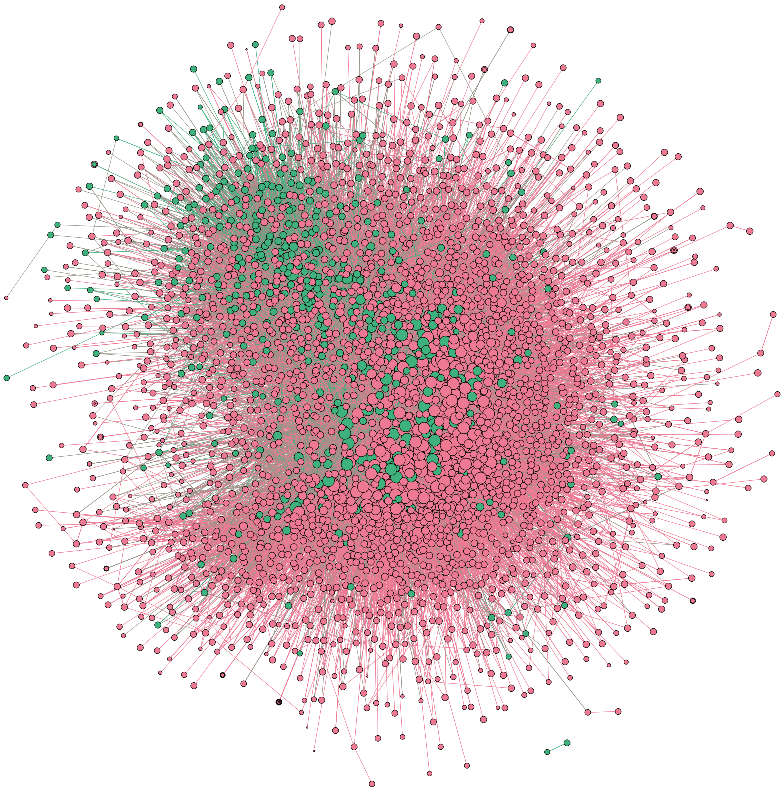


Figure 6.1: The who-follows-whom network among ED users on Twitter, laid out by the Fruchterman-Reingold algorithm [Fruchterman and Reingold, 1991]. Node colors represent dropout statues, where the red color denotes dropout and the green color denotes non-dropout. Node size is proportional to the in-coreness centrality.

($\beta = 0.044$, $P = .007$ and $\beta = 0.29$, $P < .001$, respectively), with largely comparable coefficients for covariates. Compared to the OLS estimator, the IV estimator of the effect of emotions on dropout is remarkably stronger. The Wu-Hausman test further shows a significant difference between the OLS and IV estimators ($P < .01$), suggesting the presence of endogeneity. These results indicate that ignoring endogeneity in the OLS estimation leads to an underestimation of the effect of interest. Moreover, the F-statistics in the first stage regressions show that the relevance of IV exceeds the conventional standard of $F = 10$ [Stock et al., 2002], indicating the validity of our IV.

Columns 4-5 show results of the second IV specification in which only single-way followees are used to create IV. Users who have no any single-way followees are excluded as instruments for these users' attributes are not available. Thus, the number of observations decreases as compared to that in the first IV specification. Moreover, as data on a smaller number of friends is used in the second IV specification, the relevance of IV becomes weaker but still passes the conventional test in the first stage regression. Despite such changes, the two specifications produce largely similar results. Computing Wald tests of equality of coefficients between the two IV models, we find that the

Table 6.2: Estimated effects of emotions on dropout using OLS and IV models.

	All followees				Single-way followees			
	OLS		IV		OLS		IV	
	β	P^c	β	P	β	P	β	P
Emotions	0.044	.005	0.290	<.001	0.064	<.001	0.304	<.001
#Followees	−0.0004	.01	−0.0002	.18	−0.0001	.11	−0.0001	.22
#Posts	−0.00000	.18	−0.00000	.35	−0.00001	.06	−0.00001	.14
#Followers	0.00001	.53	0.00001	.58	0.00001	.7	0.00000	.82
Active days	−0.0003	<.001	−0.0003	<.001	−0.0003	<.001	−0.0003	<.001
#Followee/day	0.001	.01	0.002	<.001	0.001	.03	0.002	.003
#Posts/day	0.0002	.72	−0.001	.38	0.0001	.85	−0.001	.32
#Followers/day	−0.003	.01	−0.005	<.001	−0.003	.02	−0.004	.002
#Tweets in use	−0.00004	.002	−0.00004	.003	−0.00003	.03	−0.00003	.03
#Followees in use	0.0004	.03	0.0002	.38	0.00000	.96	−0.0001	.41
%Active followees	−1.159	<.001	−0.812	<.001	−0.939	<.001	−0.655	<.001
⟨Followee durations⟩	0.001	.004	0.001	.16	0.001	.005	0.0005	.19
Constant	1.270	<.001	1.273	<.001	1.246	<.001	1.251	<.001
Observations	2,906		2,906		2,898		2,898	
First-stage F-statistic[a]			440.26 ($P < .001$)				158.21 ($P < .001$)	
Wu-Hausman test[b]			42.24 ($P < .001$)				14.54 ($P < .001$)	

[a] F-statistic tests the significance of the instrument from a first-stage regression of a user's emotions on followees' emotions (i.e. the instrument) and the rest of the covariates.
[b] Test the difference in estimates between OLS and IV; rejecting the null hypothesis suggests the presence of endogeneity.
[c] P-values are computed based on heteroscedasticity-consistent standard errors.

estimated effects of emotions on dropout are statistically the same across different IV specifications ($P = .8$), potentially suggesting robustness of the results.

Note that network centrality is excluded from the linear models. This is because, as shown in Figure 2, *Appendix* D, many users had dropped out long before our first observation, and the social networks of such users might largely change from the dates of their dropouts to our first observation, e.g., a user might be followed by new followers when these followers were unaware of the dropout of this user. That is, network centralities in the future are used to explain dropouts in the past for these users, which can produce misleading results in the linear models. Nevertheless, including network centrality and instrumenting for it return statistically insignificant effect of centrality on the dropout decision, confirming our argument above on the irrelevance of centrality on this binary decision to drop out or not.

6.3.3 Estimation Results of Survival Models

In the survival models, we only consider users who were active past our first observation period, so as to examine the effect of network centralities in our first-observation on users activities in the second-observation period. Table 6.3 shows mean coefficients of emotions and network centrality in the survival models. Following [Tchetgen et al., 2015], the effects of all covariates are assumed to be time dependent in estimations. Both the standard and IV models on the identical-interval censored data show that (i) positive emotions lead to a shorter survival time ($P < .05$ in the IV model), and (ii) a core position in social networks is associated with a longer survival time ($P < .05$ in both

Table 6.3: Estimated effects of emotions and centrality on survival time using Aalen's additive hazards models[a].

	All followees		Single-way followees	
	Standard (95% CI[b])	IV (95% CI)	Standard (95% CI)	IV (95% CI)
Identical-interval censoring				
Emotions	-0.018 (-0.037, 0.0002)	-0.043 (-0.083, -0.004)	-0.018 (-0.036, 0.0006)	-0.061 (-0.116, -0.011)
Centrality	0.001 (0.0008, 0.0011)	0.001 (0.0007, 0.0011)	0.001 (0.0008, 0.0011)	0.001 (0.0006, 0.0011)
Personalized-interval censoring				
Emotions	-0.016 (-0.034, 0.0031)	-0.038 (-0.08, 0.002)	-0.015(-0.034, 0.0026)	-0.056 (-0.115, -0.007)
Centrality	0.001 (0.0008, 0.0011)	0.001 (0.0008, 0.0012)	0.001 (0.0008, 0.0011)	0.001 (0.0007, 0.0011)
Observations	447	447	445	445
First-stage F-statistic[c]		66.11 ($P < .001$)		34.99 ($P < .001$)
First-stage F-statistic[d]		27.85 ($P < .001$)		12.62 ($P < .001$)

[a] All models are estimated controlling for the full list of covariates but are omitted from the tables due to space concerns. Results are available from the authors.
[b] Confidence intervals (CI) for coefficients are obtained from 1,000 bootstrap replicates. A coefficient is significant at $P < .05$ if 0 is not in 95% CI.
[c] F-statistic tests the joint significance of the two instruments from a first-stage regression of a user's emotions on followees' emotions and followees' centralities (i.e. the instruments) plus the rest of the covariates.
[d] F-statistic tests the joint significance of the two excluded instruments from a first-stage regression of a user's centrality on followees' emotions and followees' centralities (i.e. the instruments) plus the rest of the covariates.

models). Estimations on the personalized-interval censored data and using different IV specifications give similar results. The strong relevance of IV in the first stage regressions confirms the validity of IV across different models. A comparison of results between the linear and survival models further shows that these models have compatible estimators for the effect of emotions on dropout, i.e., positive emotions increase the likelihood to drop out.

6.3.4 Underlying Connection between Emotions and Dropout

While the positive association between network centrality and duration to dropout found above can be explained by prior evidence that core, centralized individuals in a social network act as a critical mass to sustain the network and maintain the network's usefulness by continuously contributing knowledge to others (i.e., actively sharing content) [Wasko and Faraj, 2005], it is unclear why individuals with positive emotions are more likely to drop out than those with negative emotions.

To better understand the relationships between emotions and dropout, we examine posting interests among users with different dropout statuses (447 non-dropout and 2,459 dropout users) and emotional states (spitted into 3 equal subsets and each contains about 968 users) based on hashtags used in users' tweets (see *Appendix D* for details).

We find non-dropouts are interested in advocating a thin ideal (e.g., using hashtags "mythinspo" and "skinny4xmas") and promoting a pro-ED identity (e.g., "edlogic" and "beautiful"). In contrast, dropouts engage in discussing their health problems (e.g., "selfharmprobz", "bulimicprobz" and "anorexicprobz") and offering emotional support for others (e.g., "anasisters" and "stayingstrong"), which implies a tendency of these users to recover from disorders [Lyons et al., 2006; Wolf et al., 2013; Yom-Tov et al., 2012]. Similarly, we split all ED users into three equal-size sets based on their emotional scores and examine hashtags used by each set of users. We find that users with negative emotions often engage in promoting thin ideals (e.g., "bonespo" and "mythinspo") [De Choudhury, 2015], showing largely overlapping interests with the non-dropouts. In contrast, users with neutral and positive emotions are more interested in discussing their health problems (e.g., "anorexicprobz" and "bulimicprobz"), opposing pro-ED promotions (e.g., "reversethinspo") and encouraging healthier body image and behaviors (e.g., "fitfam" and "fitness"), showing similar interests with the dropouts. See *Appendix D* for more detailed lists of hashtags.

Table 6.4: Spearman rank correlations between pairwise lists of hashtags posted by users with a given dropout state and by users with a given emotional state respectively[a]**.**

	Negative ($n = 61^b$)	Neutral ($n = 108$)	Positive ($n = 110$)
Non-dropout ($n = 54^b$)	0.36 ($P = .003$)[c]	-0.21 ($P = .03$)	-0.66 ($P < .001$)
Dropout ($n = 227$)	-0.33 ($P < .001$)	-0.04 ($P = .57$)	0.12 ($P = .07$)

[a] All tags in two lists l_i and l_j are considered in computing the correlation $\rho(l_i, l_j)$. Tags in each list are ranked by TF-IDF scores [Sparck Jones, 1972] and the TF-IDF score of tag t in list l_i is 0 if l_i does not contain i.
[b] The number of hashtags posted by users with a given state.
[c] The Spearman correlations r of hashtags posted by users with different dropout and emotional states, where $\rho \in [-1, 1]$ with 0 indicating no correlation. $P-$values testing for non-correlation are reported in parentheses.

Measuring the Spearman rank correlation ρ between pairwise lists of hashtags posted by users with a given state (e.g., dropped-out or not, and positive or negative), we find a positive correlation between negative users and non-dropouts in hashtag usage ($\rho = 0.36$, $P = .003$ in Table 6.4), indicating similar posting interests among these users. A similar pattern occurs between positive users and dropouts. In contrast, users with other pairs of states show a negative correlation or non-correlation in hashtag usage, indicating their discrepancies in posting interests. These results reveal a possible underlying connection between positive emotions and dropout. Compared to users with positive emotions, those with negative emotions have more similar interests to active members (i.e., non-dropouts) in the ED community. Finding similarities with other members in a community can enhance a sense of belonging to the community and positively increase intention to engage in community activities [Casaló et al., 2013; Malinen, 2015]. Therefore, it is not surprising that negative users are less likely to drop out than positive users in our estimations.

6.4 Discussion

This chapter provides the first estimates of the effects of personal emotions and interpersonal social networks on dropout in online ED communities. The present work has several strengths. First, we base our analysis on incentive theory to explore determinants of users online behaviors (i.e., dropout), allowing us to study users behaviors in a more systematic way than most prior studies that often focus on a single type of determinant (e.g., individual attributes [Hughes et al., 2012; Orr et al., 2009] or social attributes [Garcia et al., 2017; Wang et al., 2012; Xing et al., 2018]). Second, we use automated sentiment analysis techniques to measure users emotions and network analysis methods to quantify users sociometric statuses in an online community, leading to higher efficiency than traditional research methods such as surveys [Casaló et al., 2013; Chiu et al., 2006; Lai and Chen, 2014; Orr et al., 2009; Sheeks and Birchmeier, 2007]. Third, we apply an IV approach to both linear probability and survival models, which enables us to achieve a more consistent estimate of human behavior in online settings than traditional methods (e.g., OLS) used in prior studies [Chiu et al., 2006; Lai and Chen, 2014; Wu, 2018]. Overall, we find that positive emotions increase the likelihood of dropout in ED individuals and accelerate the dropout process on Twitter. In contrast, a central position in the social network of ED individuals at an earlier stage is associated with prolonged participation of an individual at a later stage. These findings are verified across a variety of robustness checks. Next, we present a detailed discussion about these findings.

Despite differences in methodology, our findings align with prior studies in psychological and social media research [Corstorphine, 2006; Malinen, 2015; Orr et al., 2009]. Our results suggest that ED users with negative emotions have high levels of participation on Twitter. This aligns with prior survey studies on social media use (e.g., Facebook use), where people with social anxiety and shyness (i.e., personality traits that are often correlated with multiple negative emotions such as feeling lonely, isolated and unhappy [Farmer and Kashdan, 2012]) are found to spend more time online [Amichai-Hamburger et al., 2016; Orr et al., 2009; Sheeks and Birchmeier, 2007]. An explanation for this is the online disinhibition effect [Suler, 2004], i.e., because of anonymity in online interactions, people with social inhibitions (e.g., those who are socially anxious or shy and those with a stigmatized health problem [Lapidot-Lefler and Barak, 2015]) might be more willing share personal feelings and reveal themselves in online interactions than offline interactions, in order to meet their social and intimacy needs [Sheeks and Birchmeier, 2007]. Additional analyses on users' posting interests reveal that users with negative emotions share similar interests with active users. This allows us to confirm the validity of our results via the social capital theory [Chiu et al., 2006; Nahapiet and Ghoshal, 2000], i.e., sharing common attributes (e.g., interests and vision) with other members can enhance a sense of belonging and positive feeling toward a community, which drives people to actively engage in the community.

Consistent with positive associations between network centrality and active participation in other online communities [Garcia et al., 2017; Wasko and Faraj, 2005], we find that central users in the social network of an ED community tend to have a longer-lasting participation in the community. This result is to be expected for several reasons. First, users who are centrally embedded in a group have a relatively high number of social ties to other members, which can lead these users to feel being socially accepted and approved, as well as a strong sense of belonging to the group. Prior studies have consistently shown that recognition from other members and identification within an online community increase an individual's commitment to the community [Chiu et al., 2006; Kollock, 1999; Lai and Chen, 2014; Nahapiet and Ghoshal, 2000]. Second, information shared by central users is likely to spread to the majority of a community through social ties, and their central positions in the community may promote other members to trust such information [Wasko and Faraj, 2005]. This implies that central users have a greater potential than peripheral users in influencing members' opinions, emotions and behaviors in online communities [Tang and Li, 2015]. Thus, compared to peripheral users, feeling influential may provide an additional incentive for central users to continue participating.

In line with prior studies on online ED communities [Chancellor et al., 2016c; De Choudhury, 2015; Yom-Tov et al., 2012], we find that ED users on Twitter have different stances on ED, where users with negative emotions often share pro-ED content and those with positive emotions often share pro-recovery content. As pro-ED content often contains thin-ideal images and harmful tips for weight loss/control [Bardone-Cone and Cass, 2006; Maloney, 2013; Wilson et al., 2006], this result aligns with clinical evidence on ED treatment showing that more emotional distress is associated with a higher risk to learn and develop dysfunctional coping behaviors among ED sufferers [Corstorphine, 2006]. Thus, as suggested by prior studies [Mulveen and Hepworth, 2006], engaging in pro-ED content may serve as a coping mechanism to deal with emotional pressures and stress of ED. A possible explanation for the association between engaging in harmful online content and coping with stress is sensation seeking [Zuckerman, 2008], a basic personality trait defined as the seeking of varied, novel, complex and intense sensations and experiences, and the willingness to take risks. Several studies have shown that sensation seeking is prominent in adolescence (i.e., the age that disordered eating often develops [Association et al., 2013]) and closely related to pathological Internet use, such as use of violent sites [Slater, 2003] and Internet dependence [Lin and Tsai, 2002].

Our study also offers new insights into online ED communities. First, ED users have a high dropout rate (85% in our sample) and a short lifespan between an account creation to lost posting on Twitter (with 6 months of median time to drop out). This aligns with views of online ED communities as hidden, secretive groups [Casilli et al., 2013], but also indicates the dynamic characteristics of these communities. Second, users who discuss their health problems and share pro-recovery content (i.e., pro-recovery users) have lower levels of posting activities (i.e., a higher dropout rate) than those who share pro-ED content (i.e., pro-ED users) on Twitter. This can be explained as follows. Due to common interests in ED, pro-recovery and pro-ED groups are likely to be connected in the same social networks, and content shared within a group is hence likely to be visible to the other group. However, exposure to content from the antagonist group can have distinct effects in pro-ED and pro-recovery groups. Exposure to pro-ED content is harmful for pro-recovery users and can impede their recovery process [Campbell and Peebles, 2014; Maloney, 2013], while exposure to pro-recovery content can instead stimulate harmful behaviors in pro-ED users (e.g., actively sharing pro-ED content) [Yom-Tov et al., 2012]. Thus, pro-recovery users might tend to leave such an online community to avoid a risk of further deterioration or relapse. Our finding may also explain why pro-ED content is found being more pervasive than pro-recovery content across social media sites [Chancellor et al., 2016c; De Choudhury, 2015; Yom-Tov et al., 2012], e.g., almost five times in terms of unique publishers on Tumblr [De Choudhury, 2015]. Third, ED users tend to connect with others with the same dropout states on Twitter. This implies that whether an individual drops out from online communities depends on whether others in the individuals social networks drop out. In other words, dropout in online ED communities is not only a function of individual experience or individual choice but also a property of group interactions, e.g., homophily [McPherson et al., 2001] and social contagion effects [Coviello et al., 2014].

