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An Investigation of Autism Support Groups on Facebook

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AN INVESTIGATION OF AUTISM SUPPORT GROUPS ON FACEBOOK

by

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ABSTRACT

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Autism-affected users, such as autism patients, caregivers, parents, family members, and researchers, currently seek informational support and social support from communities on social media. To reveal the information needs of autism- affected users, this study centers on the research of users' interactions and information sharing within autism communities on social media. It aims to understand how autism-affected users utilize support groups on Facebook.

A systematic method was proposed to aid in the data analysis including social network analysis, topic modeling, sentiment analysis, and inferential analysis. Social network analysis method was adopted to reveal the interaction patterns appearing in the groups, and topic modeling method was employed to uncover the discussion themes that users were concerned with in their daily lives. Sentiment analysis method helped analyze the emotional characteristics of the content that users expressed in the groups. Inferential analysis method was applied to compare the similarities and differences among different autism support groups found on Facebook.

This study collected user-generated content from five sampled support groups (an awareness group, a treatment group, a parents group, a research group, and a local support group) on Facebook. Findings show that the discussion topics varied in different groups. Influential users in each Facebook support group were identified through the analysis of the interaction network. The results indicated that the influential users not only attracted more attention from other group members but also led the discussion topics in the group. In addition, it was examined that autism support groups on Facebook offered a supportive emotional atmosphere for group members.

The findings of this study revealed the characteristics of user interactions and information exchanges in autism support groups on social media. Theoretically, the findings demonstrated the significance of social media for autism users. The unique implication of this study is to identify support groups on Facebook as a source of informational, social, and emotional support for autism-related users. The methodology applied in this study presented a systematic approach to evaluating the information exchange in health-related support groups on social media. Further, it investigated the potential role of technology in the social lives of autism-related users. The outcomes of this study can contribute to improving online intervention programs by highlighting effective communication approaches.

DEDICATION

This study is dedicated to my dearest grandfather.

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Chapter 1. Introduction

1.1 Background

Health information seeking represents intentional, active efforts to obtain specific health information above and beyond the normal patterns of information exposure and use of interpersonal sources which distinguishes it from information scanning (Griffin, Dunwoody, & Neuwirth, 1999). Tu (2011) showed that the following three ways: Internet, publications (books, magazines, newspapers), and someone else (friends, relatives) have become the main information sources where consumers usually seek health information. Other than seeking from publications and someone else, searching online has increased from 2001 to 2010. It was realized that health information seeking plays an increasingly important role in users' online activities.

The trend towards the use of the Internet for health information purposes is rising. In 2010, according to findings from Health System Change (HSC)'s nationally representative 2010 Health Tracking Household Survey, 50% of all American adults reported seeking information about a personal health concern during the previous 12 months (Tu, 2011). The proportion of American consumers seeking health information online was 15.9% in 2001, rose greatly to 31.1% in 2007, and finally reached 32.6% in 2010. Based on a September 2012 survey in the USA, 72% of Internet users said they looked online for health information within the past year (Pew Research Center, 2015). According to the report of European Citizens' Digital Health Literacy published in 2014, over 75% of Europeans considered the Internet as a good resource for looking up health information and 60% reported using the Internet to search health information (European Commision, 2014). As reported by a survey conducted in 2015, 68.4% of patients in Scotland had previously acquired online health information (Moreland, French, & Cumming, 2015). Deering and Harris (1996) identified three typical purposes of consumer health information: individual healthcare, medical treatment, and public health concerns. Among the 16 major health topics, ranging from specific diseases to diet to health insurance, it turned out that specific diseases or medical problems dominated Americans' online queries (Pew Research Center, 2015).

Autism is a developmental disorder that appears in the first 3 years of life. It is characterized by substantial deficits in communication and social functioning, as well as restrictive, repetitive and stereotyped behavior (Volker & Lopata, 2008). People with autism experience diverse social and emotional difficulties such as struggles with social skill and communication impairment (Mazurek, 2013). Previous studies revealed the especial challenges faced by autism patients are associated with social communication, social integration, and social imagination (Roffeei, Abdullah, & Basar, 2015). In addition, difficulties in recognizing facial expressions of emotion affect autism individuals in face-to-face interaction (Rump, Giovannelli, Minshew, & Strauss, 2009).

Today, in the Web 2.0 era, social media are pervasive, rapidly evolving, and increasingly influencing people's daily life and their health behavior. Social media provides an efficient platform for general users, patients and their relatives to access information from other users, ask help and advice from other users, make contributions to others, receive assistance from the forum, and share their experiences in the community. With the access to information on the social media platforms, people find useful information more effectively and personally than traditional information retrieval through search engines.

When it comes to adults with autism, the majority of them used social networking sites to seek social connections (Mazurek, 2013). Mazurek (2013) suggested that social media use appears to be beneficial for individuals with autism in communicating and engaging with others in a comfortable way.

Support groups on Facebook provide an efficient platform for autism patients and their caregivers where they can ask for help and advice from other users, make contributions to others, receive assistance from the group members, and share their experiences in the community. This can also be a place where group members interact with each other and exchange information. However, there have been few studies that looked into what kind of information is being shared and how users interact with each other.

This research centers on the study of autism-affected user's behavior within communities on social media. The research objects are the autism support groups on Facebook. Those groups consist of autism patients, their relatives, caregivers, researchers and physicians. Some groups are dedicated to general autism-related users, and others are more focused on particular populations (e.g. women autistics, mothers of autistic children). Social network analysis, topic modeling, sentiment analysis, and inferential analysis are proposed to conduct a systematic analysis on autism support groups on Facebook.

1.2 Significance

The overarching goal of this consumer health information study is to help both health consumers and healthcare providers. Health information obtained from the Internet may play a role in patients' health care outcomes. Understanding how people create, share, and consume information can help researchers understand patients' and caregivers' needs in online health communities and assist the way peer patients seek out health information online. The implications of this study come from two aspects: theoretical and practical.

The theoretical implications lie in the uncovering of emerging patterns and information exchange among autism support groups on Facebook. The methodology proposed in this study can be employed to explore online social support communities focusing on other health concerns. In practice, this study examines topics derived from messages posted to autism support groups on Facebook. The revealed topics identify the issues that individuals with autism are concerned about on a daily basis and how they address such concerns in the form of group communication. Identifying influential users in a support group can assist the group administrators to recognize group members' contributions and reinforce positive behaviors within the group.

1.3 Research problem, questions and hypotheses

Social media, especially social networking sites, have become significant online venues for the exchange of health-related information and advice. Prior studies have focused primarily on investigating the prevalence of online health information seeking behavior. However, few studies looked into what kind of information is being shared and how users interact with each other within the health-related online communities.

1.3.1 Research problem

With the fast permeation of social media into the health domain, this study centers on the study of users' behavior within autism communities on social media. The primary research problem of this study is to investigate the users' behavior appearing within the autism support groups on Facebook. The research objects are the autism support groups on Facebook. The autism support groups on Facebook refer to any existing Facebook groups dedicated to autism-related topics. The autism support groups consist of autism patients, their relatives, caregivers, researchers and physicians. The users' behavior consists of two primary facets of characteristics:

behavior-based characteristics and content-based characteristics. Specifically, behavior-based characteristics represent the communication pattern among group members, while content-based characteristics describe the content pattern derived from the communication.

Based on the primary problem, this study aims to address the following four research questions and the associated sub-questions. Toward the research questions, the corresponding null hypotheses were proposed in the study.

1.3.2 Research question 1 (RQ1)

RQ1: How do users interact with each other in autism support groups on Facebook based on social network analysis?

To address the overall research problem in this study, the first research question aims to unveil how users communicate with each other within autism support groups on Facebook. By answering this question, what types of interactions autism-affected users are engaging in with each other can be unveiled.

Facebook allows users to communicate with each other through various interactions. Within Facebook groups, the online interactions refer to various types of activities among group members, such as making comments, clicking “thumbs up”, etc. The major activities on Facebook include “posting”, “commenting”, “reacting (liking)”, “tagging”, and “sharing”. Within autism support groups on Facebook, users are able to perform all of those activities.

However, when it comes to groups, sharing activities can be divided into two types: sharing-in and sharing-out. Sharing-in refers to share the outside information into a group, while sharing-out means sharing the information posted in the group to one’s own timeline or to a specific target as a message. Group members are able to create new wall posts to the group and share information (e.g. images, videos, webpages) from outside online resources to the group. In contrast to posting in the group and sharing into the group, the online interactions among group members including “commenting”, “reacting (liking)”, “tagging”, and “sharing-out” involve two users. Types and frequencies of the activities provide the quantitative evidence necessary to examine the interaction among group members.

Activity	**Category of activity**	**Description**
Post	Individual activity	Create a new post
Share-in	Individual activity	Share information from outside resources into a group
Comment	Interaction	Make a comment to other’s post
React (like)	Interaction	Click the “thumbs up” to other’s post
Tag	Interaction	Tag other user embedded in a post
Share-out	Interaction	Share group discussions to outside

Table 1. Descriptions of group activities

Members in a group and the interactions among the group members construct a social network that depicts the characteristics of the group. In the social network, actors represent the group members, while interactions among group members are displayed as connections among actors. The features of the constructed social networks of autism support groups on Facebook identify the characteristics of the group interactions among group members.

Social networks can be characterized based on two levels of measurements: network-level (macro-level) and actor-level (micro-level). Figure 1 presents a series of measurements used in social network analysis, and the hierarchical relations among the measurements. Network-level measurements capture the features of the whole network, while actor-level measurements quantify the positional characteristics of an actor in a social network. In this case, network-level measurements represent the traits of the autism support groups on Facebook, whereas actor-level measurements indicate the features of individual group members.

A variety of network-level measurements is adopted to describe the patterns of the interactions appearing in each autism support group on Facebook. Network-level measurements depict the pattern of the way actors are connected. Figure 1 summarizes a host of network-level measurements that characterize the social networks created by the group members and their interactions in the autism support groups on Facebook. Different measurements depict the features of a social network from diverse perspectives. Network size refers to the number of actors in a social network, which indicates the number of group members in a group. Cohesion is concerned with the connectedness of the network. Network density can be seen as the simplest measure of cohesion, which calculates the proportion of all possible connections that are actually present (Borgatti, Everett, & Johnson, 2013). The network density of a social network indicates the speed at which information or resources diffuse among the actors. The interactions between a pair of group members are not required to be mutual. For example, the person who receives the comment might not reply to the one who sends the comment. With a directed social network, reciprocity indicates the ratio of the number of pairs of actors with a reciprocated connection relative to the number of pairs with any connection (Hanneman & Riddle, 2005). Centralization refers to the extent a network is dominated by a single node (Borgatti et al., 2013). Centralization quantifies the extent to which a network is centralized as a whole. Actor-level measurements are defined in the following paragraphs. Detailed calculation methods of each network measurement are presented in Chapter 3.

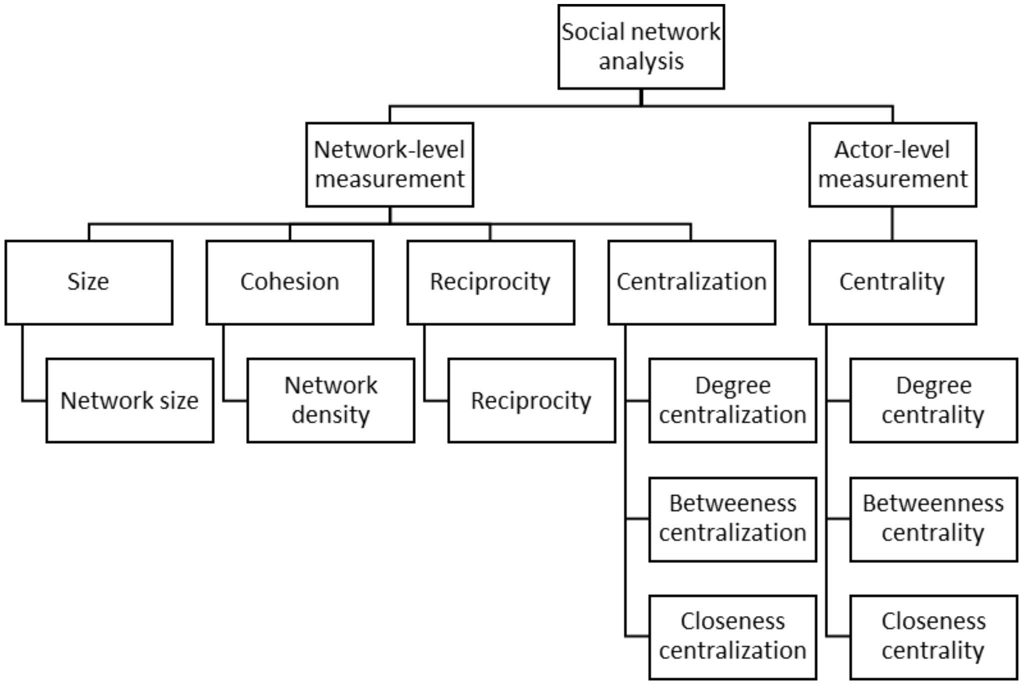

Figure 1. Social network measurements

1.3.2.1. RQ1.1 & RQ1.2

The defined autism support groups on Facebook were created to discuss a wide range of topics regarding autism. Each group may have one or more focused topics (e.g. education, fundraising) or targeted population (e.g. parents of autistic children, autistic youth). In this study, on one hand, the author classifies the autism support groups into different categories and associated sub-categories according to the focused topic of a certain group. The approaches adopted in this study to define such categories and sub-category are discussed in the Chapter 3.

On the other hand, group members can be categorized into two types based on their gender. Facebook users are able to set the gender in the account profile. Table 2 presents the classification of the autism support groups on Facebook and the gender categories of group members.

		Category of autism support groups on Facebook		
		Category 1	Category i	Category n
Group members	Male			

Female	

Table 2. Classification of autism support groups and group members on Facebook

In addition to the pattern of interactions that occur in the groups, this study also examines the disparity and the similarity between the male group members and female group members and among groups focused on different topics. Therefore, the following two sub-questions were explored. Figure 2 presents the structure of RQ1 and the corresponding RQ1.1 and RQ1.2.

RQ1.1: Are there any differences between male group members and female group members in terms of interactions in autism support groups on Facebook?

RQ1.2: Are there any differences among the defined categories in terms of online interactions in autism support groups on Facebook?

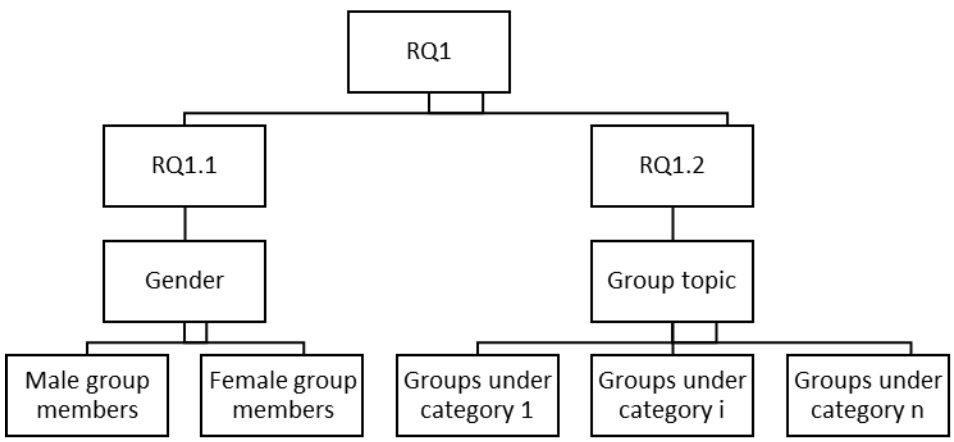

Figure 2. Structure of RQ1

As discussed above, centralization characterizes a whole social network, while centrality captures the feature of an individual actor in the network. Over the past years, a number of centrality measures have been proposed by sociologists to detect the structural characteristics of entities in a network. Each centrality measure demonstrates special characteristics of the relationship among the nodes in a network. The centrality indicators are designed to identify the importance of each node from different perspectives. Degree centrality refers to the number of connections an actor has to other actors in the network. The degree centrality can be seen as an index of its potential communication activity. Freeman's (1978) betweenness centrality is based upon the frequency with which a point falls between pairs of other points on the shortest paths connecting them. Betweenness is useful as an index of the potential of a point for control of communication. Closeness centrality can be calculated by the inverse of summing the geodesic distances from that point to all other points in the graph (Freeman, 1978). Closeness is a measure of the degree to which an individual is near all other individuals in a network.

1.3.2.2. Hypothesis group 1

To compare the gender differences in structural features of group members in the autism support groups on Facebook, inferential analysis is applied to contrast the centrality measures (i.e. degree centrality, betweenness centrality, closeness centrality) of each actor in the network.

Therefore, the following three hypotheses were tested to answer the RQ1.1:

$H_{01(a)}$: There are no significant differences between male group members and female group members in terms of the interactions in autism support groups on Facebook based on the degree centrality.

$H_{01(b)}$: There are no significant differences between male group members and female group members in terms of the interactions in autism support groups on Facebook based on the betweenness centrality.

$H_{01(c)}$: There are no significant differences between male group members and female group members in terms of the interactions in autism support groups on Facebook based on the closeness centrality.

Considering the category attribute of each group, the following three hypotheses were to compare between the male group members and female group members that both belong to the same group:

$H_{02(a)}$: There are no significant differences between male group members and female group members in each of the defined categories in terms of the interactions in autism support groups on Facebook based on the degree centrality.

$H_{02(b)}$: There are no significant differences between male group members and female group members in each of the defined categories in terms of the interactions in autism support groups on Facebook based on the betweenness centrality.

$H_{02(c)}$: There are no significant differences between male group members and female group members in each of the defined categories in terms of the interactions in autism support groups on Facebook based on the closeness centrality.

$H_{01(a)}$, $H_{01(b)}$, $H_{01(c)}$, $H_{02(a)}$, $H_{02(b)}$, and $H_{02(c)}$ compose the hypothesis group 1. The independent variable of the hypothesis group 1 is gender. The dependent variable of the hypothesis group 1 is the interactions in autism support groups on Facebook. The dependent variables can be measured by the degree centrality of each actor, the betweenness centrality of each actor, the closeness centrality of each actor, respectively.

1.3.2.3. Hypothesis group 2

The following three hypotheses were tested to answer the RQ1.2:

$H_{03(a)}$: There are no significant differences among the defined categories in terms of the interactions in autism support groups on Facebook based on the degree centrality.

$H_{03(b)}$: There are no significant differences among the defined categories in terms of the interactions in autism support groups on Facebook based on the betweenness centrality.

$H_{03(c)}$: There are no significant differences among the defined categories in terms of the interactions in autism support groups on Facebook based on the closeness centrality.

Hypothesis group 2 consists of $H_{03(a)}$, $H_{03(b)}$, and $H_{03(c)}$. The independent variable of the hypothesis group 2 is the defined category of the group. The dependent variable of the hypothesis group 2 is the interactions in autism support groups on Facebook. The dependent variables can be measured by the degree centrality of each actor, the betweenness centrality of each actor, the closeness centrality of each actor, respectively.

1.3.3 Research question 2 (RQ2)

RQ2: Who are the influential users based on interactions in autism support groups on Facebook?

The second research question aims to identify who are the influential users based on interactions, also called major players, in the autism support groups on Facebook. The influential users usually have more impact on others in the group. Within a group, some group members occupy a more central positions compared to others, and thus possess more advantages in controlling the information flow among group members. The influential users based on interactions can be discovered through the analysis of different activities that users conduct in the group, i.e. “posting”, “sharing-in”, “commenting”, “reacting (liking)”, “sharing-out”, and “tagging”. The activities that users perform quantify users’ contribution to the group. In addition, the data from the interactions provide the quantitative evidence necessary to examine the information exchange in the group.

In this study, the influential users based on interactions in autism support groups on Facebook can be discovered through social network analysis. The fundamental components of social network analysis are actors (nodes/vertices) and relations (ties/edges). One of the main purposes of social network analysis is to identify the core actors in a network. Actor-level centrality measures assist in the identification of influential users. The key players in the social network can be determined based on each centrality measurement: betweenness, closeness, and degree. Group members who possess higher centralities in the group are considered “important” with regard to the relative positon of an actor within a network.

1.3.3.1. RQ2.1 & RQ2.2

In addition to finding out the influential users based on interactions, the characteristics of the influential users and the way that these influential users interact with others in the group are further examined. Therefore, the following sub-questions were explored:

RQ2.1: What are the characteristics of the influential users in autism support groups on Facebook?

RQ2.2: How do the influential users interact with others in autism support groups on Facebook?

To answer RQ2.1 and RQ2.2, the characteristics of the influential users and their interaction patterns in autism support groups are also investigated through the social network analysis. The characteristics of the influential users come from the following aspects: the frequency and content of the posts that the user creates and shares in the group. Taking group members as the actors and interactions as the connections in the network, the interaction patterns of the influential users can be measured by the frequency of each type of interaction.

1.3.4 Research question 3 (RQ3)

RQ3: What are the discussion topics that emerged from the discussions in autism support groups on Facebook?

The online activities conducted by group members in autism support groups on Facebook produce rich textual content in addition to the interaction connections between users. In this study, the textual content mainly consists of two parts: the original posts submitted by group members, and the comments made by other members.

The content created by users in the process of the group interactions reveals the concerns, interests, and other potential information behind the information sharing actions among group members. The content-based analysis uncovers the topics that emerge from group discussions. It provides knowledge regarding the information need of autism-affected users.

1.3.5 Research question 4 (RQ4)

RQ4: What are the sentiment characteristics of discussions in autism support groups on Facebook?

People dealing with autism face huge economic costs and emotional stress (Saha & Agarwal, 2016). Emotional support has been considered as a significant element for the social support that the communities on social media provide to the community members. Saha and Agarwal (2016) identified that members of the autism community convey active and upbeat attitude in the community to counter stress and anxiety experienced by other members. Measuring the sentiment characteristics assesses how frequent positive and negative attitudes appear in the autism support groups on Facebook. It describes the interactions among group members from the emotional perspective. It also examines the effectiveness of autism support groups on Facebook performing as an avenue of emotional support.

In this study, the sentiment is quantitatively analyzed from the content of autism support groups on Facebook to understand how group members engage with social and emotional support. Sentiment analysis is applied to the posts and comments disseminated by group members within the group to measure the emotion.

1.3.5.1. RQ4.1 & RQ4.2

In addition, the following two sub-questions were explored to compare the sentiment characteristics between male group members and female group members, and among the defined categories.

RQ4.1: Are there any differences between male group members and female group members in terms of sentiment characteristics in autism support groups on Facebook in each of the defined categories?

RQ4.2: Are there any differences among the defined categories in terms of sentiment characteristics in autism support groups on Facebook?

1.3.5.2. Hypothesis group 3

The following two hypotheses were tested to answer the RQ4.1:

H_{04}: There are no significant differences between male group members and female group members in terms of the sentiment in autism support groups on Facebook.

H_{05}: There are no significant differences between male group members and female group members in each of the defined categories in terms of the sentiment in autism support groups on Facebook.

H_{04} and H_{05} compose the hypothesis group 3. The independent variable of the hypothesis group 3 is gender. The dependent variable of the hypothesis group 3 is the sentiment appearing in autism support groups on Facebook. The dependent variable can be measured by the sentiment scores of the content posted by the group members.

1.3.5.3. Hypothesis group 4

The following two hypotheses were tested to answer the RQ4.2:

H_{06}: There are no significant differences among the defined categories in terms of the sentiment in autism support groups on Facebook.

H_{07}: There are no significant differences among the defined categories in terms of the sentiment of group members with the same gender in autism support groups on Facebook.

H_{06} and H_{07} compose the hypothesis group 4. The independent variable of the hypothesis group 4 is the defined category of the group. The dependent variable of the hypothesis group 4 is the sentiment appearing in autism support groups on Facebook. The dependent variable can be measured by the sentiment scores of the content posted by the group members.

1.4 Definitions of terms

Before the exploration of consumer health information seeking in social media, key terms must be identified and defined. This section summarizes the key terms and the definitions employed in this study.

1.4.1 Autism

Autism, or autism spectrum disorder (ASD), refers to a group of developmental disorders (NIMH, n.d.). According to U.S. National Library of Medicine, autism, also called pervasive developmental disorder (PDD), is “a lifelong developmental disability that affects how a person communicates with and relates to others” (MedlinePlus, n.d.). Autism occurs during the first three years of a person's life. It influences an individual’s brain functions and the way in which these functions make sense of the world (Roffeei et al., 2015). Autism affects the way that an individual acts and interacts with others, communicates, and learns (MedlinePlus, n.d.). Individuals with autism syndrome share certain difficulties that may affect them in different ways such as experiencing learning disabilities that require special types of support (Roffeei et al., 2015).

1.4.2 Autism-affected users

Autism occurs early in an individual's life and lasts throughout his/her whole lifetime. Individuals with autism often encounter challenges with a wide range of social interactions and activities. It involves a variety of people who appear in his/her life. These so called autism-affected users include parents, family members, classmates, schoolteachers, and caregivers.

1.4.3 Social media

With the development of mobile and web-based technologies, social media create highly interactive platforms where individuals and communities share, co-create, discuss, and modify user-generated content (Kietzmann, Hermkens, McCarthy, & Silvestre, 2011). In 2010, Kaplan and Haenlein (2010) defined social media as "a group of Internet-based applications that build on the ideological and technological foundations of Web 2.0, and that allow the creation and exchange of user-generated content" (p. 61).

There currently exist numerous and diverse social media sites that vary in terms of their functionality for society and individual users. Relying on a set of theories in the field of media research (social presence, media richness) and social processes (self-presentation, self-disclosure), social media sites can be classified into the following six types: blogs, social networking sites, virtual social worlds, collaborative projects, content communities, virtual game worlds (as shown in Table 3). (Kaplan & Haenlein, 2010)

	Social presence/ Media richness		
	Low	Medium	High
High	Blogs (e.g. Blogger)	Social networking sites (e.g., Facebook)	Virtual social worlds (e.g., Second Life)
Low	Collaborative projects (e.g., Wikipedia)	Content communities (e.g., YouTube)	Virtual game worlds (e.g., World of Warcraft)

Table 3. Classification of social media sites (Kaplan & Haenlein, 2010, Table 1)

The 21st century no doubt is witnessing an explosion of social media. Pew Research Center reported that almost all of the major social media platforms have witnessed a significant increase in the proportion of U.S. adults who used them over the past four years (Duggan, 2015). Based on the Pew Research Center's survey conducted March 17, 2015 through April 12, 2015, which sampled 1,907 adults, 72% of adults use Facebook (Duggan, 2015). According to this survey, the proportions of adults who use the five main social media sites (Facebook, Pinterest, Instagram, LinkedIn, and Twitter) have continued rising between 2012 and 2015. While Facebook remains the most popular social media site among Internet users in the past four years, other sites, such as Pinterest and Instagram, have experienced significant growth between 2012 and 2015 (Duggan, 2015). In addition to having a very large user base, Facebook continues to have the most engaged users (70%) who log on daily, including 43% of them who check in several times a day (Duggan, 2015). Considering the high popularity and accessibility of Facebook and Twitter, this study mainly took these two social media platforms as examples.

1.4.4 Facebook

Facebook, launched in 2004, has become the most popular social networking site worldwide (as of August 2017), as ranked by the number of active user accounts (Statista, 2017). After signing up on Facebook, a user is able to fill in his/her profile and start to interact with others on Facebook. Like other social networking sites, Facebook offers an important mechanism for "being friends". Users can become friends by sending friend requests to others and accepting friend requests from others. Users with friend relationships may see each other's posts in the News Feed. On Facebook, the friendship is a binary state of connection between two registered users. In addition to general user account, Facebook also provides other types of account, such as Groups, Pages, Community Pages, etc. Facebook Pages enable businesses, organizations and public figures to connect with their customers or fans on Facebook (“Pages,” n.d.). Users who like a Page can keep track with the updates about the Page including posts, photos or videos in their News Feed. Community pages appear to be a type of Facebook pages. Different from other Facebook pages creating for business, company, organization, etc., Facebook community pages are built around topics, causes or experiences (Socialbakers, 2012).

1.4.5 Facebook group

Created in 2004, Facebook reached 1.79 billion monthly active users as of the third quarter of 2016 (“Facebook users worldwide 2016,” 2016). As the most popular social network worldwide, Facebook allows users to perform general social media activities such as posting status updates, other content and messaging each other (“Facebook users worldwide 2016,” 2016), etc. In addition, Facebook users may join user groups based on alumni relationships or shared interests.

Facebook has a group mechanism to provide Facebook users a space where they can communicate about shared interests with certain people (“Groups”, n.d.). Facebook groups provide a space to communicate about shared interests with other users. Groups can be created by any registered users for a variety of purposes such as classmate reunions, sports teams, study groups, etc. Figure 3 shows an example of the homepage of a Facebook group.

Any registered users can create groups for a variety of reasons such as family reunion, after-work sports team, book club, etc. The privacy settings of a group may be customized depending on who you want to be able to join and see the group (“Groups,” n.d.). The group's privacy settings can be customized as public groups, closed groups, and secret groups (“Friending”, n.d.).

Regarding the privacy settings, there are three types of Facebook groups: public groups, closed groups, and secret groups (“Groups,” n.d.). Table 4 summarizes the access limits for groups with different privacy settings. Secret groups are the most private type since no one can see the group’s name except the current and former group members. It means secret groups do not appear in a Facebook search if the searcher is not a current or former member. Therefore, this study is unable to include the investigation of those secret groups. As for public and closed groups, anyone can join or be added or invited to a public group, whereas for a closed group people have to ask to join or be added or invited by a current member.

In a certain Facebook group, there are a range of interactions a group member may have with the group and other group members. The most common activity is to post a message, a photo or a video. All group members are notified about the new posts in a group unless they adjust their group notification settings (“Join and Interact with Groups,” 2016). Any Facebook users has access to the content that appears in public groups, while only group members are able to see things that are posted in closed or secret groups.