To conclude, this chapter presents a systematic characterization of attrition in an ED community on Twitter. Our analysis offers the first attempt towards the estimators of the effects of personal emotions and network centrality on dropout behaviors in individuals affected by ED on Twitter. Our results provide new insights into the trajectories that ED communities develop online, which can help public health officials to better understand individual needs in using online ED communities and provide tailored support for individuals with different needs.

Chapter 7

Conclusion

Social media provide a non-judgmental environment for people with a stigmatized health condition, such as eating disorders (ED), to discuss their illnesses and to seek health-related information, but also facilitate social interactions among individuals with similar or common health-related interests. These online interactions allow us to study online health communities as a connected whole rather than isolated individuals, and to sought explanations for human behavior from the network of people with whom an individual interacts more than the individual alone. Insights into the patterns of social networks can provide a better understanding of organizational behavior in an online health community and guide novel interventions that promote organizational well-being.

In this thesis, we study online ED communities from a network perspective. Our methods follow the typical steps of data analysis and involve data collection, pattern exploration and statistical modeling. First, we develop a data collection method to gather individuals affected by ED and their social networks on Twitter. Second, we explore community structures in online ED communities and characterize social norms in groups of individuals with a different stance of ED. Third, we explore the relationships among different types of communication took place within online ED communities. Finally, we model the effects of personal attributes and social networks on individuals' participation in online ED communities. We believe that our findings shed new light on how people form online health communities and can have broad clinical implications on disease prevention and online intervention. In this chapter, we summarize the contributions of each part in this thesis and their implications, and then discuss our future work and challenges.

7.1 Contributions and Implications

The contributions and implications of each part in the thesis are summarized as follows.

7.1.1 Data Collection

In Chapter 3, we explore how to detect individuals affected by ED and collect their online social networks on Twitter. The main contributions of this chapter are:

- We present a snowball sampling method to sift ED individuals and their social networks from Twitter. Unlike prior methods that gather data by surveys or by filtering users who post ED-related content [Chancellor et al., 2016c; De Choudhury et al., 2013b; Wood, 2015], we sample individuals who self-identify as ED in their profile descriptions on Twitter and expand the sample group with snowball sampling through their social networks of followees/followers, thereby recovering connected communities of individuals who are likely to display ED on Twitter.
- Comparing the differences between ED and two sets of non-ED users in social status, behavioral patterns and psychometric properties, we show that our sampled ED dataset captures key characteristics of ED, e.g., young ages, prevailing urges to lose weight even if being clinically underweight, high social anxiety, intensive self-focused attention, deep negative emotion, increased mental instability, and excessive concerns of body image and ingestion.
- We show that users' behaviors and content generated on Twitter can help to identify whether or not a user is affected by ED by training SVM classifiers to distinguish between ED and non-ED users. The classifiers have achieved an accuracy of more than 97%, and the differences of ED and non-ED users are more easily distinguishable than those between two sets of non-ED users. This further confirms the reliability of our sampling method in targeting ED populations on Twitter.
- Using the social networking data between ED users, we investigate the social interactions among ED peers and explore the presence of homophily in the ED communities on Twitter. We find that ED users who show similar tweeting preferences, concerns about death, habits in using language and body weight tend to preferentially interact with one another.

These findings can help to understand the way an ED community develops on social media and have several implications for public health. First, while individuals affected by a socially stigmatized health problem are often hard-to-reach through traditional health care services, social media provide a non-judgmental environment for these individuals to naturally disclose their illnesses and interact with others. Thus, self-reported health information on social media may help health care professionals to reach disordered people. Second, we find the presence of homophily in online ED communities, i.e., individuals with similar heath states tend to connect with one another on social media. This sheds light on developing automated techniques to sample data for larger communities with a health problem through individuals' online social networks, going beyond those who have self-identified as disordered online. Finally, individuals' behaviors displayed on social media can indicate their health conditions. Thus, analyzing user-generated data on social media may be useful for health care professionals to timely track and identify risk factors of health problems, particularly for lifestyle-related conditions.

7.1.2 Social Structures

In Chapter 4, we examine how individuals with different stances on ED interact with one another and how individuals' psychological properties can be associated with their positions in the social network of an online community. The main contributions of this chapter are as follows.

- We present a clustering analysis based on users' posting interests to explore natural groupings of users affected by ED online. We find that two natural communities of users are present among those who engage in sharing ED-related content on Twitter. Rather than assuming a priori that communities are featured by a certain posting pattern in prior studies [Chancellor et al., 2016c; De Choudhury, 2015; Oksanen et al., 2015; Yom-Tov et al., 2012], this unsupervised approach finds communities of users based on the similarity of users' posting interests.
- We develop an automated approach based on sentiment analysis techniques [Thelwall et al., 2010] to identify the stance of an online community on a health problem like ED. We show that the two communities found above have a pro-ED and pro-recovery tendency respectively. Compared to previous qualitative methods [Arseniev-Koehler et al., 2016; Borzekowski et al., 2010; Giles, 2006; Maloney, 2013], this approach is more effective to handle large volumes of user-generated data online.
- We represent users' interactions through Twitter conversations by a directed, weighted communication network and measure the network structures to reveal how different communities of users interact with one another. We find that individuals tend to interact with others in the same community, with extremely limited interactions across communities. The segregation between communities in social networks is likely to be reinforced by negative emotions in inter-community interactions.
- We explore the underlying mechanisms that dictate users' social interactions by studying users' behavioural characteristics (e.g., social activities and language use online) and social norms within an online community [Jackson, 1965]. We find that users' psychological properties reflected by their behaviours of language use in tweets can strongly shape their social interactions online and affect their positions

in social networks, in different ways in communities that have different social norms.

These findings provide a new perspective to understand how people maintain online ED communities and can have relevance for public health. First, social media are not only a valuable medium for reaching individuals who are affected by ED, but also for identifying larger groups who seek recovery from ED and would benefit more from treatment. Second, automated analysis on social media data can complement self-report based psychiatric assessments on ED and help to tailor specific interventions for pro-ED and pro-recovery individuals through non-reactive and non-intrusive measurements of their behaviours online. Third, while online support groups have been increasingly used for promoting health behaviour change [Latkin and Knowlton, 2015], here we find that the influence of these groups may be limited due to the network organization. A strong segregation between groups in social networks might undermine behavioural contagion across groups [Jackson and López-Pintado, 2013]. Thus, health interventions over support groups may need to account for the fact that structures and dynamics of individuals' social networks can affect the intervention outcomes. Finally, as health promotion programs become more community oriented, community opinion leaders have been widely used in public health to promote organizational well-being [Valente, 2012; Valente and Pumpuang, 2007]. Traditional methods for identifying effective opinion leaders primarily rely on surveys and interviews [Valente and Pumpuang, 2007]. However, these methods are often time-consuming and hard to implement in large communities. The observations from our study complement previous work on opinion-leader identification through analysing naturally occurring data on social media.

7.1.3 Information Flows

In Chapter 5, we explore how different types of information flow through an online ED community and how indivxiduals' activities in communicating different types of information influence one another. The main contributions of this chapter are as follows.

- We demonstrate the use of unsupervised clustering methods to identify the types of content discussed in online ED communities. Unlike previous studies that assume a type of content with predetermined features (e.g., a set of keywords) [Arseniev-Koehler et al., 2016; Chancellor et al., 2016c; De Choudhury, 2015; Oksanen et al., 2015; Syed-Abdul et al., 2013; Tiggemann et al., 2018; Yom-Tov et al., 2012], our approach allows themes of content to emerge from the data, which can reduce bias due to predetermined assumptions and provide an overall view of the full range of topics discussed in an online ED community.
- We propose to represent types of communication in online ED communities by a multilayer network in which each layer is a network representing interactions among

the same set of users in discussing a specific topic. Compared to traditional mono-layer networks [Newman, 2010], multilayer networks provide (i) a more natural representation of a communication system by capturing the multiplex nature of human interactions [Boccaletti et al., 2014; Kivelä et al., 2014; Nicosia and Latora, 2015], and (ii) a more elegant and flexible way for incorporating multidimensional information. Based on this multilayer representation, we (i) characterize different types of communication by measuring structures of single-layer networks in the multilayer communication network, and (ii) examine interdependencies of different communication by measuring structural correlations of inter-layer networks.

- We study dynamics of user communication and reveal underlying processes that lead to correlations of communication on different topics. By measuring structural changes and stability in a sequence of temporal, multilayer networks that are built based on users' conversations over time, we find that (i) actors previously engaged in pro-recovery communication are likely to engage in pro-ED communication in the future and (ii) actors engaged in sharing pro-ED content have frequent entries into and exits from the corresponding communication network.

These findings provide new insights into the multiplex and dynamic interactions in an online ED community. They can have the following implications for public health. To prevent ED and minimize the negative impact of pro-ED content online, many social media sites have begun to ban *thinspo* content. Our results show that pro-ED communities may engage in disseminating other content that is related to *thinspo* but has not been banned online, e.g., *body* image. Exposure to such content can potentially reinforce individuals' engagement in pro-ED communication and weaken their engagement in pro-recovery communication, which may be used as alternatives to the *thinspo* content to avoid censorship [Boepple et al., 2016; Chancellor et al., 2016d]. Thus, to enhance health outcomes, content-based interventions should account for the relationships of types of content which can be extracted automatically as we did in this study. Another common intervention strategy in public health is network-based intervention which focuses on using social network data to promote organizational well-being [Valente, 2012]. One typical approach in this strategy is identifying community opinion leaders to accelerate behavior change [Laranjo et al., 2014; Valente and Pumpuang, 2007]. We show that people can have different roles in different types of interactions and these roles can change over time. Thus, network-based interventions should account for the multiplex and dynamic nature of social interactions for identifying appropriate opinion leaders for a targeted community.

7.1.4 Behavioral Change

In Chapter 6, we investigate the characteristics of dropout behaviors among ED communities on Twitter and estimate the causal effects of personal emotions and social networks on dropout behaviors. The main contributions of this chapter are as follows.

- Leveraging the longitudinal data on posting activities of ED users spanning 1.5 year, we find that ED users have relatively short periods of activity on Twitter, with one half of our sample dropping out at 6 months after account creation. Unlike previous studies that focus on examining how people engage in an online ED community [Chancellor et al., 2017, 2016d; Oksanen et al., 2015; Syed-Abdul et al., 2013; Yom-Tov et al., 2012], we first systematically characterize the dropout behaviors in online ED communities, allowing us to gain a more comprehensive understanding of people's participation in these communities.

- Based on the incentive theory [Kollock, 1999], we explore the effects of individuals' emotions, network centralities in a community on their activities of engagement in the community. Using an instrumental variable (IV) approach [Angrist et al., 1996] and survival analysis [Miller Jr, 2011] methods, we show that individuals' emotions and network centralities at a earlier stage strongly affect their dropout states at a later stage. Based on evidence on emotional contagion and social influence [Aral and Nicolaides, 2017; Coviello et al., 2014; Ferrara and Yang, 2015; Kramer et al., 2014], we use the attributes of an individuals followees (i.e., people who are followed by the individual) as instruments of the individuals attributes. We find that users with positive emotions are more likely to drop out and have shorter-lasting periods of activity online than users with negative emotions, while central users in a social network have longer-lasting participation than peripheral users.

- By inspecting tweeting interests among users with different levels of emotions, as well as among users with and without dropout, we further find that users who seek recovery from ED tend to have more positive emotions and are more likely to drop out, while those who promte ED as a lifestyle choice tend to have more negative emotions and are less likely to drop out on Twitter.

Our findings reveal the determinants of dropout behaviors in online ED communities and are of practical relevance to the promotion of public health over social media. First, the decision to maintain active participation in an online community can be caused by intrinsic and extrinsic characteristics/traits of the participants, e.g., personal emotions, interests and social networks. Such self-selection bias can lead to the sample not being representative of the whole population, and hence researchers need to consider both active and dropped-out users for a well-rounded picture of online health communities. This is particularly important for public health officials to make special efforts to reach these dropouts and offer more intensive support when they are trying to recover. Second, high attrition rates are often regarded as negative outcomes in online interventions, particularly in those delivered over a purposely designed website [Eysenbach, 2005; Maher et al., 2014; ter Huurne et al., 2017]. However, this may or may not be the case in interventions over general social media sites (e.g., Twitter) depending on how targeted populations use these sites. For example, when an intervention is delivered in an online community in which members often shared harmful content, a high attrition rate (i.e., members dropping out of the harmful community) may not be a negative outcome. Using automated data-mining techniques to track users' behaviors (e.g., emotions and posting interests), as used in this work, can provide more detailed information about people's use of online health communities and improve our understanding of attrition in online interventions. Third, interventions that recommend content containing positive emotions to ED users (not limited to ED-related content but more general content containing happiness and inspiration) may reduce their engagement in a harmful online community. This aligns with Fredrickson's broadenandbuild model which argues that cultivating positive emotions is useful to prevent and treat mental health problems [Fredrickson, 2000]. Finally, intervention strategies could be tailored for different individuals depending on their positions in the social network of an online community. For example, identifying central individuals as change agent might enhance the efficacy and cost effectiveness of an intervention, due to their greater influence potential through larger numbers of social ties [Valente, 2012], but also their longer-lasting effects through longer-term participation in the community.

7.2 Future Work

The presented work in this thesis can be extended in several ways. We take three for example, with operational difficulties from easy to hard. All the proposed future work revolves how to use social networks to gain useful insights into online health communities, so as to develop effective programs for disease prevention and online intervention.

7.2.1 Characterizing Patterns of Information Diffusion

In Chapter 5, we observe that different types of information are diffused through online ED communities in different ways. We can obtain a better understanding of these patterns based on the theory of innovation diffusion, a theory that aims to explain how, why and at what rate new information, ideas, practices and technology spread through a population. Rogers [2010] formally defined diffusion as a process in which an innovation is communicated through certain channels over time among the members of a social system. According to this definition, four elements affect the spread of an innovation, namely the innovation itself, communication channels, time and a social system. In particular, the network structure of a social system usually plays a crucial role in information diffusion [Dobbins et al., 2001; Peres et al., 2010], and the majority of information spreads in populations through weak ties of a social network [Granovetter, 1973]. Early studies on innovation diffusion often focused on developing theoretical models or characterizing a diffusion process in empirical data from a macroscopic point of view, such as measuring the rate of adoption; the rate of adoption over time (often showing a S-shaped curve [Rogers, 2010]); the stages in the adoption process (including stages of knowledge, persuasion, decision, implementation, and confirmation); and the modification of the innovation [Valente, 1996]. However, empirical studies from a microscopic view (such as predictive models) are limited, mainly because prior studies often collected data via survey and lacked detailed temporal information on a diffusion process.

Over the past decades, the development of information techniques, such as social media and mobile devices, has facilitated the accessibility to rich data of an individual's daily experience and largely accelerated the research of innovation diffusion based on empirical data. Innovation diffusion over networks has been a fundamental research topic in network science and received intensive attention from many fields such as physics, biology, and computer science [Guille et al., 2013; Li et al., 2017]. Recent studies on information diffusion over social media focus on the following questions. The first one is *what information, events or topics are popular and spread widely* [Cai et al., 2015; Lu and Yang, 2012; Takahashi et al., 2014]. Lu and Yang [2012] predicted the trends of topics on Twitter based on Moving Average Convergence-Divergence, a tendency indicator for technical analysis of stocks [Appel, 2005], measured from users' textual content. Beyond the textual information, Takahashi et al. [2014] proposed a probability model to analyze a user' mentioning behavior in social networks and detected the emergence of a new topic based on the anomalies measured in the model. The second question is *how and via which patterns or paths such information is diffusing, and will be diffused in the future* [Bourigault et al., 2014; Guille and Hacid, 2012; Leskovec et al., 2007; Rodriguez et al., 2011]. Leskovec et al. [2007] employed the classic SIS (Susceptible-Infected-Susceptible) model for epidemics [Bailey et al., 1975] to explore topological patterns of information propagation cascades in blog graphs. In contrast, Bourigault et al. [2014] formulated information diffusion as a process in a continuous space and presented a new class of information diffusion models based on the heat diffusion kernel. Finally, *who or which factors affect the diffusing process* is another hot topic in the literature [De Choudhury et al., 2010; Romero et al., 2011]. Romero et al. [2011] proposed a method that quantifies the influence and passivity of users based on their information forwarding activity. De Choudhury et al. [2010] argued that sampling methods considering both network topology and users attributes (such as activity) estimate information diffusion with lower error, compared to random or activity-only based sampling.

We plan to explore the patterns of information diffusion in ED communities over social media in terms of the above questions. Exploring the first question is valuable to understand the interests and preferences of disordered populations on social media. Although this question has been partially explored in Chapter 5 by detecting popular topics discussed in Twitter conversations, we shall examine whether we can observe similar topics in other types of activities on information sharing on social media, such as retweeting on Twitter. Exploring the second question is useful to predict the transmission intensity of different pieces of information such as “pro-ED” or “pro-recovery” messages in these communities, and approximately estimate the potential influence of a health-related promotion message. Exploring the last question can provide clues to quantify the influence and passivity of disordered individuals in spreading given information, so as to design effective intervention methods that promote the diffusion of healthy information and suppress the spread of harmful information over social media.

7.2.2 Identifying Mechanisms of Peer Effects

In Chapter 6, we find that recognition from peers can influence an individual’s behavior online. Social media provide vast information on individuals’ social relationships, which allows us to further model and clarify how peer effects work in an online health community. In traditional models of peer influence, peers’ behaviors are often regarded as a social norm, imposing a cost if individuals deviate from the majority of their peers [Balsa and Díaz, 2018]. Technically, the marginal utility to an individual to perform an behavior can be modeled as a function of the average amount of the behavior taken by peers [Boucher et al., 2014; Glaeser and Scheinkman, 2000; Manski, 1993]. Given each peer with an identical effort, the effect of peers’ behaviors on individual outcomes is homogeneous across members in a group, expressed by a *local-average* effect. However, recent evidence has suggested that peer effects can be heterogeneous across individuals who have different levels of exposure to others in a group, i.e., occupying different positions in a social network [Ajilore et al., 2014; Ballester et al., 2006; Ghiglino and Goyal, 2010; Liu et al., 2014]. People who have more friends engaged in a specific action are more likely to be exposed to and engage in the action, which can be captured by the sum of peer efforts, so called a *local-aggregate* effect. The difference between the average and aggregate effects is whether network positions affect peer effects.

Despite a minor change between these alternative models, they have largely different policy implications [Ghiglino and Goyal, 2010; Liu et al., 2014]. If the local-average effects matter, group-level policies are in need to change the norm in a group, i.e., the group’s perception on what should be regarded as a normal behavior. In contrast, if the local-aggregate effects matter, individual-level policies should focus on those who have a large number of social ties. This is not only because these individuals are risky due to high exposure to others’ behaviors, but also because they are effective to create a high level of strategic complementarities where the efforts of two or more agents in a social group can mutually reinforce one another [Bulow et al., 1985]. The latter factor can further lead to a social multiplier where a policy applied to an individual can lead to a greater impact on the entire peer group than on the individual [Glaeser et al., 2003]. The average and aggregate effects have been examined in several contexts [Ajilore et al., 2014; Liu et al., 2014]. Liu et al. [2014] proposed a unified model incorporating both local-aggregate and local-average effects. They used network intransitivity properties [Bramoullé et al., 2009] to identify each effect and found that the average effects explained peer effects in study effort while both two effects explained peer effects in sport activities. Ajilore et al. [2014] used a similar method to examine peer effects in obesity and overweight. They found that peer effects in BMI can be explained by both average and aggregate effects, while those in overweight operate mainly via the aggregate effects.

So far, little is known about how the average and aggregate peer effects work in online social networks and whether they did in the same ways as in offline social networks. We would like to follow prior studies and use advanced statistical models to identify the mechanisms of peer effects in online ED communities.

7.2.3 Distinguishing Influence and Homophily Processes

In Chapters 3 and 4, we observe that people with similar attributes are often connected together in online ED communities. A fundamental question in social network analysis is to understand the interplay between similarity and social connections [Crandall et al., 2008]. The similarity of friends in a social network can be due to two reasons. First, people tend to form new ties to others who are already similar to them, i.e., homophily or selection. Second, people and their friends influence one another so that they become similar after building social connections, i.e., social influence. Disentangling the effects of homophily and contagion has practical significance in the research of public health. In a social network of disordered individuals, if the social network is contagion-driven over health conditioning features, then the influential individuals should be identified and intervened to promote the health states of other members in the community. In contrast, if the social network is homophily-driven, then larger disordered populations can be reached through the social networks starting from a small seeding sample, and all individuals should be provided equal attentions in an intervention.

Following prior studies [Aral et al., 2009; Lewis et al., 2012], we have tracked day-by-day activities of users in an ED community for more than 2 years to gain their longitudinal behavioral, social networking and self-reported health-related data on Twitter. Based on such information, statistical models such as stochastic actor-based modeling [Lewis et al., 2012; Snijders et al., 2010], sample-matched estimation method [Aral et al., 2009] and IV estimation approach [Angrist et al., 1996] will be tried to distinguish the effects of homophily and contagion in the online ED community.

7.3 Further Challenges

Apart from new opportunities, the use of social media data has several challenges in the research on public health. Below, we discuss three challenges related to this thesis.

7.3.1 Ethical Issues

The first and most important challenge is ethics. User-generated data on social media provides vast recodes on individuals' everyday lives, ranging from their physical activities, social events, discussions of politics to psychological processes and conversations on private matters. A big concern in using social media data for research purposes is whether such data should be considered *private* or *public* [Moreno et al., 2013; Townsend and Wallace, 2016]. A common standard is: if users have agreed with a term that their data may be accessed by third parties in a social media platform, the data can be considered public [Townsend and Wallace, 2016]. For example, most social media platforms allow users to choose their privacy settings—users can set their profile information as private (i.e., limiting profiles assess to certain approved friends), or pubic (i.e., allowing anyone access to their profiles) [Moreno et al., 2013]. However, these privacy settings might change when users were aware of their participation in a study without informed consent, and these changes are often hard to be noticed by researchers. This is different from traditional data collection methods such as surveys, in which informed consent is usually built in the research design and participants are required to sign a consent form. Even if informed consent can be acquired, key aspects of such consent, such as the right to withdraw, are highly complicated in social media research, e.g., whether deleting a post or account means a withdraw from research [Hewson and Buchanan, 2013]. Another important ethical issue is anonymity, particularly when data is shared outside of a research team [Townsend and Wallace, 2016].

In this thesis, our study protocol was approved by the Ethics Committee at the University of Southampton. All data we collected is *public* information on Twitter and available via the Twitter APIs. In each part of this thesis, any data that has been set as *private* is excluded from our study. No personally identifiable information is used in this study and all results are anonymized before publishing.

7.3.2 Data Biases

The second challenge is data biases which can arise from several sources. We list the following sources of biases for example.

Selection bias in using social media. In this thesis, we study ED based on social media data. However, the populations using social media may be different from the general population. For example, the results in Chapter 3 show that the major of our ED users are younger based on their self-reported information. Also, in Chapter 6, we observe that ED users with more positive emotions tend to drop out on Twitter. Thus, the focus of social media, and data collected from these platforms can introduce biases towards individuals with specific demographic attributes or personality traits, making the collected samples not representative of the entire population affected by ED. Moreover, users of different social media platforms may be different from one another, as users of the same platform may share similar preferences in user-interaction interfaces. For example, people interact mainly by sharing textual tweets on Twitter and by sharing photos on Instagram. Thus, the studies in this thesis are limited to ED communities on Twitter and their results cannot be generalized to other social media platforms.

Sampling bias in data collection. So far, the mainstream approach to sample populations affected by a health problem on social media is filtering users who self-reported a diagnosis of illness online [Chancellor et al., 2016a; Coppersmith et al., 2014; De Choudhury, 2015; De Choudhury et al., 2013b]. However, self-diagnosis information may be itself self-censored by users to align with their personality traits and perceptions of their audience on a platform. Some sufferers may not self-report their experience of illness and would be excluded by these collection methods. Such sampling bias is also unavoidable in our data collection methods. For example, while our computational and manual validations show that we are highly likely to have collected a set of individuals suffered from ED (high precision) in Chapter 3, our samples do not guarantee high recall—we missed populations that were not identified by our collection methods. This problem in data collection may also bias our analyses on online ED communities. For example, in Chapter 4, we observe that the number of pro-ED users is larger than that of pro-recovery users, which aligns with prior evidence that pro-ED communities are more common than pro-recovery communities on social media [Chancellor et al., 2016c; De Choudhury, 2015; Yom-Tov et al., 2012]. However, this may be caused by the fact that pro-recovery users have a broader range of posting interests (not limited to ED-related topics) while pro-ED users strongly focus on sharing "thinspiration" content [Yom-Tov et al., 2012]. Thus, we are likely to miss pro-recovery/recovered users who did not post any ED-related content in their recent tweets.

7.3.3 Gap between Online and Offline Behaviors

People's behaviors online may not fully reflect who they are and what they do in real world. To attract attention from other users, individuals may create fake profiles that reflect their "ideal self" [Ellison et al., 2006] and manage their online self-presentations [Magdy et al., 2017]. Such gap between online presentations and offline behaviors can also arise in the studies of this thesis. For example, like other health-related studies based on social media data [Chancellor et al., 2017, 2016c; De Choudhury, 2015; De Choudhury et al., 2013b], we measure users' health states based on their presentations online (in Chapters 3 and 4). We do not have any clinical indication on their actual states. Such ground-truth data is often hard to obtain because of ethical concerns and privacy issues, making it difficult to verify the reliability of these online presentations. Even if people disclose reliable information on social media, some offline behaviors are missing and not captured in user-generated data online, such as viewing behaviors. Thus, for instance, we miss users who actively browse content but never post online, even though these users may indeed have learned disordered behaviors from such content in real world. In addition to technical issues in recording users' behaviors, the absence of offline behaviors in online data can also arise from users' usages of social media tools. As social media profiles are not identical and nonrenewable identifiers, people may have multiple profiles on the same social media platform or other platforms, and use each profile at different time periods for different purposes (e.g., personal and business accounts). Thus, activities of an user account online may merely reflect parts of a person's offline behaviors. For example, in Chapter 6, users dropped out from an online community may have other profiles online, and we cannot be sure whether they will engage in the same or a similar community using a different user account.

Appendix A

Appendix: Supporting Information for Chapter 2

A.1 Basic Concepts in Network Analysis

Basic concepts that often occur in social network analysis are introduced below.

Degree: For a node i, degree is the number of edges connected to i, noted as k_i. In a directed graph, we can define in-degree k_i^{in} as the number of edges connecting to i and out-degree k_i^{out} as those from i to others. In this case, we have $k_i = k_i^{in} + k_i^{out}$.

Weight: Each edge $e_{i,j}$ can ba assigned with an numerical value $w_{i,j}$. The interpretation of these weights depends on the properties of the network at hand. For example, the weight of an edge may refer to as the number of mentions that one user has conducted to the other in a mention graph on Twitter; in a geographic graph, the weight might refer to as the distance between two cities.

Strength: The sum of the weights of all edges associated with a given node i, noted as s_i. Similar to in- and out-degree, we can define in-strength s_i^{in} and out-strength s_i^{out} in a directed graph, and $s_i = s_i^{in} + s_i^{out}$.

Density: The fraction of links in a network relative to the maximal number of possible links.

Distance: The distance between two nodes in a graph is the minimum number of edges one needs to go through, if traveling from one node to the other.

Centrality: Centrality measures the importances of nodes in a graph, such as identifying the most influential individuals in a social network. Centrality has a wide number of meanings, leading to many different definitions of centrality and different measures that capture network attributes in different ways [Borgatti, 2005].

The simplest measure of centrality is counting the number of neighbors (known as “degree” centrality), where nodes with more neighbors tend to be more central. Other popular measures of centrality include closeness, betweenness [Freeman, 1978], eigenvector centrality [Newman, 2010], PageRank centrality [Page et al., 1999], hubs and authorities measured via the HITS algorithm [Kleinberg, 1999].

Connected Component: A connected component in undirected graphs is a sub-graph in which any two nodes are connected to one another, and has not connections to additional nodes in the super-graph. A component that contains a significant proportion of all the nodes is called a giant component. In a directed network, we can differentiate two types of components: strongly connected components and weakly connected components. A strongly connected component is a maximum set of nodes such that for each pair of nodes i and j, a direct edge from i to j always co-exist with a direct reverse edge from j to i. On the other hand, in a weakly connected component each node can reach any others by edges regardless of their directions.

Assortativity: A preference for nodes in a network to connect to others that are similar [Newman, 2002, 2003]. Assortativity in terms of nodes' degree are often measured in network science, i.e., quantifying if nodes tend to connect with other nodes with similar degree, though the similarity can be measured in terms of other attributes of nodes [Newman, 2010]. The most common measure is the assortativity coefficient which is the Pearson correlation coefficient of degree between pairs of linked nodes [Newman, 2002].

A.2 Common Network Properties

Several properties are found to appear commonly in the study of social networks. A first typical property is the *small-world* property, which describes that the average distance between nodes in a network is short, typically scaling logarithmically with the total number of nodes [Watts and Strogatz, 1998]. A second property is the *heavy-tailed* degree distributions, stating that many nodes in a network have low degree while a small number of nodes have high degree, with a distribution following a power-law (or exponential) format [Barabási and Albert, 1999]. This property is often examined by inspecting the fraction $P(k)$ of nodes in the network that have a particular degree k, as:

$$P(k) \sim k^{-\gamma}, \tag{A.1}$$

where γ is a parameter and $2 < \gamma < 3$ in most social networks [Clauset et al., 2009]. A third property is *clustering*, or *network transitivity*, which describes that two nodes connecting with the same third node have a high probability of connect with each other [Girvan and Newman, 2002; Watts and Strogatz, 1998]. In social networks, two of one's friends are more likely to know each other than two people chosen at random from the population. This property can measured by the clustering coefficient C [Watts and Strogatz, 1998]:

$$C = \frac{3 \times \text{number of triangles}}{\text{number of all triplets}}. \tag{A.2}$$

Precisely, C is the probability that two of one's friends are friends themselves [Girvan and Newman, 2002]. Another property that many networks commonly have is *community/modular structure* [Girvan and Newman, 2002; Newman, 2010], stating that a network can be partitioned into clusters (or subsets) of nodes with dense connections internally and sparser connections across clusters. Communities in a social network may be real social groupings, by factors such as common location, interests or family memberships among individuals [Fani and Bagheri, 2017]. To date, there are various methods to detect communities in a network [Girvan and Newman, 2002; Newman and Girvan, 2004], such as Newman's leading eigenvector method [Newman, 2006a], modularity optimization [Clauset et al., 2004; Newman, 2004; Newman and Girvan, 2004], the Lounvain method [Blondel et al., 2008], random works [Pons and Latapy, 2005], label propagation [Raghavan et al., 2007] and Infomap [Rosvall and Bergstrom, 2008]. The methods used this thesis are as follows.

Lounvain method: This method searches for a partition of a network that maximizes modularity using a greedy optimization approach. Modularity is a measure to qualify how well a partition is by evaluating the density of links within the same community compared with those across different communities [Newman, 2006b]. For a weighted graph, modularity is defined as:

$$Q = \frac{1}{2m} \sum_{i,j} \left[A_{i,j} - \frac{k_i k_j}{2m} \right] \sigma(c_i, c_j), \tag{A.3}$$

where $A_{i,j}$ is the edge weight between nodes i and j, and m is the sum of all edge weights. k_i and k_j are the sum of edges associated with i and j, respectively. $\frac{k_i k_j}{2m}$ gives the expected weight of edge between i and j. c_i and c_j denote communities of i and j respectively. Function $\sigma(c_i, c_j)$ equals to 1 if $c_i = c_j$ and 0 otherwise. The values of Q ranges $[-0.5, 1)$, where a positive value indicates that the number of edge within clusters exceeds the expected number by chance. The Lounvain method optimizes Q by two phrases: first, it finds small communities that optimize local modularities; then each small community is grouped into one node, and forming a new network. The two phrases are repeated until an optimal modularity is achieved, generating a hierarchical structure of communities [Blondel et al., 2008]. A notable feature of the Lounvain method is its high efficiency, compared to other methods [Clauset et al., 2004; Pons and Latapy, 2005; Wakita and Tsurumi, 2007]. However, like other modularity-optimization based methods such as the Girvan-Newman algorithm [Newman and Girvan, 2004] and greedy modularity optimization methods [Clauset et al., 2004; Newman, 2004], the Lounvain method often suffers from a problem called the resolution limit [Fortunato and Barthelemy, 2007]. A method is considered to have a resolution limit if it fails to identify modules smaller than a scale in large networks so that well-defined modules are merged together.

Infomap: The Infomap algorithm finds community structures in networks by minimizing the description length of a random walkers movements on a network. The basic assumption is that a random walker tends to be trapped in communities than to move across communities. This approach searches for a module partition $\mathbf{M}$ of n nodes into m modules that minimizes the expected description length of a random walker. Given a partition $\mathbf{M}$, the average description length of a single step is:

$$L(\mathbf{M}) = q_{\curvearrowright} H(\mathfrak{L}) + \sum_{i=1}^{m} p^{i}_{\circlearrowright} H(\mathfrak{p}^{i}), \tag{A.4}$$

where $q_{\curvearrowright}$ is the probability that random walker switches communities and $H(\mathfrak{L})$ is the entropy of module names in $\mathbf{M}$. $p^{i}_{\circlearrowright}$ is the fraction of within-module movements in module i and the probability of existing module i. $H(\mathfrak{p}^{i})$ is the entropy of the within-module movements. The first part of Eq. A.4 measures the entropy of inter-module movements, and the second part describes the entropy of intra-module movements [Rosvall and Bergstrom, 2008]. Compared with other methods such as modularity optimization, Infomap is less likely to suffer from the resolution limit and is more capable to resolve a large number of finer-grained modules [Kawamoto and Rosvall, 2015].

Appendix B

Appendix: Supporting Information for Chapter 4

B.1 Data Details

We analyse a dataset collected from Twitter, a social media platform that allows millions of users to post and interact with short messages ("tweets"). Users can "follow" others to receive their updates, forward ("re-tweet" and "RT") tweets to their own followers, or mention and reply to ("@") others in tweets. People can also label tweets with hashtags ("#") to makes it easier for users to find tweets with a specific theme or topic. All data used in our analysis is public information, available via the Twitter APIs. As shown in Fig. D.1, we build our dataset in the following phases.

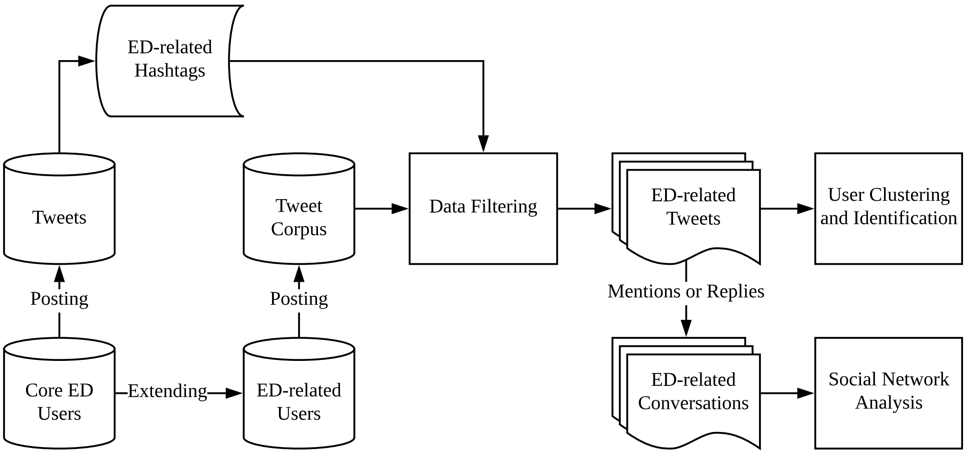


Figure B.1: Diagram representing the data flow and analysis process in our study.