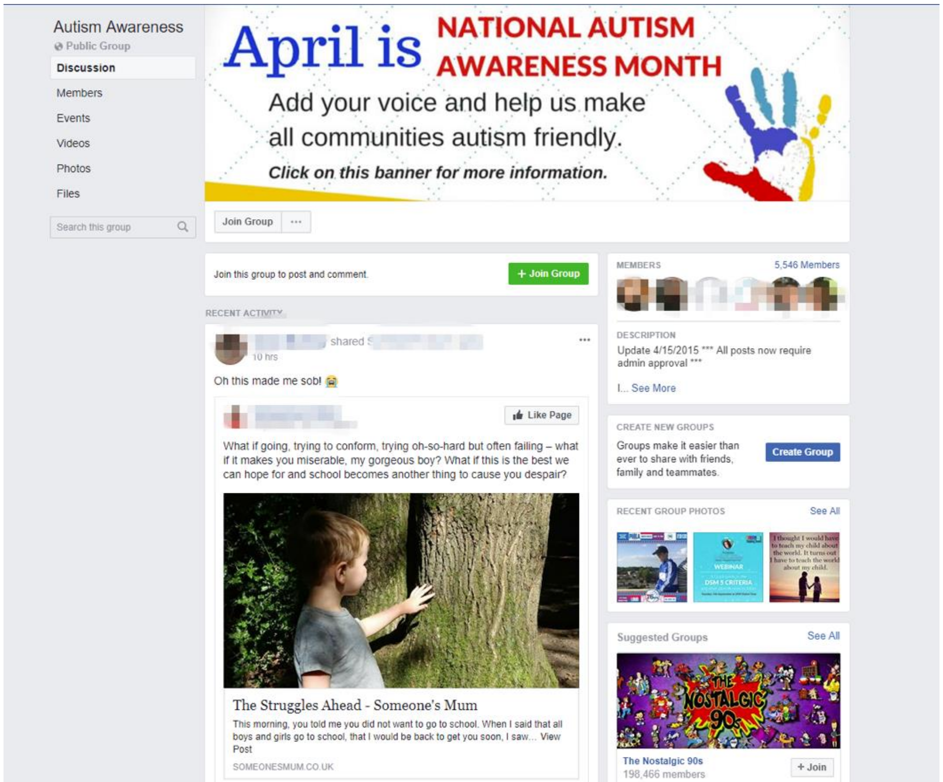

Figure 3. An example of a Facebook group homepage

	Group privacy setting		
	Public group	**Closed group**	**Secret group**
Join the group	Anyone can join or be added or invited by a member	Anyone can ask to join or be added or invited by a member	Anyone, but they have to be added or invited by a member
See the group description	Anyone	Anyone	Current and former members
See the group posts	Anyone	Only current members	Only current members
Find the group in search	Anyone	Anyone	Current and former members
See stories about the group (e.g. News Feed and search)	Anyone	Only current members	Only current members

Table 4. Privacy settings for Facebook groups

1.4.6 Interactions in Facebook group

Facebook users post status, photos, videos, and interact with friends and family members in their online social network. Users are able to conduct various activities with other users, such as making comments to posts, giving “like” to posts, sharing-out posts, and tagging other users in their own posts. In addition, messaging on Facebook allow users to instantly reach their friends by sending texts, photos, links, etc. To keep the confidentiality of group members, sharing-out can only be conducted in the public groups. In this study, the interactions among group members refer to the interactive activities that can be done in the group, including “commenting”, “reacting (liking)”, “tagging”, and “sharing-out”.

1.4.7 Social network analysis

In social science, the theory of networks has been adopted to explain social phenomena in a wide variety of disciplines ranging from psychology to economics (Borgatti, Mehra, Brass, & Labianca, 2009). Borgatti et al. (2009) regarded social network theory as a gold mine that “provides an answer to a question that has preoccupied social philosophy since the time of Plato, namely, the problem of social order: how autonomous individuals can combine to create enduring, functioning societies” (p. 892).

The history of social network analysis can be traced back to the 1930s. By the 1980s, social network analysis had become an established field within the social sciences (Borgatti et al., 2009). About ten years later, social network analysis was applied to a wide range of fields such as physics and biology (Borgatti et al., 2009). To date, social network analysis has been widely employed by a great number of disciplines and has become a multidisciplinary method.

Social network analysis has been defined as a strategy for investigating social structures through the use of network and graph theories (Otte & Rousseau, 2002). The axiom on which social network analysis rests is that structure matters (Borgatti et al., 2009). Social network analysis provides a framework that measures structural relations between members of a network. While social network analysis has many applications, the ultimate purpose underlying all applications of this method is to reveal useful insights occurring in the behind-the-scenes development and interactions in a network.

The fundamental components of social network analysis are actors (nodes/vertices) and relations (ties/edges). An actor may represent an individual person or may represent a group of people or organization (Knoke & Yang, 2008). In addition, Hansen, Shneiderman, and Smith (2010) indicated that actors need not be limited to people, but can also represent items such as web pages, key word tags, or videos. A pair of any two actors in the network is often referred to as a dyad, and so a relation can be defined as "a specific kind of contact, connection, or tie between a pair of actors, or dyad" (Knoke & Yang, 2008, p. 7). Borgatti et al. (2009) divided dyadic relations into four basic types: "similarities, social relations, interactions, and flows" (p. 894) (as shown in Table 5). Social network research focuses primarily on the way that these different kinds of ties affect each other (Borgatti et al., 2009).

Similarities			Social Relations				Interactions	Flows
Location	Membership	Attribute	Kinship	Other Role	Affective	Cognitive		
e.g., same spatial & temporal space	e.g., same clubs, same events etc.	e.g., same gender, same attitude etc.	e.g., mother of, sibling of	e.g., friend of, boss of, student of, competitor	e.g., likes, hates, etc.	e.g., knows, knows about, sees as happy etc.	e.g., sex with, talked to, advice to, helped, harmed, etc.	e.g., information, beliefs, personnel, resources, etc.

Table 5. A typology of ties studied in social network analysis (Borgatti et al., 2009, Figure 3)

1.4.8 Centrality

One of the main purposes of social network analysis is to identify the core actors in a network. Over the past years, a number of centrality measures have been proposed by sociologists to detect the structural characteristics of entities in a network. The centrality indicators are designed to identify the "core" authors from different perspectives. The degree centrality can be seen as an index of its potential communication activity. Freeman's (1978) betweenness centrality is based upon the frequency with which a point falls between pairs of other points on the shortest paths connecting them. Betweenness centrality can be used to assess the potential of an actor for control of communication in the knowledge flow network.

1.4.9 Content analysis

Content analysis has been widely studied for about 60 years (Krippendorff, 2012). It was probably first defined in Webster and Gove's *Webster's Third New International Dictionary of the English Language* in its 1961 edition as "analysis of the manifest and latent content of a body of communicated material (as a book or film) through classification, tabulation, and evaluation of its key symbols and themes in order to ascertain its meaning and probable effect" (as cited in Krippendorff, 2012, p. 1). Then, Neuendorf (2002) provided a briefer and well-known definition of content analysis as "the systematic, objective, quantitative analysis of message characteristics". Under both definitions, the main purpose of content analysis can be seen as revealing the underlying information behind the material. Although, certain arguments still exist in the scholarly literature as to the specific scope of content analysis (Neuendorf, 2002), this study tends to treat both qualitative and quantitative methods dealing with the content as content analysis.

The informative nature of social media makes it a great platform to conduct content analysis. Using the information obtained from social media, researchers can gain valuable insights into the beliefs, values, attitudes, and perceptions of social media users by using the user-generated content (Lai & To, 2015).

Content analysis can be carried out by analyzing textual material including text from media products to interview data (Flick, 2009). Traditionally, content analysis involved human interviews followed by a transcription process to transfer the audio material into the textual material. Today, gathering, analyzing, and grouping information available in social media relies more on crawlers and specific software.

1.4.10 Topic modeling

Topic modeling provides a powerful tool to identify latent content patterns from content. It views documents as mixtures of probabilistic topics and helps discover a set of topics that appear in a collection of documents (Griffiths & Steyvers, 2004). It has been widely applied in a range of social media research to reveal the topics.

1.4.11 Sentiment analysis

Sentiment analysis, also known as opinion discovery, centers on identifying the viewpoint underlying the documents. One particular and common type of sentiment analysis is to detect the sentiment polarity, which is the overall orientation of a certain text is positive or negative (Lau, Wang, Man, Yuen, & King, 2014). Since early 2000, sentiment analysis has been applied to the analysis of online movie reviews, the discovery of public sentiment, the prediction of election, etc. The rapid growth of the field of sentiment analysis coincides with the surge of content on social media (Liu, 2012).

1.4.12 Consumer health information

Before the exploration of consumer health information, key terms in this study must be identified and defined. Based on the U.S. National Library of Medicine sources, health information refers to general health, drugs and supplements, specific populations, genetics, environmental health and toxicology, clinical trials, and biomedical literature (NLM, 2014). Generally speaking, all the information related to the above topics may be treated as health information.

The American Medical Informatics Association, Consumer Health Informatics Working Group, the International Medical Informatics Association, and Nursing Informatics Interest Group have all proposed the definition of “health information consumer” to be people who “seek information about health promotion, disease prevention, treatment of specific conditions, and management of various health conditions and chronic illnesses” (Lewis, Eysenbach, Kukafka, Stavri, & Jimison, 2006, p. 1). Consumption of health information appears not only by persons with specific health conditions and their friends and family, but also by people with public health concerns (Lewis et al., 2006). Therefore, consumers of health information consist of a much broader population than patients.

Patrick and Koss proposed the definition of consumer health information as:

> any information that enables individuals to understand their health and make health-related decision for themselves and their families. This includes information supporting individual and community-based health promotion and enhancement, self-care, shared (professional-patient) decision-making, patient education, patient information and rehabilitation, health education, using the healthcare systems and selecting insurance or healthcare provider. (Suess, 2001)

Deering and Harris (1996) also advocated this definition and further identified three typical purposes of consumer health information: individual healthcare, medical treatment, and public health concerns.

1.4.13 Health information on social media

Definitions of social media abound over the last decade (Eckler, Worsowicz, & Rayburn, 2010). Kaplan and Haenlein (2010) defined social media as “a group of Internet-based applications that build on the ideological and technological foundations of Web 2.0, and that allow the creation and exchange of user-generated content" (p. 61). Today, in the Web 2.0 era, social media is pervasive, rapidly evolving, and increasingly influencing people's daily life and their health behavior.

With the emergence of Web 2.0, the concept of Medicine 2.0 was put forward to adapt to the improved Internet environment. Eysenbach (2008) identified five major aspects of Medicine 2.0 as: 1) social networking, 2) participation, 3) apomediation, 4) openness, and 5) collaboration. Within these themes, social media is a central venue to the ideas of Web 2.0 and Medicine 2.0 and is a potentially powerful tool to engage users to enable the seeking of "relevant" information (Eysenbach, 2008). A wide variety of social platforms aim to expand the way consumers share information about personal health, physicians, and treatments (Bradley, 2013). Pho suggested that "social media is where the future is, and most importantly, that's where our patients are going to be" (as cited in Prasad, 2013, p. 492). E-patients retrieve information on social network rather than completely receive it, and their contribution is more hands on rather than simply accepting a paternalistic viewpoint (Prasad, 2013).

1.5 Summary

Figure 4 summarizes the structure of the research problem, research questions, and associated hypotheses proposed in this study. The primary research problem of this study is to investigate the users' behavior appearing within the autism support groups on Facebook. The four research questions were proposed to answer the research problem in this study. Basically, RQ 1 and RQ 2 center on the behavior-based characteristics, and RQ 3 and RQ 4 deal with content-based characteristics. And there were four hypothesis groups associate with the four sub-questions.

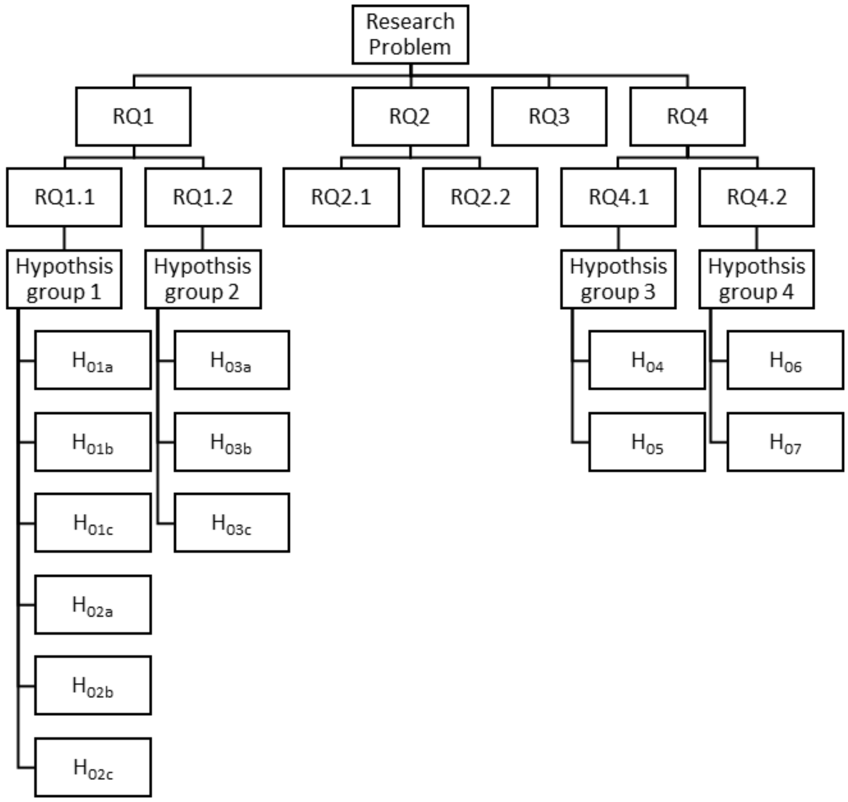

Figure 4. Structure of research problem, research questions, and associated hypotheses

Chapter 2. Literature review

2.1 Introduction

As people increasingly rely on self-help, consumer health informatics has been a rapidly developing area. There appears to be an increased demand from users to access health information and participate in medical decision making. Consumer health information resources provide health information to lay users to empower patients, caregivers, families, and consumers; improve decisions; and ultimately foster better public health outcomes (Keselman, Browne, & Kaufman, 2008). Due to the availability of health information on the Internet, consumers tend to engage in online health-seeking from professional medical websites and contribute to online health communities.

2.2 Health information seeking online

Health information seeking represents intentional, active efforts to obtain specific health information above and beyond the normal patterns of information exposure and use of interpersonal sources which distinguishes it from information scanning (Griffin et al., 1999). Health information seeking can be further defined as:

> Any non-routine media use of interpersonal conversation about a specific health topic and thus includes behaviors such as viewing a special program about a health-related treatment, using a search engine to find information about a particular health topic on the Internet, and/or posing specific health-related questions to a friend, family member, or medical practitioner outside the normal flow of conversation. (Niederdeppe et al., 2007)

2.2.1 Seeking health information online

In 2010, 50% of all American adults reported seeking information about a personal health concern during the previous 12 months (Tu, 2011). The Pew Internet & American Life Project (http://www.pewinternet.org) has tracked online activities since early in 2000, including a focus on consumer use of online health information (Goldberg et al., 2011). It was realized that health information seeking plays an increasingly important role in users' online activities.

The 2010 Health Tracking Household Survey asked participants whether they had sought or obtained information about a personal health concern from a variety of sources other than their doctor, including books, magazines or newspapers; television or radio; friends or relatives; and the Internet during the past 12 months. The survey results described the information sources where consumers sought health information in 2001, 2007, and 2010 (Tu, 2011). The proportion of consumers seeking health information online was 15.9% in 2001, rose greatly to 31.1% in 2007, and finally reached 32.6% in 2010. Tu (2011) showed that three ways (Internet; publications such as books, magazines, newspapers; and someone else such as friends and relatives) have become the main information sources where consumers usually seek health information.

Internet access drives information access. In a national survey conducted in 2002, the Pew Internet Project found that 62% of Internet users, or 73 million people in the United States, have gone online in search of health information (Fox, 2008). Online Health Search 2006 estimated that 80% of American Internet users, or some 113 million adults, have searched for information (Fox, 2006). The number of American adults who searched for information on at least one health topic a day has increased from 6 million in 2001 to 8 million in 2006. These surveys indicate that the trend towards the use of the Internet for health purposes is rising.

2.2.2 Health topics searched online

Based on a September 2012 survey, 72% of Internet users said they looked online for health information within the past year (Pew Research Center, 2015). Their searches included serious conditions, general health information, and minor health problems (Fox & Duggan, 2013).

The Pew Internet & American Life Project Survey asked participants if they had used the Internet to search for at least one of 16 major health topics online, ranging from specific disease to diet to health insurance (Fox, 2006). According to Fox (2006), from 2002 to 2006, the following five topics continued to be the most commonly searched topics: specific diseases or conditions (63% in 2002, 66% in 2004, and 64% in 2006); certain medical treatment or procedure (47% in 2002, 51% in 2004, and 51% in 2006); diet, nutrition, vitamins, or nutritional supplements (44% in 2002, 51% in 2004, and 49% in 2006); exercise or fitness (36% in 2002, 42% in 2004, and 44% in 2006); and prescription or over-the-counter drugs (34% in 2002, 40% in 2004, and 37% in 2006) (Pew Research Center, 2015). The updated survey conducted in 2012 showed that specific diseases or medical problem continue to dominate people's online queries (Fox & Duggan, 2013).

2.2.3 Search strategies

When it comes to the last session in which they sought health or medical information, 77% of online health seekers show they began at a search engine such as Google, Bing, or Yahoo. Another 13% started with a site that specializes in health information, like WebMD. However, only 2% stated that they started their search at a more general site like Wikipedia, and only 1% pointed out that they began with a social network site like Facebook (Fox & Duggan, 2013).

In terms of the search strategy, (Eysenbach & Köhler, 2002) reported that all of their 21 participants used search engines as a starting point instead of medical portals or the sites of medical societies or libraries. With search engines, participants were very successful in finding answers to health questions by refining various search terms and exploring the first few results by rough examination of the content of the page. Younger health seekers are more likely to start at a search engine, whereas older health seekers tend to start at a specific website that they know provides health information (Fox, 2006).

2.3 Consumer health information seeking in social media

Consumption of health information occurs by not only persons with specific health conditions and their friends and family but also by people with public health concerns (Slack, 2005). Therefore, consumers of health information consist of a much broader population than patients. Pew Research Center (2013) reported in 2012 that among online health information seekers, 16% tried to find others who might share the same health concerns; 30% of Internet users have consulted online reviews or rankings of health care services or treatments; and 26% of Internet users have read or watched someone else's experience about health or medical issues. It is notable that online peers have been an important information source for consumers' health concerns.

2.3.1 Prevalence of health information seeking in social media

People with access to the Internet are more likely to be greater health information seekers than those without access. To date, for the most part, health information seeking studies have primarily focused on static websites such as Medline and on search engines (Keselman et al., 2008). There has not been much focus on patients' information seeking patterns and behaviors in online health communities. In an online community, consumers could be searching for personalized information that would either supplement or reinforce the information that they have already received from other sources. This type of information seeking has not been properly explored in the informatics literature. More studies in this area would enhance the understanding of how information seeking effectiveness can be improved in online communities.

Given the rapid growth of health information on social media, more and more consumers engage in consulting health issues on different social media platforms. Based on a national phone survey conducted in September 2012, 8% of Internet users have posted a health-related question online or shared their own personal health experience online (Fox & Duggan, 2013). Among those participants, 40% have shared their personal health experiences; 19% have asked specific health questions; 38% have done both.

Thackeray, Crookston, and West (2013) demonstrated that people did employ social media for seeking health information. Of 1745 adult respondents, 41.15% of them consulted online rankings or reviews, 31.58% of them used social networking sites for health, 9.91% of them posted reviews, and 15.19% of them posted a comment, question, or information. In addition, this study discovered that people with a chronic disease were nearly twice as likely to refer to online rankings.

Prybutok and Ryan (2015) investigated where 18- to 30-year-old college students seek health information on the Internet. Participants specified social media sites 33 times (32.7% of the total time). The authors concluded that social media show great promise as effective sources of medical information for this age group. When it comes to more specific information about food-related risks, social media (including micro blogs, forums, blogs, social networking sites and YouTube) were also listed by participants as a complementary information seeking channel (Kuttschreuter et al., 2014). Among the youth participants from Canada, Rasmussen-Pennington, Richardson, Garinger, and Contursi (2013) found that the most popular websites for seeking mental health information were YouTube, FMyLife (more popularly known as FML), and Facebook. In respect to drug information, 51.0% (2478 of 4861) of Japanese consumers reported that they have obtained drug information from social media sites (Kishimoto & Fukushima, 2011). The participants considered Yahoo!Chiebukuro (Japanese Yahoo!Answers) as the most widely used online source for drug information (Kishimoto & Fukushima, 2011). In addition to gaining information from online peers, Van de Belt et al. (2013) revealed that 25.4% of Dutch people would like to consult their physician in social media and 21.2% of Dutch people were willing to communicate with their physician using a webcam.

In recent years, the number of online health communities has increased rapidly as more patients seek to access alternate sources of health information as well as to connect with other patients with the same or similar disease. The large number of such communities is a testament to their popularity among health consumers (Jadad, Enkin, Glouberman, Groff, & Stern, 2006). According to Nambisan's (2011) research, this has prompted many healthcare organizations (HCOs) including Kaiser Permanente, Johns Hopkins, etc., to provide access to online communities for their patients as part of their overall patient support services.

2.3.2 Discussion topics emerging from health information in social media

Social media applications on the Internet are empowering, engaging, and educating for health care consumers and providers (Sarasohn-Kahn, 2008). Consumers use social media for a variety of purposes, ranging from emotional support to health conditions management. The most popular questions consumers asked to a medicines information service on Facebook were related to adverse effects, treatment options for conditions, and drug interactions (Benetoli, Chen, Spagnardi, Beer, & Aslani, 2015).

Park and Park (2014) examined cancer-related information from an online community. The results revealed that the majority (71.4%) of the postings were associated with medical topics. These medical related topics consisted of the following nine sub-topics: treatment (24.1 %), diagnosis (19.6 %), symptom (12.9 %), prognosis (4.5 %), prevention (3%), risk factors (2.9%), alternative medicine (2.0%), medication (1.5%), and diet (0.9%). Thus treatment (24.1 %) was the most frequently discussed medical topic, whereas the most frequently discussed non-medical topic was recommendations for hospitals or doctors (11.5 %). In addition, this study also revealed that breast cancer (34.2 %) was the most searched type of cancer, followed by cervical cancer (12.8 %) and liver cancer (5.3 %).

When it comes to specific information related to cervical cancer, Westbrook and Zhang (2015) uncovered 8 topics from the discussions in an online question and answer forum: causes, prevention, symptoms, diagnosis, prognosis, treatment, remission, and end of life. Among these topics, prevention issues, potential causes of cervical cancer, and specific prevention strategies became the major concerns (57% of all the posts).

As a common chronic disease, people suffering from diabetes have sought diabetes-related information from online sources for decades (Zhang, Zhao, & Dimitroff, 2014). Through the coding analysis of the transaction log from a social question and answers forum, Zhang and Zhao (2013) identified 12 major topics about diabetes: cause and pathophysiology (6.6%), sign and symptom (8.59%), diagnosis and test (11.48%), organ and body part (5.97%), complication and related disease (8.23%), medication (6.69%), treatment (6.42%), education and information resource (7.96%), affect (6.96%), social and culture (7.50%), lifestyle (6.15%), and nutrient (17.45%). In the follow-up study, Zhang et al. (2014) conducted an across category analyses and discovered the associations between certain symptoms and specific body parts, and between certain diagnosis and appropriate medications.

Obesity has been one of the major health concerns facing a large volume of people worldwide. Liang and Scammon (2011) observed an obesity support group and revealed the following 11 discussion themes from the threads appearing in the group: surgeries (e.g. gastric bypass surgeries), drugs (e.g. *Alli*), self-support (e.g. exercise, penpal and healthy eating), commercial weight loss programs (e.g. *Slim-Fast* and *WeightWatchers*), weight loss (e.g. the motivation for weight loss), health and medical problems (e.g. diseases caused by overweight or obesity), social anxiety (e.g. depression caused by poor self-esteem), parenting (e.g. childhood obesity), doctors (e.g. relationships between doctors and obese patients), products (e.g. comfortable clothes and airlines seat), and public policy (e.g. Medicaid). Among those themes, social anxiety and self-support dominated consumers' discussions.

Because of the substantial disability and burden of depression, people with depression seek information, advice, and opinions from other individuals experiencing the same problem from online support groups (Barney, Griffiths, & Banfield, 2011). Thematic analysis revealed 6 broad themes from users' discussions: coping with depression (40.2%), medication (11.1%), professional treatment and services (9.3%), understanding depression (7.5%), disclosure and stigma (17.3%), and comorbid mental health problems (14.6%). Clearly, coping with depression was the most concerning problem for the participants.

2.3.3 Seeking health information from online peers

Different from the traditional ways of information search, social media offers health information seekers access not only to the information on the platforms, but also to other users (Zhao & Zhang, 2017). The basic idea behind so-called peer-to-peer healthcare is consulting about health issues with other peers. Social media connects patients with others who have the same concerns. This started the connected health era. Fox (2013a) even recognized that the most exciting innovation in health care today is "people talking with each other" (para. 2).

Pew Research Center (2013) reported that among online health information seekers, 16% tried to find others who might share the same health concerns in 2012; 30% of Internet users have consulted online reviews or rankings of health care services or treatments; and 26% of Internet users have read or watched someone else's experience about health or medical issues. It is notable that online peers have been an important information source for consumers' health concerns since 2012.

People living with chronic diseases and their caregivers are especially likely to seek out peer advice online (Fox, 2013b). Seeking information from peers online is a new way of pursuing health by banding together and sharing knowledge. Practical tips from fellow patients and caregivers can have far-reaching implications for clinical outcome (Fox, 2013b).

One of the particular characteristics of consulting with online peers rather than general websites is that other patients can explain what it really feels like and what to expect next in a way that only someone with personal experience can articulate (Preece, 1999). Moreover, instead of entering keywords into a search engine and then receiving a vast number of links, social media encourages consumers to actually "ask" a question on the platforms and then wait for the real "answers" from peers.

2.3.4 Seeking health information from online communities

Online health communities (OHC) provide patients with the open platforms to obtain information and seek social support. Many of these health communities serve as an essential social function by enabling people with medical problems to propose and discuss their concerns with others. Studies have also confirmed the sentimental values of the interactions on the online health forum when the research targeted Q&A forums. Taking the American Cancer Society Cancer Survivors Network (CSN) as a case of an online forum for a specific disease, Qiu et al. (2011) studied the sentiment benefits and dynamics in a large-scale health-related electronic community to find that an estimated 75%-85% of CSN forum participants change their sentiment in a positive direction through online interactions with other community members. Apart from the emotional support, CSN also had the highest influence in medical, lifestyle, and treatment issues (Portier et al., 2013). Furthermore, Nambisan (2011) defined four dimensions to assess patients' online community experience (OCE): pragmatic, empathic, sociability, and usability. All of these four dimensions impacted positively on patient's attitudes.

Because of their potential importance, online health communities which focused on various diseases were studied by scientists. Gooden and Winefield (2007) applied a thematic analysis of gender differences and similarities of breast and prostate cancer to online discussion boards. According to the study from Winkelman and Choo (2003), the virtual patient community, integrated within the functioning health-care organization, embodied the following four elements: adequate information (knowledge), self-regulatory skills development, building a sense of self-efficacy and construction of a social support system. Bers, Gonzalez-Heydrich, and Demaso (2003) showed one well-documented example of a healthcare organization-sponsored virtual patient community, Zora (an animated virtual community for pediatric hemodialysis patients) has been found in limited clinical trials to help children and families cope with the disease.

Studies on autism related to online information seeking and sharing have been widely explored. For autism patients and their relatives, Mansell and Morris 2004) found that joining online communities is apparently the most frequently applied method to obtain autism-related information. Clifford and Minnes (2013) studied the evaluation of parents of autistic children in an online support group and they concluded that parents who participated in the group reported being satisfied with the support they received and found the group helpful.

In addition to the specific health communities, more general social networking sites (SNSs) such as Facebook and Twitter also serve as the venue to seek medical information and track and share symptoms. SNSs allow individuals to post profile information, construct a list of friends, and communicate with others using both synchronous and asynchronous messaging tools (Rau, Gao, & Ding, 2008). Given the fast permeation of SNSs into the health domain and the strong diffusion power these tools have, a deeper understanding of SNSs as a venue for fulfilling people's health-related needs and impacting public health becomes necessary. With diabetes patients, Greene, Choudhry, Kilabuk and Shrank (2010) demonstrated that not only the patients, but also their family members and their friends used Facebook to share personal clinical information, to request disease-specific guidance and feedback, and to receive emotional support. However, Greene et al. (2010) pointed out that using social networking sites for health and wellness information is not a popular behavior among college students. The participants were skeptical about the quality of information on Facebook and concerned about the lack of medical knowledge of their friends or peers. Such controversial concerns call for more clear assessment criteria to measure the quality of health information on SNSs.

In summary, Internet access motivated consumers to seek health-related information online over the last 25 years. Although adults with health questions continue to consult with health professionals and offline resources, users have recognized that seeking health information online provides a significant supplement (Fox, 2011b). Moreover, with the emergence of a variety of general and specific social media applications, consumers gain further benefits from peer-to-peer health care and online health communities.

2.3.5 Accessing consumer health information in social media: pros and cons

Social media applications on the Internet are empowering, engaging, and educating health care consumers and providers (Sarasohn-Kahn, 2008). Consumers use social media for a variety of purposes, ranging from emotional support to health conditions management. Although social media has the potential to combine all the best features of existing health information sources, accessing health information in social media could be a paradox for consumers.

2.3.5.1. Benefits of accessing consumer health information in social media

(1) Social support and empathy

Social media can facilitate the empathy associated with lay person sources and the feedback from online peers (Gray, Klein, Noyce, Sesselberg, & Cantrill, 2005). An interesting issue rising from the research of online information seeking is the reason why consumers tend to seek help from websites or online virtual communities. In general, in the offline health context, social support has been associated with many health benefits including reducing stress, minimizing the possibility of depression, and strengthening the immune system (Dean & Lin, 1977). These benefits from social support, although not empirically proven, are considered to be some of the most critical benefits of online health communities (Nambisan, 2011). Based on the study of the online cancer environment and data from an online survey of cancer patients, Beaudoin and Tao (2007) found that seeking information and support from online resources leads to increases in social support, community, and coping; and decreases in loneliness, depression, and anxiety. Price, Mercer, and MacPherson (2006) proved that patients' perceived empathy was shown to have a direct impact on health outcomes. Therefore, social support should be considered as an important factor when providing care and help to consumers.