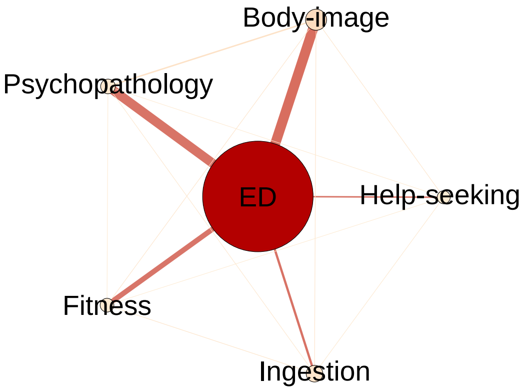
B.1.1 Sampling Disordered Users

To sample individuals with eating disorders (ED) on Twitter, we adopt an approach used in previous work for detecting ED-related communities from social media sites like Twitter [Wang et al., 2017]. We begin by tracking the public tweet stream using "eating disorder", "anorexia", "bulimia" and "EDNOS" from Jan. 8 to 15, 2016, leading to 1,169 tweets that mention common ED. From the authors of these tweets, we obtain 33 seed users who self-diagnosed with ED. We identify users as ED-diagnosed if they self-report both ED-diagnosis information (e.g., "eating disorder", "edprob" and "proana") and personal bio-information (e.g., body weight) in their Twitter profile descriptions (i.e., a sequence of user-generated text describing their accounts below profile images). Then, we expand the set of seed users by using a snowball sampling through users' social networks of followees/followers on Twitter. At each sampling stage, we filter out non-English speaking accounts and finally obtain 3,380 unique users (called *core ED users*). Our annotation results on randomly selected 1,000 users from the core ED sample show that almost all of the checked users are suspected of having ED and 95.2% of the users are labelled as being highly likely to have ED (see [Wang et al., 2017] for more details on data collection and validation). We further collect all followees and followers of these core ED users, leading to a large sample of ED-related users ($n = 208,065$). For each user, we retrieve up to 3,200 (the limit returned from Twitter APIs) of their most recent tweets, resulting in a corpus of 241,243,043 tweets. The retrieval process finished on Mar. 2, 2016.

B.1.2 Filtering ED-related Tweets

To examine users' conversations on ED, we extract ED-related messages from our tweet corpus by searching for tweets that contain at least one ED-related hashtag. To identify an appropriate set of ED-related hashtags and avoid introducing bias, we detect ED-related topics from hashtags used by the core ED users. We consider hashtags posted only by the core ED users rather than those posted by the whole user sample, since the whole sample contains a large number of users who have only weak connections to ED (e.g., celebrities and marketing accounts). Not all topics collected based on hashtags used by the whole user sample are directly related to ED, thus making it harder to identify ED-related topics.

Based on the topic locality assumption that semantically similar hashtags tend to appear in the same tweets together, and hence similar hashtags are likely to be densely connected in their co-occurrence networks [Davison, 2000; Weng and Menczer, 2015], we construct an undirected, weighted hashtag co-occurrence network. In this network, each edge runs between two nodes representing two hashtags if the two hashtags co-occur in a tweet posted by the core ED users, with a weight counting the number of tweets containing the two attached hashtags. To filter out noise, we only consider hashtags used by more than three distinct users and observed in more than three tweets. The resulting network contains 4,915 nodes and 34,121 edges. Then, we detect densely connected clusters in this network by using the Infomap algorithm [Rosvall and Bergstrom, 2008] which finds cluster structures by minimizing the description length of a random walkers movements on a network. We obtain 1,200 clusters, where 872 topic clusters have only a single hashtag and 328 clusters have more than one hashtags. Fig. B.2 shows the largest topic clusters in the hashtag co-occurrence network. From these generated topic clusters, we select ED-related topics (e.g., "ED") based on previous studies on ED-related content on social media [Chancellor et al., 2016c; De Choudhury, 2015; Juarascio et al., 2010]. After removing generic tags such as "#skinny" and "#staystrong", we obtain 375 unique ED-related hashtags such as "#thinspo", "#edproblems" and "#proana". Finally, we search for tweets containing any of these tags in our tweet corpus, yielding 633,492 public ED-related tweet messages posted by 41,456 unique users.

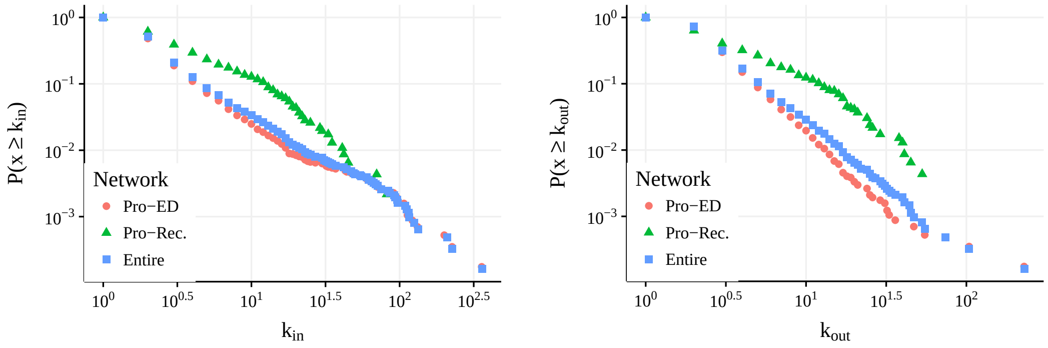


Topic	*Example #Hashtags*
ED	thinspo, edproblems, thinspiration, proana, ana, skinny, staystrong, thighgap, edprobs, ed, eatingdisorder.
Body-image	picslip, fat, fml, failure, fatass, progress, fuck, ugh, reversethinspo, fatty, ugly, gross, ew, disgusting, fail.
Ingestion	myfitnesspal, tweetwhatyoueat, twye, eatclean, healthy, yum, vegan, calories, breakfast, food, yummy.
Psychopathology	selfharm, depression, depressed, anxiety, sad, suicide, cutting, triggering, selfharmproblems, suicidal.
Fitness	fitfam, fitness, workout, getchallenged, exercise, fitfeb, noexcuses, fit, health, gym, fitfamlove, skinnyteams.
Help-seeking	replytweet, help, please, confused, curious, anafam, advice, previoustweet, lasttweet, now, prettyplease.

Figure B.2: Top plot shows the largest topic clusters in the co-occurrence network of hashtags posted by the core ED users. Each node is a cluster of hashtags on the topic as labelled. Node size is proportional to the total frequency of all hashtags in the cluster, and edge width is proportional to the co-occurrences between tags from two attached clusters. Bottom table lists example hashtags of clusters, ranked by their frequencies.

B.1.3 Constructing Communication Network

We track user-user conversations/communication on ED by searching for the ED-related tweets in which authors mention or reply to other users. Since a user can join a Twitter conversation by either mentioning or replying to others in a tweet [1], we do not distinguish the two types of interactions in this analysis. Compared with other types of interactions such as who-follows-whom and who-retweets-whom relationships on Twitter, the direct interactions through Twitter conversations have been shown to exhibit more similar characteristics to real person to person social interactions [Gonçalves et al., 2011; Huberman et al., 2008]. Based on the reciprocal mentioning and replying relationships between users in these conversations on ED, we build a directed, weighted communication network to describe how users interact with one another. Bidirectional edges denote mutual interactions, with larger weights indicating more frequent or persistent interactions between two individuals. We only consider the interactions that both senders and recipients exist in our data. All of our analyses focus on the users connected in the communication network. Fig. B.3 shows the degree distributions of communication networks among pro-ED and pro-recovery communities.



(a)

(b)

Figure B.3: (a) In-degree and (b) out-degree distributions of communication networks. We add 1 to all values of degrees to account for nodes with zero-degrees.

B.2 User Clustering Analysis

B.2.1 Hashtag Clustering

We characterize users' interests in ED based on their usages of hashtags in the ED-related tweets. However, multiple hashtags can be developed to represent the same event, theme or object on Twitter, e.g., both "#thinspo" and "#proana" refer to the promotion of

[1] https://help.twitter.com/en/using-twitter/mentions-and-replies

behaviours related to anorexia nervosa and encouraging people to lose weight. To capture the semantic relatedness of hashtags, we shift attention from single hashtags to more general categories, i.e., clusters of semantically related hashtags. Similar to our previous method on identifying ED-related hashtags, we construct hashtag co-occurrence network from the ED-related tweets and use Infomap to detect finer-grained sub-topics on ED. After removing hashtags with low frequencies (occurring in more than 3 tweets) and engagement (used by more than 3 distinct users), the resulting network contains 5,732 nodes and 126,635 edges. We detect 140 topic clusters from the network. Fig. B.4 shows the most frequent topic clusters in the hashtag co-occurrence network of the ED-related tweets.

Note that, although topics in Fig. B.4 can be regarded as the sub-concepts of the "ED" topic in Fig. B.2, the network in Fig. B.4 is not a subgraph of the network in Fig. B.2. This is because these networks are built based on tweets posted by two different sets of users, where the network in Fig. B.2 is built from all tweets posted by the core ED users, while the network in Fig. B.4 is built from ED-related tweets posted by the whole user sample (see Fig. D.1). Moreover, an ED-related tweet can contain both an ED-related hashtag identified in Fig. B.2 and other hashtags. Thus, the size of hashtag co-occurrence network in Fig. B.4 is not necessary smaller than that in Fig. B.2.

B.2.2 User Profiling

We profile users by their interests in these ED-related sub-topics found above. Given a user u, we track the sequence of n_u hashtags (with repetition) that she/he used in the ED-related tweets, $(h_1, h_2, ..., h_{n_u})$. Each hashtag h_i is attached to a topic $T(h_i)$ as:

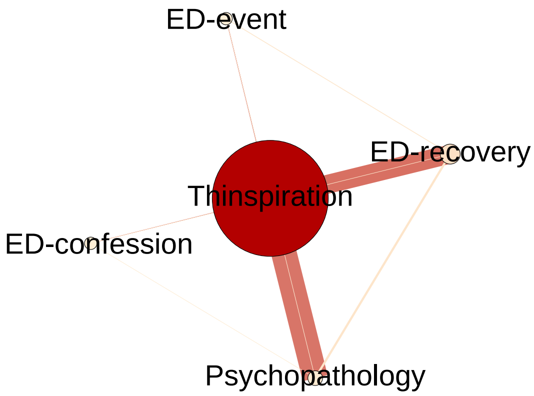
$$T(h_i) = \begin{cases} C(h_i) & \text{if } h_i \text{ exists in the hashtag co-occurrence network} \\ T_{|C|+1} & \text{otherwise} \end{cases} \tag{B.1}$$

where $C(h)$ is a sub-topic containing h and $|C|$ is the number of clusters found in the hashtag co-occurrence network. $T_{|C|+1}$ is a dummy topic to host all hashtags that are not in the co-occurrence network (e.g., low-frequency tags). Each user is represented as a vector which is constructed by computing the proportions of hashtags across different sub-topics:

$$\vec{u} = \left(P(T_1), P(T_2), ..., P(T_{|C|+1})\right) \tag{B.2}$$

where

$$P(T_j) = \frac{\sum_{1 \le i \le n_u} I(h_i, T_j)}{n_u}, \tag{B.3}$$



Cluster	*Example #Hashtags*
Thinspiration	thinspo, thinspiration, edproblems, skinny, ana, proana, eatingdisorder, thighgap, anorexia, ed, edprobs.
ED-recovery	eatingdisorders, edrecovery, recovery, mentalhealth, bodyimage, recoverywarriors, edawareness.
Psychopathology	depression, selfharm, depressed, anxiety, suicide, suicidal, sad, quotes, cutting, alone, cut, cat, broken.
ED-confession	bulimicprobz, anorexicprobz, edprobz, awkward, willbeskinny, selfharmprobz, wasted, noselfcontrol, noforreal.
ED-event	internationaledmeetup, edsoldiers, australia, melbourne, australianeatingdisorders, aussie, pink, pinkribbon.

Figure B.4: Top plot shows the largest topic clusters in the hashtag co-occurrence network of the ED-related tweets. Each node is a cluster of hashtags on the topic as labelled. Node size is proportional to the total frequency of all hashtags in the cluster, and edge width is proportional to the co-occurrences between between tags from two attached clusters. Bottom table lists example hashtags of clusters, ranked by their frequencies.

and $I(h_i, T_j)$ is a function indicating whether hashtag h_i is associated with topic T_j, defined as:

$$I(h_i, T_j) = \begin{cases} 1 & \text{if } T(h_i) = T_j \\ 0 & \text{otherwise.} \end{cases} \tag{B.4}$$

B.2.3 User Clustering

We perform the k-means clustering algorithm on these vectors to partition users into k clusters. To identify an appropriate number of clusters in the data, we run k-means by setting different values of k (a parameter specifying the number of expected clusters) and select the value of k that maximizes the average Silhouette coefficient [Rousseeuw, 1987]. The Silhouette coefficient is a measure of how appropriately the data have been clustered by computing how similar an object is to its own cluster compared to other clusters. Given a set of samples $\{x_1, x_2, ..., x_n\}$, the average Silhouette score over all samples is:

$$s = \frac{1}{n} \sum_i \frac{b_i - a_i}{\max\{b_i, a_i\}}, \tag{B.5}$$

where a_i is the mean distance between a sample x_i and all other samples in the same cluster. b_i is the mean distance between x_i and all other samples in the next nearest cluster. We use the Euclidean distance to measure the distance between two samples. The Silhouette score ranges from -1 to 1, where a high value indicates a better clustering and scores in the range between 0.71 to 1.0 indicate a strong structure in data [Kaufman and Rousseeuw, 2009]. The value of k that maximizes the Silhouette score is often regarded as the natural number of clusters in data. To obtain a reliable estimation on the cluster number, we run the pipeline of hashtag clustering, user profiling and clustering 100 times. In each run, we calculate the average Silhouette scores given different values of $k \in [2, 20]$.

B.3 Community Identification

To investigate the identities for the two groups of users found above, we (i) examine users' posting interests in the ED-related tweets, (ii) measure users' attitudes on different types of ED-related content, and (iii) manually check a random sample of users in the two groups.

B.3.1 Posting Interests

Table B.1: The most prominent hashtags used by two groups of users, ranked by NPMI.

Group	*#Hashtags*
A	thinspo, thinspiration, edproblems, skinny, proana, thighgap, skinny4xmas, ana, edprobs, anasisters, weightloss, proed, thin, hipbones, fitspo, diet, bonespo, mia, ribs, anafamily, thinkthin, perfection, legs, edgirlprobs, collarbones, edlogic, bones, staystrong, legspo, picslip, skinny4xmastips, mythinspo, mustbethin, edthoughts
B	eatingdisorders, edrecovery, recovery, bodyimage, mentalhealth, recoverywarriors, marchagainsted, edawareness, mentalillness, endstigma, bellletstalk, ended, eds, aedchat, hope, nedawareness, annawestinact, adiosed, endthestigma, rdchat, carers, treatment, eatingdisorder, annaslaw, skinnygirl, selflove, skinnygirlproblems, endthewait

We examine hashtags that each group of users post in the ED-related tweets to study their posting interests. We have shown the most frequent hashtags and their co-occurrence networks used by each group of users in the main text. In order to filter out common terms and obtain a more intuitive comparison, we here use *Normalized Pointwise Mutual Information* (*NPMI*) [Bouma, 2009], an information theoretical association measure, to rank the relative prominence of a hashtag in a group of users. Given $f(h, g)$ is the frequency of hashtag h used by users from group $g \in \{A, B\}$, the *NPMI* between h and g is computed as:

$$NPMI(h, g) = \left(\log \frac{P(h, g)}{P(h)P(g)}\right) / (-\log P(h, g)) = \left(\log \frac{f(h, g)N}{f(h)f(g)}\right) / \left(-\log \frac{f(h, g)}{N}\right) \quad \text{(B.6)}$$

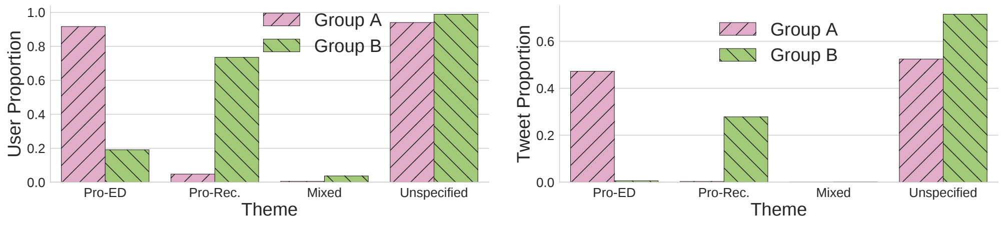
where $f(h) = \sum_g f(h,g)$ is the frequency of a tag used by all users from both two groups, and $f(g) = \sum_h f(h,g)$ is the total frequency of all hashtags used by users in group g. $N = \sum_g \sum_h f(h,g)$ is the total frequency of all tags used by all users. Table B.1 shows hashtags that have the largest *NPMI* values in the two groups of users respectively, where *NPMI* is computed only for hashtags that are used in more than three tweets and by more than three distinct users.

B.3.2 Attitudes on ED-related Content

We categorize the ED-related tweets into "pro-ED", "pro-recovery", "mixed" and "unspecified" themes based on the concurrences of hashtags indicative of a pro-ED and pro-recovery tendency in tweets. Based on previous studies on characterizing pro-ED and pro-recovery content on social media [Arseniev-Koehler et al., 2016; Chancellor et al., 2016c; De Choudhury, 2015; Oksanen et al., 2015; Syed-Abdul et al., 2013; Yom-Tov et al., 2012], we identify two clusters of hashtags that are indicative of pro-ED and pro-recovery tendencies respectively from the topic clusters of hashtags found in the ED-related tweets (see Fig. B.4). After removing generic tags, we obtain 134 pro-ED and 39 pro-recovery tags. Table B.2 lists examples of the pro-ED and pro-recovery hashtags we used.

Table B.2: Most frequent pro-ED and pro-recovery hashtags.

Topic	*#Hashtags*
Pro-ED	thinspo, thinspiration, proana, bonespo, proed, legspo, mythinspo, promia, thinspiraton, thinsporation, thinspogoals, thinspos, thinspothursday, thinspoquotes, proanamia, thinsperation, bonesspo, thinspirationoftheday, thinsp, proanatips, thinspoooo
Pro-recovery	edrecovery, recovery, recoverywarriors, ended, treatment, anorexiarecovery, prorecovery, recoveryispossible, eatingdisorderrecovery, anarecovery, recover, recoverywarrior, edtreatment, recoveryisworthit, teamrecovery, bulimiarecovery, recoveryninjas



(a)

(b)

Figure B.5: (a) Proportions of users engaged in different themes from each group. (b) Proportions of tweets involved in different themes posted by each group.

Table B.3: Sentiments of two groups of users on different themes of content. "All" denotes all content regardless of their assigned themes. Two-sided MannWhitney U tests evaluate the differences of means between groups, significance levels: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Theme	*Group A* $(\mu \pm \sigma)$	*Group B* $(\mu \pm \sigma)$	z	p
Pro-ED	0.52 ± 1.20	-0.30 ± 1.28	11.39	0.00 ***
Pro-Rec.	0.14 ± 1.35	0.31 ± 1.25	-3.45	0.00 ***
Mixed	0.23 ± 1.20	0.50 ± 1.36	-0.68	0.50
Unspecified	-0.13 ± 1.39	0.17 ± 1.30	-38.12	0.00 ***
All	0.18 ± 1.34	0.21 ± 1.29	-4.92	0.00 ***

Fig. B.5 shows the statistics of users and tweets involved in different themes from the two groups. Table B.3 reports the statistics of sentiments (measured by SentiStrength [Thelwall et al., 2010]) that the two groups of users express in tweets on different themes. In the main text, we normalize the sentiment scores with z-scores. Given a tweet i posted by user u from group g with a sentiment score $S_{u,i}$, the $z-$score for this sentiment score $z_{u,i}$ is

$$z_{u,i} = \frac{S_{u,i} - \bar{S_g}}{\sigma(S_g)}, \tag{B.7}$$

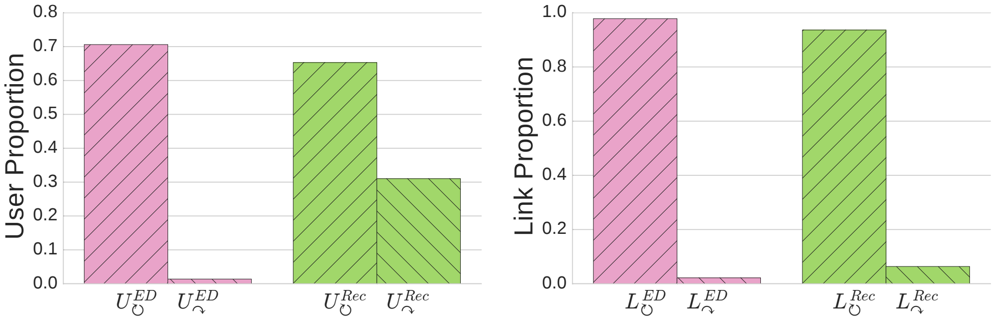
where $\bar{S_g}$ and $\sigma(S_g)$ are the mean sentiment of all tweets posted by users from group g and the standard deviation respectively (i.e., items in the "all" line in Table B.3).

B.3.3 Manual Annotation

To verify our results, we go through the Twitter homepages of a random sample of 100 users, where 50 users are from group A and 50 users are from group B. Based on users' posted tweets, images and friends' profiles, we annotate each user into three categories: pro-ED, pro-recovery and not-sure. We observe that 83 users manifest a pronounced pro-ED or pro-recovery tendency on Twitter, with 39 users from group A and 44 users from group B. If we assume the group A as a pro-ED cohort and the group B as a pro-recovery cohort, the Cohens κ between our manual annotation and the above clustering analysis on these 83 users is $\kappa = 0.85$.

B.4 Emotional Interactions

We measure sentiments in inter- and intra-community tweet messages to examine emotional interactions. Based on the community labels of source and target nodes, we categorize interaction links in the communication network into four types: links within the pro-ED community ($L^{ED}_{\circlearrowleft}$), links from the pro-ED community to the pro-recovery community ($L^{ED}_{\curvearrowright}$), links within the pro-recovery community ($L^{Rec}_{\circlearrowleft}$), and links from the pro-recovery community to the pro-ED community ($L_{\curvearrowright}^{Rec}$). Fig. B.6 shows the statistics of users and links on each type of interactions.



(a) (b)

Figure B.6: (a) Proportions of users who launched intra- and inter-community links $U_{\circlearrowleft}$ and $U_{\curvearrowright}$ in pro-ED (ED) and pro-recovery (Rec) communities respectively. (b) Proportions of intra- and inter-community links $L_{\circlearrowleft}$ and $L_{\curvearrowright}$ over all links sourced from pro-ED (ED) and pro-recovery (Rec) communities respectively. Red and green colours annotate pro-ED and pro-recovery communities repetitively.

Table B.4: Means and standard deviations of sentiments in inter- and intra-community messages. Each line describes the statistics of inter- and intra-community interactions sourced from a given community. Two-sided MannWhitney U tests evaluate the differences of mean sentiments at each line, significance levels: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Community	$\mu_{\circlearrowleft} \pm \sigma_{\circlearrowleft}$	$\mu_{\curvearrowright} \pm \sigma_{\curvearrowright}$	z	p
Pro-ED	0.44 ± 1.36	0.15 ± 1.33	3.04	0.002 **
Pro-recovery	0.43 ± 1.26	-0.07 ± 1.38	6.82	0.000 ***

Table B.4 lists the means and standard deviations of sentiments associated with each type of links. In the main text, we normalize the sentiment scores of links with z-scores. Given a tweet message sent from a user in community i to another user in community j with a sentiment score $S_{i,j}$, the z-score is:

$$z_{i,j} = \frac{S_{i,j} - \bar{S}_i}{\sigma(S_i)}, \tag{B.8}$$

where $\bar{S}_i$ and $\sigma(S_i)$ are the mean sentiment and standard deviation of all messages sent from users in community i. The mean and standard deviation of sentiments for all messages sent from the pro-ED community are $\bar{S_{ED}} = 0.43$ and $\sigma(S_{ED}) = 1.36$, while those sent from the pro-recovery community are $\bar{S_{rec}} = 0.40$ and $\sigma(S_{rec}) = 1.27$, significantly different at $p < 0.05$ in a two-sided MannWhitney U test.

B.5 Measures on User Characteristics

We consider 22 measures on social activities and language use in tweets to characterize users' social behaviours and psychometric properties exhibited on Twitter.

B.5.1 Social Activities

The measures on social activities include:

Social Capital. We measure users' social capital by their overall numbers of followees, tweets and followers observed from their profile information respectively.

Activity. We use the average numbers of followees, tweets and followers per day (from the date of account creation to the date of last post in our observation) to measure the activity of a user.

Interaction Preference. We measure the proportions of tweets that involve different types of interactions (i.e., re-tweeting, mentioning and replying) in a user's most recent tweets we collected. We only consider the mentions that are directly used by a user; any mentions in an original tweet that users re-tweeted are ignored.

Interaction Diversity. We also measure whether a user tends to interact with various individuals or certain specific people. Following previous studies [Eagle et al., 2010; Weng and Menczer, 2015], we use entropy as a diversity measure. Given a user u, we track the sequence of people interacted by u (denoted as T_u) in u's historical tweets. The interaction diversity of u in terms of a type of interactions I is measured by the entropy of such interactions with different targets $v \in T_u$:

$$H(u, I) = -\sum_{v \in T_u} p(I_v) \log p(I_v), \tag{B.9}$$

where $I \in \{\text{re-tweet}, \text{mention}, \text{reply}\}$, and $p(I_v) = \frac{\#I_v}{\sum_{j \in T_u} \#I_j}$. $\#I_v$ is the number of interactions I with target v. Larger entropy values indicate a higher diversity of interests that a user has.

B.5.2 Language Use

We adopt the psycholinguistic lexicon LIWC [Tausczik and Pennebaker, 2010] to characterize users' language use in tweets. This lexicon decomposes text data into 80 psychologically relevant variables, corresponding to different emotion, linguistic styles, personal concerns, and so on. Based on the cognitive behavioural theory of ED [Fairburn et al., 1999], we frame 5 types of variables that measure cognitive attributes and thought patterns associated with ED from LIWC outcomes: (1) concerns of body image, eating behaviours and health, comprising *body* and *ingest* and *health*; (2) interpersonal awareness and focus, comprising *1st personal singular (I)* and *1st personal plural (we)*; (3) social concern, encoded by *social*; (4) abusive language and negation use, measured by *swear* and *negate*; (5) affective processes, comprising positive emotion (*posemo*) and negative emotion (*negemo*).

B.6 Community Norms

B.6.1 Characterizing Social Norms

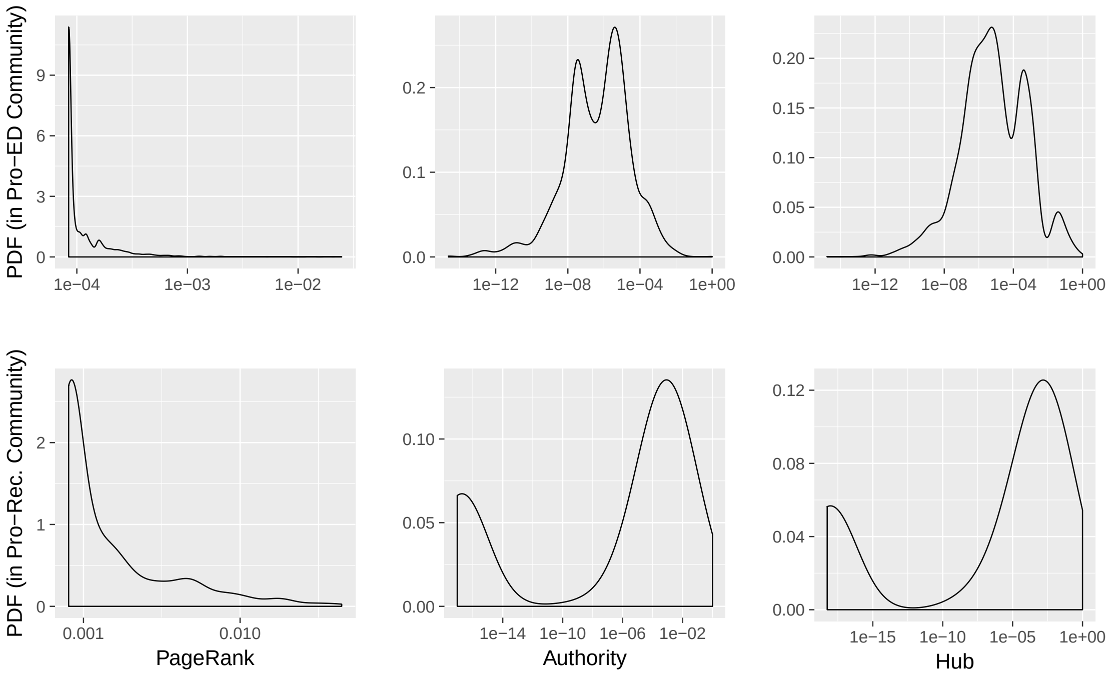


Figure B.7: Probability density functions of PageRank, authority and hub centralities measured in pro-ED and pro-recovery communities. The values of centralities are logarithmic scaled (base=10).

In addition to users' attributes measured by LIWC, we define a metric to measure the tendency that a use promote a pro-ED or pro-recovery tendency (called *pro-strength*). The basic ideal of this metric is that continuously making highly positive comments on pro-ED or pro-recovery content in tweets indicates a strong tendency of a user to promote a pro-ED or pro-recovery lifestyle and behaviour. Given user u who belongs to a community $c \in \{\text{pro-ED}, \text{pro-recovery}\}$, has totally N_u tweets in our tweet corpus, and posts a set of tweets T_c each of which contains one or more c-related hashtags, the pro-strength of u is:

$$Prostr(u) = \frac{\sum S_u(t|t \in T_c)}{N_u}, \tag{B.10}$$

where $S_u(t)$ is the sentiment of u in tweet t. Note that we use the total number of tweets N_u instead of the number of T_c(i.e., $|T_c|$) in the denominator of the above equation, in order to capture the tendency that a user posts pro-ED or pro-recovery content in her/his all tweets.

Fig. B.7 shows the distributions of PageRank [Page et al., 1999], authority and hub centralities (produced by the HITS algorithm [Kleinberg, 1999]) that are measured from the intra-community communication networks among pro-ED and pro-recovery users respectively. Since PageRank gives a constant weight to nodes without any in-degree, the distributions of PageRank centralities are smoother than those of HITS centralities (i.e., without multiple peaks). Note that the ranges of centralities are different across networks with different sizes.

B.6.2 Regression Models

We use linear robust regression models since these models require less restrictive assumptions, as compared with the least squares regression [Andersen, 2008]. Each model predicts the centrality of a user in a communication network based on an attribute of the user (such as concerns on body or positive emotion), along with several covariates that may affect a user's mention and reply interactions on Twitter or the process of measuring network centrality. These covariates include the total numbers of followers (#followees), tweets (#tweets), followers (#followers) that a user has, fractions of historical tweets that the user mentions (%mention) and replies to (%reply) others, and the number of historical tweets that the user has in our data (#historical tweets). Robust regression can be estimated by the iterated re-weighted least squares (IRLS), in which the influence of outliers (i.e., observations that do not follow the pattern of the other observations) are down-weighted to provide a better fit to the majority of the data. There are several weighting functions that can be used for IRLS. We use the Huber's weighting function [Huber et al., 1964] in our analysis. The complete lists of variables and their coefficients in each model are reported in Tables B.5-B.15. Note that we only consider users who are within the giant weakly connected components of the intra-community networks, due to the dominance of the giant components and incomparable PageRank values of nodes across disconnected components. Thus, the numbers of users/observations in the regression analysis are smaller than those reported in the main text.

Table B.5: Coefficients estimated for centrality as a function of *body* and covariates. Parentheses refer to standard errors.

	Dependent variable:					
	(PageRank)		(Authority)		(Hub)	
	Pro-ED	Pro-Rec.	Pro-ED	Pro-Rec.	Pro-ED	Pro-Rec.
Body	0.0001^{**}	-0.018^{*}	0.00001^{***}	-0.015	0.00001	-0.019
	(0.00005)	(0.008)	(0.00000)	(0.011)	(0.00003)	(0.032)
#Followees	-0.00001^{***}	-0.0001^{***}	-0.00000^{***}	-0.0001	0.00000^{**}	0.0002
	(0.00000)	(0.00004)	(0.00000)	(0.0001)	(0.00000)	(0.0002)
#Tweets	-0.00000^{***}	0.0002^{*}	-0.00000^{***}	0.0002	0.00000^{***}	-0.0004
	(0.00000)	(0.0001)	(0.00000)	(0.0001)	(0.00000)	(0.0003)
#Followers	0.00002^{***}	0.0002^{***}	0.00000^{***}	0.0002^{**}	-0.00000^{***}	-0.0002
	(0.00000)	(0.00003)	(0.00000)	(0.0001)	(0.00000)	(0.0001)
%Mention	-0.00002^{***}	0.0005^{*}	-0.00000^{***}	0.0003	0.00000	0.004^{***}
	(0.00000)	(0.0002)	(0.00000)	(0.0003)	(0.00000)	(0.001)
%Reply	0.00003^{***}	-0.0001	-0.00000	-0.001^{*}	-0.00000	-0.001
	(0.00000)	(0.0003)	(0.00000)	(0.0005)	(0.00000)	(0.001)
#Historical Tweets	0.000^{***}	-0.00000	0.000^{***}	-0.00000	-0.000	0.00000^{*}
	(0.000)	(0.00000)	(0.000)	(0.00000)	(0.000)	(0.00000)
Constant	0.0001^{***}	-0.0004	0.00000	-0.001	0.00000	0.003
	(0.00000)	(0.0004)	(0.00000)	(0.001)	(0.00000)	(0.002)
Observations	5,584	388	5,584	388	5,584	388
Note:						*p<0.05; **p<0.01; ***p<0.001

Table B.6: Coefficients estimated for centrality as a function of *ingest* and covariates. Parentheses refer to standard errors.

	Dependent variable:					
	(PageRank)		(Authority)		(Hub)	
	Pro-ED	Pro-Rec.	Pro-ED	Pro-Rec.	Pro-ED	Pro-Rec.
Ingest	0.0001^{***} (0.00003)	0.006^{*} (0.003)	0.00001^{***} (0.00000)	0.014^{***} (0.004)	0.0001^{***} (0.00002)	0.035^{**} (0.011)
#Followees	-0.00001^{***} (0.00000)	-0.0001^{*} (0.00004)	-0.00000^{***} (0.00000)	0.00004 (0.0001)	0.00000^{**} (0.00000)	0.0003 (0.0002)
#Tweets	-0.00000^{***} (0.00000)	0.0001 (0.0001)	-0.00000^{***} (0.00000)	0.0001 (0.0001)	0.00000^{***} (0.00000)	−0.0004 (0.0003)
#Followers	0.00002^{***} (0.00000)	0.0002^{***} (0.00003)	0.00000^{***} (0.00000)	0.0001^{*} (0.00005)	-0.00000^{***} (0.00000)	−0.0002 (0.0001)
%Mention	-0.00001^{***} (0.00000)	0.0005^{*} (0.0002)	-0.00000^{***} (0.00000)	0.0005 (0.0003)	0.00000 (0.00000)	0.004^{***} (0.001)
%Reply	0.00003^{***} (0.00000)	0.0003 (0.0003)	−0.00000 (0.00000)	−0.001 (0.0005)	−0.00000 (0.00000)	0.0004 (0.001)
#Historical Tweets	0.000^{***} (0.000)	−0.00000 (0.00000)	0.000^{***} (0.000)	0.00000 (0.00000)	−0.000 (0.000)	0.00000^{*} (0.00000)
Constant	0.0001^{***} (0.00000)	−0.001 (0.0004)	0.00000 (0.00000)	-0.002^{**} (0.001)	−0.00000 (0.00000)	0.001 (0.002)
Observations	5,584	388	5,584	388	5,584	388
Note:						*p<0.05; **p<0.01; ***p<0.001

Table B.7: Coefficients estimated for centrality as a function of *health* and covariates. Parentheses refer to standard errors.