In the social question and answer forum setting, results from Worrall and Oh (2013)'s study also revealed that social and emotional support are important criteria. Users illustrated greater consideration of the social, emotional and community-based support they value from the site (Worrall & Oh, 2013). When it comes to the social networking sites setting, Liang and Scammon (2011) detected similar situations. Their findings demonstrated that interactions on health-related social networking sites facilitate tailored health communication by providing informational and emotional support to the seekers.

Across different social media platforms, social and emotional supports were emphasized as some of the most critical benefits of obtaining health information from social media settings. Two studies (Liang & Scammon, 2011; Rasmussen-Pennington et al., 2013) identified that consumers who have embarrassing, socially stigmatizing, or disfiguring illnesses such as obesity and mental health issues, were more eager to seek help from social media. Empathy is facilitated in social media utilization in that the user can access help from the virtual communities while controlling their level of disclosure of their identity and condition (Gray et al., 2005). While social media platforms may be neutral in terms of empathy, they facilitate the contact between individuals, especially for online self-care and social support (Gray et al., 2005).

Moreover, the perception of social support from health-related social networking sites was significantly associated with three outcomes: (a) getting a positive attitude toward being healthy, (b) obeying recommendations posted by others, and (c) pursuing extra information from one's doctor (Hether, Murphy, & Valente, 2014). Providing support to others on the social media sites showed associations with seeking additional information from other sources and following the recommendations received from the sites (Hether et al., 2014). Price et al. (2006) proved that patients' perceived empathy was shown to have a direct impact on health outcomes. Therefore, social and emotional support should be considered as an important factor when providing care and help to consumers.

Empathy is facilitated with social media utilization in that the user can access help from the virtual communities while controlling their level of disclosure of their identity and condition as they want (Gray et al., 2005). It was notable that the use of online communities to seek health information simulates a more natural inter-person interaction rather than interacting with websites or search engines. Whilst the social media itself as a platform may be neutral in terms of empathy, it facilitates the contact between individuals, especially for online self-care and social support (Gray et al., 2005). Patients with depression, who usually feel socially isolated, reported that they perceived considerable support from their online interactions in online depression support groups (Houston, Cooper, & Ford, 2002).

(2) Interactivity and personalization

Previous research showed that the interactive capabilities of a certain medium reflect a particularly attractive feature that motivates online health information seeking (Thompson, 2014). More specifically, virtual support groups may be used to satisfy needs for social interaction/support, while other interactive tools can assist in health decision making and understanding of medical results.

The emergence of social media changed the way consumers communicate with the Internet. Instead of relying on the feedbacks from search engines, social media encourages users to post questions on the application and then receive feedbacks from peers. When posting questions in social media, consumers state their detailed circumstances and background information, and thus the feedbacks they receive could fit their specific and personalized conditions. Through the personalized interactions, consumers could perceive the saliency of the information (Gray et al., 2005).

Until recently the primary communication model of public health information rested on the authority, such as a health institution, the ministry of health or a journalist, to publish the information to the public (McNab, 2009). Social media has changed the monologue to an interactive dialogue (McNab, 2009). Social media allows organizations to talk to their customers, for customers to talk to each other, and for customers to talk to the organization (Thackeray, Neiger, Smith, & Wagenen, 2012). Anyone with information and access to social media can be a content creator in addition to being a consumer.

(3) Consumer-centered information

With the abundant user-generated content in social media, health information sharing becomes more democratic and patient controlled, encouraging users to exchange health-related information that they need and therefore making the information more patient- and consumer-centered (Chou, Hunt, Beckjord, Moser, & Hesse, 2009). People exchange experiences about their own health issues to help each other understand what might lay ahead (Fox & Duggan, 2013). For consumers who are newly diagnosed with a certain disease, there are so many former and current patients behind the resources in social media, and much of the "homework" has already been done for a consumer (Landro, 1999).

In addition to the information regarding certain diseases, consumers are able to consult online reviews of particular drugs or medical treatments, doctors or other providers, and hospitals or medical facilities. Those reviews and comments were created by real previous consumers and based on their real experiences. Referring to other users' actual thoughts and views instead of the advertisements might assist patients in making more-informed decisions.

(4) Staying current

Increased access to mobile devices together with the uses of social media enables consumers to access health information more quickly and directly than at any time in history (McNab, 2009). Particularly, when facing the emergence of public health issues, such as the explosion of H1N1, accessing the latest news and prevention suggestions become more urgent to consumers. Social media enhances the speed of information dissemination and communication during public health emergencies or outbreaks (Thackeray et al., 2012).

(5) Visual materials

As of September 2010, 25% of Internet users have watched an online video about health or medical issues (Fox, 2011a). We can expect this ratio to continue to rise with wide access to both Internet and mobile devices. Social networks might also overcome the borders and geographic boundaries with the long-distance video technologies (Hawn, 2009). For example, American Well.com, a social network for doctors and patients, provides remote video conferencing between doctors and patients.

2.3.5.2. Drawbacks of accessing consumer health information in social media

Of course, along with the benefits mentioned above, there are risks and potential downsides in accessing consumer health information in social media. Although health information on social media is accessible and free; information sources, information quality and authority frequently become the most concerned issue when people consider using the information. In comparison with the Internet (6.0 of 10) and family/friends (5.9 of 10), information retrieved via social media were listed as the least reliable source (3.8 of 10) (Van de Belt et al., 2013). This was confirmed by the results from Rutsaert, Pieniak, Regan, McConnon, and Verbeke (2013)' study which pointed out that trustworthiness was the main barrier preventing consumers from using social media as an information channel. Specifically, Facebook and Twitter received the lowest trust as information channels (2.92 of 7 and 3.12 of 7, respectively), whereas Wikipedia had a good reputation (5.27 of 7) (Rutsaert et al., 2013). In contrast, Cole, Watkins, and Kleine (2016) suggested that the health information found in three online discussion forums was of reasonably good quality and only a very small proportion was considered to be factually incorrect (4/79). This study claimed that the discussion forums do seem to be able to produce health information of acceptable quality.

(1) Information privacy

Although social media is offering novel opportunity for interaction among their users, at the same time, they seem to attract users' attention to the privacy concerns social media raise (Acquisti & Gross, 2006). When people communicate with others on social media, they usually need to expose some of their private information, such as age, gender, health condition, and sometimes even their diagnoses, to receive more specific and personal health suggestions.

Hawn (2009) believed that physicians' concern over privacy is one reason the use of social media in health care hasn't taken off even more quickly. Consumers might hesitate to participate in the online self-help groups due to the heavy concerns about the disclosure of their identities and conditions. Moreland, et al. (2015) reported that a large proportion of users were concerned that a website might sell or give away information about what they did online (139/207, 67.1%). However, in relation to concern for security and privacy, only a small proportion of patients (36/535, 6.7%) actually checked the website privacy policy to see how their data may be used.

(2) Information quality and authority

With regard to health information, the principle dilemma of the social media is that, while its user-generation nature is desirable for accessing abundant real experiences, it raises questions about the quality and authority of information available. This may inhibit its usefulness. Quality and authority issues arise with the proliferation of consumer-oriented health information available on social media platforms. Different from professional journals and academic databases, any consumer is able to post medical information, without any control, on a variety of user-friendly social media platforms that are accessed by millions of users.

A number of rating systems and filtering tools have been developed to help users identify the reliable websites. However, when it comes to social media, the platform provider, to a large extent, are not supposed to control the free-speaking right of users. Therefore, compared to health-related websites, it becomes even harder to ensure the quality and authority of the user-generated health information in social media. In fact, a large number of social media applications currently cannot find credible and enforceable protection of consumers from potential harm (Risk & Dzenowagis, 2001).

Regarding people with serious mental illness, online peer-to-peer connections are influencing the way people cope with their symptoms and seek mental health care; yet, there are risks inherent in fostering advice from peers in the online health communities who possess unknown credentials (Naslund, Aschbrenner, Marsch, & Bartels, 2016). Not only do individual users participate in social media, but also the medical product/drug manufacturers and retailers actively participate in social media. This creates another vital limitation impacting the reliability and validity of health information in social media. Some product manufacturers have an interest in creating fake comments about their products in social media. In contrast to the advertisements on other media such as newspaper or TV, these hidden advertisements appearing on social media platforms are difficult for consumers to identify. Relying on the information accessed from social media to deal with the health condition may cause crucial consequences. In order to overcome such limitation, consumers need to be aware of the existence of the spam account and spamming comments and distinguish the fake information from the real information sharing.

In summary, compared to other means, accessing health information from social media certainly has its pros and cons. The benefits come primarily from the following aspects: social support, empathy, interactivity, personalization, consumer-centered information, staying current and visual materials. However, the nature of user-generated content in social media introduces ethical issues regarding privacy, as well issues of the quality and validity of the information.

2.4 Gender differences in online health information seeking

2.4.1 Gender differences in the Internet usage

Gender has been identified as a strong predictor of perceptions and behaviors that have implications for online information searching (Hupfer & Detlor, 2006). There were copious studies looking into the gender disparity in the Internet usage. Horvat, Oreski, and Markic (2011) conducted an extensive literature review of attitudes toward the Internet and gender issues regarding the Internet usage. Several studies argued that the male population have dominated the Internet usage (Horvat et al., 2011). Ford and Miller (1996) studied the use of the Internet based on a sample of 75 undergraduate and postgraduate university students. Significant differences were found for gender. Male students seem to enjoy browsing around the Internet. Female students, by comparison, stated that they feel themselves unable to find what they want effectively. Weiser (2000) showed that males use the Internet mainly for entertainment and leisure, while women tend to use it mainly for interpersonal communication and educational assistance. When it comes to online behaviors, three times as many male students tended to participate in the group discussions than female students did (Nachmias, Mioduser, & Shemla, 2000).

Although a number of studies attested male domination in terms of the usage of, and the attitude towards, the Internet (Horvat et al., 2011); few studies claimed that gender gap in the use of the Internet has been narrowing down in recent years (Luan et al., 2008). Luan et al. (2008) revealed no gender disparity in the Internet usage among 152 student teachers. The female student teachers spend as much time online as their male counterparts. Results from the college student population also indicated that the gender gap in the Internet usage has nearly closed (Odell, Korgen, Schumacher, & Delucchi, 2000).

Copious studies identified males were more likely to be internet users than females, but when examining online health information users, females became the dominant users (Lorence & Park, 2007). Moreover, Ek (2015) investigated the gender differences in health information behaviors in the Finnish population aged 18-65. It was noted that men usually lack the motivation to involve in the health-related information (Ek, 2015).

2.4.2 Gender differences in health information processing and seeking

Gender differences have been noticed in a range of environments. The prevalence of gender-related disparities regarding how health information is processed and used has been well documented (Lorence & Park, 2007). Katz, Ruzek, Miller, and Legos (2004) investigated the gender differences in patients' information needs and concerns and came to the conclusion that no statistically significant differences were found between male and female patients. However, when it comes to health-related information consultation, Thornburg (1981) found females were more likely to consult their mothers whereas males would consult their peers. Further, Obermeyer et al. (2004) indicated that female family members have been the main information source of medicine use for both males and females.

More males in the United States suffer severe chronic conditions and die nearly 7 years younger than females (Courtenay, 2000). It has been observed that men tend to be more hesitate to search for sources of health-related information due to gender role strains and social constructions of masculinity (Courtenay, 2000; Ek, 2015). Exiting studies, both prior to the Internet and since the Internet appeared, that have specifically testified gender as a variable in health information seeking behaviour also clearly demonstrates that women are more active seekers of health-related information than men (Ek, 2015). In addition, results from Kim, Choo, and Ranney (2014) found that female patients more preferred to use computers, the Internet, and social networks for technology-based innervations. Females are also found to be more willing to give positive assessments of searching for online health information in comparison to males (Rice, 2006). Moreover, being female has been identified as one of the strongest and most consistent influences on using the Internet to seek for health information (Rice, 2006).

Obermeyer et al. (2004) investigated the differences in women's and men's behaviors of medication use. Gender differences were found in the frequencies of medicine taken. In addition, women were generally more likely to report symptoms/conditions than men were. Men usually give brief statements, while women provide richer descriptions with details (Obermeyer et al., 2004). This analysis also observed gendered patterns of health information processing that women were more concerned about the health communication than men were (Obermeyer et al., 2004).

2.5 Autism-affected users on social media

2.5.1 Social challenges of autism patients

"Autism spans a spectrum of behaviors and abilities, from nonverbal children needing intensive therapy for basic life skills to highly intelligent adults who live independently but have trouble with social communication" (Attwood, 2006). Individuals with autism have difficulties in making eye contact with others, understanding nonverbal social cues (e.g. facial expressions), perceiving non-literal language, thinking flexibly, and following others' viewpoints (Seltzer et al., 2003). Previous studies unveiled the social challenges of adults with autism including intense isolation, problems initiating interactions, communication difficulties, and a desire for facilitated social interactions and socially appropriate behavior, and alternative modes of communication (Burke, Kraut, & Williams, 2010).

With respect to autistic children, they generally require constant special care and attention from their parents, family, classmates, schoolteachers, and caregivers. Such difficulties present daily challenges for parents and/or caregivers of children with autism (Roffeei et al., 2015). Therefore, not only the autism patients themselves suffer from social challenges, people surrounding them face daily difficulties as well.

2.5.2 Social media use of autism-affected users

Individuals with autism have been found to have a propensity towards the use of computer (Kientz, Goodwin, Hayes, & Abowd, 2013), which enables the emerging technologies facilitates their communications. Beyond browsing on the Internet, Burke et al. (2010) pointed the value of online communities for people with autism as providing them a forum to interact with others having similar interests, and ask for advice and self-advocacy with others with similar life stories or diagnoses.

Through the examining of 108 adults with autism, Mazurek (2013) showed that autistic adults who use social media are more likely to have a close friend than those who do not use such media (66.3% compared to 33.3%). In addition, individuals with autism who used social networking sites for enhancing social functioning were more likely to have a best friend and experience closer with such a friend (Mazurek, 2013). These findings are consistent with previous studies showing that social networking use is associated with increased relationship closeness with existing friends, particularly among socially anxious individuals (Baker & Oswald, 2010).

Regarding the use of social media usage among youth with autism, only 13.2% of them spent time on social media (email, internet chatting) (Mazurek, Shattuck, Wagner, & Cooper, 2012). Compared with youth with other disability (speech/language impairments, learning disabilities, intellectual disabilities), Mazurek et al., (2012) found that rates of social media use were lower for autistic youth. Meanwhile, female youth with autism were discovered to have significantly higher odds of using a computer for social media involvement (Mazurek et al., 2012).

Stendal and Balandin (2015) explored the experience of virtual worlds, as a type of social media, by people with autism through a case study. The results suggested that people with autism enjoy engaging in a virtual worlds and feel even more comfortable communicating in the virtual world context than the physical world (Stendal & Balandin, 2015). Virtual worlds offer a venue for people with autism to be a part of a virtual society, lowers communication barriers experienced in the physical world, and gives the participant a unique opportunity to create and maintain friendships (Stendal & Balandin, 2015).

Burke et al. (2010) examined the successes and challenges adults with the high-functioning autism experience when using online communities for social support. Through an analysis of the semi-structured interviews with 16 adults on the high-functioning end of the autism spectrum, interest-based online communities were deemed as helpful in overcoming barriers to initiating contact with other people. Many interviewees used fan pages and profile data to connect with people and base their interaction on shared interests (Burke et al., 2010). In some cases, the relationships formed online moved to the physical world successfully. Some participants also appreciated the birthday reminder functions and the “like” button on social networking sites. However, participants who used online communities organized around autism expressed their dissatisfactions with the relationships they formed online. One of the subjects mentioned that his experience in autism-specific communities online was full of drama, because the community was supportive as first but became cliquish later.

Roffeei et al. (2015) analyzed two autism support groups on Facebook using a deductive content analysis approach. It was found that the highest percentage of messages were about informational support (30.7%) and emotional support (27.8%) (Roffeei et al., 2015). A majority of the discussions are related to challenges and difficulties in caring and raising autistic children, as well as children’s social life and self-care routines (Roffeei et al., 2015).

2.6 Social network analysis applied in social media research

The recent growth of interest in using social network analysis techniques has been sparked partially by the proliferation of social media sites, such as Facebook and Twitter, which offer existing networks of friends and followers (Scott, 2012). Social network analysis is paramount to understanding the social behavior of social network members. In the view of social network analysis, social media applications can be seen as social networks wherein users are nodes with the relationships between users represented as edges of the network.

Data gathered from different social media sites has been investigated using social network analysis. Using tweets extracted from Twitter during a series of floods occurring in 2010 and 2011, Cheong and Cheong (2011) applied social network analysis to identify active players in online communities and their effectiveness in disseminating critical information.

Gilbert, Karahalios, and Sandvig (2008) investigated the behavioral differences between rural and urban social media users based on data collected from MySpace. Through the analysis of those social networks of friends, the authors found that rural users' online friends live much closer than urban users' friends (Gilbert, Karahalios, & Sandvig, 2008).

2.6.1 Information sharing in social media

Information sharing has been one of the most significant functions of social media. For microblogs (e.g., Twitter), Java, Song, Finin, and Tseng (2007) reported that the main types of user intentions are: daily chatter, conversations, sharing information and reporting news. On social media, information sharing occurs with the process of information flow. Therefore, borrowing from Proferes's (2015) definition of information flow on Twitter, information sharing in social media can be defined as: the means by which information, as a resource, is transmitted from a sender towards a receiver.

Previous studies gained some insight on information flow issues on different social media platforms. However, few studies explored the information sharing process in social media. As the information sharing process appears with the communication among online users and the information flows on the platforms, previous research on communication and information flow inspires the exploration of information sharing in social media. The Shannon-Weaver model of communication proposed a linear communication model that incorporates information flows as they operate across the constituent parts of sender, message, transmission, noise, channel, reception, and receiver (Proferes, 2015). Despite some criticism about this model (Chandler, 2011), Shannon and Weaver's model serves as an excellent starting point to describe the information sharing process on social media. Inspired by Shannon and Weaver's model (Shannon, 1948), Proferes (2015) generated a simpler model to show the information flow process on Twitter, which includes: sender, information, channel, and potential receiver(s). Considering more features of various social media, the information sharing process can be diagrammed as the model in Figure 5.

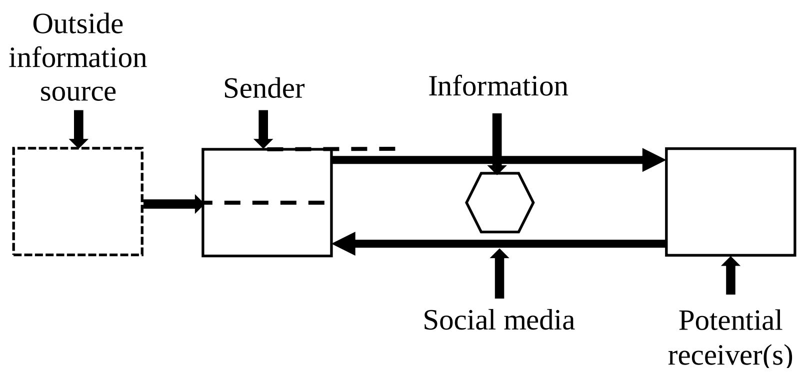

Figure 5. Diagram of information sharing process in social media (adapted from Proferes, 2015, Figure 3)

In this diagram, social media serves as the channel through which information can be shared and transferred. It is important to note that the transmission of information in social media is in a mutual way. It means that senders can transfer information to potential receivers, and then receivers may share information with the sender through comments or “likes”.

As shown in Figure 5, information represents the content being shared between sender and potential receivers. Due to the fact that users generate different types of content in diverse social media sites, information in this diagram can be in a variety of forms in addition to text. On social networking sites and microblogs, such as Facebook, a person posts a status to his/her timeline, and his/her friends on Facebook will receive such information and potentially make comments. In online discussion groups and question and answer forum, such like Yahoo!Answer, users create a question or discussion topic, and then all members in the forum or group will see the information and possibly reply to it. In addition to the text information flowing in the above social media sites, on content communities (e.g., YouTube), videos become the main type of information being shared along with text information being exchanged in the form of comments.

Outside information source is an optional component in the information sharing process. It occurs when the information sender shares an URL directing to the link outside the current site, or shares information that includes a citation to other resources (e.g., books, journals, and newspapers). In this case, the sender shares the outside information together with his/her original information with the potential receivers.

2.6.1.1. Actor/nodes of a social media in information sharing

As diagramed in Figure 5, the four critical elements of describing any information sharing on social media sites, therefore, are: 1) the means/channel by which information is being shared (e.g., Facebook, Twitter, and YouTube); 2) the shared information (e.g., posts, statuses, URLs, tweets, and videos); 3) the sender; and 4) the potential receivers. The two fundamental actors in the information sharing process are information sender and information receiver. Theoretically, a user’s every action in social media is making him/her either an information sender or an information receiver.

The impressive growth of social media makes it more akin to a broadcast medium, which is especially true for some of the most popular sites such as Facebook and Twitter. Social media’s striking popularity has attracted traditional and popular news sources such as the British Broadcasting Corporation (BBC) and the Cable News Network (CNN). In addition, high-profile users also join the network, including celebrities in various fields (e.g., Oprah Winfrey, Michael Jordan, Taylor Swift) and politicians (e.g., Barack Obama), and other influential people (Cha, Benevenuto, Haddadi, & Gummadi, 2012).

Due to the potential marketing values, the actors involved in social media can range from individuals to organizations (e.g., archives, libraries, and museums), companies, brands, and even TV programs. For example, Vanwynsberghe, Boudry, Vanderlinde, and Verdegem (2014) analyzed the distribution of information on social media and how librarians deal with social media as an organization. Since public libraries have always connected people with information, social media urge modern librarians to use and distribute information in all media, including digital and social media.

In addition, according to the characteristics of user behavior, actors in social media play different roles other than the senders or the receivers in the information process. Studying the relative roles of numerous actor/nodes of a social media helps us better understand how information is shared on social media sites. By analyzing the structure of the network connection and the distribution of links on Twitter, Cha et al. (2012) classified three types of users in information sharing: 1) mass media sources such as BBC; 2) grassroots users, including most of ordinary users; and 3) evangelists, consisting of opinion leaders, politicians, celebrities, and local businesses.

As for the numerous actors involved in social media, the attribute data that describe each of them can provide more insights to understand the phenomenon. In addition to the username, attribute data describe demographic characteristics of a person, such as age, gender, race, home town, place he/she lived, education experiences, and work experiences. Especially for some of the social networking sites such as Facebook, people sometimes use them to check-in, which means the places (cities, parks, restaurants, etc.) he/she has been can also be collected from the sites. Furthermore, a number of people tend to use their real selfies as the profile pictures, and then users’ real looks may be also available and can be harvested for investigation.

In addition to the demographic information, data depicting users' statuses on the platform assist researchers in understanding the users' popularity and engagement in the system. This type of data may include the number of followers and followings on Twitter, the number of friends on Facebook, the number of people he/she connected to and who connect to him/her on My Space, etc. Basic statistics such as how many posts/tweets/photos the user has published on the sites are also available to be collected.

From the behavior angle, a Canadian company has created a segmentation model to identify six social media persona types: no shows, newcomers, onlookers, cliquers, mix-n-minglers and sparks (Bosomworth, 2012). More detailed descriptions of these roles are:

- No Shows (41% of the US population): these are people least involved with social media, if at all; they also infrequently engage in online commerce
- Newcomers (15%): passive users of a single social media network such as Facebook, primarily to enhance relationships that they have offline
- Onlookers (16%): active users only in the sense that they watch others via social channels on a regular basis but share almost no personal information
- Cliquers (6%): active users of one network who tend to be influential among their small group of friends and family
- Mix-n-Minglers (19%): those who regularly share and interact with a diverse group of connections via social media
- Sparks (3%): most active and deeply engaged users of social media who serve as enthusiastic online ambassadors for their favorite brands. (Bosomworth, 2012)

2.6.1.2. Functions of actor/nodes

During the first decade of the web's prominence from the early 1990s onwards, the majority of web users were consumers of content that were created by a relatively small amount of publishers (Agichtein, Castillo, Donato, Gionis, & Mishne, 2008). Beginning in the early 2000s with user-generated content becoming increasingly popular on the web, more and more users started to participate in the information sharing process as content producers, rather than just as information consumers.

Social media stimulates a critical shift in how user-generated information is being created, transferred and consumed (Leskovec, 2011). How that information is shared between numerous actors is central to understanding the social network in social media. Considering the information sharing process shown in Figure 5, actors of social media engage in basically four types of functions: information creation, information propagation, influence dissemination, and information reception and consumption.

2.6.1.3. Information creation

Information creation is the starting point of the information sharing process. When social media users post a new message or video, ask a question, or start a new discussion topic, they perform as an information creator. Java et al., (2007) studied users' intentions when using Twitter. Using the link structure, the authors identified that a certain proportion of nodes act as information sources in the social network formed via social media. The information creator is the person who creates information for other users in the same platform to see. This type of user publish blog posts or web pages, upload videos/images/audio and share content online. On Twitter, a previous study found that most posts users created were about daily routine or what they were currently doing (Java et al., 2007). This fact reflects one of the most common reasons why general public users engage in social media: recording their daily life and sharing it with others. It accounts for most common users of general social networking sites such as Twitter and Facebook. According to Cha, Haddadi, Benevenuto and Gummadi (2010), grassroots users usually play the content creation function in information sharing.

Besides creating a new message on social media sites, people who respond to content posted by others are also creating information. This type of information creation could include posting ratings and reviews of products or services in online discussion groups, making comments on blogs and forums, answering questions in online question and answer forums, and contributing to articles in Wikipedia. Users who would like to interact with others by responding to other users are usually more engaged in social media.

Unlike grassroots, when an information source which has a large number of followers generates a new message in social media, the information he/she creates potentially possesses great opportunity to be shared by others. In this case, the information sender might become a hub in the information sharing network, since a lot of other users receive the information. Based on Cha et al. (2010)'s classification, this type of users could be mass media sources or evangelists. They may post updates at regular intervals or infrequently. Despite infrequent updates, their creations are responded to by a large number of followers due to the valuable nature of their updates. By gathering and analyzing 1.7 billion tweets, Cha et al. (2012) identified that mass media sources play a vital role in reaching the majority of the audience in any major topics, whereas evangelists introduce both major and minor topics to audiences who are further away from the core of the network and would otherwise be unreachable.

Some of the information in social media could be generated by automated tools or fake accounts. These are defined as spam messages. The spammers produce ads or false information that might threaten other users on the platform. From a security point of view, how to detect spammers in social media has attracted the attention of security researchers. Stringhini, Kruegel, and Vigna (2010) identified characteristics that allowed users to detect spammers, and built a tool to detect spammers in a social network. Using the tool they developed, 15,857 spammers were correctly detected on Twitter (Stringhini et al., 2010).

2.6.1.4. Information propagation

Information propagation takes place when users forward the content they received to the social network forming in social media. In the information sharing process, transferring information is a critical function that actors can perform. According to the information sources, there are two types of information dissemination: transferring outside information to the current platform and forwarding information created by users on the same platform.

Originally, different social media platforms were independent of each other. However, transferring content between different social media sites connects them together. The most common form of this type of propagation is by sharing an URL that directs to sources on another site. Taking Twitter as an example, this can be characterized by tweets referring to particular URL (photos, video, web pages, etc.) (Asur & Huberman, 2010). Java et al. (2007) found that about 13% of all the posts Twitter contains have some URLs in them. Due to the distinct content each social media site possesses, sharing outside URLs is frequently used to make information circulation among social media feasible. Thorson et al. (2013) defined such phenomena as media ecology and explored how and what types of video content are shared and circulated across both YouTube and Twitter. The authors reported that during a protest movement, sharing a YouTube video on Twitter using protest-related keywords or hashtags increased chances of the video reaching more interested audiences.

Another type of information propagation is sharing information within the same social media sites. Users are able to share other's messages on their own social media page which makes it possible to be seen by their followers or friends. To realize such function, Twitter created a specific and famous mechanism named "retweet". A retweet is known as a post originally made by one user that is forwarded later by another user (Asur & Huberman, 2010). Retweets are useful for sharing posts and links of interest to users that users have read but not produced (Asur & Huberman, 2010).

By gathering and analyzing 1.7 billion tweets, Cha et al. (2012) demonstrated that different types of users play different functions in the information sharing process. From the perspective of social network analysis, in a broadcast medium like Twitter, users with large in-degrees (i.e., having many followers) can effectively spread information to a large number of nodes (Cha et al., 2012). Within an audience there are different types of social media users and there are ways for businesses to better engage these users.

2.6.1.5. Influence dissemination

In the information sharing process, not only information, but also ideas, opinions, news, product reviews, and influence are transmitted in social media. The dissemination of influence is one of the most significant functions of actors in the information sharing process in social media. What are the important factors in determining actors' influence? One aspect of this can be measured by the level of attention certain actors receive in the form of followers who subscribe to their accounts to automatically receive the content they generate (Romero, Galuba, Asur, & Huberman, 2011). Another aspect is determined by the actual propagation of their content through the network (Romero et al., 2011), such as the total retweet rates.

Many factors can impact the influence of a social media user, such as the quality and frequency of the content he/she generates. In order for individuals to become influential, they must not only obtain attention and thus be popular, but also must engage more with the information creation actions on social media (Romero et al., 2011). Cha et al. (2012) identified those influential actors as evangelists and also called them opinion leaders, hubs, or connectors. The influential and most active people in a social network can be extremely useful in propagating their own point of view, as well as setting which topics dominate the public agenda (Romero et al., 2011).

The study of actors of influence propagation in social media has been particularly active for a number of years in fields such as sociology, communication, marketing and political science. Companies in different fields analyze actors in social media data to perform analytics and sentiment analysis or find influencers (Leskovec, 2011). Motivated by applications to marketing, Kempe, Kleinberg, and Tardos (2003) developed an efficient algorithm to target a set of most "influential" actors of a social network that could trigger a large cascade of further adoptions. As tourism becomes an information-intense industry, Xiang and Gretzel (2010) reported that many of these social media websites assist consumers in posting and sharing their travel-related comments, opinions, and personal experiences that then serve as information for others.

2.6.1.6. Information reception and consumption

Information reception refers to receiving information from social media. Users who receive the information are receivers as shown in Figure 5. Generally, any time users check their feeds or surf on social media sites, they are performing the function of information reception in the information sharing process. A large study of information propagation within Twitter reveals that the majority of users acts as passive information consumers and does not forward the content to the network (Romero et al., 2011). Zeckman (2012) named those users as lurkers, while Cha et al. (2012) identified them as grassroots. Especially for Twitter, Cha et al. (2012) reported that grassroots users are relatively passive in helping spread the news, although they account for 98% of the network. In addition, Java et al. (2007) proposed that some users use social media to seek information. They rarely post information but they follow other users regularly.