	Dependent variable:					
	(PageRank)		(Authority)		(Hub)	
	Pro-ED	Pro-Rec.	Pro-ED	Pro-Rec.	Pro-ED	Pro-Rec.
Health	0.0001^{*}	−0.003	0.00000	−0.003	0.00004	0.003
	(0.0001)	(0.004)	(0.00000)	(0.006)	(0.00004)	(0.016)
#Followees	-0.00001^{***}	-0.0001^{**}	-0.00000^{***}	−0.00004	0.00000^{**}	0.0002
	(0.00000)	(0.00004)	(0.00000)	(0.0001)	(0.00000)	(0.0002)
#Tweets	-0.00000^{***}	0.0001^{*}	-0.00000^{***}	0.0002	0.00000^{***}	−0.0004
	(0.00000)	(0.0001)	(0.00000)	(0.0001)	(0.00000)	(0.0003)
#Followers	0.00002^{***}	0.0002^{***}	0.00000^{***}	0.0002^{**}	-0.00000^{***}	−0.0002
	(0.00000)	(0.00003)	(0.00000)	(0.0001)	(0.00000)	(0.0001)
%Mention	-0.00002^{***}	0.0004	-0.00000^{***}	0.0003	0.00000	0.004^{***}
	(0.00000)	(0.0002)	(0.00000)	(0.0003)	(0.00000)	(0.001)
%Reply	0.00003^{***}	−0.00002	-0.00000^{*}	-0.001^{*}	−0.00000	−0.0005
	(0.00000)	(0.0004)	(0.00000)	(0.001)	(0.00000)	(0.001)
#Historical Tweets	0.000^{***}	−0.00000	0.000^{***}	−0.00000	−0.000	0.00000^{*}
	(0.000)	(0.00000)	(0.000)	(0.00000)	(0.000)	(0.00000)
Constant	0.0001^{***}	−0.001	0.00000	-0.001^{*}	0.00000	0.002
	(0.00000)	(0.0004)	(0.00000)	(0.001)	(0.00000)	(0.002)
Observations	5,584	388	5,584	388	5,584	388
Note:						*p<0.05; **p<0.01; ***p<0.001

Table B.8: Coefficients estimated for centrality as a function of i and covariates. Parentheses refer to standard errors.

	Dependent variable:					
	(PageRank)		(Authority)		(Hub)	
	Pro-ED	Pro-Rec.	Pro-ED	Pro-Rec.	Pro-ED	Pro-Rec.
I	-0.00004^{*}	-0.005^{*}	-0.00000^{*}	-0.011^{**}	-0.00001	-0.024^{**}
	(0.00002)	(0.002)	(0.00000)	(0.003)	(0.00001)	(0.008)
#Followees	-0.00001^{***}	-0.0001^{**}	-0.00000^{***}	-0.00004	0.00000^{**}	0.0002
	(0.00000)	(0.00004)	(0.00000)	(0.0001)	(0.00000)	(0.0002)
#Tweets	-0.00000^{***}	0.0002^{*}	-0.00000^{***}	0.0003^{*}	0.00000^{***}	-0.0002
	(0.00000)	(0.0001)	(0.00000)	(0.0001)	(0.00000)	(0.0003)
#Followers	0.00002^{***}	0.0002^{***}	0.00000^{***}	0.0001	-0.00000^{***}	-0.0004^{*}
	(0.00000)	(0.00004)	(0.00000)	(0.0001)	(0.00000)	(0.0001)
%Mention	-0.00002^{***}	0.0003	-0.00000^{***}	0.0001	0.00000	0.003^{***}
	(0.00000)	(0.0002)	(0.00000)	(0.0004)	(0.00000)	(0.001)
%Reply	0.00002^{***}	0.0003	-0.00000^{**}	-0.001	-0.00001	0.001
	(0.00000)	(0.0003)	(0.00000)	(0.001)	(0.00000)	(0.001)
#Historical Tweets	0.000^{**}	-0.00000	0.000^{***}	-0.00000	-0.000^{*}	0.00000^{*}
	(0.000)	(0.00000)	(0.000)	(0.00000)	(0.000)	(0.00000)
Constant	0.0001^{***}	-0.0004	0.00000^{**}	-0.001	0.00000	0.003
	(0.00000)	(0.0004)	(0.00000)	(0.001)	(0.00000)	(0.002)
Observations	5,584	388	5,584	388	5,584	388

Note: *p<0.05; **p<0.01; ***p<0.001

Table B.9: Coefficients estimated for centrality as a function of *we* and covariates. Parentheses refer to standard errors.

	Dependent variable:					
	(PageRank)		(Authority)		(Hub)	
	Pro-ED	Pro-Rec.	Pro-ED	Pro-Rec.	Pro-ED	Pro-Rec.
We	0.0004*	0.009*	−0.00001	0.007	−0.00001	0.014
	(0.0002)	(0.004)	(0.00001)	(0.006)	(0.0001)	(0.015)
#Followees	−0.00001***	−0.0001**	−0.00000***	−0.00004	0.00000**	0.0002
	(0.00000)	(0.00004)	(0.00000)	(0.0001)	(0.00000)	(0.0002)
#Tweets	−0.00000***	0.0002*	−0.00000***	0.0002	0.00000***	−0.0003
	(0.00000)	(0.0001)	(0.00000)	(0.0001)	(0.00000)	(0.0003)
#Followers	0.00002***	0.0002***	0.00000***	0.0001*	−0.00000***	−0.0003
	(0.00000)	(0.00004)	(0.00000)	(0.0001)	(0.00000)	(0.0001)
%Mention	−0.00002***	0.0004	−0.00000***	0.0003	0.00000	0.003***
	(0.00000)	(0.0002)	(0.00000)	(0.0003)	(0.00000)	(0.001)
%Reply	0.00002***	0.0001	−0.00000*	−0.001*	−0.00001	−0.0005
	(0.00000)	(0.0003)	(0.00000)	(0.0005)	(0.00000)	(0.001)
#Historical Tweets	0.000***	−0.00000	0.000***	−0.000	−0.000	0.00000*
	(0.000)	(0.00000)	(0.000)	(0.00000)	(0.000)	(0.00000)
Constant	0.0001***	−0.001	0.00000*	−0.001*	0.00000	0.002
	(0.00000)	(0.0004)	(0.00000)	(0.001)	(0.00000)	(0.002)
Observations	5,584	388	5,584	388	5,584	388
Note:						*p<0.05; **p<0.01; ***p<0.001

Table B.10: Coefficients estimated for centrality as a function of *social* and covariates. Parentheses refer to standard errors.

	Dependent variable:					
	(PageRank)		(Authority)		(Hub)	
	Pro-ED	Pro-Rec.	Pro-ED	Pro-Rec.	Pro-ED	Pro-Rec.
Social	-0.00004^{*}	0.001	-0.00000	0.0004	-0.00000	0.001
	(0.00002)	(0.002)	(0.00000)	(0.002)	(0.00001)	(0.006)
#Followees	-0.00001^{***}	-0.0001^{**}	-0.00000^{***}	-0.00004	0.00000^{**}	0.0002
	(0.00000)	(0.00004)	(0.00000)	(0.0001)	(0.00000)	(0.0002)
#Tweets	-0.00000^{***}	0.0001^{*}	-0.00000^{***}	0.0002	0.00000^{***}	-0.0004
	(0.00000)	(0.0001)	(0.00000)	(0.0001)	(0.00000)	(0.0003)
#Followers	0.00002^{***}	0.0002^{***}	0.00000^{***}	0.0002^{**}	-0.00000^{***}	-0.0002
	(0.00000)	(0.00003)	(0.00000)	(0.0001)	(0.00000)	(0.0001)
%Mention	-0.00002^{***}	0.0004	-0.00000^{***}	0.0003	0.00000	0.004^{***}
	(0.00000)	(0.0002)	(0.00000)	(0.0003)	(0.00000)	(0.001)
%Reply	0.00003^{***}	0.0001	-0.00000	-0.001^{*}	-0.00001	-0.001
	(0.00000)	(0.0003)	(0.00000)	(0.001)	(0.00000)	(0.001)
#Historical Tweets	0.000^{***}	-0.00000	0.000^{***}	-0.000	-0.000	0.00000^{*}
	(0.000)	(0.00000)	(0.000)	(0.00000)	(0.000)	(0.00000)
Constant	0.0001^{***}	-0.001	0.00000^{*}	-0.001^{*}	0.00000	0.002
	(0.00000)	(0.0004)	(0.00000)	(0.001)	(0.00000)	(0.002)
Observations	5,584	388	5,584	388	5,584	388

Note: *p<0.05; **p<0.01; ***p<0.001

Table B.11: Coefficients estimated for centrality as a function of *swear* and covariates. Parentheses refer to standard errors.

	Dependent variable:					
	(PageRank)		(Authority)		(Hub)	
	Pro-ED	Pro-Rec.	Pro-ED	Pro-Rec.	Pro-ED	Pro-Rec.
Swear	-0.0002^{*}	-0.009	-0.00000	-0.048	-0.0001	-0.241^{**}
	(0.0001)	(0.022)	(0.00000)	(0.033)	(0.00004)	(0.090)
#Followees	-0.00001^{***}	-0.0001^{**}	-0.00000^{***}	-0.00004	0.00000^{**}	0.0002
	(0.00000)	(0.00004)	(0.00000)	(0.0001)	(0.00000)	(0.0002)
#Tweets	-0.00000^{***}	0.0001^{*}	-0.00000^{***}	0.0002	0.00000^{***}	-0.0003
	(0.00000)	(0.0001)	(0.00000)	(0.0001)	(0.00000)	(0.0003)
#Followers	0.00002^{***}	0.0002^{***}	0.00000^{***}	0.0001^{*}	-0.00000^{***}	-0.0003^{*}
	(0.00000)	(0.00004)	(0.00000)	(0.0001)	(0.00000)	(0.0001)
%Mention	-0.00002^{***}	0.0004	-0.00000^{***}	0.0003	0.00000	0.003^{***}
	(0.00000)	(0.0002)	(0.00000)	(0.0003)	(0.00000)	(0.001)
%Reply	0.00002^{***}	0.0001	-0.00000^{*}	-0.001^{*}	-0.00001^{*}	-0.0003
	(0.00000)	(0.0003)	(0.00000)	(0.0005)	(0.00000)	(0.001)
#Historical Tweets	0.000^{***}	-0.00000	0.000^{***}	0.000	-0.000	0.00000^{*}
	(0.000)	(0.00000)	(0.000)	(0.00000)	(0.000)	(0.00000)
Constant	0.0001^{***}	-0.001	0.00000^{*}	-0.001	0.00000	0.003
	(0.00000)	(0.0004)	(0.00000)	(0.001)	(0.00000)	(0.002)
Observations	5,584	388	5,584	388	5,584	388
Note:						*p<0.05; **p<0.01; ***p<0.001

Table B.12: Coefficients estimated for centrality as a function of *negate* and covariates. Parentheses refer to standard errors.

	Dependent variable:					
	(PageRank)		(Authority)		(Hub)	
	Pro-ED	Pro-Rec.	Pro-ED	Pro-Rec.	Pro-ED	Pro-Rec.
Negate	−0.0001*	−0.011	−0.00001**	−0.017	−0.00003	−0.044
	(0.0001)	(0.006)	(0.00000)	(0.010)	(0.00003)	(0.025)
#Followees	−0.00001***	−0.0001**	−0.00000***	−0.00004	0.00000**	0.0002
	(0.00000)	(0.00004)	(0.00000)	(0.0001)	(0.00000)	(0.0002)
#Tweets	−0.00000***	0.0002*	−0.00000***	0.0002	0.00000***	−0.0003
	(0.00000)	(0.0001)	(0.00000)	(0.0001)	(0.00000)	(0.0003)
#Followers	0.00002***	0.0002***	0.00000***	0.0001*	−0.00000***	−0.0003*
	(0.00000)	(0.00004)	(0.00000)	(0.0001)	(0.00000)	(0.0001)
%Mention	−0.00002***	0.0004	−0.00000***	0.0002	0.00000	0.003***
	(0.00000)	(0.0002)	(0.00000)	(0.0004)	(0.00000)	(0.001)
%Reply	0.00002***	0.0001	−0.00000**	−0.001*	−0.00001	−0.0004
	(0.00000)	(0.0003)	(0.00000)	(0.001)	(0.00000)	(0.001)
#Historical Tweets	0.000***	−0.00000	0.000***	−0.00000	−0.000*	0.00000*
	(0.000)	(0.00000)	(0.000)	(0.00000)	(0.000)	(0.00000)
Constant	0.0001***	−0.0004	0.00000**	−0.001	0.00000	0.003*
	(0.00000)	(0.0004)	(0.00000)	(0.001)	(0.00000)	(0.002)
Observations	5,584	388	5,584	388	5,584	388
Note:						*p<0.05; **p<0.01; ***p<0.001

Table B.13: Coefficients estimated for centrality as a function of *posemo* and covariates. Parentheses refer to standard errors.

	Dependent variable:					
	(PageRank)		(Authority)		(Hub)	
	Pro-ED	Pro-Rec.	Pro-ED	Pro-Rec.	Pro-ED	Pro-Rec.
Posemo	−0.00002	−0.004	0.00000	−0.005	−0.00003	0.0004
	(0.00003)	(0.003)	(0.00000)	(0.004)	(0.00002)	(0.011)
#Followees	-0.00001^{***}	-0.0001^{**}	-0.00000^{***}	−0.00003	0.00000^{**}	0.0002
	(0.00000)	(0.00004)	(0.00000)	(0.0001)	(0.00000)	(0.0002)
#Tweets	-0.00000^{***}	0.0002^{*}	-0.00000^{***}	0.0002	0.00000^{***}	−0.0004
	(0.00000)	(0.0001)	(0.00000)	(0.0001)	(0.00000)	(0.0003)
#Followers	0.00002^{***}	0.0002^{***}	0.00000^{***}	0.0002^{**}	-0.00000^{***}	−0.0002
	(0.00000)	(0.00004)	(0.00000)	(0.0001)	(0.00000)	(0.0001)
%Mention	-0.00002^{***}	0.001^{*}	-0.00000^{***}	0.0004	0.00000	0.003^{***}
	(0.00000)	(0.0002)	(0.00000)	(0.0003)	(0.00000)	(0.001)
%Reply	0.00003^{***}	0.0002	-0.00000^{**}	−0.001	−0.00000	−0.001
	(0.00001)	(0.0004)	(0.00000)	(0.001)	(0.00000)	(0.001)
#Historical Tweets	0.000^{***}	−0.00000	0.000^{***}	−0.00000	−0.000	0.00000^{*}
	(0.000)	(0.00000)	(0.000)	(0.00000)	(0.000)	(0.00000)
Constant	0.0001^{***}	−0.001	0.00000	−0.001	0.00000	0.002
	(0.00000)	(0.0004)	(0.00000)	(0.001)	(0.00000)	(0.002)
Observations	5,584	388	5,584	388	5,584	388
Note:						*p<0.05; **p<0.01; ***p<0.001

Table B.14: Coefficients estimated for centrality as a function of *negemo* and covariates. Parentheses refer to standard errors.

	Dependent variable:					
	(PageRank)		(Authority)		(Hub)	
	Pro-ED	Pro-Rec.	Pro-ED	Pro-Rec.	Pro-ED	Pro-Rec.
Negemo	−0.0001**	−0.013**	−0.00001***	−0.018*	−0.0001***	−0.066***
	(0.00003)	(0.005)	(0.00000)	(0.008)	(0.00002)	(0.020)
#Followees	−0.00001***	−0.0001**	−0.00000***	−0.00005	0.00000**	0.0002
	(0.00000)	(0.00004)	(0.00000)	(0.0001)	(0.00000)	(0.0002)
#Tweets	−0.00000***	0.0001*	−0.00000***	0.0002	0.00000***	−0.0004
	(0.00000)	(0.0001)	(0.00000)	(0.0001)	(0.00000)	(0.0003)
#Followers	0.00002***	0.0002***	0.00000***	0.0001*	−0.00000***	−0.0003*
	(0.00000)	(0.00003)	(0.00000)	(0.0001)	(0.00000)	(0.0001)
%Mention	−0.00002***	0.0003	−0.00000***	0.0002	0.00000	0.003***
	(0.00000)	(0.0002)	(0.00000)	(0.0004)	(0.00000)	(0.001)
%Reply	0.00002***	0.00001	−0.00000***	−0.001*	−0.00001**	−0.001
	(0.00000)	(0.0003)	(0.00000)	(0.001)	(0.00000)	(0.001)
#Historical Tweets	0.000**	−0.00000	0.000***	0.00000	−0.000*	0.00000*
	(0.000)	(0.00000)	(0.000)	(0.00000)	(0.000)	(0.00000)
Constant	0.0001***	−0.0001	0.00000**	−0.001	0.00000	0.005*
	(0.00000)	(0.0004)	(0.00000)	(0.001)	(0.00000)	(0.002)
Observations	5,584	388	5,584	388	5,584	388
Note:						*p<0.05; **p<0.01; ***p<0.001

Table B.15: Coefficients estimated for centrality as a function of *prostrr* and covariates. Parentheses refer to standard errors.

	Dependent variable:					
	(PageRank)		(Authority)		(Hub)	
	Pro-ED	Pro-Rec.	Pro-ED	Pro-Rec.	Pro-ED	Pro-Rec.
Prostrr	0.0001***	0.004*	0.00001***	0.004	−0.00000	0.039***
	(0.00001)	(0.002)	(0.00000)	(0.002)	(0.00001)	(0.006)
#Followees	−0.00001***	−0.0001***	−0.00000***	−0.0001	0.00000**	0.0001
	(0.00000)	(0.00004)	(0.00000)	(0.0001)	(0.00000)	(0.0002)
#Tweets	−0.00000***	0.0002*	−0.00000***	0.0002	0.00000***	−0.0003
	(0.00000)	(0.0001)	(0.00000)	(0.0001)	(0.00000)	(0.0003)
#Followers	0.00002***	0.0003***	0.00000***	0.0002**	−0.00000***	−0.0002
	(0.00000)	(0.00004)	(0.00000)	(0.0001)	(0.00000)	(0.0001)
%Mention	−0.00002***	0.0005*	−0.00000***	0.0004	0.00000	0.004***
	(0.00000)	(0.0002)	(0.00000)	(0.0003)	(0.00000)	(0.001)
%Reply	0.00003***	0.0001	−0.00000*	−0.001*	−0.00001	−0.0003
	(0.00000)	(0.0003)	(0.00000)	(0.001)	(0.00000)	(0.001)
#Historical Tweets	0.000**	−0.00000	0.000***	−0.00000	−0.000	0.00000*
	(0.000)	(0.00000)	(0.000)	(0.00000)	(0.000)	(0.00000)
Constant	0.0001***	−0.001	0.00000	−0.002*	0.00000	0.002
	(0.00000)	(0.0004)	(0.00000)	(0.001)	(0.00000)	(0.002)
Observations	5,584	388	5,584	388	5,584	388
Note:						*p<0.05; **p<0.01; ***p<0.001

Appendix C

Appendix: Supporting Information for Chapter 5

C.1 ED-related hashtags

We identify ED-related users by searching for users who posted an ED-related hashtag in tweets. The ED-related hashtags are obtained by (i) detecting clusters of hashtags that frequently co-occur in a tweet posted by 3,380 ED users, using a similar method that we used to detect topics of conversations in the main text; (ii) selecting ED-related clusters of tags based on prior evidence from language use in online ED-related content [Chancellor et al., 2016c; De Choudhury, 2015; Yom-Tov et al., 2012]; and (iii) removing generic tags (e.g., #skinny and #food) from the selected clusters. Ref. [Wang et al., 2018a] for details. We obtain 375 ED-related hashtags in total and Table C.1 lists examples of these hashtags.