Whether called lurkers or grassroots users, this social media personality type represents a large proportion of social media users who tend to simply listen and absorb information, but not necessarily participate in information creation and spreading. In addition, Suzuki and Calzo (2004) studied online teen bulletin boards, and found that many visitors spent considerable time "lurking," or reading others' posts without posting any reply. However, due to the huge amount of those users, a connection with a lurker can be very valuable if approached correctly. Users who follow a lot of others easily obtain and gather information, thus potentially they might be influenced more by information in social media.

In summary, considering the information sharing process, users perform the following four types of functions in social media: information creation, information propagation, influence dissemination, and information reception and consumption. Note that not only different users play various functions, but also an individual may serve different roles at different times. A true understanding of how information is shared and what users' functions are in the information spreading process is critical to conducting social media research.

2.6.2 Relationships/edges of the social media in information exchange

Social media are often considered innovative and different from traditional media such as television, film, and radio because they allow direct interaction with others (Pempek, Yermolayeva, & Calvert, 2009). Such interactions build up the relations between users. Relationships are one of the most important elements of social media, as Gilbert and Karahalios (2009) stated “relationships make social media social” (p. 211).

Many types of connections create a large social system that researchers can analyze with the math, tools, and insights of social network analysis (Hansen et al., 2010). Posting information in the form of blog posts, comments, and tweets establishes a connection between the producers and the consumers of information. Social media sites such as Twitter allow users to interact with each other and thus form a social network. Vygotsky's (1978) sociocultural theory of learning held that people learn through social interaction and the sharing of ideas and experiences. For online environment, social media promotes a variety of interactions for users and thus diverse relationships emerged through these interactions. For example, Facebook users can frequently interacted with each other through “likes”, comments, photos, tags, polling, events, inbox messages, and online chatting (Ma & Chan, 2014).

2.6.2.1. Explicit and implicit relationships

Actors in social media are connected to one another explicitly and implicitly. Users intentionally and knowingly build explicit connections whereas implicit connections are inferred from their movements in social media (Hansen et al., 2010). Explicit connections refer to the relations that users intentionally create. The various types of connections supported by social media applications are defined by the primary functions of the sites. Friending, by which both people need to recognize each other as a friend before they are connected, might be the most common type of explicit social media connections on social media (Hansen et al., 2010). For example, on Facebook, a given user’s friend list is available on his/her home page, and thus it can be accessed and collected to construct the user’s ego network. Viswanath, Mislove, Cha, and

Gummadi (2009) reported that the average number of friends in Facebook was over 120 in 2009, while the average number of friends surged to 338 among adult Facebook users in 2014 (Smith, 2014). In addition to the friend relations between users, other social media sites also allow user to follow (e.g. Twitter), connect to (e.g. MySpace), subscribe to (e.g. YouTube) other users, all of which represent directed ties between users.

Implicit relationships are generated when users interact with each other in any way the social media allows, such as replying to a post, retweeting a tweet, sending a message, giving a "like", and so on. Although the interactions on each site might be diverse, once a user interacts with others, a certain type of relation occurs between them. Most common interactive connections include making comments to other's posts on Facebook, retweeting other's tweets or mentioning others on Twitter, answering other's questions on Yahoo!Answer, and liking other's photos on Pinterest, etc. The implicit relations actually represent users' interaction behavior and movements within the social media communities. Other more subtle connections might be yielded by joining the same Facebook group, following the same persons, or being tagged in a common photo. No matter whether the relationships are implicit or explicit, they can be utilized to construct a social network with the involved users being the actors and the connections being the edges.

2.6.2.2. Patterns of relationships

These days, most social media sites can be seen as information sharing systems, where users follow other users in order to receive and exchange information along the social links. In a social network, information relationships determine what kinds of information are being exchanged, between whom, and to what extent (Haythornthwaite, 1996).

From the perspective of social network analysis, patterns of the relationships between actors describe how information moves around the network and indicate how actors are positioned to facilitate or control the information flow (Haythornthwaite, 1996). In addition, the structure of the social network building (by the ties between users) reveals the likelihood that individuals are able to access a particular piece of information.

2.6.2.3. Strength of relationships

The strength of the tie is another critical feature of relationships between social media users. In the offline world, social science researchers have investigated the theme of tie strength for decades (Gilbert & Karahalios, 2009). In social media, the relationships between actors are treated as either friend or not friend. However, Gilbert and Karahalios (2009) argued that relationships in fact fall everywhere along the spectrum between these two types. The authors, thereby, proposed a model to distinguish between strong and weak ties in social media.

While previous studies have shed light on the strength of relationships in social media, an important aspect of the social network has been disregarded: the fact that relationships between actors can grow stronger or weaker as time goes by. Viswanath et al. (2009) studied the evolution of interactions between users in the Facebook social network to capture this phenomenon. The authors found that links in the interaction network tend to appear and disappear rapidly over time, and that the strength of ties exhibits a general decreasing trend of activity as the social network link ages (Viswanath et al., 2009).

2.6.2.4. Roles of relationships/edges

Apparently, various relationships play different roles (Gilbert & Karahalios, 2009). Relationships among actors are the venue through which the information disseminates.

(1) Friend relationships

Among different types of social media platforms, social networking sites such as Facebook and LinkedIn offer an important mechanism for “being friends/connected”. Users may send an invitation to the person they are interested in. Then, if the person who receives the friend request accepts it, the two involved users become friends. Once becoming friends, any updates a user posts appear in his/her friend’s news feed thereby remaining a friend enables people to track others’ information creations easily.

Friendship is defined as “a relationship involving voluntary or unconstrained interaction in which the participants respond to one another personalistically” (Lea, 1989). Similar to the real world and generally speaking, friendship is expected to be a binary state of relationship. Friend relationships in social media are akin to the real world peer-to-peer relations in that they are the primary information exchange venues. Java et al. (2007) identified that most social media relationships can fall into the friend relationship category. There could be many sub-categories of friend relationships in social media, such as classmates, friends, family and co-workers. Sometimes users may also add a stranger as a friend.

Building and maintaining friend relationships are significant components for social networking sites. Although, social media platforms do not provide options to specify differing degrees of friend relationships, it is not surprising that users would behave differently when they exchange information with individual Facebook friends. Therefore, in regard to relationship strength and quality, following a previous study conducted by Baym, Zhang, and Lin (2004), Bryant and Marmo (2012) classified Facebook friend relationships as occurring in close, casual, and acquaintance forms.

Among college students, Pempek et al. (2009) discovered that Facebook was used most often for interaction with friends with whom the students had a pre-established relationship offline. A recent survey of college students in the U.S. showed that students use the social networking sites to interact with their offline acquaintances in order to maintain friendships rather than to find new friends (Ellison, Steinfield, & Lampe, 2007).

From the social network perspective, a network built on friend relationships can be defined as a friend network. Due to the default setting of the social media platforms, a user is meant to receive all of his/her friends' updates. However, the friend relationships do not promise communications and other interactions. In fact, within the virtual friend network, Golder, Wilkinson, and Huberman (2007) discovered that nearly all communication was found to occur between "friends," but only a small proportion of "friends" exchanged messages.

(2) Follow relationships

While most social networking sites allow only a binary state of friend relationship, unsurprisingly it has been observed that not all links are created equal. Some blogs and microblogging platforms such as Twitter have a function called follow, which allows a user to subscribe to another user's information creation without any permission requests. A following relationship is assumed to be built based on a common interest or a shared attribute (Yamashita, Sato, Oyama, & Kurihara, 2013). However, within Twitter you can feel free to follow someone named B regardless of his/her permission and B will not receive what you say in his/her timeline until he/she chooses to follow you back. In other words, the relationship between users in Twitter-like microblog websites is directed and therefore, information is transmitted in a directed line.

The follow relationship seems to be primarily related to information consumption (Myers, Sharma, Gupta, & Lin, 2014). Different from friend relationships, the purposes of following other users in social media may not be because of any meaningful social relationship but to receive news, especially in the case that the followed users are news publishers (e.g., CNN Breaking News) or celebrities (e.g., Ellen DeGeneres). However, Myers et al. (2014) argued that sometimes follow relationships can be built on social ties, e.g., following one's colleagues, family members, and friends. In such cases, the information exchange between them might be more than only the follower receiving information from the followed person.

From the view of social network structure, the follow relationships construct a social network between Twitter users. Myers et al. (2014) analyzed the topological features of the Twitter follow graph, and they pointed out that users with high in-degrees are more visible and are therefore more likely to receive new edges, further increasing their inbound degrees. In regards to information exchange, high-profile and popular accounts hold more potential to send information to a broader audience. In addition, researchers suggested that the follow relationships could be utilized to cluster Twitter users (Yamashita et al., 2013).

(3) Interaction relationships

Social media can be seen as an interactive information network where a certain part of information dissemination appears along interaction edges. Different social media platforms certainly offer a variety of movement and interaction mechanism to their users. When asked about the behaviors they engage in on the site, Facebook users' preferences point toward "liking" content that others have posted and commenting on photos as the activities they engage in most often (Smith, 2014). Although the interactions on each site might be diverse, once users interact with others, a certain type of relations occurs between them. Four regular and popular roles of the interaction relationships are summarized as liking, commenting, sharing, and messaging.

a) Liking and favoriting

Smith (2014) reported that 44% of Facebook users "like" content posted by their friends at least once a day, with 29% doing so several times per day. A "like" (on Facebook) or "favorite" (on Twitter) serves as a digital version of an acknowledging nod or a thumbs up (which is the depiction of the "like" button). It has been realized that from Facebook "likes" it is possible to decipher an individual's level of openness, conscientiousness, extraversion, agreeableness and neuroticism (Entis & Advisor, 2015). Thus, it suggests that the like relationships might be used to group users with common interests.

b) Commenting

People make comments to other's information creation to express themselves. Twitter offers this function named "reply", whereas Facebook uses "comment". On Facebook, 31% of users comment on other people's photos on a daily basis, with 15% doing so several times per day (Smith, 2014). Clearly, comment is a more informative format than "like". It provides more text about people's feelings than clicking a "like".

Interestingly, Hansen et al. (2010) proposed that replies are better indicators of social ties than follower/friend relationships. The authors who made this suggestion were inspired by Huberman, Romero, and Wu (2009), who observed that even though people have a large number of friends in social media, the proportion of those friends who they actually exchange messages with is rather small in comparison.

c) Sharing

Retweeting, which appears to be the key mechanism for information exchange, is an interesting interaction in Twitter. Retweeting can be understood as a form of information diffusion since the original tweet is propagated to a new set of audiences, namely the followers who retweet the tweet as the retweeter (Suh, Hong, Pirolli, & Chi, 2010). In addition, people often add more content such as their comments with the original tweets.

On Facebook, sharing mechanism achieves the retweeting function on Twitter. Retweeting relationships between the follower and the followed person sometimes present not only the information flow, but also the retweeter's judgments and feelings to the original author. Most times this relationship tends to reflect the positive evaluations of the tweets and the authors. Suh et al. (2010) stated that retweeting might be created to entertain a specific audience, to comment on someone's tweet, to publicly agree with someone, or to save tweets for future personal access. A social media scientist also suggested that retweets are used to spread interesting web pages, videos, and other web content to other users (Zarrella, 2009).

As we can see above, retweeting has been one of the most important venues of information exchange. Suh et al. (2010) identified that a study on retweeting relationships would help to understand why certain tweets spread more widely than others did. The authors investigated a number of tweet features, and found out URLs and hashtags have a strong relationship with retweetability (Suh et al., 2010).

d) Messaging

Apart from the public communication forms (e.g., comments), both Facebook and Twitter provide a way of private and real-time information exchange: sending messages. Facebook's messaging capability is similar to that of regular web-based email except that messages may only be sent to one recipient at a time (distribution lists are not allowed). Messages may be sent to any user, even if the user is not in one's network and even if the sender does not know the recipient's regular email address.

Twitter allows users to "tweet to 'someone'", which generates a message starting with a "@" sign and connecting with the username of "someone". Similarly, for Facebook, users can directly write on someone's timeline. In both cases, the message appears on the sender's timeline. The receiver gets the information as a notification but it does not show on the receiver's timeline. For Facebook, a very common content of this type of public message is birthday wishes to friends.

e) Mentioning and tagging

On Twitter, a “mention” is a Tweet that contains another user’s @username anywhere in the body of the Tweet (Twitter, n.d.). The “mention” mechanism on Facebook is the fraternal twin to Twitter’s @mention feature (Mathews, 2011). In addition, Facebook users can not only mention other people, pages, and groups in the text of their posts, but they also can tag others in photos, videos and notes.

Both mentioning and tagging can be seen as a public conversation between the user who posts material and the users who are mentioned or tagged. These types of interactions can be viewed as a conversation between users in a public forum. Moreover, people who “friend” the poster of materials are also able to see this material and the interactions between users involved in the public sharing of said material. A “mention” in social media connects the creator of information with other involved users, as well as provides the context of this interaction. Ashton (2015) analyzed the Twitter mentions network in its entirety, and differentiated the broadcasters from the receivers in the network using measures of in-degree and out-degree.

In summary, both friend and follow relationships are built on users’ connections, while interaction relationships are constructed based on users’ activities with others. Moreover, the roles of the relationships resulting from these interactions differentiate types of interpersonal activities, which include liking and favoriting, commenting, sharing, messaging, and mentioning and tagging.

2.6.3 Network measurements

A number of network measurements assist researchers in gaining insights to the structures of the social network, especially when combining them with some statistical tests. Lewis, Kaufman, Gonzalez, Wimmer, and Christakis (2008) used ordinary least squares regression to see how gender, race/ethnicity, SES, and online activity are associated with the two variables of users' Facebook friend network: betweenness centrality and network density. Interestingly, the results showed that females tend to have significantly less dense Facebook friend networks than do males. Since the network density was identified as an indicator of the extent to which individuals identify with their friends (Brown, 1990), the authors suggested that females are more socially active on social networking sites and "have a greater diversity of 'network resources' at their disposal" (Lewis et al., 2008). In addition, they also concluded that less active students and students who joined Facebook more recently generally have denser networks and smaller betweenness.

Nodal degree is another crucial measure for social network analysis. It commonly indicates an actor's involvement in network activities (Knoke & Yang, 2008). In a directed network such as the follow relationship network on Twitter, a node possesses two types of degree measures: in-degree (indicating how many followers a user has) and out-degree (indicating how many accounts a user follows). Cha et al. (2012) articulated that the out-degree to in-degree ratio decreases as a user has more followers, which suggested that the less popular a user is, the more actively he/she follows others.

2.7 Content-based analysis applied in social media research

2.7.1 Data collection and data analysis

Ideally, all types of information flowing in social media, ranging from textual material to photos, radios and videos, may serve as the sources of content analysis. Considering the ease of data processing, textual contents such as posts, tweets, replies and comments, are more often collected and analyzed by researchers. In regards to data collection, a variety of social media platforms provide the application programming interface (API) to facilitate the developer to tap into the collective knowledge of millions of users. For example, Facebook Graph API and

Twitter API assist with collecting a given user's updates and gathering posts containing certain keywords.

In the past, content analysis was mostly conducted manually, with investigators interpreting text by classification, categorization, and subjective interpretation. These days, a number of lexical software and natural language processing (NLP) tools have been invented to aid the data analysis process especially for the user-generated content in social media.

A variety of software and toolkits are available to collect content from different social media sites, as well as carry out various analyses. Netlytic (http://netlytic.org/) is a cloud-based text analyzer and social networks visualizer. Netlytic can gather data conversations on social media sites such as Twitter, YouTube, blog comments, online forums and chats. In addition, it can also automatically summarize large volumes of text, to discover and visualize social networks (Netlytic, 2014). Through text processing and network analysis, it can help researchers and others to identify key and influential constituents, and discover how information and other resources flow in a network (Netlytic, 2014). DiscoverText (http://discovertext.com/) is a cloud-based platform which helps users archive, filter, search, and classify text (Stoll, 2015). Many valuable features are combined with this platform including: capture, filter, de-duplicate, cluster, search, human code, and machine-classify large numbers of small, unstructured units of text (Stoll, 2015). IBM SPSS Text Analytics for Surveys software can be applied to transform unstructured text into quantitative data and gain insight using sentiment analysis (IBM, 2014). This software adopts NLP technologies specifically designed for mining the user-generated text.

2.7.2 Topic modeling

Topic modeling seeks to automatically reveal the latent topics from a set of documents through machine learning. Hofmann (1999) first proposed a generative data model – called the

Probabilistic Latent Semantic Indexing (PLSI) – that represents each document as a probability distribution over a set of topics. While Hofmann's work provided some advantages for document indexing, it may lead to serious problems of overfitting (Blei, Ng, & Jordan, 2003). To overcome the limitations of PLSI, Blei, Ng, and Jordan presented a three-level hierarchical Bayesian model, which is known as Latent Dirichlet Allocation (LDA). In the LDA model, each document is modeled as a finite mixture over an underlying set of topics, where each topic is modeled as a mixture over an underlying set of terms. Follow-up efforts to extend content-level LDA modeling have been made using different approaches, such as the Author-Conference-Topic (ACT) model (Tang et al., 2008), correlated topic model (CTM) (Blei & Lafferty, 2006), interactive topic modeling (Hu, Boyd-Graber, Satinoff, & Smith, 2014), and supervised Latent Dirichlet Allocation (sLDA) (Mcauliffe & Blei, 2008). Most topic modeling studies explored the relationships between documents and topics.

2.7.3 Applications

The products of user-generated content on social media dramatically increases every day - even every minute. Such incredibly abundant information contains a great wealth of content and opportunities for exploration through content analysis. Researchers have thrown insights into the application of content analysis of information flowing on different social media sites for various purposes.

2.7.3.1. Trending detection

Due to the interactive nature of social media, the user-generated knowledge offers an efficient source to gain insights into the trending topics about which people talk. Therefore, Twitter is able to provide a real-time platform that can predate the best newspapers in informing the web community about the emerging topics (Cataldi, Di Caro, & Schifanella, 2010). Trends are typically driven by emerging events, breaking news and general topics that attract the attention of a large fraction of social media users (Mathioudakis & Koudas, 2010). Trend detection is thus of high value to news reporters and analysts, as they might point to fast-evolving news stories.

In fact, Twitter itself lists 10 up-to-date trending topics on the homepage of every user. The official Twitter Trends are determined by an algorithm and are personalized for each user based on who you follow and your location. This algorithm identifies “topics that are popular now, rather than topics that have been popular for a while or on a daily basis, to help you discover the hottest emerging topics of discussion on Twitter that matter most to you” (Twitter, n.d.). Although Twitter has not released the Trends algorithm, researchers suggest that potential trends are discovered by polling all tweets for repeated hashtags. Their trend status is determined by a combination of times tweeted and volume of tweets containing the hashtag (Wilson, 2012). Such speculations suggest that the Twitter Trends are yielded from a series of content analysis.

In addition to Twitter Trends, researchers make efforts to discover the trends from Twitter automatically. Cataldi et al. (2010) proposed a novel topic detection technique that permits retrieval in real-time the most emergent topics expressed by the community. The method extract the emerging topics by analyzing in real-time the emerging terms expressed by the tweets. For identifying the emerging keywords, the authors assigned a “content energy” to a given term based on its effective contribution. This means the given term’s usage is extensive and emergent in the considered time interval but not in the previous ones.

However, same as some of traditional trends detection studies, Cataldi et al. (2010) did not consider the structural features of information flowing in social media. To address this gap, Budak, Agrawal, and Abbadi (2011) established so called coordinated and uncoordinated trends, which take friend relationship network into account to identify topics that are highly discussed among the identified clustered users and distributed users.

In respect to information flowing on different social media platforms, content analysis was utilized to compare the differences of the trending topics. Yu, Asur, and Huberman (2011) observed that there were vast differences between the content that was shared on Sina Weibo (a Chinese microblogging social network) and that of Twitter. As a result, people tended to share jokes, images and videos on Sina Weibo, whereas on Twitter the trending topics were mainly related to events in the news (Yu et al., 2011).

2.7.3.2. Topic discovery

Frequently content analysis is employed to code text in terms of certain subjects and themes, and eventually seek a categorization for the phenomena of interest (Bryman, 2012). When it comes to the social media era, analyzing the information flowing on various platforms is likely to be involved when the researcher seeks to discourse the topics and themes in the user-generated texts.

As people increasingly rely on the self-help resources, the online communities of social media sites provide an efficient platform for people to help each other. For example, autism patients and their caregivers can visit social media sites where they can ask for help and advice from other users, make contributions to others, receive assistance from the group members, and share their experiences in communities such as support groups on Facebook, e.g. “Autism Group” **(**www.facebook.com/groups/48701140761/).

Based on the log data from a social Q&A forum, Zhang and Zhao (2013) used content analysis to investigate the consumers’ discussion topics related to diabetes. Through the data coding analysis, the authors found 12 categories of questions and answers that user discussed within the forum: Cause & Pathophysiology, Sign & Symptom, Diagnosis & Test, Organ & Body Part, Complication & Related Disease, Medication, Treatment, Education & Info Resource, Affect, Social & Culture, Lifestyle, and Nutrient.

Using online support groups as the data sources, Klemm, Hurst, Dearholt, and Trone (1999) articulated that four categories (information giving/seeking; encouragement/support; personal opinion; and personal experience) accounted for approximately 80% of responses across the online cancer support groups. By investigating a larger data set, Seale, Ziebland, and Charteris-Black (2006) produced categories more inductively. The authors archived 12,757 postings from the two most popular UK based breast and prostate cancer support groups, and then generated 15 categories of keywords that emerged from the group discussions: Greetings, Support, Feelings, Health care staff, Health care institutions and procedures, Treatment, Disease/disease progression, Body parts, Clothing and appearance, Tests and diagnosis, Internet and web forum, People, Knowledge and communication, Research, Lifestyle, and Superlatives (Seale et al., 2006).

Different from the above studies conducting the traditional manual coding processes, topic modeling technique is gaining increasing attention to help with the topic discovery from social media (Hong & Davison, 2010). Given the characteristics of tweets, Zhao et al. (2011) proposed a Twitter-LDA (Latent Dirichlet Allocation) model that treats each tweet as a single document. By applying this new model to data from Twitter, 11 categories of tweets emerged: Family & Life, Arts, Style, World, Tech-Sci, Business, Twitter, Sports, Health, Education, and Travel. They discovered that Family & Life dominated the information flowing on Twitter. Reddick, Chatfield, & Ojo (2017) also employed topic modeling methods to explore the topics of government related posts on Facebook.

Above all, in addition to social network analysis, content analysis remains another useful method for social media research - in particular by using text data extracted from social media platforms. Researchers have applied content analysis to discover trending topics and discussion topics based on the information flowing in social media.

2.8 Sentiment analysis and opinion mining

Sentiment analysis deals with the task of identifying positive and negative opinions, emotions, and evaluations from text (Wilson, Wiebe, & Hoffmann, 2005). Sentiments and potentially expressed opinions are significant components of user-generated information flowing in social media sites. Therefore, with the increase use of social media, sentiment analysis [denoted the same field as opinion mining (Pang & Lee, 2008)], has been widely applied to identify whether a text flowing in social media is subjective or objective, and whether the opinion it stated is positive or negative (Thelwall, Buckley, & Paltoglou, 2011). Sentiments extracted from information flowing in social media can be utilized to improve the forecasting power of social media. In addition, further studies might help to understand how sentiments are created, how positive and negative opinions propagate and how they influence people (Asur & Huberman, 2010).

One of the core ideas of sentiment analysis is to set a classification approach in order to label the polarity (positive, negative or neutral) of a given text. Asur and Huberman (2010) constructed a sentiment analysis classifier using the LingPipe linguistic analysis package. However, given the importance of the corpus to the analysis performance, Pak and Paroubek (2010) collected a corpus of 300,000 tweets from Twitter and built a Twitter-based sentiment classifier that is able to determine positive, negative and neutral sentiments for a tweet.

2.8.1 Mechanism of sentiment analysis

In general, sentiment analysis has been carried out at three levels: document level, sentence level, and entity and aspect level (Liu, 2012). Table 6 summarizes the descriptions and the characteristics of the three levels of sentiment analysis.

Analysis level	**Complex level**	**Description**
Document level	Simplest task	Sentiment classification of whole document
Sentence level	More complex	Identifying Subjective/Objective sentences
Entity and Aspect level	Advanced	Detect the target, source, or complex attitude types

Table 6. Descriptions of the three levels of sentiment analysis

Sentiment analysis techniques can be broadly classified into two types: lexicon-based approaches and machine learning approaches (as shown in Figure 6). Lexicon-based solutions rely on sentiment dictionaries, while machine learning solutions automatically or semi-automatically learn to detect the affective content of text (Kim, Jeong, Kim, Kang, & Song, 2016; Paltoglou & Thelwall, 2017). The lexicon-based approach detects the sentiment based on a sentiment lexicon, which includes a collection of known and precompiled sentiment terms. It is divided into dictionary-based approach and corpus-based approach. that use statistical or semantic methods to find sentiment polarity. Dictionary-based approach adopts general dictionary, whereas corpus-based approach uses the domain-specific corpus.

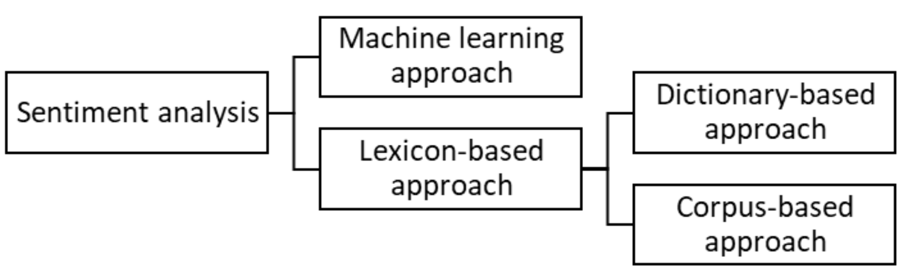

Figure 6. Classification of sentiment analysis

2.8.2 Applications

The rich and diverse data provided by social media applications has been facilitating the progress of the research field of sentiment analysis (Kumar & Sebastian, 2012). The sentiments reflected by social media content can be applied in predicting real-world outcomes. Gruhl, Guha, Kumar, Novak, and Tomkins (2005) showed that the content of blog postings could successfully predict books' sales rank prior to spikes. Later on, Liu, Huang, An, and Yu (2007) proposed a Probabilistic Latent Semantic Analysis (PLSA) model to measure the hidden sentiment from blog posts, and confirmed the predictive power of blogs in predicting the future product sales.

Social media is increasingly being commercially exploited for purposes such as automatically extracting and even predicting customer opinions about products or brands (Thelwall et al., 2011). Twitter and Facebook are a focal point of a number of sentiment analysis studies, and the most common application is to monitor the real-time reputation of a specific brand on Twitter and/or Facebook (Feldman, 2013). As for predicting the box-office values for movies, Asur and Huberman (2010) analyzed the sentiments present in tweets and demonstrated the efficacy at improving predictions after a movie has released. Interestingly, Bollen, Mao, and Zeng (2011) employed two real-time sentiment-tracking tools, namely OpinionFinder that measures positive vs. negative mood and Google-Profile of Mood States (GPOMS), to measure public mood from daily Twitter feeds. Eventually, the authors suggested that public sentiment, as expressed in large-scale collections of Twitter posts, could indeed be used to predict the stock market.

2.9 Summary

Recent years have witnessed a surge in research studying how information is shared, exchanged, and flows on social media platforms. Applying social network analysis to social media research permits the discovery of the intricacies of online user behavior. Social networks that are constructed by social media users and the relationships between them represent how information is spread around the environment.

Since the early 2000s, user-generated content has become increasingly popular on the web. Users participate in the information sharing process and perform multiple functions. Social media presents a unique opportunity to answer longstanding and important social science questions about the interaction among different types of individuals who have different roles in the diffusion of information (Cha et al., 2012). In the process of information sharing, social media users perform the following different functions: information creation, information propagation, influence dissemination, and information reception and consumption. Studying the relative roles different users play in information propagation enables us to understand how various users engage in social media.

Relationships that emerge from social media can be very revealing. Different players in social media are interconnected through bidirectional social links as well as unidirectional subscriber links that they use to exchange information. There are a number of significant roles that the relationships perform in social media regarding information exchange; all of which can be grouped into three categories: friend, follow, and interaction relationships. Interaction relationships built by the interpersonal activities between users can be further divided into the following types: liking, favoriting, commenting, sharing, messaging, mentioning, and tagging.

Content-based analysis sheds light on understanding information flow in social media. Traditional content analysis methods have been widely applied to social media research, while the application of topic modeling in analyzing social media content has proliferated over the past years. The applications of topic modeling in social media research focus primarily on detecting the trends and discovering the discussion topics.

Above all, social media users and the relationships among them form online social networks. Relying on social network analysis, researchers are able to gain insights on how information is being shared and exchanged in social media. Topic modeling, however, does not answer the question "how", but instead "what" themes are underlying the information flow. Therefore, the integration of social network analysis and topic modeling together may provide more in depth understanding into how and what information is being disseminated and spread in social media.

2.10 Limitations and gaps in literatures

Some of the extant research on autism patients' attitudes and behaviors reported their hesitations of the use of social media. More recently, some studies illuminated the active engagements in the online social communities in this population. Through the qualitative research methods, such as questionnaires and interviews, few studies reported how autism patients perceived and felt about their online experiences. However, information regarding how people affected by autism interact with each other on social media is sparse.

Various factors contribute to how user participate in the online health communities, such as, income, class, gender, race, the educational level and geographical location. However, surprisingly little research attention has been directed to understanding gender differences in health information seeking on social media (Ford, Miller, & Moss, 2001), especially in the autism-related populations. This study aims to investigate if gender might be attributed to the disparity in the interaction patterns among group members in the autism support groups on Facebook.

Given the paucity of research regarding autism-affected users' online interactions on social media, this study aims to investigate how autism-affected users interact with each other in the autism support groups on Facebook. Furthermore, gender differences of autism-affected users in the way how group members interact with each other and the sentiment they expressed were investigated.

Chapter 3. Research Methodology

3.1 Introduction

This study centers on the research of autism-affected users' behavior within communities on social media. The research objects are the autism support groups on Facebook. Those groups consist of autism patients, their relatives, caregivers, researchers, and physicians.

In this study, the research population was all public Facebook groups that relate to autism. Since the population tends to be very large, a selecting strategy was proposed to select the selected groups from the population. All selected autism support groups on Facebook compose the sample that was intended to be representative of the population.

Then, the research data were gathered from each selected group. For each group, all of the wall posts and the related components were extracted from Facebook. Each post included the following components: the user who created the post, the content of the post, the tag(s) within the post, the specific time when it was posted, the total likes it received, the Facebook user(s) who liked the post, the total number of comments it received, and the content of each comment.

Social network analysis, topic modeling, sentiment analysis, and inferential analysis were employed to analyze the data collected from support groups regarding autism on Facebook. In order to construct the social network among the group members, all of the involved Facebook users' information was extracted from the raw data sets and served as the nodes in the network. The relationships between the nodes were built based on the following interactions: commenting, reacting (liking), tagging, and sharing-out. Each social network data was imported to UCINET software to conduct the social network analysis and to find the interaction patterns and the influential users within the autism-related support group on Facebook.

Topic modeling was then conducted to analyze the information shared and flowed within the groups. This included the content of the posts and the comments. Both the original posts and the comments may have included texts, photos, and videos. Through topic modeling analysis, discussion themes were discovered from the raw data.

Inferential statistics covers the techniques which allow researchers to explore in-depth relationships between variables and interpret the complicated resultant data pattern (Zhang, Zhao, & Wang, 2016). In this study, inferential analysis was applied to a set of social network measures generated from the social network analysis. The measures included degree centrality, betweenness centrality, closeness centrality, etc. Applying inferential analysis enabled this study to discover the communication pattern differences between groups; for example, using modified ANOVA analysis to identify whether there were any significant differences of the network features among the groups from different categories.

Figure 7 describes the data collection and data analysis process applied in this study. The detailed data collection methods and the data analysis methods applied to different types of data are discussed in the following sections.

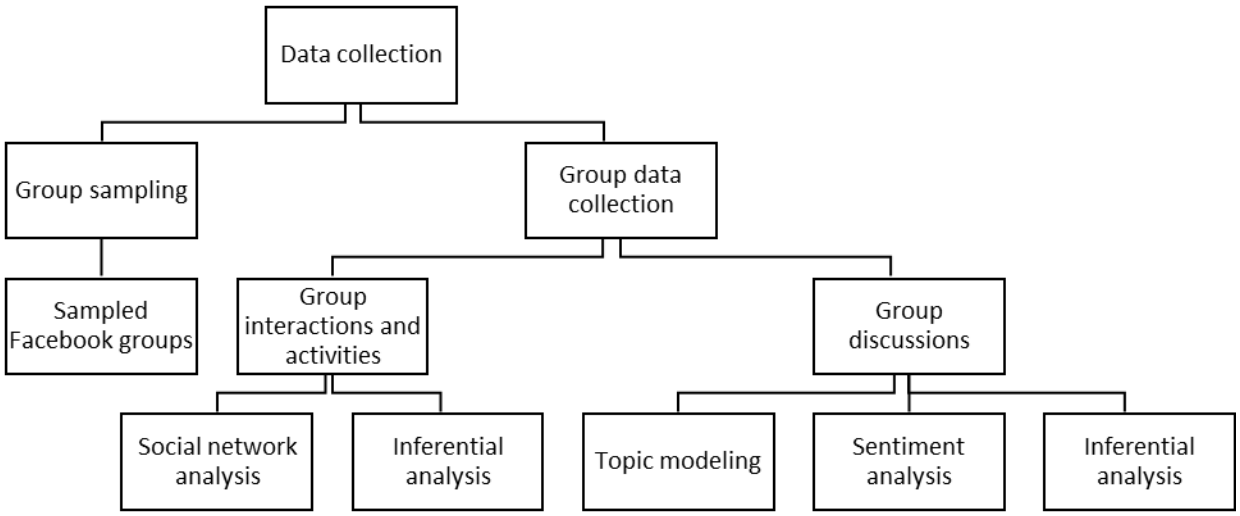

Figure 7. Data collection and data analysis process

3.2 Sampling and data collection

The data collection in this study consisted of two parts. The first step was to select sampled autism support groups on Facebook. After deciding certain groups, the second step was to gather the proper data from sampled Facebook groups, including group interactions and group discussions.

3.2.1 Sampling strategy

The purpose of this study was to investigate the autism support groups on Facebook, thus the screening strategy focused on finding the appropriate Facebook groups. Based on the definition from PubMed Health (Board, 2012), autism is also called autistic spectrum disorder (ASD) and pervasive developmental disorder (PDD). In order to reach broad data sources, the following autism-related terms were used to search the groups on Facebook: “autism”, “autistic”, “asperger”, “aspie”, “pervasive developmental disorder”, “ASP”, and “PDD”. However, the abbreviation “ASP” and “PDD” returned too many unrelated groups in the pilot study since they could represent many words other than autistic spectrum disorder and pervasive developmental disorder. Therefore, five search terms were finally adopted to find targeted Facebook groups.

As a preliminary exploration, on May 18-20, 2015, Facebook search engine was utilized to search for each of the following search terms: “autism”, “autistic”, “asperger”, “aspie”, and “pervasive developmental disorder”. The search was restricted to Facebook groups. Individual users and public pages were excluded. To be included in the study, the groups had to meet the following criteria: (1) the group was related to autism; (2) the group possessed more than 50 group members; and (3) the group operated in English. The first criterion ensured that the sampled groups could be related to the research problem and research questions. The second criterion ensured the conduction of further social network analysis and inferential analysis, while the third criterion ensured the process of content analysis of information shared in the group. For each group identified in the search results, the researcher manually checked the purpose and the operation language of the group through the group title and group description, and recorded the number of group members via group profile. Table 7 summarizes the first-step screening results in the pilot study. In total, 341 Facebook groups met the requirements.

Search term	Number of search results	Number of appropriate groups
autism	380	147
autistic	2201	89
asperger	2221	93
aspie	200	15
pervasive developmental disorder	10	3

Table 7. First-step screening results through the pilot study

Yet, 341 groups still exceeded the research load for this study. From the group title and description, the basic aims of a group were determined. Through a thorough analysis of the group purposes, all appropriate groups were categorized into the following categories: (1) Care support group; (2) Autism with other related diseases; (3) Treatment and therapy; (4) Society and

Education; (5) Autism patient group; (6) Scope; (7) Specific autism type; (8) Commercial and research; (9) Patient and society; and (10) Special discussion. In addition, groups in each category were further divided into several sub-categories. Table 8 summarizes the categories and the sub-categories of the autism-related Facebook groups.

Category	Sub-category
Care support group	Mother General family members and caregivers Partner (wife/spouse) Parents
Autism with other related diseases	Sensory Processing Disorder Ehlers Danlos Syndrome/ Hypermobility Syndrome Neurological/behavioral challenge Down Syndrome Type 1 Diabetes Dyslexia
Treatment and therapy	Essential Oils Chlorine dioxide MAPS Treatment
Society and education	Awareness Fundraising and charity Art Education Non-profit organization
Autism patient group	Women Teenager Christian Adults Youth Islam LGBT
Scope	Local support National support Global support
Specific autism type	Severe autism High-functioning autism
Commercial and research	Consumer group Consultancy services Research
Patient and society	Friend seeking Relationship Job

	Protest
Special discussion	Buying and selling Gift

Table 8. Categories and sub-categories of the autism-related Facebook groups

In the process of group categorization, each group from the first-step screening results was classified into one or multiple first-level category/categories based on its group purpose. Groups within each first-level category were then assigned to only one sub-category. It means a given group may associate with multiple categories but only one sub-category under a certain category based on its primary purpose. This requirement ensured the exclusiveness among the sub-categories under a given category. For example, if an autism support group was dedicated to topics about how parents educate autistic children, this group would be classified into both the *Care support group* category and the *Society and education* category, while it would be classified into the *Parents* sub-category in the *Care support group* category and the *Education* sub-category in the *Society and education* category.

To achieve sufficient information, the researcher tended to choose the largest groups that were available. Finally, a total of five public Facebook groups became the final sample groups.

3.2.2 Group data collection procedure

In this study, the research data were from Facebook. Relying on the above discussion of the screening strategies, data collection process was carried out. Five public Facebook autism support groups, each selected from a distinct category (i.e. Awareness, Treatment, Parents, Research, and Local support), became the data sources. According to Facebook, anyone can access the posts in public groups. After joining the groups, a flyer was posted in the groups notifying the process of this study. The comparably largest and most active groups in which group members showed no uncomfortable feelings to the study were selected as the sample groups. In addition, the author intentionally chose groups focusing on diverse topics.

After identifying the sampled groups, data collection for this study centered on the extraction of the interactions and content that appeared in each group. However, the targeted groups might have been created at different time. Some groups might have been built for several years, while some might be created several months before the data collection. If all of the group interactions were considered after the creation of each group, it would be unfair for the newer groups because the time range of their data collection was shorter. Therefore, in order to ensure the fair comparativeness among the groups, a 6-month period was set as the time range of data collection. The researcher conducted a pilot investigation on the potential groups that could be sampled. As a result, data from the potential groups during a 6-month time span was sufficient for the following analysis. The time span was flexible to be expanded if there were not sufficient data for data analysis procedures when the final data collection was conducted.

Data collection included two parts. Data from the sampled public groups was gathered using NodeXL. NodeXL, produced by Microsoft Research, is an extendible toolkit for network overview, discovery and exploration (Smith et al., 2009). NodeXL offers the powerful and easy-to-use interactive network visualization and analysis functions for representing generic graph data, performing advanced network analysis and visual exploration of networks (Microsoft Research, 2015). The tool supports data collection from Facebook and Twitter, and imports the graph data (nodes and edge lists) into an Excel spreadsheet. NodeXL enables the capture of some pertinent aspects of Facebook, i.e. posts, likes, shares, comments. However, due to the limits of Facebook API, NodeXL can only collect data from the public groups.

Data from each of the sampled groups was collected and then saved in the Excel spreadsheet for further analysis. As shown in Figure 8, on the home page of each group, all of the wall posts created by group members were accessed. Each post included the following information: the Facebook user who created the post, the content of the post, the tag(s) within the post, the specific time when it was posted, the total likes it received, the Facebook user(s) who liked the post, the total share-outs it received, the Facebook user(s) who shared the post, the total number of comments it received, and the content of each comment. For each comment replied to in the original post, it possesses the following components: the Facebook user who made the comment, the content of the comment, the specific time when it was made, the total likes it received, and the Facebook user(s) who liked the comment. As for the content of the posts and the comments, they may have contained text(s), URL(s), photo(s), and even video(s).

Figure 8. The homepage of an example Facebook group

Sometimes, group members posted a link or a picture in the group using the Facebook share-in function (as shown in Figure 9). In this case, this post would be treated as information shared-in instead of as a typical post, in order to represent the share-in behavior in the group. Information shared-in has all of the possible components of a post, such as the creator, the content, the total likes it received, etc. The gender distributions of sampled groups were presented in section 4.1.1.

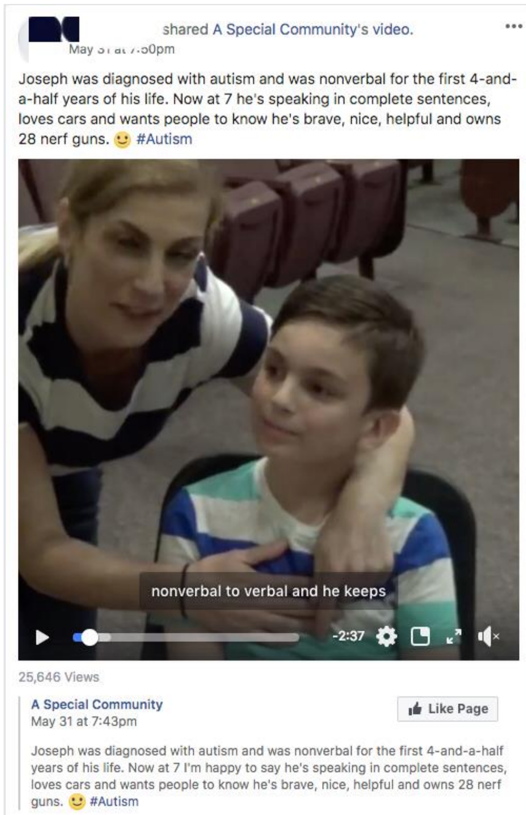

Figure 9. An example of a share-in group post

3.3 Social network analysis

3.3.1 Types of data

Ideally, all types of information existing in social media (ranging from textual material to photos, audios, and videos) serve as the data source for further analysis. Because of the nature of social media, each application can be seen as a social network composed of actors, connections, and information flowing in the network. Based on the data formation and utilization, data harvested from Facebook can be classified into the following types: actors, connections, and content.

3.3.1.1 Actors

Actors are the main component of social media. Basically, actors can be construed as the users acting in social media. As some of the most famous social media sites (e.g. Facebook, Twitter) being strikingly popular, the platforms attract not only the ordinary users but also popular news sources and high-profile users to join the network, including traditional media (e.g., BBC, CNN), celebrities in various fields (e.g., Oprah Winfrey, Michael Jordan, Taylor Swift), politicians (e.g., Barack Obama), and other influential figures (Cha et al., 2012). Often the actors represent individual people but some of them could be organizations such as workgroups, teams, institutions, and companies, as well as virtual objects such as brands, TV shows, software, and cartoon roles.

In this study, each Facebook user in a given autism group serves as an actor in the social network analysis. Figure 10 presents an example of how each node represents a group member. In Figure 10, User 1, User 2, and User 3 participate in the same Facebook autism group. In order to protect the user privacy, the Facebook usernames are replaced by serial numbers.

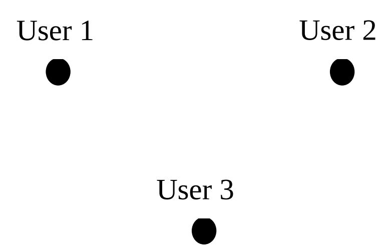

Figure 10. Nodes in autism support groups on Facebook

3.3.1.2 Connections

When considering a social media application as a social network, connections among users build up the network. All of the social media applications provide certain types of connection capabilities to the users. The basic types of connections occurring in the social media sites can be classified into two types: explicit connections or implicit connections (Hansen et al., 2010). Users intentionally and knowingly build explicit connections, whereas implicit connections are inferred from the users' movements in social media (Hansen et al., 2010).

With respect to analysis of social media, connection data become especially critical since it can help to apply the social network analysis to social media environment. Both the reciprocated relations (e.g. friending) and the unilateral relations (e.g. following) serve as the links that connect users in networks. Therefore, gathering connections between a certain number of individual users and then building the network among them helps to explain online social behavior and target the influential users.

In this study, the primary explicit connections between users in a Facebook autism group are participating in the same group. The implicit connections linking two actors result from activities including commenting, reacting (liking), tagging, and sharing-out. The research questions in this study center on discovering the interaction patterns among users in autism support groups on Facebook. Thus, this study focuses on the investigation of the implicit connections among actors.

Figure 11 presents an example of connections between users in a Facebook autism group. In Figure 11, User 1 has liked one post created by User 2 so there is a reacting (liking) connection between them. User 3 has made comments to posts generated by User 2 several times so there are commenting connections between these two users. As can be seen from Figure 11, the connections are directed from users who initiate the connections to users who receive the connections. In addition, the thickness of a link indicates the strength of the connection.

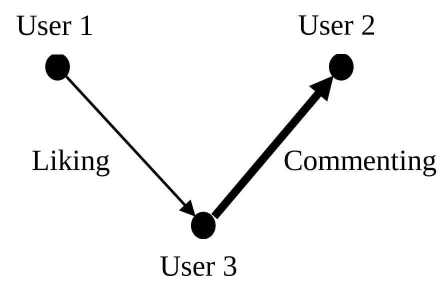

Figure 11. Connections in autism support groups on Facebook

3.3.1.3 Network

Actors and connections together construct networks. The activity network on the social networking sites refers to the network formed by users who actually interact through the methods provided by the social networking sites (Viswanath et al., 2009). Constructing the activity network enables the discovery of the influential users in the groups, and identification of the interaction patterns among group members.

In Facebook groups, group members post new messages, photos, or links to the groups, and then others can make comments to the posts and express "like" to a piece of content. In addition to simply posting a message, group members can also tag other users in their posts. Therefore, there are four types of interactions by group members involved in the groups: commenting, reacting (liking), tagging, and sharing-out. Those interactions build connections between actors, and thus construct interaction networks in terms of the types of the activity.

To indicate the strength of connections between users, frequencies of different types of connections between any two users are combined to determine the total frequency of interactions between those two users (as shown in Figure 12).

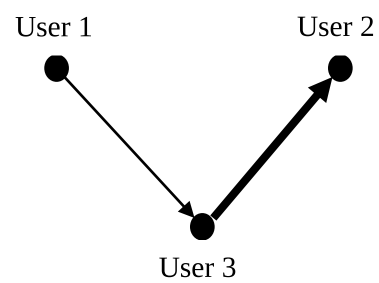

Figure 12. Activity network of autism support groups on Facebook

3.3.2 Creation of the related matrices

After all data in the selected groups are collected, multiple matrices are generated. These matrices define relationships among the involved actors in terms of making comments, marking a like to a post, tagging others in a post, and sharing one's post out of the group. The generation of matrices is vital and crucial for social network analysis.

Creation of original node-node matrices

(1) Comment Node-Node Matrix (CNNM): Description of comment

$$CNNM = \begin{pmatrix} c_{11} & \cdots & c_{1r} \\ \vdots & c_{ij} & \vdots \\ c_{r1} & \cdots & c_{rr} \end{pmatrix} \quad (1)$$

Here r is the number of all nodes/actors who were involved in the commenting interactions. c_{ij} is a cell in the matrix, which refers to the number of comments that actor i made to the posts from actor j.

(2) Like Node-Node Matrix (LNNM): Description of like

$$LNNM = \begin{pmatrix} l_{11} & \cdots & l_{1w} \\ \vdots & l_{ij} & \vdots \\ l_{w1} & \cdots & l_{ww} \end{pmatrix} \quad (2)$$

Here w is the number of all nodes/actors who were involved in the reacting (liking) interactions. l_{ij} is a cell in the matrix, which refers to the number of likes that actor i made to the posts from actor j.

(3) Tag Node-Node Matrix (TNNM): Description of tag

$$TNNM = \begin{pmatrix} t_{11} & \cdots & t_{1n} \\ \vdots & t_{ij} & \vdots \\ t_{n1} & \cdots & t_{nn} \end{pmatrix} \quad (3)$$

Here n is the number of all nodes/actors who were involved in the tagging interactions. t_{ij} is a cell in the matrix and it refers to the number of posts that actor i created, in which actor j was tagged.

(4) Share-out Node-Node Matrix (TNNM): Description of tag

$$SNNM = \begin{pmatrix} s_{11} & \cdots & s_{1p} \\ \vdots & s_{ij} & \vdots \\ s_{p1} & \cdots & s_{pp} \end{pmatrix} \quad (4)$$

Here p is the number of all nodes/actors who were involved in the sharing-out interactions. s_{ij} is a cell in the matrix, which refers to the number of posts that actor i shared-out posted by actor j.

These four matrices are not symmetric because when actor i made a comment on the post of actor j, or tagged j in a post, or liked a post of actor j, or shared a post of actor j, it does not mean that actor j made a comment on the post of an actor i, or tagged i in a post, or liked a post of actor i, or shared a post of actor i. It is an important characteristic of the four matrices. In addition, if there was an interaction connection between actor i and actor j, the frequency that actor i acted on actor j may not be equal to the frequency that actor j acted on actor i.

Normalization of the original node-node matrices

Each of the original matrices has to be normalized before these matrices can be combined. In the normalization, the size of a normalized original matrix should be equal to the size of the final node-node mega matrix (FNNMM); the order of the actors in the normalized original matrix should be the same as the order of the actors in the FNNMM. The normalized matrices are symmetric. The sizes of all normalized matrices are equal to the number of actors who were involved in any of the four types of connections: commenting, reacting (liking), tagging, and sharing-out.

(5) Normalized Comment Node-Node Matrix (NCNNM) is defined as:

$$NCNNM = \begin{pmatrix} c'_{11} & \cdots & c'_{1q} \\ \vdots & c'_{ij} & \vdots \\ c'_{q1} & \cdots & c'_{qq} \end{pmatrix} (5)$$

Here q is the number of actors who were involved in any of the four types of connections. If an actor in NCNNM does not appear in the CNNM, it means that it is a newly added actor. Then the cells in its corresponding row and column are set to 0 in the NCNNM. This is an important procedure for the normalization process. All other cells in the normalized matrix are the same value as the original matrix. The NCNNM and FNNMM should share the same matrix structure for the purpose of the normalization.

(6) Normalized React (like) Node-Node Matrix (NLNNM) is defined as:

$$NLNNM = \begin{pmatrix} l'_{11} & \cdots & l'_{1q} \\ \vdots & l'_{ij} & \vdots \\ l'_{q1} & \cdots & l'_{qq} \end{pmatrix} (6)$$

As described above, if an actor in NLNNM does not appear in the LNNM, it means that it is a newly added actor. Then the cells in its corresponding row and column are set to 0 in the NLNNM. All other cells in the normalized matrix are the same value as the original matrix.

(7) Normalized Tag Node-Node Matrix (NTNNM) is defined as:

$$NTNNM = \begin{pmatrix} t'_{11} & \cdots & t'_{1q} \\ \vdots & t'_{ij} & \vdots \\ t'_{q1} & \cdots & t'_{qq} \end{pmatrix} \quad (7)$$

As described above, if an actor in NTNNM does not appear in the TNNM, it means that it is a newly added actor. Then the cells in its corresponding row and column are set to 0 in the NTNNM. All other cells in the normalized matrix are the same value as the original matrix.

(8) Normalized Share-out Node-Node Matrix (NSNNM) is defined as:

$$NSNNM = \begin{pmatrix} s'_{11} & \cdots & s'_{1q} \\ \vdots & s'_{ij} & \vdots \\ s'_{q1} & \cdots & s'_{qq} \end{pmatrix} \quad (8)$$

As described above, if an actor in NSNNM does not appear in the SNNM, it means that it is a newly added actor. Then the cells in its corresponding row and column are set to 0 in the NSNNM. All other cells in the normalized matrix are the same value as the original matrix.

Above all, the NCNNM, the NLNNM, the NTNNM, the NSNNM and the FNNMM share the same matrix structure for the purpose of the normalization.

Creation of the final node-node mega matrix

Finally, the FNNMM is created based on the above four normalized matrices after the normalization process. The FNNMM should possess the characteristics of all the four normalized matrices.

(9) Final node-node mega matrix (FNNMM) is defined as:

$$FNNMM = NCNNM + NLNNM + NTNNM + NSNNM$$

$$= \begin{pmatrix} c'_{11} + l'_{11} + t'_{11} + s'_{11} & \cdots & c'_{1q} + l'_{1q} + t'_{1q} + s'_{1q} \\ \vdots & c'_{ij} + l'_{ij} + t'_{ij} + s'_{ij} & \vdots \\ c'_{q1} + l'_{q1} + t'_{q1} + s'_{q1} & \cdots & c'_{qq} + l'_{qq} + t'_{qq} + s'_{qq} \end{pmatrix} \quad (9)$$

3.3.3 Network measurements

As discussed in the Introduction chapter, a number of network measurements assist researchers in gaining insights to the structures of the social network. Both network-level and actor-level measurements reveal the interaction patterns from different perspectives. Network-level measurements aim to identify the connection patterns among all nodes in a network, while actor-level measurements focus on revealing the characteristics of an individual node. Table 9 summarizes the network measurements employed in this study, and the research questions and hypotheses that each measurement aims to answer and test.

Level of measurement	**Measurement**	**Research question**	**Hypothesis**
Network-level	Network size	RQ1.1, RQ1.2	
	Network density	RQ1.1, RQ1.2	
	Reciprocity	RQ1.1, RQ1.2	
	Degree centralization	RQ1.1, RQ1.2	
	Betweenness centralization	RQ1.1, RQ1.2	
	Closeness centralization	RQ1.1, RQ1.2	
Actor-level	In-degree	RQ2.2	
	Out-degree	RQ2.2	
	Degree centrality	RQ1.1, RQ1.2, RQ2	H_{01a}, H_{02a}, H_{03a}, H_{04a}
	Betweenness centrality	RQ1.1, RQ1.2, RQ2	H_{01b}, H_{02b}, H_{03b}, H_{04b}
	Closeness centrality	RQ1.1, RQ1.2, RQ2	H_{01c}, H_{02c}, H_{03c}, H_{04c}

Table 9. Network measurements and serving research questions

3.5.3.1. Network-level measurements

As shown in Table 9, the investigation of the network-level measurements serves to answer the RQ1.1 and the RQ1.2. Seven network-level measurements were adopted to describe the patterns of the interactions appearing in each autism support group on Facebook, including network size, network density, reciprocity, and centralization (degree centralization, betweenness centralization, and closeness centralization). Network size refers to the number of actors in a network. Network density measures the number of connections in the network, expressed as a proportion of the number possible. The network density of a social network implies the speed at which information or resources diffuse among the actors. In the context of an interaction network, reciprocity indicates the extent to which connections in a directed network are mutually linked.

Centralization refers to the extent a network is dominated by a single node (Borgatti et al., 2013). Freeman's general formula for centralization is measured as summing the difference between each node's centrality and the centrality of the most central node, and then dividing the sum by the maximum possible value where the star-shape network would get (Borgatti et al., 2013). Each type of centralization measurements (degree centralization, betweenness centralization, and closeness centralization) can be calculated by using the corresponding centrality measurements (degree centrality, betweenness centrality, and closeness centrality).

3.5.3.2. Actor-level measurements

Actor-level centrality measurements are used to further compare the differences among different autism support groups on Facebook. In-degree and out-degree measure the frequencies of connections a given actor received and launched. In-degree of an actor is the number of connections leading to that actor, while the out-degree of an actor is the number of connections leading away from that actor.

Three actor-level centrality measurements (i.e. degree centrality, betweenness centrality, closeness centrality) were adopted to measure the positional importance of group members in the group. Degree centrality refers to the number of connections incident upon a node. The degree centrality implies the potential communication ability of a certain actor. Actors with higher degree centrality have higher probability of receiving and transmitting the information flows, and thus can be considered to have influence over other actors in the network (Abraham, Hassanien, & Snášel, 2010).

Geodesic distance between two actors refers to the number of edges in the shortest path connecting them. The betweenness centrality of a node *j* is defined as the share of times that a node *i* needs the node *j* in order to reach a node *k* via the shortest path (Borgatti, 2005). Betweenness centrality evaluates the degree with which an actor controls the flow of information in the network. Actors with higher betweenness centrality act as the "brokers" (Abraham et al., 2010). In the context of autism support groups on Facebook, group members with higher betweenness centrality bear more possibility to control the communication among group members.

Closeness centrality basically measures how close a node is located with respect to every other node in the network (Abraham et al., 2010). Closeness centrality can be calculated as the inverse of the sum of the geodesic distances between each actor and every other actor in the network (as shown in Equation 8). Actors with higher closeness are able to reach (or be reached by) more other nodes in the network through geodesic or shortest paths. An actor that is close to many others can instantly communicate and interact with others without going through many intermediaries (Makagon, McCowan, & Mench, 2012).

3.5.3.3. Measurement definitions

Given a network N with n nodes, that is, the size of the network N is n. Here n_i, n_j, and n_k are three nodes in the network. The total connections of n_i is $d(n_i)$, which means the degree of n_i is $d(n_i)$. Similarly, the in-degree centrality and out-degree centrality is equal to the in-degree and out-degree of the node, respectively. The number of the maximum connections for n_i in the network is n-1 when n_i is directly connected to all other nodes. $C_D(n_i)$ refers to the degree centrality for the n_i, $C_B(n_i)$ refers to the betweenness centrality for the n_i, and $C_C(n_i)$ refers to the closeness centrality for the n_i. $C_D(N)$ refers to the degree centralization for the network N, $C_B(N)$ refers to the betweenness centralization for the network N, and $C_C(N)$ refers to the closeness centralization for the network N. Based on the above assumptions, the following equations describe the definitions of the network-level measurements and actor-level measurements applied in this study.

The network size of a network N is defined as:

$$Size(N) = n \qquad (10)$$

The network density for a direct network N is defined as:

$$Density(N) = n(n-1) \qquad (11)$$

Here l is the total number of connections in network N, and $l^{\leftrightarrow}$ is the total number of reciprocated connection. The reciprocity is defined as:

$$Reciprocity(N) = \frac{l^{\leftrightarrow}}{l} \qquad (12)$$

The degree centrality for n_i is defined as:

$$C_D(n_i) = \mathrm{d}(n_i) \qquad (13)$$

Here g_{ijk} is the number of paths from node i to node k that pass through node j, while g_{ik} is the number of all the paths from node i to node k in the network. The betweenness centrality for n_j is defined as:

$$C_B(n_j) = \sum_{i<k} \frac{g_{ijk}}{g_{ik}} \qquad (14)$$

Here $g(n_i, n_j)$ is the geodesic distance from node i to node j. The closeness centrality for n_i is defined as:

$$C_C(n_i) = \left[\sum_{j=1}^{n} g(n_i, n_j)\right]^{-1} \qquad (15)$$

Here $C_D\ (n^*)$ is the maximum degree centrality in N and $C_D\ (n_i)$ is the degree centrality of a node in N; $C_B\ (n^*)$ is the maximum betweenness centrality of any node in N and $C_B\ (n_i)$ is the betweenness centrality of a node in N; and $C_C\ (n^*)$ is the maximum closeness centrality of any node in N and $C_C\ (n_i)$ is the closeness centrality of a node in N. The degree centralization, betweenness centralization, and closeness centralization are defined as:

$$C_D\ (N) = \frac{\sum_{i=1}^{n}[C_D(n^*) - C_D(n_i)]}{(n-1)(n-2)} \qquad (16)$$

$$C_B\ (N) = \frac{\sum_{i=1}^{n}[C_B(n^*) - C_B(n_i)]}{(n-1)(n-2)} \qquad (17)$$

$$C_C\ (N) = \frac{\sum_{i=1}^{n}[C_C(n^*) - C_C(n_i)]}{(n-1)(n-2)} \qquad (18)$$

3.3.4 Centrality normalization

Notice that in order to test the proposed hypotheses; the centrality measurements between two networks were compared. For instance, the comparison between the centrality measurements derived from one autism support group and the centrality measurements derived from another autism support group. The size of a network, which is the number of nodes in the network, may affect the centrality values according to their definitions. The larger a network size is, the bigger the centrality of a node may be. To avoid the possible negative impact of network sizes on the comparisons, the network sizes were normalized to achieve plausible test results in the study. After the normalization, the comparisons across different networks were sound.