Table C.1: Examples of hashtags used to filter ED-related content.

thinspo, edproblems, thinspiration, proana, ana, thighgap, edprobs, ed, eatingdisorder, anorexia, mia, skinny4xmas, bonespo, hipbones, proed, bulimia, ednos, edfamily, edlogic, thinkthin, legspo, promia, edthoughts, mythinspo, anorexic, edgirlprobs, edprobz, anamia, eatingdisorders, internationaledmeetup, edlife

C.2 Statistics of conversations

Figure C.1(a) shows an example how we aggregate tweets into conversations. We obtain 1,044,573 conversations consisting of 2,206,919 tweets. The average number of tweets in a conversation is 2.11, with a standard deviation of 1.93. Figure C.1(b) shows the distribution of numbers of tweets $|C_i|$ in each conversation C_i. We see that many conversations contain a small number of tweets while a few have very large numbers of

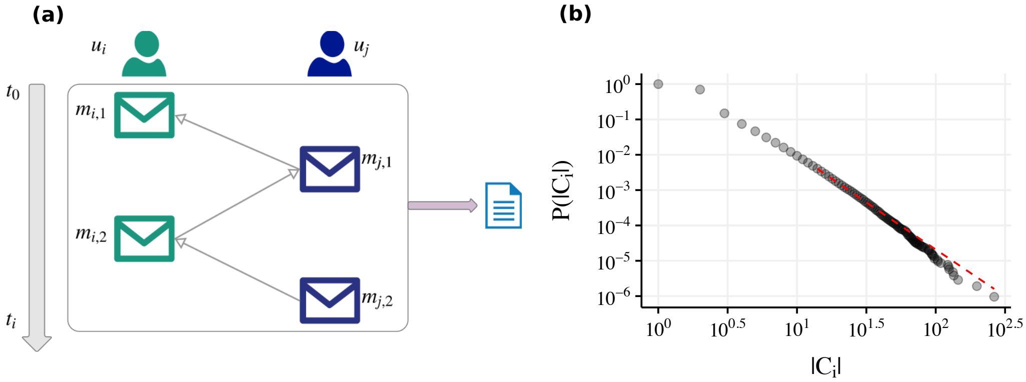


Figure C.1: (a) Aggregating tweets by conversations. If user u_i posts tweet message $m_{i,1}$ at time t_0, user u_j posts tweet $m_{j,1}$ at time t_1 to reply to $m_{i,1}$, and the two users further have two subsequent interactions through $m_{i,2}$ and $m_{j,2}$, then the conversation D_i between u_i and u_j is represented as $D_i = \langle m_{i,1}, m_{j,1}, m_{i,2}, m_{j,2} \rangle$. (b) Distribution of conversation sizes. The red line fits a power-law distribution with exponent $\lambda = 3.65 \pm 0.04$.

tweets, suggesting the heterogeneity of conversation sizes. Also, the straight line on the logarithmic histogram indicates a power law in the distribution [Barabási and Albert, 1999]. To quantify this pattern, we fit a power-law function $P(|C_i|) = |C_i|^{-\lambda}$ using the maximum likelihood estimator and calculate p-value for the goodness of fit via a bootstrapping procedure [Clauset et al., 2009]. From $N = 1,000$ bootstrap replications, we obtain the fitted values of exponent λ with the mean value $\mu = 3.65$ ($\sigma = 0.04$) and $p = 0.18$, confirming a power-law distribution in the sizes of conversations. This may imply a preferential attachment process that people tend to follow hot conversations in which many users have already involved.

Note that about 7% of tweets in the 1,044,573 conversations had already been deleted at the time of our data collection. Only content of 2,062,690 tweets were retrieved and used in the content analysis of main text. Moreover, these tweets are posted by 66,316 distinct users, where 24,860 users are absent in our user sample of 41,456 ED-related users. Although not all the new users are strongly related to ED, to preserve the integrity of communication flow, we included these new users in the network analysis of the main text.

C.3 Statistics of topics

Figure C.2 gives descriptive statistics for the 26 topics identified above. As shown in Figure C.2(a), most hashatags (83%) are classified into five topics with IDs 2, 4, 8, 16 and 22 respectively. These topics have been talked about by a large number of users in tweets (Figures C.2(b) and (c)), indicating their popularity among users. By inspecting the numbers of tweets that contain a hashtag labeled with a topic per month, we find that users have consistently high levels of engagement in sharing these five topics over time (Figure C.2(d)). In contrast, other topics are much less popular. To avoid analyzing topics of interest to a specific subgroup of online ED communities, we focus on analyzing the five popular topics.

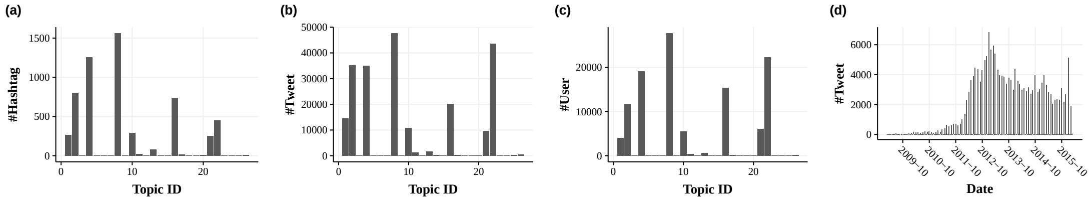


Figure C.2: Characterization of the 26 topics found in hashtag co-occurrence networks. (a) The numbers of hashtags in each topic labeled by an ID in x-axis. (b) The number of tweets containing a hashtag in each topic. (c) The number of users who posted a hashtag of each topic. (d) The numbers of tweets on the five most popular topics per month.

C.4 Null models for testing inter-layer correlations

We use the following null models to evaluate the significance of inter-layer correlations.

Hypergeometric model: a null model testing the correlations of nodes' activities across layers in a multilayer network [Nicosia and Latora, 2015]. In this model, the number $N^{[\alpha]}$ of active nodes at each layer α is fixed to be that in the original multilayer network and $N^{[\alpha]}$ nodes are randomly sampled to be active at a layer α by a uniform probability from all N nodes of the network. The null hypothesis of this model is that the activity of a node at a layer is uncorrelated from its activities at other layers. We use this model to assess the correlations of users' activities in different communication, i.e., empirical results of multiplexity.

Independent multilayer node-permutation model: an extension of the node-label permutation model [Croft et al., 2011], in which we randomly reshuffle the identities of nodes (i.e., IDs of the corresponding users) while keeping the topology (i.e., the degrees of nodes, the edges and the weights attached to edges) at a layer α intact. However, reshuffling the identities of all nodes (i.e., both active and inactive nodes) at a layer can lead to variations in the activities of nodes at the layer, which makes randomized networks not comparable to the original multilayer network. To maintain the activities of nodes across layers, we only reshuffle nodes that are active at each layer of the original multilayer network. The null hypothesis is that individuals can occupy any network position at a layer and their positions at the layer are unrelated to those at other layers. We use this model to evaluate the correlations of users' roles in different communication, i.e., empirical results of in-/out-strength correlations of nodes across layers.

Independent multilayer configuration model: a model testing the relations of link structures across layers in a multilayer network [Paul and Chen, 2016]. In this model, we fix the degree sequences of nodes at each layer α and randomly rewire the edges at α. The null hypothesis is that nodes' interconnections at a layer are independent from those at other layers. We use this model to assess the correlations of users' connectivities in different communication, i.e., empirical results of link overlaps.

Independent directed-weight reshuffling model: an extension of the directed-weight reshuffling model [Opsahl et al., 2008]. For each layer α, we fix the network structure at α (i.e., the degrees of nodes and the links), and reshuffle weights locally for each node across its out-links. That is, weights are reshuffled within links sourced from the same node at each layer. In this way, randomized networks preserve not only nodes' activities and contacts, but also their engagement levels (i.e., out-strengths) across layers in the original multilayer network. The null hypothesis is that the strength of a link between two nodes at a layer is unrelated to those at other layers. We use this model to test the correlations of users' interaction strengths in different communication, i.e., empirical results of link strengths across layers.

C.5 Statistics of temporal multilayer networks

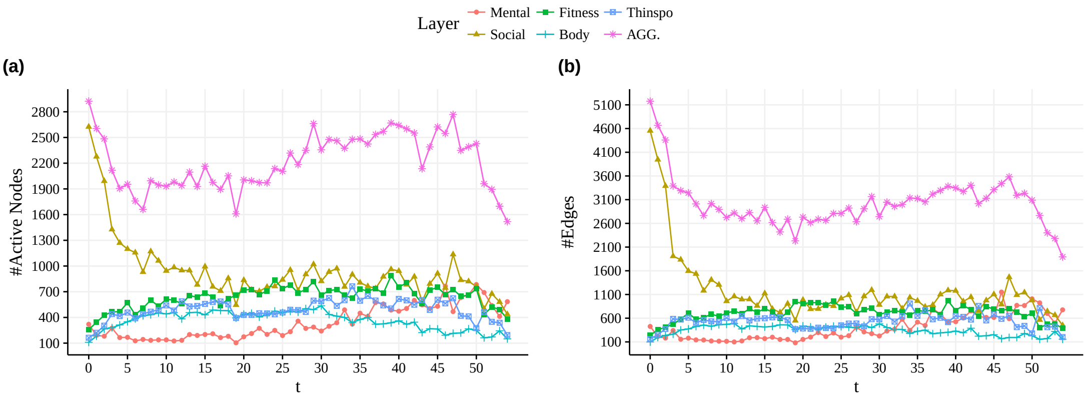


Figure C.3: Statistics of temporal multilayer networks. (a) Numbers of active nodes and (b) numbers of directed links at each individual layer of a temporal multilayer network and the aggregated network of all layers (AGG.) at time t.

Figure C.3 shows the numbers of active nodes and edges at each layer of the generated temporal multilayer networks, as well as the numbers of nodes and edges in the aggregated networks over time. While different single-layer networks show different trends in the numbers of active nodes and links, the total numbers of actors and connections in each temporal multilayer network (i.e., statistics for the aggregated networks) are sufficiently large to provide reasonably statistical power.

Appendix D

Appendix: Supporting Information for Chapter 6

D.1 Data Statistics

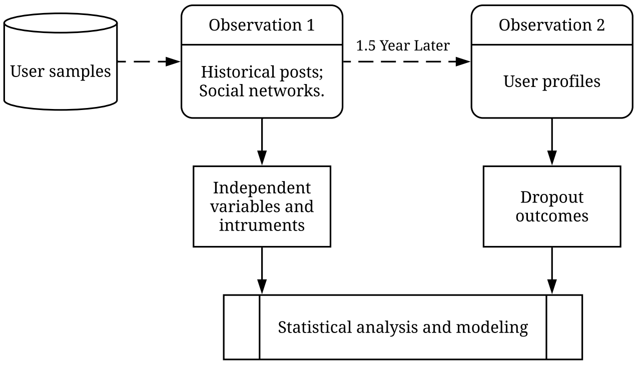


Figure D.1: Diagram of data collection and analysis procedures.

Figure D.1 shows a diagram of our data collection and analysis processes. Table D.1 shows descriptive statistics of users stratified by dropout states that are observed in our second observation period. The differences between dropouts and non-dropouts are measured with the Mann-Whitney U-test. The U-test is a nonparametric test with the null hypothesis that the distributions of two populations are equal. This test does not need the assumption of a specific distribution in data (e.g., a normal distribution in the t-test), well suitable for statistics on social media that often follow a non-normal (e.g., power law) distribution [Kwak et al., 2010]. For intuitive comparisons, we report a standardized U as a z-score. Moreover, the Bonferroni correction is used to counteract the problem of multiple comparisons. Compared to dropouts, non-dropouts show more negative emotions and higher network centralities. The network centralities are measured based on a following network containing 208,063 nodes and 1,347,056 directed

Table D.1: Descriptive statistics of users by dropout and non-dropout states.

Attributes	All ($n = 2,906$)		Non-dropout ($n = 447$)		Dropout ($n = 2,459$)		*U*-test	
	Mean	SD	Mean	SD	Mean	SD	z^b	P^c
Emotions	-0.09	0.36	-0.13	0.33	-0.08	0.37	-3.06	.03
Centrality	29.35	16.22	35.89	15.25	28.16	16.11	9.26	<.001
#Followees	309.34	483.29	533.19	862.29	268.64	360.69	10.32	< .001
#Posts	899.62	2225.44	2298.01	4566.24	645.42	1281.62	16.02	<.001
#Followers	308.15	752.74	656.25	1422.54	244.87	525.09	13.64	<.001
Active days	348.20	403.06	732.17	524.86	278.40	332.03	18.43	<.001
#Followee/day	4.16	19.07	1.75	4.87	4.60	20.60	-8.69	<.001
#Posts/day	4.41	7.54	3.85	5.82	4.51	7.81	-1.13	1
#Followers/day	2.66	8.23	1.57	3.03	2.85	8.84	-4.97	<.001
#Tweets in use	614.43	827.33	1244.17	1078.79	499.96	715.65	16.47	<.001
#Followees in use	242.13	366.69	405.27	639.19	212.47	280.92	9.56	<.001
%Active followees	0.43	0.16	0.53	0.17	0.41	0.15	13.70	<.001
⟨Followee durations⟩[a]	193.18	83.24	243.42	89.64	184.05	78.65	13.23	<.001
⟨Followee emotions⟩[a]	0.06	0.16	0.01	0.16	0.07	0.16	-8.75	<.001
⟨Followee centralities⟩[a]	29.38	9.04	28.04	8.70	29.62	9.08	-3.65	.004

[a] ⟨Followee x⟩ denotes the average values of a user's followees in terms of statistics x.
[b] A z-score measures the extent of a variable in non-dropout group being larger than that in dropout group.
[c] P-values for two-tailed tests with Bonferroni correction.

edges. All nodes are connected in a single weakly connected component and the average degree of the network is 6.5.

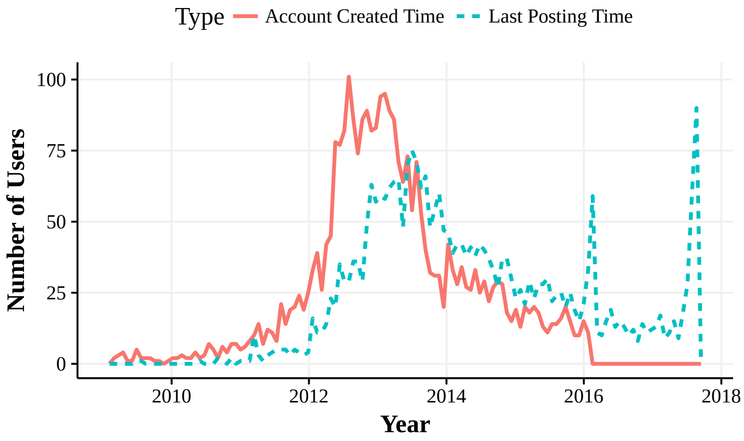


Figure D.2: Number of users along with time points when users created a Twitter account and posted the last tweet.

Figure D.2 shows details on dates when users joined and dropped out on Twitter. Most users were active during 2012 to 2014, during which 1,944 users (67%) joined Twitter. Two notable peaks in the curve of last posting time occur at the dates of our two observations. The first peak indicates that some users were lost to follow up (e.g., accounts were deleted), and the second peak indicates that many users were still actively posting tweets until our observations ended.

Figure D.3 shows demographic information of ED users, extracted from users' Twitter profile descriptions using regular expressions. To avoid noise (i.e., extremely small or large values), we only consider users whose values are in the 95% confidence intervals of the whole distribution of a statistic (except for gender). We obtain 357 users who self-reported gender information and 84% of these users ($n = 300$) are female (see Figure D.3(a)). There are 1,030 users who reported their ages in total. After excluding those with extremely small and large values of age, Figure D.3(b) shows the distribution of age among ED users ($n = 1,015$), and the mean age of these users is 17.3. The majority of females and young ages in the ED users align with clinical evidence that ED are often developed among young females [Abebe et al., 2012; Association et al., 2013]. Figures D.3(c) and (d) further show the distributions of height (with the mean of $\mu = 165.1$cm) and weights ($\mu = 57.6$kg for current weight and $\mu = 49.4$kg for goal weight) among ED users. Comparing the distributions of weights, we see that the values of goal weights are smaller than those of current weights. This implies that most ED users attempt to lose weight. Moreover, we calculate BMI (Body Mass Index) for users who reported information about both height and weight. Figure D.3(e) shows the distributions of users' current ($\mu = 21.1$) and goal ($\mu = 18.4$) BMIs. Compared to the reference values of BMI for girls at the age of 17.3 years from World Health Organization (WHO)[1], we find that 58% of users ($n = 574$ among 991 users) have a current BMI lower than 21.1 (the reference value of median BMI), and 55% of users ($n = 619$ among 1,123 users) have a goad BMI lower than 18.5 (the reference BMI for underweight). Note that we do not include users' demographic attributes in our estimation models due to a low fraction of users who have these attributes (e.g., only 357 of 3,380 users with gender information).