As a result, the normalized degree centrality (including in-degree and out-degree) for n_i is defined as:

$$C'_D(n_i) = \frac{C_D\ (n_i)}{n-1} \qquad (19)$$

Here the number of pairs of nodes in the network is *(n-1)(n-2)/2*. The normalized betweenness centrality for n_i is defined as:

$$C'_B(n_i) = \frac{C_B\ (n_i)}{(n-1)(n-2)/2} \qquad (20)$$

Here *n-1* stands for the minimum possible distance from node n_i to the *n-1* other nodes in the network. The normalized closeness centrality for n_i is defined as:

$$C'_C(n_i) = \frac{C_C\ (n_i)}{\frac{1}{(n-1)}} = (n-1)C_C\ (n_i) \qquad (21)$$

3.3.5 Influential users based on interactions

Commenting and reacting (liking) are two of the most popular activities on Facebook. Both interactions create implicit relationships between members in a Facebook group. Hansen et al. (2010) even proposed that comments are better indicators of social ties than follower/friend relationships. Considering the nature of the interaction of commenting and reacting (liking), both comment network and react (like) network were treated as directed networks. In a directed graph, the out-degree measures the number of edges leaving a given vertex, and the in-degree measures the number of edges incident upon a given vertex (Butts, 2006). In the comment network, the in-degree means the number of comments a certain member received, whereas the out-degree indicates the number of comments a certain member created to others. It also applies to the like network. Cha et al. (2012) suggested that users with large in-degrees can effectively spread information to a large number of nodes.

The top scorers in terms of out-degree (number of comments and likes sent out) were users actively creating the connections with others in the network. Users with higher out-degrees showed more interest in interacting and communicating with others.

Apart from the raw degree of the actors, centrality is one of the most important structural attributes of social networks (Freeman, 1978). Betweenness centrality is based upon the frequency with which a point falls between pairs of other points on the shortest paths connecting them (Freeman, 1978). According to the research of Cheong and Cheong (2011), these users can be viewed as opinion leaders in the support group since being on the shortest paths between other members they are able to control the flow of information in the network.

Figures generated from NetDraw depict the interaction networks among group members in terms of the commenting activity, the reacting (liking) activity, the tagging activity, and the sharing-out activity. The nodes represent individual group member and are shown as circles while the directed links represent commenting or reacting (liking) movements from one to another. The size of the nodes indicates the betweenness centrality of the user in the network. The frequencies of the interactions define the strength of the connections and are illustrated by the thickness of the ties between users. Individuals who possessed larger betweenness centrality are positioned as the hubs in the networks.

3.4 Topic modeling

3.4.1 Text preparation process

Standard text mining systems usually operate on prepared documents. User-generated textual data appearing in social media, Internet webpages, etc. may not be controlled. Therefore, those data need to be cleansed and processed before further analysis.

Text preparation process refers to a series of steps to prepare the raw text before more in-depth natural language processing, e.g. topic model training. Text preparation commonly consists of the selection, cleansing and preprocessing of text (Liddy, 2000). Figure 13 describes the text preparation procedures applied in this study.

In this study, the text preparation process was operated by Python scripts using NLTK toolkits. Tokenization utilizes a simple regular expression model to extract the tokens from the sentences (Kao & Poteet, 2007). After removing all punctuation and lowercasing all tokens, text containing stop words (e.g. “the”, “is”) can be filtered based on a list of stop words adopted by the NLTK toolkit. The stemming procedure employs the classic Porter algorithm (Porter, 1980). Finally, all text needed to be cleansed and checked manually to insure the accuracy of the subsequent analyses.

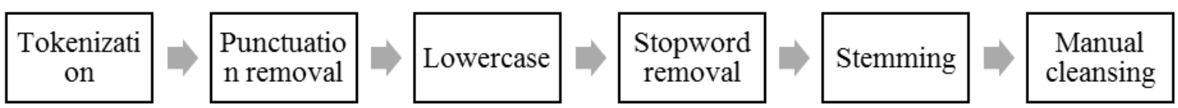

Figure 13. Text preparation process

3.4.2 Latent Dirichlet Allocation (LDA)

Griffiths and Steyvers (2004) proposed Latent Dirichlet Allocation (LDA) as a particular generative model for topic discovery. LDA assumes a latent structure consisting of a set of topics, and the words that appear in a paper reflect the particular set of topics (Griffiths & Steyvers, 2004). The basic idea behind LDA considers documents as random mixtures over latent topics where each topic is represented by a distribution over words (Blei, Ng, & Jordan, 2003). Figure 14 represents the probabilistic graphical model of a LDA model (Blei et al., 2003).

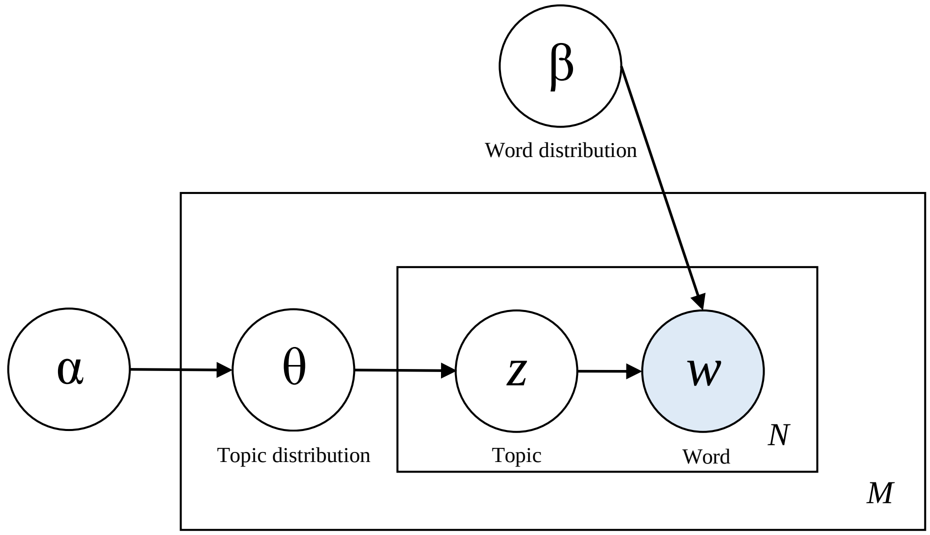

Figure 14. Graphical model representation of LDA

Following the methods introduced by Griffiths and Steyvers (2004), in this study the LDA model was implemented in *Python* with *gensim* package (Řehůřek & Sojka, 2010) using the Gibbs Sampling inference method. The hyperparameters α and β control the amount of smoothing in the model estimation process. A greater value indicates more smoothing and a smaller value indicates less smoothing. The hyperparameters α was set to 50/K (K is the number of topics) while β equals 0.01. The number of iterations was set as 500. The settings of α and β were based on the suggestion of Steyvers and Griffiths (2007) where they found it worked well with many different text collections.

3.4.3 LDA model evaluation

The pre-specified numbers of topics influence the performance of the topic model training. The topics discovered by LDA capture the correlations between words in documents, but LDA cannot generate the correlations among the captured topics (Cao, Xia, Li, Zhang, & Tang, 2009). Too few topics do not allow authors to be distinguished, whereas too many may cause relationships to be weaker (Lu & Wolfram, 2012). Ideally, topics identified from the documents are supposed to be distinctive from each other. One way to evaluate the LDA model is through the interactive visualization supporting rapid experimentation for interpretive hypotheses (Murdock & Allen, 2015).

LDAvis handles the model checking problem to aid topic interpretation by displaying the ranking of terms within topics and the relevance among topics (Sievert & Shirley, 2014). It presents topic-word and topic-topic relationships alongside composition information. In this study, the *pyLDAvis* package (Sievert & Shirley, 2014) was implemented in *Python* to visualize the models generated from the group discussions, as well as assist the modeling checking process. Different values of K, or numbers of topics, are tested. The author assessed the outcomes and decided the most reasonable outcome based on the data.

3.5 Sentiment analysis

Sentiment analysis, also known as opinion discovery, centers on identifying the viewpoint underlying the documents. One particular and common type of sentiment analysis is to detect whether the sentiment polarity, which is the overall orientation of a certain text, is positive or negative (Lau et al., 2014).

3.5.1 Lexalytics

Lexalytics has been around since 2003 and offers sentiment analysis via its Salience engine which is marketed as an on-premise solution. Lexalytics' key message is State-of-the-art technologies to turn unstructured text into useful data. Lexalytics' sentiment analysis tools can be configured to determine sentiment on a range of levels. In addition to identifying whether a given document of text is positive, negative, or neutral, Lexalytics is able to assign a specific score to show how strong that sentiment is ("Text Analytics," 2016).

One significant feature of Lexalytics is the adaption to social media content. Professional writing tends to be well written with solid grammar and punctuation, which helps significantly in the processing of the text to measure sentiment (Catlin, 2011). Streams on social media such as Facebook and Twitter, however, often contain some creative grammar and considerable grammar mistakes. Considering the features of social media texts, Catlin (2011) claimed that the results of Lexalytics in measuring sentiment have been exceptional.

The first step of scoring the sentiment of a document is to break the document into its basic parts of speech (Lak & Turetken, 2014). Lexalytics applies well-defined techniques to tag the various parts of speech and reaches extremely high accuracy (Lak & Turetken, 2014). Moreover, Lexalytics includes a very large dictionary of sentiment bearing phrases along with their relative sentiment scores (Lak & Turetken, 2014). In order to determine the sentiment of the overall document, Lexalytics developed its own scoring algorithms: using a proprietary way to add up the weighted phrases. The software identifies the sentiment phrases (e.g. negation, good) first, and then uses the syntax matrix to determine the syntactic effect of the ordering of the words ("Text Analytics," 2016).

3.5.2 Sentiment analysis processes

In this study, Lexalytics carried out the sentiment analysis on the content from each group. Figure 15 summarizes the procedures of sentiment analysis. All of the initial posts and the replies were combined together as the input data set for the sentiment analysis. Each source text contained one or more sentences that the users created. Lexalytics identifies the emotive phrases within each source text and then combines them to discern the overall sentiment of the text. The automatic sentiment scoring method scores each text according to the same algorithm, and thus can avoid human biases (Lak & Turetken, 2014). Lexalytics provided sentiment scores in the range of -2 to +2, along with the sentiment categories (positive, neutral, or negative) in which the text appeared.

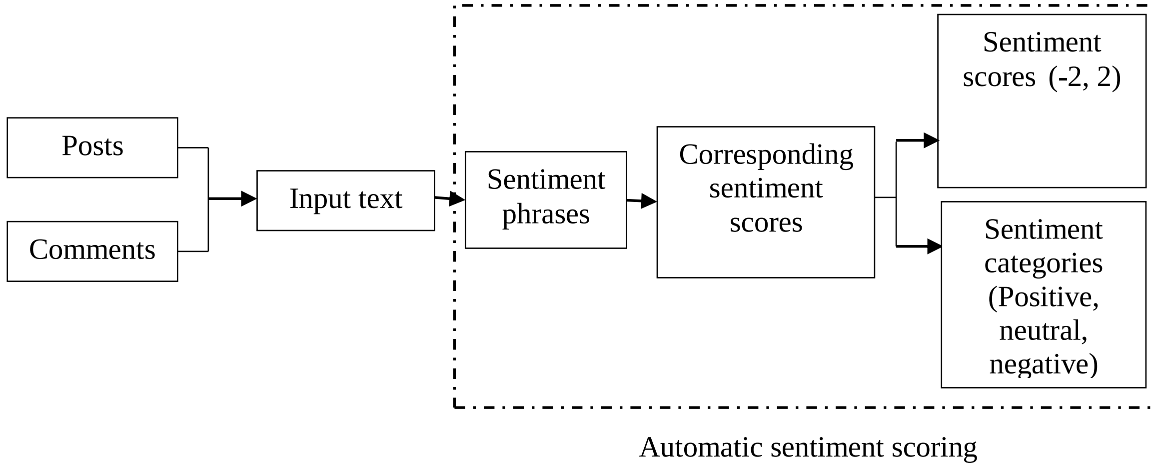

Figure 15. Sentiment analysis process

3.6 Inferential analysis

Inferential statistics have been used to investigate the user behaviors on social media (Jansen, Sobel, & Cook, 2011). In this study, inferential analysis served to examine the differences and similarities between autism support groups on Facebook under different categories. The use of statistical analysis of the characteristics of autism support groups on Facebook was essential to understand the social media use of autism-affected users.

In this section, the inferential analysis that was applied to test each hypothesis is discussed in detail. For each of the hypotheses, the independent and dependent variables and other important factors are stated, and a discussion of how the data was organized is included.

Inferential analysis on a social network is based on relations among actors of the network, not on relations between variables. The relations among the actors on the network were defined in the final node to node mega matrix (FNNMM). The matrix describes interactions among the nodes/actors. The centrality (including degree, betweenness, and closeness) were calculated based on the matrix. In other words, the relations among the actors depended on each other.

Standard inferential tests assume that the variables are drawn from a population with a particular distribution, such as normal distribution (Borgatti et al., 2013). It implies that traditional inferential statistical method like t-test and ANOVA test cannot apply directly to the network actor data because the traditional inferential statistical methods generally assume independent observations. The unique exponential random graph models (ERGMs) for inferential statistical analysis (Borgatti et al., 2013) present a unique way to address the issue. The models successfully solve the problem that observations must be statistically independent and the observations must follow a normal distribution.

The significance level (α) for all tests was equal to 0.05. If the resultant *p*-value of a null hypothesis test was smaller than 0.05, the null hypothesis was rejected. Otherwise, the null hypothesis failed to be rejected. If a modified ANOVA test was rejected, then a follow-up investigation was conducted to detect the reason of the rejection.

3.6.1 Hypothesis group 1

RQ1.1: Are there any differences between male group members and female group members in terms of interactions in autism support groups on Facebook?

> $H_{01(a)}$: *There are no significant differences between male group members and female group members in terms of the interactions in autism support groups on Facebook based on the degree centrality.*
>
> $H_{01(b)}$: *There are no significant differences between male group members and female group members in terms of the interactions in autism support groups on Facebook based on the betweenness centrality.*
>
> $H_{01(c)}$: *There are no significant differences between male group members and female group members in terms of the interactions in autism support groups on Facebook based on the closeness centrality.*
>
> $H_{02(a)}$: *There are no significant differences between male group members and female group members in each of the defined categories in terms of the interactions in autism support groups on Facebook based on the degree centrality.*

$H_{02(b)}$: There are no significant differences between male group members and female group members in each of the defined categories in terms of the interactions in autism support groups on Facebook based on the betweenness centrality.

$H_{02(c)}$: There are no significant differences between male group members and female group members in each of the defined categories in terms of the interactions in autism support groups on Facebook based on the closeness centrality.

Since there are five defined categories investigated in this study, each of $H_{02(a)}$, $H_{02(b)}$, and $H_{02(c)}$ was then divided into 5 associated sub-hypotheses based on the categories (i.e. *Awareness, Treatment, Parents, Research,* and *Local support*). Table 10 lists the 15 sub-hypotheses associated with $H_{02(a)}$, $H_{02(b)}$, and $H_{02(c)}$.

$H_{01(a)}$, $H_{01(b)}$, $H_{01(c)}$, $H_{02(a)}$, $H_{02(b)}$, $H_{02(c)}$ and the associated sub-hypotheses compose the hypothesis group 1. The independent variable of hypothesis group 1 is gender. The valid values or levels of this independent variable are male and female. The dependent variable of the hypothesis group 1 is the interactions in autism support groups on Facebook. The dependent variable can be measured by the degree centrality of each actor, the betweenness centrality of each actor, and the closeness centrality of each actor. An independent t-test was applied to test each hypothesis in hypothesis group 1.

Category	Awareness	Treatment	Parents	Research	Local support
$H_{02(a)}$	$H_{02(a1)}$: There are no significant differences between male group members and female group members in Awareness category in terms of the interactions in autism support groups on Facebook based on the degree centrality.	$H_{02(a2)}$: There are no significant differences between male group members and female group members in Treatment category in terms of the interactions in autism support groups on Facebook based on the degree centrality.	$H_{02(a3)}$: There are no significant differences between male group members and female group members in Parents category in terms of the interactions in autism support groups on Facebook based on the degree centrality.	$H_{02(a4)}$: There are no significant differences between male group members and female group members in Research category in terms of the interactions in autism support groups on Facebook based on the degree centrality.	$H_{02(a5)}$: There are no significant differences between male group members and female group members in Local support category in terms of the interactions in autism support groups on Facebook based on the degree centrality.
$H_{02(b)}$	$H_{02(b1)}$: There are no significant differences between male group members and female group members in Awareness category in terms of the interactions in autism support groups on Facebook based on the betweenness centrality.	$H_{02(b2)}$: There are no significant differences between male group members and female group members in Treatment category in terms of the interactions in autism support groups on Facebook based on the betweenness centrality.	$H_{02(b3)}$: There are no significant differences between male group members and female group members in Parents category in terms of the interactions in autism support groups on Facebook based on the betweenness centrality.	$H_{02(b4)}$: There are no significant differences between male group members and female group members in Research category in terms of the interactions in autism support groups on Facebook based on the betweenness centrality.	$H_{02(b5)}$: There are no significant differences between male group members and female group members in Local support category in terms of the interactions in autism support groups on Facebook based on the betweenness centrality.
$H_{02(c)}$	$H_{02(c1)}$: There are no significant differences between male group members and female group members in Awareness	$H_{02(c2)}$: There are no significant differences between male group members and female group members in Treatment	$H_{02(c3)}$: There are no significant differences between male group members and female group members in Parents	$H_{02(c4)}$: There are no significant differences between male group members and female group members in Research	$H_{02(c5)}$: There are no significant differences between male group members and female group members in Local support

	category in terms of the interactions in autism support groups on Facebook based on the closeness centrality.	category in terms of the interactions in autism support groups on Facebook based on the closeness centrality.	category in terms of the interactions in autism support groups on Facebook based on the closeness centrality.	category in terms of the interactions in autism support groups on Facebook based on the closeness centrality.	category in terms of the interactions in autism support groups on Facebook based on the closeness centrality.

Table 10. Sub-hypotheses associated with $H_{02(a)}$, $H_{02(b)}$, and $H_{02(c)}$

3.6.2 Hypothesis group 2

RQ1.2: Are there any significant differences among the defined categories in terms of online interactions in autism support groups on Facebook?

$H_{03(a)}$: There are no significant differences among the defined categories in terms of the interactions in autism support groups on Facebook based on the degree centrality.

$H_{03(b)}$: There are no significant differences among the defined categories in terms of the interactions in autism support groups on Facebook based on the betweenness centrality.

$H_{03(c)}$: There are no significant differences among the defined categories in terms of the interactions in autism support groups on Facebook based on the closeness centrality.

Hypothesis group 2 consists of $H_{03(a)}$, $H_{03(b)}$, and $H_{03(c)}$. The independent variable of the hypothesis group 2 is the defined category of the group. The valid values or levels of this independent variable are the category of *Awareness, Treatment, Parents, Research,* and *Local support*. The dependent variable of the hypothesis group 2 is the interactions in autism support groups on Facebook. The dependent variable can be measured by the degree centrality of each actor, the betweenness centrality of each actor, and the closeness centrality of each actor. Since the number of the independent variable levels (5) is larger than 2 and subjects in different groups receive different treatments ("Awareness", "Treatment", "Parents", "Research", and "Local support"), a modified ANOVA analysis was conducted to test each hypothesis in hypothesis group 2.

3.6.3 Hypothesis group 3

RQ4.1: Are there any differences between male group members and female group members in each of the defined sub-categories in terms of sentiment characteristics in autism support groups on Facebook?

> *H_{04}: There are no significant differences between male group members and female group members in terms of the sentiment in autism support groups on Facebook.*
>
> *H_{05}: There are no significant differences between male group members and female group members in each of the defined categories in terms of the sentiment in autism support groups on Facebook.*

Similar to the case with $H_{02(a)}$, $H_{02(b)}$, and $H_{02(c)}$, H_{05} was then divided into 5 associated sub-hypotheses in which each sub-hypothesis was based on the sub-categories (i.e. *Awareness, Treatment, Parents, Research,* and *Local support*). Table 11 lists the five sub-hypotheses associated with H_{05}.

Category	**Awareness**	**Treatment**	**Parents**	**Research**	**Local support**
H_{05}	$H_{05(a)}$: There are no significant differences between male group members and female group members in Awareness category in terms of the sentiment in autism support groups on Facebook.	$H_{05(b)}$: There are no significant differences between male group members and female group members in Treatment category in terms of the sentiment in autism support groups on Facebook.	$H_{05(c)}$: There are no significant differences between male group members and female group members in Parents category in terms of the sentiment in autism support groups on Facebook.	$H_{05(d)}$: There are no significant differences between male group members and female group members in Research category in terms of the sentiment in autism support groups on Facebook.	$H_{05(e)}$: There are no significant differences between public groups and closed in Local support category in terms of the sentiment in autism support groups on Facebook.

Table 11. Sub-hypotheses associated with H_{05}

H_{04}, H_{05}, and five sub-hypotheses associated with H_{05} compose the hypothesis group 3. The independent variable of the hypothesis group 3 is the gender of the group members. The valid values or levels of this independent variable are male and female. The dependent variable of the hypothesis group 3 is the sentiment appearing in autism support groups on Facebook. The dependent variable can be measured by the sentiment scores of the content posted by the group members. The Mann-Whitney U test was applied to test each hypothesis in hypothesis group 3.

3.6.4 Hypothesis group 4

RQ4.2: Are there any significant differences among the defined categories in terms of sentiment characteristics in autism support groups on Facebook?

> *H_{06}: There are no significant differences among the defined categories in terms of the sentiment in autism support groups on Facebook.*
>
> *H_{07}: There are no significant differences among the defined categories in terms of the sentiment of group members with the same gender in autism support groups on Facebook.*

H_{07} was then divided into two associated sub-hypotheses based on the gender of group members (i.e. male and female). Table 12 lists the two sub-hypotheses associated with H_{07}.

Gender	Male	Female
H_{07}	$H_{07(a)}$: There are no significant differences among the defined categories in terms of the sentiment of male group members in autism support groups on Facebook.	$H_{07(b)}$: There are no significant differences among the defined categories in terms of the sentiment of female group members in autism support groups on Facebook.

Table 12. Sub-hypotheses associated with H_{07}

H_{06}, H_{07}, and the associated sub-hypotheses with H_{07} compose the hypothesis group 4. The independent variable of the hypothesis group 4 is the defined category of the group. The valid values or levels of this independent variable are the category of *Awareness, Treatment, Parents, Research,* and *Local support*. The dependent variable of the hypothesis group 4 is the sentiment appearing in autism support groups on Facebook. The dependent variable can be measured by the sentiment scores of the content posted by the group members. The Kruskal-Wallis H test was used to test each hypothesis in hypothesis group 4.

Table 13 summarizes the research question, associated hypothesis, independent variable (IV), its valid values, dependent variable (DV), its measurement, and the method used to test.

Research questions	Hypothesis	IV	Valid values	DV	Measurement	Test
RQ1.1	Hypothesis	Gender	Male, Female	Interactions	Centrality	Modified

	group 1					t-test
RQ1.2	Hypothesis group 2	Category	Awareness, Treatment, Parents, Research, Local support	Interactions	Centrality	Modified ANOVA
RQ4.1	Hypothesis group 3	Gender	Male, Female	Sentiment	Sentiment scores	Mann-Whitney U test
RQ4.2	Hypothesis group 4	Category	Awareness, Treatment, Parents, Research, Local support	Sentiment	Sentiment scores	Kruskal-Wallis H test

Table 13. Descriptions of inferential analyses applied in this study

3.7 Validity and reliability

Research methodology plays an extremely important role in a study. Both validity and reliability are the most prominent criteria for the evaluation of a research study. Winter (2000) stated that "Reliability and validity are tools of an essentially positivist epistemology." (p. 7) The fundamental issue of validity is to evaluate how well the research study actually answers the research question (Gravetter & Forzano, 2011). Primarily, reliability is concerned with the question of whether the outcomes of a study are repeatable under the same research conditions (Bryman, 2012).

Validity and reliability issues are associated with the whole research process ranging from sampling strategy, data collection, to data analysis. Through a pilot study, the occurrence of some problems under real circumstances helped the researcher to consider possible approaches to meet the validity and reliability requirements in the future.

3.7.1 Internal Validity

Roe and Just (2009) defined internal validity as the ability of a researcher to argue that observed correlations are causal. In other words, internal validity attempts to ensure that the findings or results of the research are caused by the variables under investigation not by other unaccounted for influences (Winter, 2000).

The researcher in this study investigated autism-related groups on Facebook to answer the research problem and research questions. In order to ensure the internal validity of the study, multiple search sessions using the related search terms were conducted through the Facebook search engine. Since the entire population contains far too many groups to measure and study (Gravetter & Forzano, 2011), the researcher selected a sample to provide information about the population.

Through the preliminary exploration of all qualified groups, the qualified groups were classified into 10 categories, and each category was further divided to several sub-categories. Hence, the entire set of the Facebook groups related to autism can be considered the target population.

In the design and collection of social network data, Borgatti et al. (2013) identified the following errors that may threaten the validity of the research: omission errors, commission errors, edge/node attribution errors, and data collection and retrospective errors. In this study, the researcher collected the social network data based on the behavior recorded on the group wall pages, and thus the involved actors and relationships can be clearly identified. When considering edge/node attribution errors, all of the interactions appearing within the data collection time period result in the relationships between actors. The researcher would assume the interactions observed from the wall posts included all the interactions between group members. Under such an assumption, this study was able to avoid omission errors, commission errors, and edge/node attribution errors. The social network data in this study was captured directly from Facebook instead of individuals. Therefore, this study did not meet the threats from data collection and retrospective errors.

Inferential analysis was applied to compare the social network features among groups under each category. In regards to the internal validity, the researcher sampled groups focusing on different topics, and thus ensured the findings or results of the statistical tests were caused by the group theme. In addition, this study adopts the normalized centrality measurements to avoid the possible impact of network sizes on the comparisons.

3.7.2 External validity

External validity refers to "the extent to which the results obtained in a research study hold true outside that specific study" (Gravetter & Forzano, 2011 p. 166). It concerns the generalization ability of the outcomes resulted from a study.

In order to make sure of the external validity, the researcher must select a representative sample so that the results of the study can be generalized to a population. In this study, the researcher selected large and active groups. The adoption of comparatively large groups ensured there were enough group members and rich interactions in the groups for further analyses. In addition, the large body of information and behavior appearing in the groups potentially increased the possibility that what the researcher observed in the sample can be generalized to the population.

Although this study investigated the autism support groups on Facebook, the findings of this study are applicable to online autism communities on other social media platforms, such as the autism discussion forum on WrongPlanet.net ("Autism Community Forum," n.d.). In addition, the interaction patterns of users in the Facebook groups can be generalized to other health-related groups on Facebook. The research methods adopted in this study can be applied to explore the health-related topics on other social media platforms. For example, the way that social network analysis and sentiment analysis were employed in this study can be used to examine the depression topics on question and answering forums.

3.7.3 Reliability

Reliability concerns the repeatability of the research. In this study, the research objects were the autism support groups on Facebook. Facebook groups tend to be much more dynamic, which means sometimes a group may disappear overnight. Therefore, the research attempted to sample large-size groups that usually are more sustainable. In addition, all of the wall posts of those sampled groups were saved as Adobe PDF files, in case of the disappearance of some groups.

During the sampling process in this study, all autism support groups on Facebook that met the selection criteria were classified into ten categories based on the purposes of the groups. Expert coders classified the autism support groups into the defined categories based on the group titles and group descriptions. To ensure the reliability of the study, the classification process needed to be done by coders with professional backgrounds. Measurement of the extent to which coders assign the groups to the same category is called inter-coder reliability (McHugh, 2012). The kappa statistic is widely used to test inter-coder reliability. To test the inter-coder reliability of assigning categories to groups, two coders independently coded 20 selected groups randomly selected from all groups that met the criteria. The inter-coder reliability was 0.67 according to Cohen's (1960) kappa reliability formula. According to Cohen’s interpretation, the two coders achieved a substantial agreement in the category assignments (McHugh, 2012).

Above all, this section discussed the research validity and reliability issues from the methodological perspective. Then, the background and research design of the proposed study and results from the pilot study were briefly presented. The researcher also described the steps and procedures that were carried out in the sampling, data collection, and data analysis. Based on the validity and reliability concerns, some specific considerations and detailed approaches were designed to ensure the soundness of the research outcomes. The methods developed during this study provided a foundational point from which social network analysis, inferential analysis and content analysis can be applied to study the support groups in social media.

3.8 Ethical considerations

Ethical issues play a critical role in research involving human subjects, especially in social science. Ethical considerations are established to better protect the rights of the research participants. Research ethics concern the procedures that aim to protect those who participate in the research (Schnell & Heinritz, 2006).

In this study, data was collected from Facebook groups that consisted of real Facebook users. Ethical issues were considered in the methodological procedures. Group members who participate in the sampled groups were the human subjects involved in this study. In order to protect the anonymity and confidentiality of the human subjects, all data collected from the groups were de-identified and safely stored. Quotes stated by subjects were not directly linked to specific group members. Specific names and locations was blacked out or replaced by pseudonyms in the quotes cited in the study results.

To inform the participants of the data collection processing in the sampled groups, the author posted the notification one week before the data collection started. The notifications were posted every two weeks in the groups in order to make sure that the members were informed. Since all new posts appeared on each group member’s news feed, all group members were informed. The contact information of the author was also added in the notifications. If anyone did not want his/her posts to be used in the study, he/she could have contacted the author to exclude his/her posts from this study.

The mission of the Institutional Review Board (IRB) is to protect the human subjects involved in the research. IRB aims to minimize the risks and maximize the potential benefits for human subjects who participate in research. This study has submitted the study plan and all supporting documents to the IRB at the University of Wisconsin-Milwaukee (UWM). The protocol has been granted Exempt Status after review by the IRB at the UWM through March 21, 2019.

3.9 Summary

Table 14 summarizes the research questions, sub-questions, data collection methods, and data analysis methods of this study. The four research questions respectively explored the interaction patterns among group members, identified the influential users in each group, investigated the discussion topics of each group, and examined the sentiment characteristics of group discussions. In order to answer the first two research questions, the group interactions and activities were used for social network analysis and inferential analysis. To approach the third research question, group discussions were used for topic modeling. Those group discussions were analyzed by sentiment analysis and inferential analysis to approach the fourth research question.

Research questions	**Sub-questions**	**Hypothesis**	**Data collection**	**Data analysis**
RQ1: How do users interact with each other in autism support groups on Facebook based on social network analysis?	RQ1.1: Are there any differences between male group members and female group members in terms of interactions in autism support groups on Facebook?	Hypothesis group 1	Group interactions and activities	Social network analysis, inferential analysis
	RQ1.2: Are there any differences among the defined categories in terms of online	Hypothesis group 2	Group interactions and activities	Social network analysis,

	interactions in autism support groups on Facebook?			inferential analysis
RQ2: Who are the influential users based on interactions in autism support groups on Facebook?	RQ2.1: What are the characteristics of the influential users based on interactions in autism support groups on Facebook?		Group interactions and activities	Social network analysis
	RQ2.2: How do the influential users based on interactions interact with others in autism support groups on Facebook?		Group interactions and activities	Social network analysis
RQ3: What are the discussion topics that emerged from the discussions in autism support groups on Facebook?			Group discussions	Topic modeling
RQ4: What are the sentiment characteristics of discussions in autism support groups on Facebook?	RQ4.1: Are there any differences between male group members and female group members in each of the defined categories in terms of sentiment characteristics in autism support groups on Facebook?	Hypothesis group 3	Group discussions	Sentiment analysis, inferential analysis
	RQ4.2: Are there any differences among the defined categories in terms of sentiment characteristics in autism support groups on Facebook?	Hypothesis group 4	Group discussions	Sentiment analysis, inferential analysis

Table 14. Research questions and associated methods

Chapter 4. Results

This chapter presents the results of social network analysis, topic modeling, sentiment analysis, and statistical analysis on this research exploration of interactions found in autism support groups located on Facebook.

4.1 Description of the collected data

As discussed in the data collection section, through the preliminary explorations, the investigated autism related support groups on Facebook were classified into 10 categories based on the group names and group descriptions. To qualify for the study, public groups with comparative active group discussions were chosen as the sample groups.

As a result, five Facebook autism support groups, each selected from a distinct category, were collected on December 12-15, 2017. The data collection window was set as April 1, 2017, to September 30, 2017, which covered six months of 2017. All of the group wall posts and group interactions were downloaded by NodeXL. Table 15 presents the basic descriptions of the sampled groups and the collected data. The names of the groups were not revealed for the privacy concerns.

Group	Category	Members	Involved members	Group interactions
Group 1	Awareness	5902	299	811
Group 2	Treatment	1577	297	2210
Group 3	Parents	1513	523	4515
Group 4	Research	2603	156	200
Group 5	Local support	2847	438	4716

Table 15. Descriptions of collected autism support groups

Group 1 is the largest group among the five selected groups, where only 5.1% of the group members participated in the six-month data collection period. Group 3, created for parents, family, and friends of autism patients, had 34.6% of group members engaged in the group discussions. Among the five groups, group 3 had the mos0t group members involved in the group discussions, while group 5 which provided the support for people living in a state, appeared to have the most active interactions among group members.

4.1.1 Descriptive statistics of involved group members

Various types of Facebook users can join the groups on Facebook, not only the individual users, but also other Facebook groups, Facebook Pages, and Facebook Page Communities. Among the investigated groups, the following types of roles were identified: male user, female users, Facebook pages, and Facebook groups. In a total of 14 cases, users left the gender identities or account types empty. Those users were classified as others in this study. Figure 16 describes the distributions of group members' roles in each group. Each bar represents a type of user's role, while the line indicates the total number of the involved group members. As can be seen in Figure 16, most of the involved group members (1665 out of 1713, 93.9%) were individual users. Among those individuals, female users (1319) greatly outnumbered the male users (346). To compare the behaviors between male group members and female group members, the rest of the paper focused on the individual users in the groups with user identified gender characteristics.

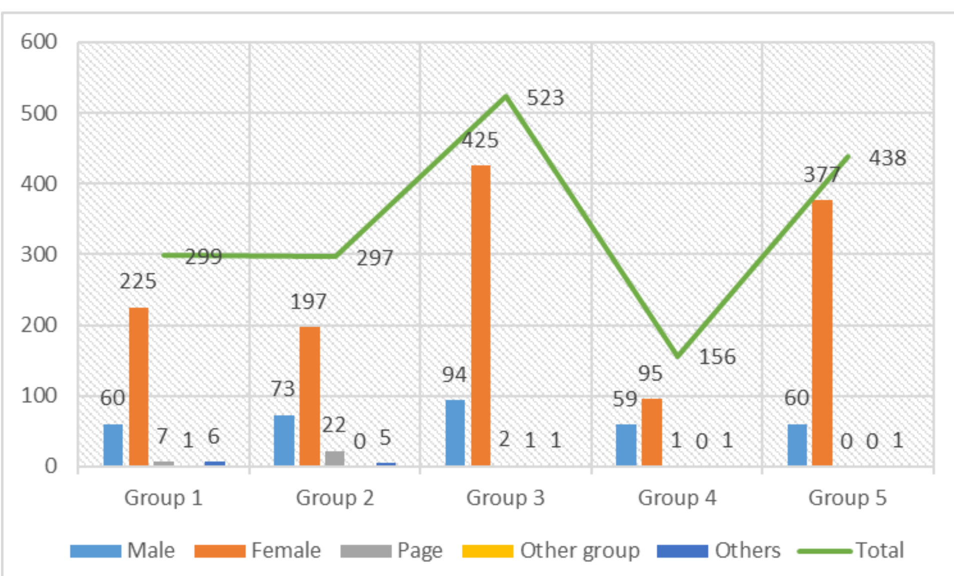

Figure 16. Distributions of group members' roles

4.2 Findings for research questions 1 (RQ1)

RQ1: How do users interact with each other in autism support groups on Facebook based on social network analysis?

The first research question aims to unveil how users communicate with each other within autism support groups on Facebook.

4.2.1 Descriptive statistics of the group interactions

Four types of group interactions were identified based on the group discussions. Table 16 provides descriptive statistics of the group interactions observed in each group. Group 5 and group 3 were the two most active groups in terms of the group interactions. Group 4 was the least active group with merely 200 interactions during the six-month period.

Group interactions	Group 1	Group 2	Group 3	Group 4	Group 5	Total
Comments	258	848	681	4	754	2545
Reactions	511	1212	3721	194	3893	9531
Tag	34	111	108	0	58	311
Share out	8	39	5	2	11	65
Total	811	2210	4515	200	4716	12452

Table 16. Basic descriptive statistics of the group interactions

Figure 17 depicts the distributions of the four types of group interactions in each group. Reactions were the most popular interactions across all groups. It is clear that group members favored giving comments and making reactions more than tagging someone or sharing others' posts out of the group.

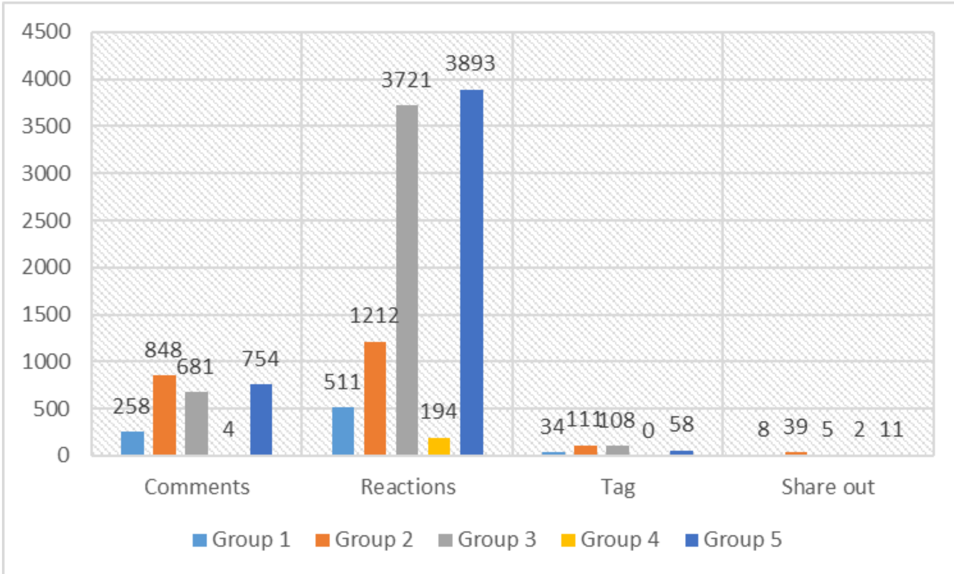

Figure 17. Distributions of group interactions

4.2.2 Network-level measurements

Network-level and actor-level measurements reveal the interaction patterns from different perspectives. Network-level measurements aim to identify the connection patterns among all nodes in a network, while actor-level measurements focus on revealing the characteristics of an individual node. Table 17 summarizes the network-level measurements of each group. The network size measured the number of group members involved in the group interactions. Clearly, Group 3 had the largest network, followed by Group 5. Group 1 and Group 2 had the similar sizes. Fewer group members engaged in the interactions in Group 4.

Network density indicates the speed at which information or resources diffuse among the actors. As shown in Table 17, Group 2 had the highest network density, which suggested that group members in Group 2 were more likely to connect with others.

Reciprocity identifies the percentage of links that are reciprocated. In Group 2, 34.2% of connections went both ways. The reciprocity of the interaction networks for Group 3 and Group

5 were less than 30% (29.2% and 26.9%, respectively). Only 4.1% of the connections were reciprocal in Group 4.

Centralization measures how much the network is linked to a central core. The degree centralization higher than 0.5 suggests the network is more likely a command and control style instead of a distributed communication (Yoon, 2011). As can be seen from Table 17, Group 2, Group 3, and Group 5 displayed the control communication style in the groups. Group 1 and Group 4 were less controlled by a central core and showed a non-command distributed communication style.

A centralized network has many of its links dispersed around one or a few central nodes (Chuang, 2013). Based on all three centralization measurements, the interaction networks of Group 5 and Group 2 appeared to be the most centralized networks among all the five groups.

	Group 1	Group 2	Group 3	Group 4	Group 5
Network size	285	270	519	154	437
Network density	0.006	0.017	0.011	0.014	0.009
Reciprocity (Arc)	0.187	0.342	0.269	0.041	0.292
Degree centralization	0.376	0.72	0.56	0.345	0.859
Betweenness centralization	83.016	118.743	132.316	46.559	200.626
Closeness centralization	0.0006	0.0012	0.0006	0.0007	0.001

Table 17. Network-level measurements of each group

Network centralization is an “umbrella concept that examines the variation in individuals' centralities within a network” (Monge & Contractor, 2003, p. 3). To further compare the centrality differences of individuals in the same groups and across different groups, statistical analyses were conducted in the following sections.

4.2.3 RQ 1.1 & Hypothesis group 1

RQ 1.1 is stated as “*Are there any differences between male group members and female group members in terms of interactions in autism support groups on Facebook?*” It examined if gender differences appeared during the group discussions.

Standard tests are not appropriate for node-level data because the aggregated measures (e.g. centrality) for each node are not independent of one another. Ucinet provides the permutation tests (also called randomization tests) to modify the standard methods, such as t-test, ANOVA, to the node-level network data (Borgatti, Everett, & Johnson, 2013).

The interactions (commenting, reacting (liking), tagging, and sharing) between group members were summarized in a Mega Matrix. The Mega Matrix of each group was constructed and entered into Ucinet. Ucinet was used to conduct the social network analysis and the statistical tests on the social network of each autism support group on Facebook.

RQ 1.1 was answered by hypothesis group 1, which consisted of a series of hypotheses and sub-hypotheses. Each hypothesis under hypothesis group 1 was created on the comparison of the centrality measure of male group members and female group members as a whole or in each support group. Centrality measures the positional characteristics of each node in a network.

A series of modified t-tests were conducted to test the hypotheses under hypothesis group 1. Table 18 summarizes the means and standard deviations (SD) of the degree centrality, the betweenness centrality, and the closeness centrality of all male group members (n=346) and all female group members (n=1319). In table 18, the p-values smaller than the significance level (0.05) are in bold and with the asterisks. The statistical results indicate that significant gender differences of group interactions were found in terms of the degree centrality ($t(1665)=3.458$, $p=0.0011<0.05$), the betweenness centrality ($t(1665)=697.820$, $p=0.0006<0.05$), and the closeness centrality ($t(1665)=-0.030$, $p=0.0001<0.05$). As a result, $H_{01(a)}$, $H_{01(b)}$, and $H_{01(c)}$ were all rejected. Based on these statistical results the author concluded that there were significant differences between male group members and female group members in terms of the interactions in autism support groups on Facebook based on the all three types of centrality measures. Based on degree centrality and betweenness centrality, male group members gained higher centrality on average, while female group members held higher centrality values than males did when measured by closeness centrality. For all three centrality measurements, male group members obtained higher standard deviations then female group members did. This suggests that more male group members tended to achieve the important positions, while their positions differed more apparently.

	Degree centrality		**Betweenness centrality**		**Closeness centrality**	
	Male	**Female**	**Male**	**Female**	**Male**	**Female**
Mean	7.217	3.759	869.913	172.093	0.341	0.371
SD	29.235	8.903	6436.784	1181.996	0.135	0.107
t-statistic	3.458		697.820		-0.030	
p-value	**0.0011***		**0.0006***		**0.0001***	

Table 18. Descriptive statistics and statistical results from $H_{01(a)}$, $H_{01(b)}$, and $H_{01(c)}$

Table 19 summarizes the means and standard deviations of the degree centrality, the betweenness centrality, and the closeness centrality of male group members and female group members in each group. Interestingly, it can be seen from Table 19, except for group 3, male group members possessed higher means and standard deviations than female group members across all three centrality measures in all the other four groups. For group 3, female group members achieved higher means of betweenness centrality and closeness centrality, and higher standard deviation of betweenness centrality than male group members did. This suggests that, different from other groups, more female group members in Group 3 tended to achieve the important positions than male group members did, while their positions differed more apparently in terms of betweenness centrality.

		Degree centrality		**Betweenness centrality**		**Closeness centrality**	
		Male	Female	Male	Female	Male	Female
Group 1	Mean	6.15	2.253	986.003	185.201	0.282	0.277
	SD	15.904	2.883	3513.867	624.231	0.059	0.047
Group 2	Mean	8.685	4.305	641.922	93.14	0.421	0.409

	SD	25.414	6.73	4080.172	295.612	0.071	0.059
Group 3	Mean	7.468	5.464	**917.63**	**7132.609**	**0.386**	**0.394**
	SD	30.871	13.665	**310.814**	**1983.052**	0.063	0.051
Group 4	Mean	3.017	1.611	276.523	79.001	0.109	0.104
	SD	7.065	1.267	964.999	212.874	0.051	0.05
Group 5	Mean	10.233	2.989	1539.953	72.337	0.461	0.45
	SD	48.14	5.577	1172.716	353.112	0.07	0.051

Table 19. Descriptive statistics from Hypothesis group 1

Table 20 shows the p-value of the modified t-tests of the gender differences in each group. In Table 20, the p-values smaller than the significance level (0.05) are in bold and with the asterisks. Based on these statistics, $H_{02(a1)}$, $H_{02(a2)}$, $H_{02(a4)}$, $H_{02(a5)}$, $H_{02(b1)}$, $H_{02(b2)}$, $H_{02(b4)}$, $H_{02(b5)}$ were rejected at the 0.05 significant level. $H_{02(c)1\text{-}5}$ failed to be rejected, which meant that there were no significant differences in the closeness centrality of males and females across all five groups. In terms of the degree centrality and betweenness centrality, significant gender differences were found in four groups (all except group 3). For group 3, no gender difference appeared based on all three centrality measures.

Centrality measurement	Group 1	Group 2	Group 3	Group 4	Group 5
Degree centrality	**t(283)=3.155, p=0.0003***	**t(268)=2.05, p=0.0163***	t(517)=0.925, p=0.3379	**t(152)=1.679, p=0.0118***	**t(434)=2.71, p=0.0158***
Betweenness centrality	**t(283)=3.1, p=0.0017***	**t(268)=1.841, p=0.0147***	t(517)=1.493, p=0.1301	**t(152)=1.831, p=0.015***	**t(434)=2.508, p=0.0496***
Closeness centrality	t(283)=0.121, p=0.4729	t(268)=0.211, p=0.1748	t(517)=-0.177, p=0.1997	t(152)=0.256, p=0.5121	t(434)=0.174, p=0.1288

Table 20. Statistical results from hypothesis group 1

4.2.4 RQ 1.2 & Hypothesis group 2

RQ1.2 is addressed as follows "Are there any differences among the defined categories in terms of online interactions in autism support groups on Facebook?" It concerns the comparison of online interactions in autism support groups that focused on different topics.

Hypothesis group 2 was broken down into three sub-hypotheses $H_{03(a)}$, $H_{03(b)}$, and $H_{03(c)}$. In contrast to the hypothesis group 1, the independent variable for each hypothesis under hypothesis group 2 was the defined category of the group. Modified ANOVA tests were conducted to test the differences between the groups based on degree centrality, betweenness centrality, and closeness centrality. Table 21 presents the statistical results from H_{02a}, H_{02b}, and H_{02c}. The author concluded that there were significant differences among the defined categories in terms of the interactions in autism support groups on Facebook based on the degree centrality ($F(4, 1665)=2.5797$, $p=0.0332<0.05$), betweenness centrality ($F(4, 1665)=2.4325$, $p=0.04<0.05$), and closeness centrality ($F(4, 1665)=3286.7258$, $p=0.0002<0.05$).

Centrality measurement	df	F-Statistic	p-value
Degree centrality	4	2.5797	**0.0332***
Betweenness centrality	4	2.4325	**0.04***
Closeness centrality	4	3286.7258	**0.0002***

Table 21. Statistical results from hypothesis group 2

According to the ANOVA test results, $H_{03(a)}$, $H_{03(b)}$, and $H_{03(c)}$ were rejected. To find out the pairs that caused the rejections, the post hoc tests were conducted by a series of t-tests using Ucinet. The p-values of the comparison results between each pair of groups based on the degree centrality, betweenness centrality, and closeness centrality are illustrated in Table 22, 23, and 24, respectively.

Degree centrality	Group 1	Group 2	Group 3	Group 4	Group 5
Group 1		**t(593)=-1.5, p=0.0025***	t(819)=-0.412, p=0.6886	t(452)=-1.371, p=0.1755	t(733)=0.347, p=0.8153
Group 2	**t(593)=-1.5, p=0.0025***		**t(818)=1.972, p=0.0166***	t(451)=0.9, p=0.423	**t(732)=2.28, p=0.0014***
Group 3	t(819)=-0.412, p=0.6886	**t(818)=1.972, p=0.0166***		t(677)=-0.929, p=0.3978	t(958)=0.772, p=0.4669
Group 4	t(452)=-1.371, p=0.1755	t(452)=0.9, p=0.423	t(677)=-0.929, p=0.3978		t(591)=1.3, p=0.19
Group 5	t(733)=0.347,	**t(732)=2.28,**	t(958)=-0.772,	t(591)=1.3,	

	p=0.8153	**p=0.0014***	p=0.4669	p=0.19	

Table 22. Statistical results for the t-tests based on the degree centrality

$H_{03(a)}$ was rejected. The statistical results indicate that the significant differences of group interactions in terms of the degree centrality were found between group 1 and group 2 (t (593) = 1.5, p=0.0025), group 2 and group 3 (t (818) = 1.972, p = 0.0166), and group 2 and group 5 (t (732) = 2.28, p = 0.0014).

Betweenness centrality	Group 1	Group 2	Group 3	Group 4	Group 5
Group 1		t(593)=0.84, p=0.5037	**t(819)=2.178, p=0.0313***	t(452)=-1.125, p=0.2598	t(733)=1.57, p=0.1184
Group 2	t(593)=0.84, p=0.5037		t(818)=0.78, p=0.5252	t(451)=-1.627, p=0.1058	t(732)=0.584, p=0.5320
Group 3	**t(819)=2.178, p=0.0313***	t(818)=0.78, p=0.5252		**t(677)=-3.225, p=0.0024***	t(958)=0, p=0.9486
Group 4	t(452)=-1.125, p=0.2598	t(451)=-1.627, p=0.1058	**t(677)=-3.225, p=0.0024***		**t(591)=2.28, p=0.0293***
Group 5	t(733)=1.57, p=0.1184	t(732)=0.584, p=0.5320	t(958)=0, p=0.9486	**t(591)=2.28, p=0.0293***	

Table 23. Statistical results for the t-tests based on the betweenness centrality

Three comparison pairs caused the rejection of $H_{03(b)}$. The significant differences of group interactions in terms of the betweenness centrality were revealed between the following three pairs: group 1 and group 3 (t (819) = 2.178, p = 0.0313), group 3 and group 4 (t (677) = -3.225, p = 0.0024), and group 4 and group 5 (t (591) = 2.28, p = 0.0293).

Closeness centrality	Group 1	Group 2	Group 3	Group 4	Group 5
Group 1		**t(593)=-4.543, p=0.0001***	**t(819)=-7.342, p=0.0001***	**t(452)=5.673, p=0.0001***	**t(733)=-7.727, p=0.0001***
Group 2	**t(593)=-4.543, p=0.0001***		**t(818)=-3.056, p=0.0001***	**t(451)=7.845, p=0.0001***	**t(732)=-3.593, p=0.0001***
Group 3	**t(819)=-7.342, p=0.0001***	**t(818)=-3.056, p=0.0001***		**t(677)=-8.9, p=0.0001***	**t(958)=-0.773, p=0.0001***
Group 4	**t(452)=5.673, p=0.0001***	**t(451)=7.845, p=0.0001***	**t(677)=-8.9, p=0.0001***		**t(591)=-9.071, p=0.0001***
Group 5	**t(733)=-7.727, p=0.0001***	**t(732)=-3.593, p=0.0001***	**t(958)=-0.773, p=0.0001***	**t(591)=-9.071, p=0.0001***	

Table 24. Statistical results for the t-tests based on the closeness centrality

$H_{02(c)}$ compared the group interactions based on the closeness centrality. As a result, it appears that there were significant differences of group interactions among groups in terms of the closeness centrality. Further analysis showed that the rejection of $H_{03(c)}$ was caused by significant differences found between all the following 10 pairs of groups: group 1 and group 2 ($t(593) = -4.543$, $p = 0.0001$), group 1 and group 3 ($t(819) = -7.727$, $p = 0.0001$), group 1 and group 4 ($t(452) = 5.673$, $p = 0.0001$), group 1 and group 5 ($t(733) = -114.005$, $p = 0.0001$), group 2 and group 3 ($t(818) = -3.056$, $p = 0.0001$), group 2 and group 4 ($t(451) = 7.845$, $p = 0.0001$), group 2 and group 5 ($t(732) = -3.593$, $p = 0.0001$), group 3 and group 4 ($t(677) = -8.9$, $p = 0.0001$), group 3 and group 5 ($t(958) = 0.773$, $p = 0.0001$), and group 4 and group 5 ($t(591) = -9.071$, $p = 0.0001$).

4.2.5 Summary

The first research question was concerned with how users communicated with each other within autism support groups on Facebook. RQ1.1 examined the gender differences in the group interactions, while RQ1.2 investigated the differences in the group interactions across groups that belong to various categories. Table 25 summarizes the associated hypotheses, independent variables (IV), measurements of dependent variables (DV), statistical tests, and generated test results with respect of RQ 1.

Through a series of inferential analyses, it was examined and determined that significant gender difference was found in the group interactions in terms of all three centrality measures (degree centrality, betweenness centrality, and closeness centrality). Male group members gained significantly more central positions in the group than the female group members did based on degree centrality and betweenness centrality, whereas females possessed significantly higher closeness centrality in the group. Based on the means and standard deviations of the centrality measures, it suggests that more male group members tended to achieve important positions than female group members did, while male group members' centralities were spread out over a large range of values.

More specifically, within each group, gender differences were found in four investigated groups (Group 1, Group 2, Group 4, and Group 5) in terms of degree centrality and betweenness centrality. The exception was Group 3 which is a parents group, where female group members and male group members were not significantly different in the group interactions. The gender differences of closeness centrality were not revealed within each group. This implies that the abilities that could instantly communicate and interact with others without going through many intermediaries did not significantly differ between male group members and female group members.

In addition, there were significant differences among the defined categories in terms of the interactions of group members with the same gender in autism support groups on Facebook based on all three centrality measures.

Research questions	Hypothesis	IV	Measurement of DV	Test	Result
RQ1.1	$H_{01(a)}$	Gender	Degree centrality	Modified t-test	Reject
	$H_{01(b)}$	Gender	Betweenness centrality	Modified t-test	Reject
	$H_{01(c)}$	Gender	Closeness centrality	Modified t-test	Reject
	$H_{02(a)}$	Gender	Degree centrality	Modified t-test	Group 1: Reject Group 2: Reject Group 3: Not reject Group 4: Reject Group 5: Reject
	$H_{02(b)}$	Gender	Betweenness centrality	Modified t-test	Group 1: Reject Group 2: Reject Group 3: Not reject Group 4: Reject Group 5: Reject
	$H_{02(c)}$	Gender	Closeness	Modified t-test	Group 1: Not reject

			centrality		Group 2: Not reject Group 3: Not reject Group 4: Not reject Group 5: Not reject
RQ1.2	$H_{03(a)}$	Category	Degree centrality	Modified ANOVA	Reject
	$H_{03(b)}$	Category	Betweenness centrality	Modified ANOVA	Reject
	$H_{03(c)}$	Category	Closeness centrality	Modified ANOVA	Reject

Table 25. Summary of the findings for RQ 1

4.3 Findings for research questions 2 (RQ2)

RQ2: Who are the influential users based on interactions in autism support groups on Facebook?

As revealed in the above section, the five investigated autism support groups on Facebook displayed relatively high centralization scores. Group 2, Group 3, and Group 5 especially presented the control communication style. The centralized networks of the five groups meant that a few group members in the groups had comparatively higher centrality scores than the others did. Group members with a high centrality score are the "stars" of the network, and can be seen as the most important or influential users due to the social benefits derive from their advantageous positions of information flow (Chang, 2009). The second research question aims to find out the influential users based on interactions within the autism support groups on Facebook.

4.3.1 Influential users based on interactions

RQ 2.1 is stated as "*What are the characteristics of the influential users based on interactions in autism support groups on Facebook?*" The five investigated autism support groups were analyzed individually. Influential users in each group were identified as group members who ranked top 20 in terms of all three centrality measures: degree centrality, betweenness centrality, and closeness centrality.

4.3.1.1. Influential users in Group 1 (Awareness group)

Table 26 summarizes the top 20 group members in Group 1 with highest degree centrality, betweenness centrality, and closeness centrality. In Table 26, 11 members (in bold) occupied the important positions in the group in terms of all three centrality measures. Figure 18 provides a full display of the interaction network of Group 1 based on degree centrality. In Figure 18, the larger the node, the higher the degree centrality value. The 11 influential users determined by all three measures are shown in bold in Figure 18. Apparently, user a41 and user a23 dominated the group communications in Group 1. Both user a41 and user a23 are male users. User a41 is a professional speaker with autism. He kept sharing a number of videos about autism patients into the group and received many reactions. User a23 is the father of a boy with autism. He asked questions about how to deal with specific situations which happened to his son, and obtained massive comments from other group members. Those comments provided not only information to code with the issue, but also supportive encouragement.

No	User	Degree	User	Betweenness	User	Closeness
1	**a41**	**114**	**a41**	**24829.29**	**a41**	**0.444**
2	**a23**	**51**	**a23**	**11243.77**	**a24**	**0.383**
3	**a120**	**20**	**a120**	**6066.621**	**a90**	**0.374**
4	a55	19	a55	4293.329	**a93**	**0.37**
5	**a147**	**18**	**a147**	**4185**	**a258**	**0.368**
6	a133	18	a133	3989.75	**a23**	**0.367**
7	**a62**	**17**	**a62**	**3484.8**	**a85**	**0.367**
8	a4	17	a4	2886.248	a87	0.367
9	a107	15	a107	2537.39	**a120**	**0.366**
10	**a93**	**14**	**a93**	**2510.548**	**a147**	**0.362**
11	**a90**	**13**	**a90**	**1880.591**	a286	0.36
12	a19	12	a19	1709.752	**a65**	**0.357**
13	a193	12	a193	1623.542	a154	0.351
14	**a85**	**12**	**a85**	**1354.013**	a276	0.351
15	**a65**	**11**	**a65**	**1329.89**	a270	0.35
16	**a24**	**10**	**a24**	**1264.077**	a281	0.349
17	a31	9	a31	1138	a284	0.349

18	**a258**	**8**	**a258**	**989.731**	**a62**	**0.345**
19	a46	8	a46	984.211	a156	0.343
20	a51	8	a51	912.299	a188	0.334

Table 26. Top 20 group members in Group 1

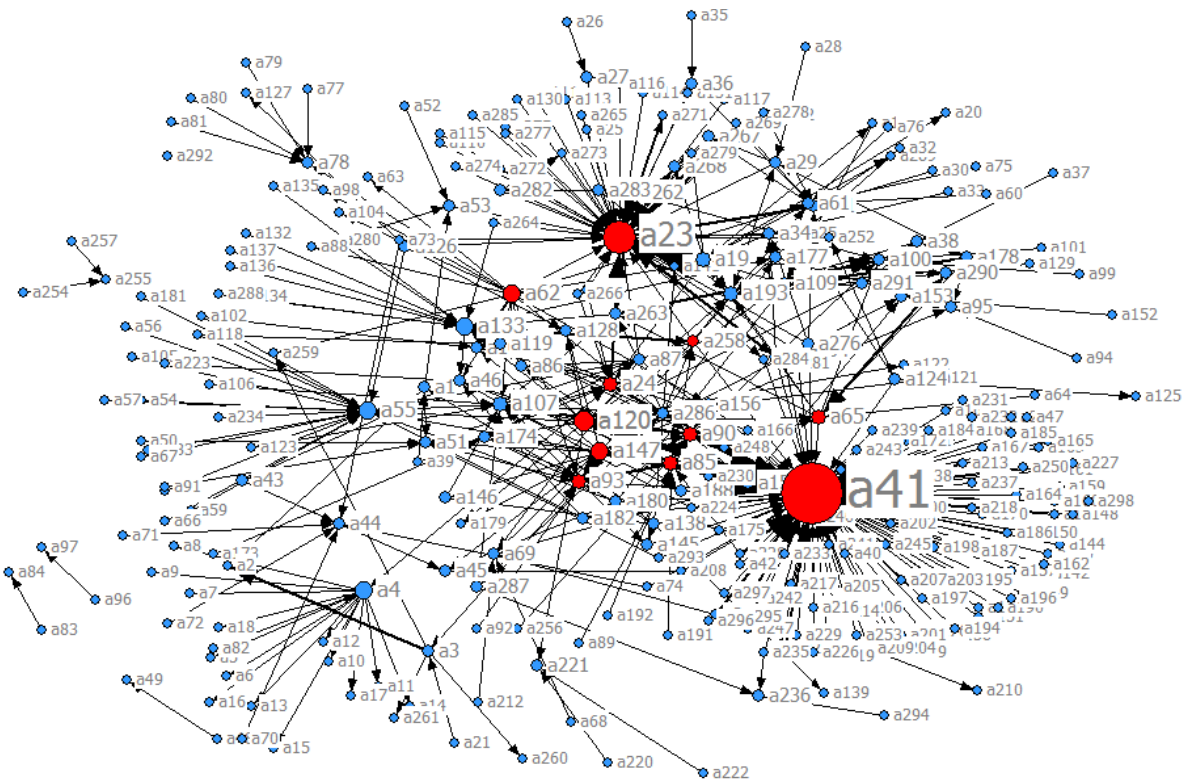

Figure 18. Visual display of the interaction network of Group 1

4.3.1.2. Influential users in Group 2 (Treatment group)

Table 27 lists the top 20 group members in Group 2 in terms of the degree centrality, betweenness centrality, and closeness centrality in the interaction network. Figure 19 provides a full display of the interaction network of Group 2 based on degree centrality. As shown in Table 27, nine users (in bold) served as dominators in the group based on all three centrality measures. User B6 is one of the three administrators for the group. He appeared to share into the group loads of links directed to a variety of online information resources (e.g. news, academic articles, and blogs) regarding the impact of Electromagnetic Field (EMF) pollution on autism. His posts obtained loads of reactions and comments, and he was willing to reply to others' comments.