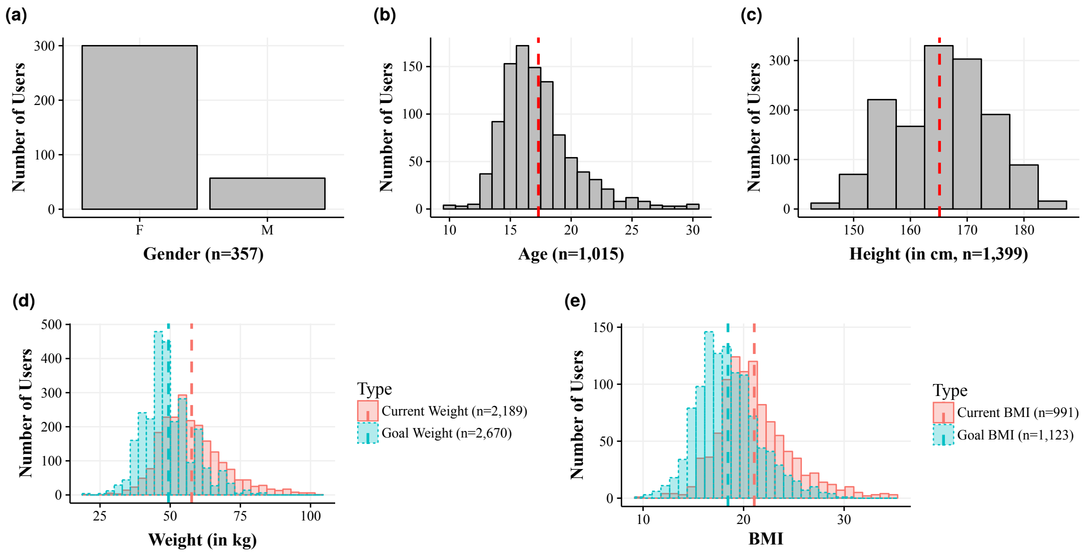


Figure D.3: Demographics of ED users, extracted from users' self-reports in their Twitter profile descriptions. A dotted line marks the mean of a corresponding statistic and the sample size for a statistic is reported in parentheses.

[1] http://www.who.int/growthref/bmifa_girls_5_19years_z.pdf?ua=1

D.2 Instrumental Variable Estimation

Suppose that one has observed independent and identically distributed data on (Y, E, X) for n users, where Y denotes the occurrence of dropout (1 for dropout and 0 for non-dropout), E denotes endogenous variables (i.e., users' emotions), and X denotes exogenous variables (i.e., covariates). We can specify a linear model to relate a decision to dropout with users' attributes on Twitter, as

$$Y = \beta_0 + \beta_1 E + \beta_2 X + U, \tag{D.1}$$

where U is an unobserved error term and βs are parameters to be estimated. As discussed previously, endogeneity issues, i.e., $cov(E, U) \neq 0$, can bias such estimates when using ordinary least squares (OLS). To produce consistent estimates, an instrumental variable (IV) estimation computed through a two step approach called 2SLS is used. In the first step, an auxiliary linear regression of instruments (i.e., the average level of emotions of a user's followees) and exogenous variables on endogenous variables runs.

$$E = \gamma_0 + \gamma_1 Z + \gamma_2 X + V, \tag{D.2}$$

where Z denotes the instruments, γs are estimable parameters and V is an error term. Following the estimation, predicted values for E are obtained via $\widehat{E} = \widehat{\gamma}_0 + \widehat{\gamma}_1 Z + \widehat{\gamma}_2 X$, and used in the second step to replace the original endogeneous variables E.

$$Y = \beta_0^{'} + \beta_1^{'} \widehat{E} + \beta_2^{'} X + U, \tag{D.3}$$

The 2SLS estimation with IV has been well studies and can be carried out by the R package AER[2].

D.3 Survival Analysis with IV

We build an additive hazards model as follow. Suppose that one has observed independent and identically distributed data on $(\tilde{T}, E, X)$ for n users, where E is the endogenous variables (i.e., emotion and centrality), X is the control variables, and $\tilde{T}$ is the time to dropout. Let U denote the unobserved error terms. Then, an additive hazards model that estimates the effect of E on $\tilde{T}$ is:

$$h(\tilde{t}|E, X, U) = \beta_0(\tilde{t}) + \beta_e(\tilde{t})E + \beta_x(\tilde{t})X + \beta_u(U|E, X, \tilde{t}), \tag{D.4}$$

where $h(\tilde{t}|E, X, U)$ is the hazard function of $\tilde{T}$ evaluated at $\tilde{t}$, conditional on E, X and U. $\beta_0(\tilde{t})$ is the unknown baseline hazard function, while $\beta_e(\tilde{t})$, $\beta_x(\tilde{t})$ and $\beta_u(U|E, X, \tilde{t})$

[2] https://cran.r-project.org/web/packages/AER/index.html

are regression functions that measure the effects of their corresponding covariates. All of these functions are allowed to vary freely over time. The model posits that conditional on X and U, the effect of E on $\tilde{T}$ is linear in E for each $\tilde{t}$, although the effect size $\beta_e(\tilde{t})$ may vary with $\tilde{t}$. A sub-model is the partially-constant hazards model which can be obtained by setting $\beta_e(\tilde{t}) = \beta_e$, where β_e is an unknown constant. Following [Tchetgen et al., 2015], we use this sub-model to measure and compare the effects of E on $\tilde{T}$ in different groups of users.

Similar to general regression models, the endogeneity problems can also bias the estimates of an additive hazards model [Chan, 2016; Li et al., 2015; Tchetgen et al., 2015]. To obtain consistent estimations, we again use an IV method where user's emotions and network centralities are instrumented by the average levels of these attributes of user's followees. To compute an IV estimator in the survival context, we use a method developed by [Tchetgen et al., 2015]. This method is based on the control-function approach. Like 2SLS, it also has two separated steps, but adds the residual from a first-stage regression of the exposure on the IV to the additive hazards model. Specifically, similar to 2SLS, the first-step regression model is:

$$E = \gamma_0 + \gamma_1 Z + \gamma_2 X + V, \tag{D.5}$$

where Z is the IV, γs are model parameters and V is the error term. Once we estimate the model parameter $\widehat{\gamma}$, we compute the residual errors as $\widehat{V} = E - \widehat{\gamma}_0 + \widehat{\gamma}_1 Z + \widehat{\gamma}_2 X$. Then, we specify the linear projection of the error U in Eq. D.4 on V as:

$$\beta_u(U|E, X, \tilde{t}) = \rho(t)V + \varepsilon(t) \tag{D.6}$$

where $\rho(t)$ is the regression coefficient, and $\varepsilon(t)$ is a random error independent of (V, Z). The model makes explicit the dependence between V and U, encoded in a non-null value of $\rho(t) \neq 0$, and induces confounding bias. The residual error $\varepsilon(t)$ introduces additional variability to ensure that the relation between U and V is not assumed deterministic. Apart from independence with (V, Z), the distribution of $\varepsilon(t)$ is unrestricted. Let $h(\tilde{t}|E, X, Z, U)$ denote the observed hazard function of $\tilde{T}$ given (E, X, Z), evaluated at $\tilde{t}$. Then, we plug Eq. D.6 into Eq. D.4 and have the following result:

$$h(\tilde{t}|E, X, Z, U) = \beta_0^{'}(\tilde{t}) + \beta_e^{'}(\tilde{t})E + \beta_x^{'}(\tilde{t})X + \rho(t)V + \varepsilon(t), \tag{D.7}$$

where $\beta_0^{'}(\tilde{t})$ is a baseline hazard function, while $\beta_e^{'}(\tilde{t})$ and $\beta_x^{'}(\tilde{t})$ are regression functions. Intuitively, the residual V captures any variation in the hazard function due to unobserved correlates of E, not accounted for in $\gamma_0 + \gamma_1 Z + \gamma_2 X$. These unobserved correlates must include any confounders of the association between E and $\tilde{T}$, and so V can be used as a proxy measure of unobserved confounders. For this reason, $\rho(t)V$ is referred to as a control function. For estimation, we use $\widehat{V}$ as an estimate of the unobserved residual V that we use to fit an additive hazards model, with regressors $(E, X, \widehat{V})$ under Eq. D.7.

Thus, in the second stage, we use Aalen's least-squares to estimate the following hazard model:

$$h(\tilde{t}|E, X, U) = \beta_0'(\tilde{t}) + \beta_e'(\tilde{t})E + \beta_x'(\tilde{t})X + \rho(t)\widehat{V} + \varepsilon(t) \tag{D.8}$$

Inference about $B(t) = (\beta_0'(\tilde{t}), \beta_e'(\tilde{t}), \beta_x'(\tilde{t}), \rho(t))^T$ for such a model has been well studied and can be obtained using the R package TIMEREG[3]. However, the standard errors and confidence intervals obtained in the package fail to appropriately account for the additional uncertainty induced by the first-stage estimation of V. We can use the non-parametric bootstrap for the whole estimation produce (including both the first-step and second-step regressions) to produce more accurate estimates of standard errors [Petrin and Train, 2010].

D.4 Null Model

We use a null model [Newman and Girvan, 2004] to test the statistical significance of the homophily pattern. Specifically, we randomly shuffle users' dropout states and re-measure homophily coefficients r [Newman, 2003] based on the shuffled states. These coefficients can be viewed as observed values of a random variable. Repeating this procedure 3,000 times, we yield the empirical distribution of homophily coefficients with a mean of $\mu = 0$ and a standard deviation of $\sigma = 0.005$. The z-score for the observed homophily (i.e., $r = 0.09$ in the main text) under this baseline distribution is $z = 16.84$ and $P < .001$, suggesting the presence of homophily.

D.5 Specifications of Data Censoring Methods

We tune the parameters of our data censoring methods based on users' activities before and after our first observation. We apply each censoring method with different parameters to data on users activities before our first observation to estimate users dropout states, and choose parameters that achieve the best agreement between the estimated dropout states and the observed states in our second observation. By setting $\pi \in [1, 300]$ days in the identical-interval censoring method, we find the optimal parameter being $\pi = 101$, with Cohens $\kappa = .68$ of the estimated dropout states and the observed dropout states of users. Such good agreement illustrates the effectiveness of the censoring approach. Similarly, by searching in a parameter space of $\pi \in [0, 200]$ days and $\lambda \in [0, 1]$, we find the optimal parameters in the personalized-interval censoring method being $\pi = 161$ and $\lambda = 0.6$, with Cohens $\kappa = .68$ as well. We use these parameters censor the dropout states of users who were active in the second observation. Figure D.4 shows the Kaplan-Meier curves of users' survival time from our first observation until our second observation using the two censoring methods. The median survival time of

[3] https://cran.r-project.org/web/packages/timereg/index.html

users is 13 months in both methods, and no significant difference is found between the two types of censorships ($P = .93$ in a log-rank test).

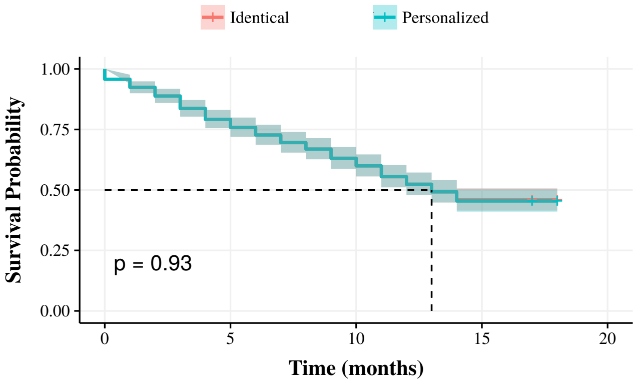


Figure D.4: Kaplan-Meier estimations of survival time.

D.6 Posting Interests of Users

To better understand the relationship between emotions and dropout, we examine associations of interests among users with different dropout statuses and emotional states. This follows past evidence that community interest is the primary motivating factor for participation in online communities [Ridings and Gefen, 2004] and people's concerns/interests reflect their emotional states [Mayer and Geher, 1996]. Since hashtags are explicit topic signals on Twitter and have been shown to strongly indicate users' interests [Weng and Menczer, 2015], we characterize users' interests based on hashtags used in their tweets.

We first examine the prevalent topics of interest for the entire ED community. To capture relationships between different topics, we build an undirected, weighted hashtag network based on the co-occurrences of hashtags in tweets posted by ED users, where an edge is weighted by the co-occurrence count of two attached tags. To filter out noise from accidental co-occurrences and spam, we only consider hashtags used by more than 50 distinct users and observed in more than 50 tweets, resulting in a network of 312 nodes and 7,906 edges. Figure D.5 shows the co-occurrence network of the most popular hashtags of interest for ED users. We observe that topics on promoting a thin ideal (e.g., "thinspo" and "thinspiration") are very prevalent in the community.

We then examine interests of users with different dropout states. We split ED users into two sets based on their dropout states in our second observation, and extract hashtags from tweets posted by each set of users. Again, tags that are used by less than 50 users and occur in less than 50 tweets in each set are excluded. To adjust tags that are popular in general, we use TF-IDF [Sparck Jones, 1972] to rank the specificity of a

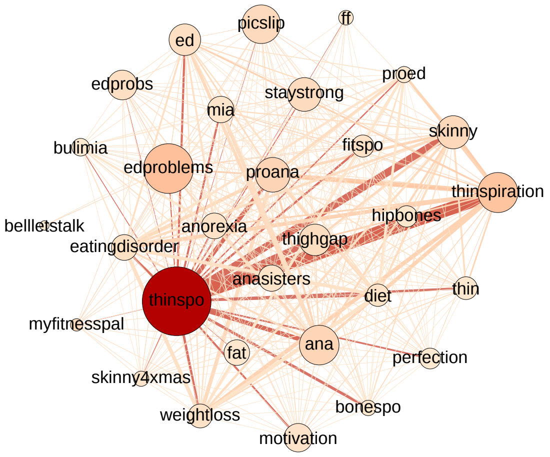


Figure D.5: The co-occurrence network of the most popular hashtags used by all ED users. Each node is a hashtag, and node size is proportional to the number of users who posted the tag. Node color is assigned based on the frequency of a tag so that high frequency is darker and low frequency is lighter. Edge width is proportional to the number of co-occurrences of two attached tags in tweets.

Table D.2: The most popular hashtags used by ED users, grouped by users' dropout states.

Dropout states	Hashtags[a]
Non-dropout	legspo, mythinspo, skinny4xmas, bonespo, goals, edlogic, eatingdisorders, edthoughts, ribs, bones, depressed, depression, edprobs, collarbones, bulimia, promia, replytweet, beautiful, anorexia, thin, hipbones, legs, ednos, ed, thighgap, weightloss, skinny, proed, selfharm, perfection, mia, thinspiration, perfect, proana, diet, eatingdisorder
Dropout	goaway, stopbullying, worthless, selfharmprobz, ew, anasisters, yay, oneday, reasonstobefit, bulimicprobz, anorexicprobz, fact, disgusting, thankgod, willpower, tweetwhatyoueat, wow, toofat, jealous, thankyou, true, anasister, anafamily, starveon, gross, teamfollowback, fuck, icandothis, tired, edfamily, relapse, stayingstrong

[a] Tags for each state are ranked in a decreasing order based on the TF-IDF score of a tag, which is calculated by the ratio of the number of users who post the tag and have a given dropout state to the number of users who post the tag in the whole user sample (i.e., regardless of users' dropout states).

tag in each set of users. Table D.2 lists the most representative hashtags in each user set, in which we find that users with different dropout states display distinct interests online. Non-dropouts are interested in advocating a thin ideal (e.g., "mythinspo" and "skinny4xmas") and reinforcing a pro-ED identity (e.g., "edlogic" and "beautiful"). In contrast, dropouts engage more in discussing their health problems (e.g., "selfharmprobz", "bulimicprobz", "anorexicprobz" and "relapse") and offering emotional support for others (e.g., "anasisters" and "stayingstrong"), which implies a tendency of these users to recover from disorders [Lyons et al., 2006; Wolf et al., 2013; Yom-Tov et al., 2012]. Together, these results imply that pro-recovery users are more likely to drop out than pro-ED users. A comparison of interests between each individual set and the entire community (see Figure D.5) further shows that the non-dropouts have dominated the

Table D.3: The most popular hashtags used by ED users, grouped by users' emotional states.

Emotional states	Hashtags[a]
Negative	bonespo, mythinspo, edlogic, bulimia, depression, starve, eatingdisorders, anxiety, anorexia, skinny4xmas, depressed, edprobs, proed, ribs, bones, edproblems, thinspo, edthoughts, thinspiration, selfharm, fuck, goals, thin, edgirlprobs, fat, sad, skinny, ednos, realityproject, ana, eatingdisorder, fatass, hipbones
Neutral	awkward, anorexicprobz, fast, mylife, bulimicprobz, please, sorry, fuckyou, myfitnesspal, ew, skinny4xmas, legspo, edfamily, gross, anafamily, ugh, ednos, workout, goals, replytweet, tmi, fatass, reversethinspo, edprobz, anaproblems, failure, flatstomach, fact, binge, fatty, fasting, suicide, depressed
Positive	eatclean, fitfam, inspiration, reasonstobefit, ff, noexcuses, fitness, loveit, winning, anasister, tweetwhatyoueat, twye, keepgoing, success, jealous, want, fitspo, beforeandafter, retweet, excited, proud, reasonstoloseweight, abcdiet, fail, justsaying, rt, motivated, workout, stayingstrong, love, myfitnesspal

[a] Tags for each state are ranked in a decreasing order based on the TF-IDF score of a tag, which is calculated by the ratio of the number of users who post the tag and have a given emotional state to the number of users who post the tag in the whole user sample (i.e., regardless of users' emotional states).

topics of discussions within the community. This is expected because the non-dropouts have prolonged participation, with 732.17 active days on average compared to 278.40 days of the dropouts (see Table D.1).

Similarly, we split ED users into three equal-size sets based on their emotional scores and obtain the most representative hashtags among each set of users in Table D.3. The results show that users with negative emotions more engage in promoting thin ideals (e.g., "bonespo" and "mythinspo"), showing largely overlapping interests with the non-dropouts. In contrast, users with neutral and positive emotions are more interested in discussing their health problems (e.g., "anorexicprobz" and "bulimicprobz"), opposing pro-ED promotions (e.g., "reversethinspo") and encouraging healthier body image and behaviors (e.g., "fitfam" and "fitness"), showing similar interests with the dropouts.

To further quantify the similarity (or association) of posting interests between users with a dropout state and those with a emotional state (as identified in Tables D.2 and D.3), we measure the Spearman rank correlation r between pairwise lists of hashtags posted by users with a given state (e.g., dropped-out or not, and positive or negative). We use the Spearman correlation because (i) it is more robust to scaling of data than other measures (e.g., cosine similarity) and (ii) it does not assume that datasets follow a specific distribution (e.g., a normal distribution in the Pearson correlation). The results of correlations are shown in Table 4 of the main text.

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