No	User	Degree	User	Betweenness	User	Closeness
1	**B6**	**217**	**B6**	**35132.2**	**B6**	**0.771**
2	**B31**	**45**	**B34**	**2388.541**	**B50**	**0.509**
3	**B50**	**44**	**B29**	**1854.116**	**B31**	**0.501**
4	**B177**	**30**	**B31**	**1844.405**	**B177**	**0.488**
5	**B34**	**30**	**B50**	**1744.398**	**B34**	**0.486**
6	B91	30	**B177**	**1351.945**	**B120**	**0.485**
7	**B120**	**28**	B73	1205.21	B91	0.485
8	**B131**	**28**	B102	1172.987	**B131**	**0.484**
9	**B29**	**25**	**B120**	**1171.63**	**B29**	**0.481**
10	B18	24	**B131**	**1064.066**	B52	0.476
11	B102	21	B118	979.986	**B125**	**0.474**
12	B35	20	**B125**	**918.804**	B18	0.474
13	B52	19	B116	751.441	B35	0.471
14	B84	19	B89	705.784	B140	0.468
15	**B125**	**17**	B114	656.324	B251	0.468
16	B228	17	B12	645.643	B260	0.467
17	B276	16	B86	606.816	B102	0.466
18	B114	15	B180	589	B276	0.466
19	B116	15	B190	449.735	B209	0.465
20	B118	15	B195	444.786	B275	0.465

Table 27. Top 20 group members in Group 2

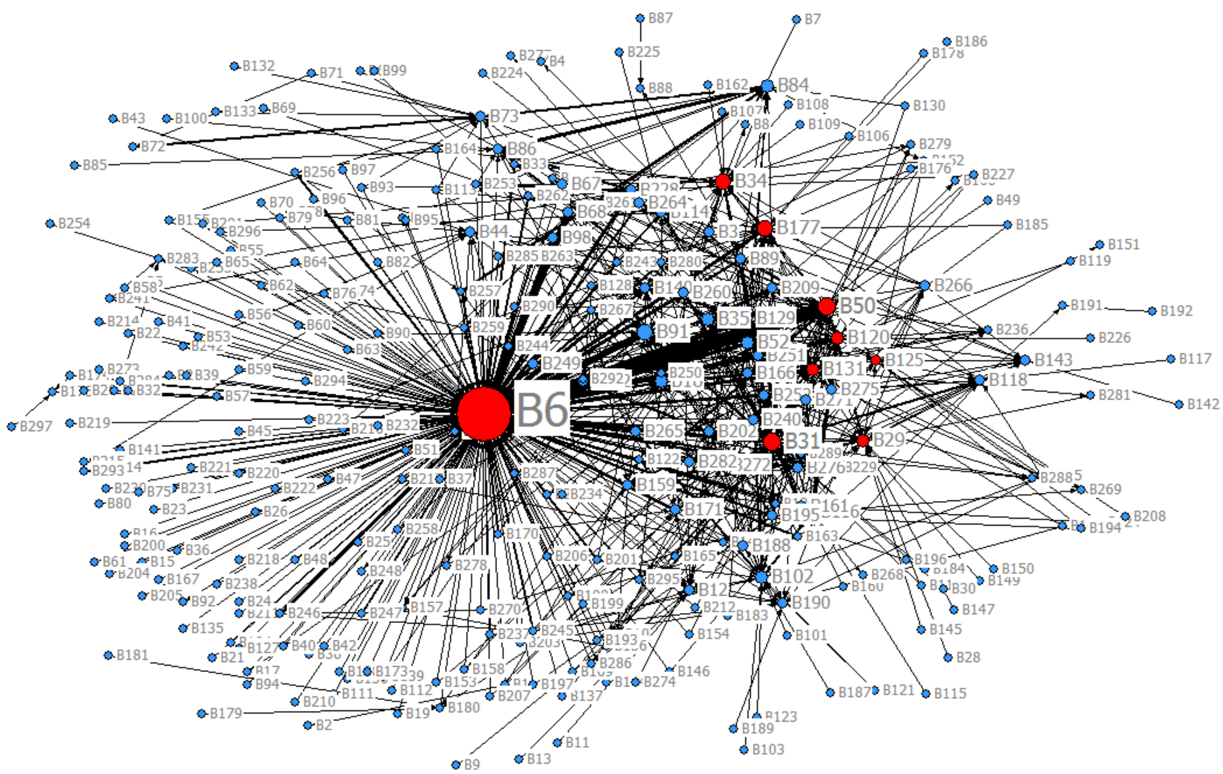

Figure 19. Visual display of the interaction network of Group 2

4.3.1.3. Influential users in Group 3 (Parents group)

For Group 3, Table 28 lists the top 20 users in the interaction network in terms of the degree centrality, betweenness centrality, and closeness centrality. Figure 20 displays the interaction network of users in Group 2. The sizes of the nodes were determined based on degree centrality. As shown in Figure 20, 12 users (in bold) possessed more important positions in the group interaction network in terms of all three centrality measures. Among them, user E4 and user E52, who are two of the six group administrators, gained the most attentions. As group administrators, both user E4 and user E52 posted greeting messages to the group to welcome new group members. In addition to the welcome messages, user E4, a father with an autistic boy, also posted various cartoon and comic pictures describing encouraging ideas about autism. Those posts tended to attract more reactions from other group members.

No	User	Degree	User	Betweenness	User	Closeness
1	**E4**	**297**	**E4**	**69222.52**	**E4**	**0.694**
2	**E52**	**179**	**E52**	**30618.52**	**E52**	**0.593**
3	**E39**	**120**	**E1**	**15429.94**	**E39**	**0.557**
4	**E1**	**101**	**E41**	**11910.23**	**E1**	**0.515**
5	**E41**	**85**	**E39**	**11761.39**	**E41**	**0.505**
6	**E54**	**67**	**E54**	**10292.99**	E92	0.487
7	E37	53	E37	9330.109	**E72**	**0.486**
8	**E72**	**51**	**E72**	**7407.121**	**E70**	**0.485**
9	**E70**	**49**	**E70**	**4841.837**	**E253**	**0.484**
10	**E106**	**42**	E29	2872.614	**E54**	**0.484**
11	**E253**	**40**	**E253**	**2680.231**	**E106**	**0.48**
12	**E51**	**34**	E124	2068.001	**E14**	**0.478**
13	E207	32	**E106**	**1827.591**	E345	0.478
14	**E14**	**31**	E104	1747.008	**E51**	**0.478**
15	E92	31	**E51**	**1658.832**	E207	0.475
16	E29	25	E286	1653.553	E137	0.472
17	E137	25	E183	1561.214	E215	0.469
18	E215	25	**E14**	**1548.384**	E373	0.467
19	E231	22	E298	1484.252	E246	0.465

20	E148	22	E143	1133.76	E480	0.465

Table 28. Top 20 group members in Group 3

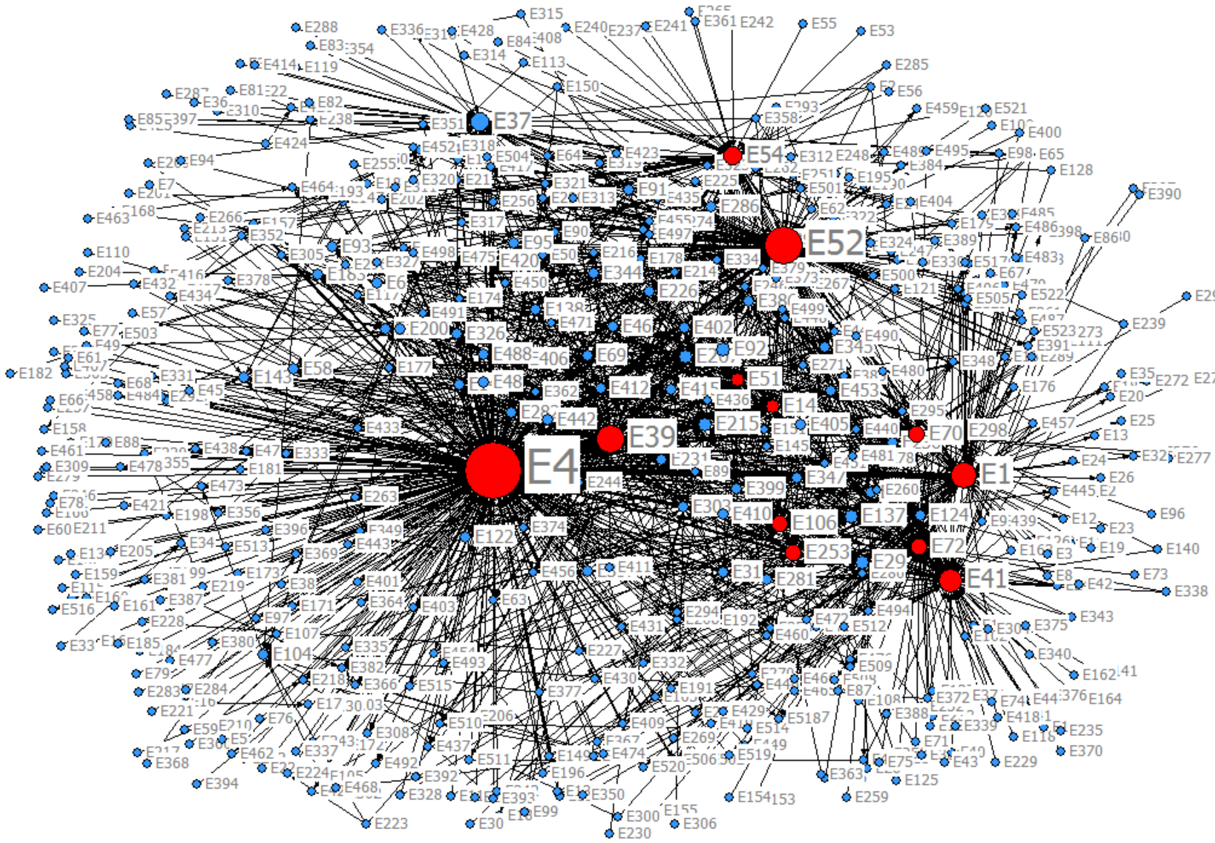

Figure 20. Visual display of the interaction network of Group 3

4.3.1.4. Influential users in Group 4 (Research group)

The top 20 group members with the highest value of degree centrality, betweenness centrality, and closeness centrality in the interaction network of Group 4 is summarized in Table 29. Figure 21 shows the interaction network in Group 4. Eight users (in bold) who reached the high centralities based on all three measures are shown in bold in Table 29 and presented as red nodes in Figure 21. User C2 served as the “star” node in the group interaction network as shown in Figure 21. He is the administrator and the creator of the group, and also an occupational therapist. His posts primarily focused on the related research, workshops, conferences, training programs, etc.

No	User	Degree	User	Betweenness	User	Closeness
1	**C2**	**55**	**C2**	**7276.8**	**C2**	**0.301**
2	**C11**	**9**	**C17**	**1436**	**C11**	**0.26**
3	C6	9	**C11**	**1142.367**	**C80**	**0.254**
4	**C29**	**8**	C51	1104	C10	0.251
5	C21	7	C6	1045.033	**C39**	**0.251**
6	**C80**	**7**	**C39**	**899.7**	C122	0.25
7	C51	5	**C29**	**759**	**C17**	**0.25**
8	C108	5	C21	759	**C63**	**0.25**
9	C122	5	C132	751.5	**C29**	**0.249**
10	**C39**	**4**	**C127**	**746**	C132	0.248
11	**C127**	**4**	C125	638	C86	0.248
12	C12	4	C139	563.5	**C127**	**0.246**
13	**C63**	**4**	C12	510.367	C62	0.246
14	C4	4	C108	510	C88	0.245
15	C8	4	**C80**	**482.683**	C53	0.244
16	C129	4	**C63**	**436.133**	C75	0.244
17	C88	4	C4	363	C45	0.243
18	C9	4	C10	346.55	C87	0.243
19	C86	4	C8	291.083	C96	0.242
20	**C17**	**3**	C129	261	C1	0.241

Table 29. Top 20 group members in Group 4

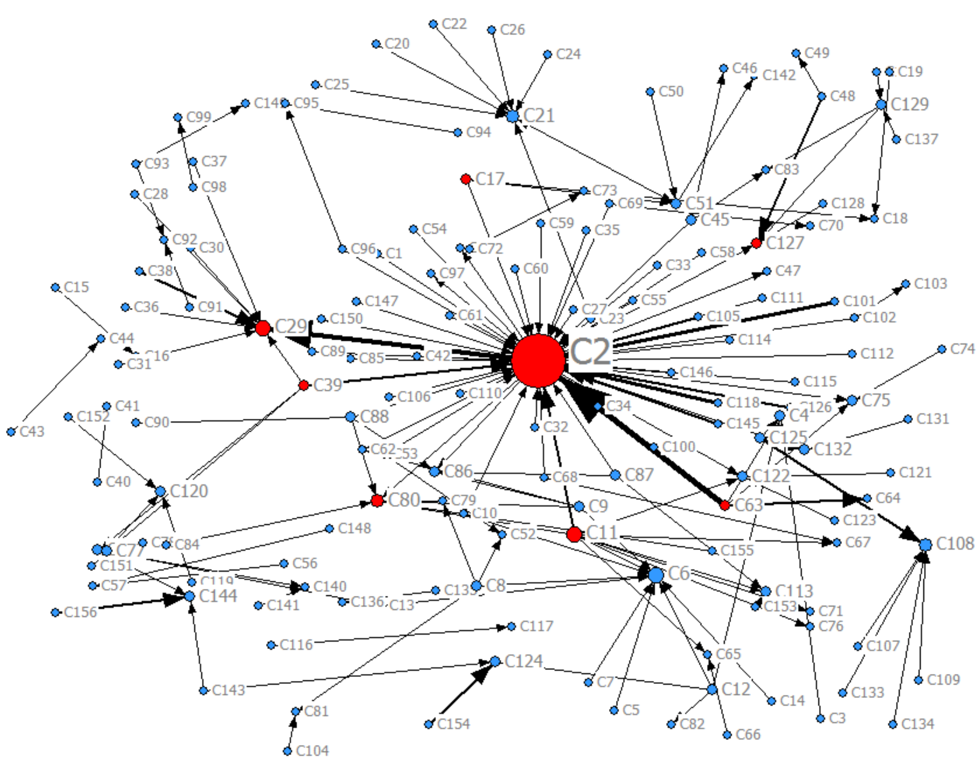

Figure 21. Visual display of the interaction network of Group 4

4.3.1.5. Influential users in Group 5 (Local support group)

Table 30 summarizes the top 20 group members in Group 5 with the highest values of degree centrality, betweenness centrality, and closeness centrality. Figure 22 presents the interaction network of Group 5. There were 13 members (in bold in Table 30 and colored with red in Figure 22) who are located at the core positions in the group based on all three centrality measures. User D14 is one of the six group administrators. He is the founder of the group and became the most central player in the group. He shared many posts from other Facebook groups, Pages, Communities, to the group. Some examples include a photo depicting "*Proud parent of a shining star with autism*" and a link entitled "*Anxiety may alter processing of emotions in people with autism.*" Being the father of a girl with autism, he posted messages and photos about the daily life of his daughter, such as her first day of school. The posts regarding his daughter gained a number of comments and reactions from other group members.

No	User	Degree	User	Betweenness	User	Closeness
1	**D14**	**377**	**D14**	**87346.08**	**D14**	**0.874**
2	**D15**	**52**	**D15**	**3675.677**	**D15**	**0.521**
3	**D269**	**43**	**D33**	**3155.19**	**D269**	**0.509**
4	**D65**	**43**	**D269**	**2752.35**	D133	0.508
5	**D108**	**37**	**D108**	**2341.329**	**D65**	**0.508**
6	**D17**	**33**	**D26**	**1690.805**	**D17**	**0.505**
7	D133	29	**D279**	**1466.606**	D93	0.501
8	D93	29	**D123**	**1256.636**	**D108**	**0.498**
9	**D33**	**26**	**D65**	**1055.862**	**D33**	**0.495**
10	**D123**	**23**	**D3**	**981.932**	**D123**	**0.494**
11	**D301**	**20**	**D301**	**956.331**	D268	0.49
12	**D279**	**18**	D387	814.421	**D301**	**0.49**
13	**D3**	**18**	D231	579.206	D58	0.49
14	**D26**	**17**	D328	551.305	**D26**	**0.486**
15	D268	16	**D91**	**500.745**	D97	0.484
16	**D91**	**15**	D85	477.768	**D279**	**0.483**
17	D97	15	**D17**	**464.353**	**D3**	**0.483**

18	D85	14	D30	461.403	D350	0.483
19	D324	14	D324	457.262	**D91**	**0.483**
20	D321	14	D59	446.186	D30	0.482

Table 30. Top 20 group members in Group 5

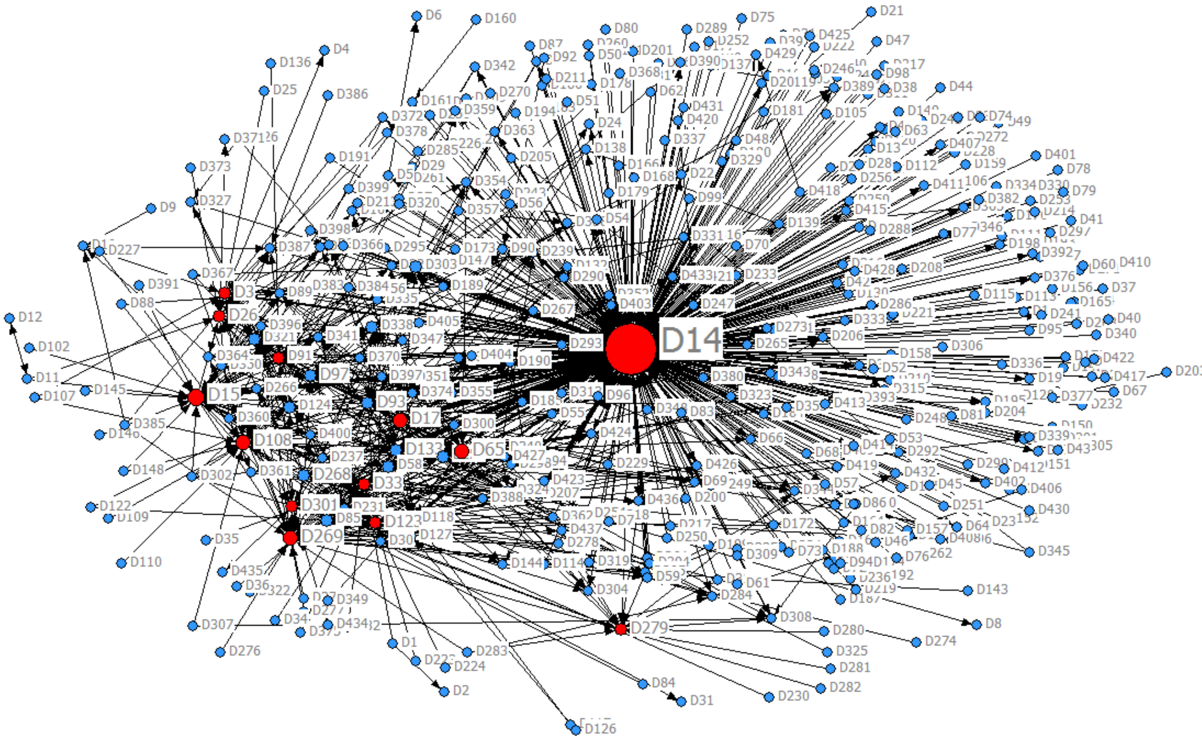

Figure 22. Visual display of the interaction network of Group 5

4.3.2 Gender distribution of influential users

The backgrounds of the influential users were investigated by visiting their Facebook profile pages. As a result, all of the 53 key actors were individual Facebook users. Figure 23 shows the gender distribution of the influential users identified in each group. Among the five support groups, 32 out of the 53 influential users were female users while 21 were male users. Group 3 and Group 5 were dominated more by female opinion leaders, while the majority of the opinion leaders were male users in Group 4.

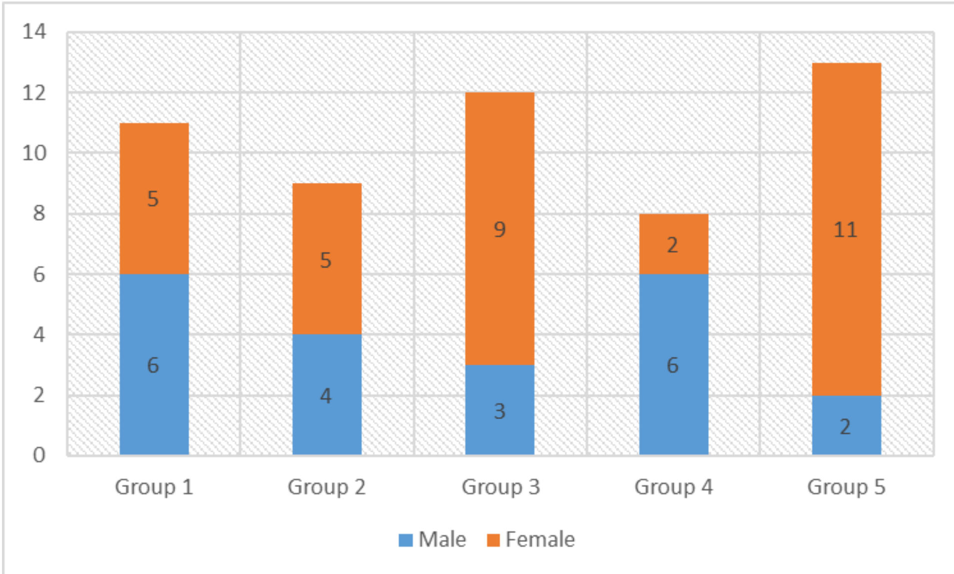

Figure 23. Gender distribution of influential users

4.3.3 Interactions of influential users

RQ2.2 is stated as "How do the influential users interact with others in autism support groups on Facebook?" RQ2.2 centers on the investigation of the interaction features of the influential users identified in the five support groups. Figure 24 shows the in-degree and out-degree of the influential users. Among the 53 influential users identified by the three centrality measures, 31 of them reached higher in-degree values than out-degree values. This means they received the interactions more from other group members than they initiated interactions with others. User D14 from Group 5 was the most popular user, who was reached by 327 group members (74.7% of all involved group members). User E4 from Group 3 was the most motivated user, who actively gave responses to 162 group members (30.9% of all involved group members).

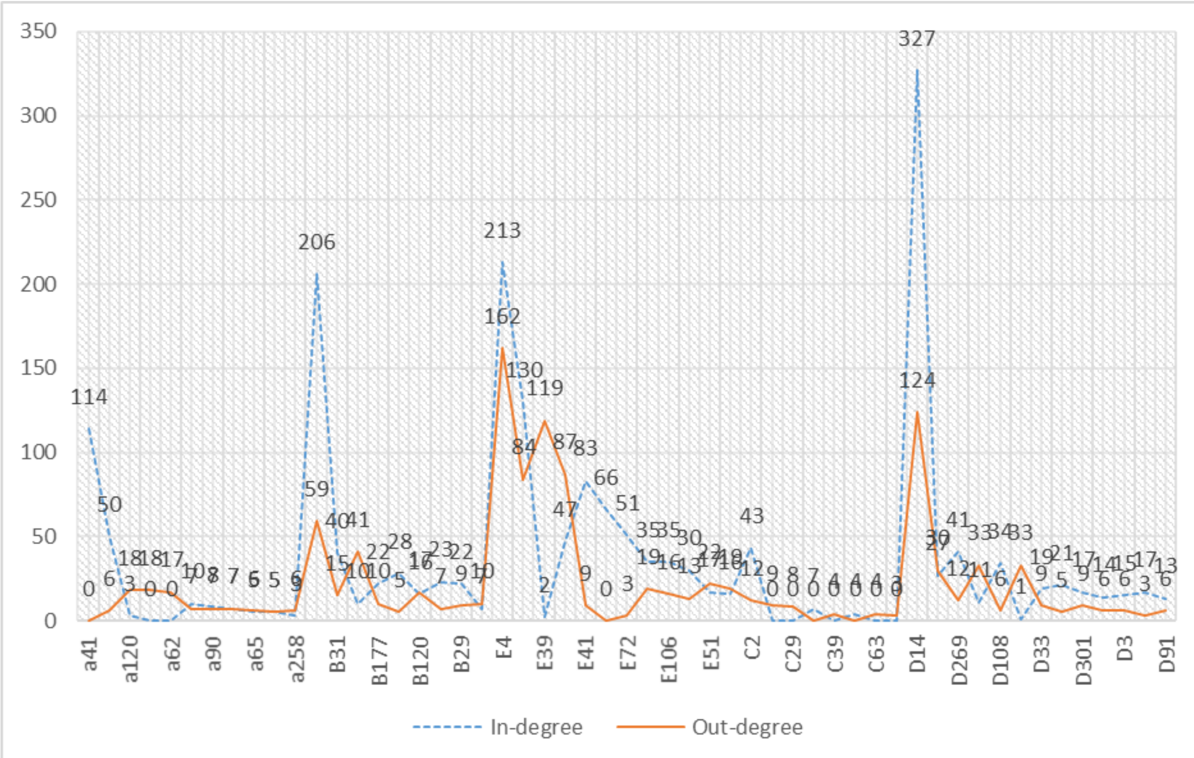

Figure 24. In-degree and out-degree of influential users

Table 31 summarizes the detailed frequencies of each type of interactions the influential users performed in each group. Basically, influential users actively participated in group interactions. On average, the identified opinion leaders posted 7.2 original messages in the groups. Clearly, they were willing to share with group members and to originate discussions. For commenting activity, 37 out of the 53 (69.8%) influential users received more comments from others rather than commenting more on others' posts. Similarly, 30 out of 53 (56.7%) opinion leaders attracted more reactions rather than making more reactions to others. Even for the influential users, sharing and tagging activities were rarely performed in the support groups. There were six influential users who shared messages in the group out. Among these users, user E1 in Group 3 shared 75 messages out of the group. Tagging was a little more common than sharing. There were 15 users who tagged others in their own posts. User B6 in Group 2 was tagged 31 times by other group members.

Group	Influential users	Posts	Comments	Received comments	Reactions	Received reactions	Share	Being shared	Tag	Being tagged
Group 1	a41	30	0	15	0	198	0	4	0	0
	a23	2	36	99	0	25	0	0	2	4
	a120	0	4	0	36	3	0	0	0	0
	a147	0	0	0	37	0	0	0	0	0
	a62	0	1	0	24	0	0	0	0	0
	a93	12	6	6	9	19	0	0	1	0
	a90	2	8	2	32	29	0	0	0	0
	a85	2	2	3	13	8	0	0	0	0
	a65	1	8	8	4	3	0	0	0	0
	a24	1	11	3	3	5	0	0	0	0
	a258	0	10	3	3	5	0	0	0	0
Group 2	B6	40	129	217	52	565	0	29	9	31
	B31	6	27	30	16	65	15	1	0	6
	B50	1	37	14	96	5	0	0	14	4
	B177	8	13	12	19	25	0	0	1	0
	B34	3	3	4	5	45	0	2	0	0
	B120	2	25	20	45	20	0	1	0	0
	B131	7	12	9	14	30	0	0	0	0
	B29	1	10	10	6	20	0	1	4	6
	B125	1	0	0	13	7	0	0	0	0
Group 3	E4	31	95	220	608	1275	1	1	6	6
	E52	54	46	101	251	377	1	1	0	5
	E39	2	3	0	748	2	0	0	0	0
	E1	5	125	23	106	97	75	1	0	0
	E41	8	6	22	8	163	0	0	0	0
	E54	20	0	5	1	153	0	0	0	0
	E72	4	0	3	4	67	0	0	0	0
	E70	7	3	6	47	50	0	0	0	0
	E106	6	10	8	11	48	0	0	0	0
	E253	10	5	5	63	89	0	0	0	0
	E51	2	3	2	43	24	0	0	0	0
	E14	0	5	10	30	12	0	0	2	0
Group 4	C2	27	0	0	18	62	0	1	0	0
	C11	0	0	0	10	0	0	0	0	0
	C29	0	0	0	0	14	0	0	0	0
	C80	1	0	1	0	6	0	0	0	0
	C39	1	0	0	6	0	0	0	0	0
	C127	2	0	0	0	5	0	0	0	0
	C63	0	0	0	11	0	0	0	0	0

	C17	0	0	0	3	0	0	0	0	0
Group 5	D14	49	140	279	560	2963	1	9	8	10
	D15	6	2	6	125	36	0	0	0	0
	D269	7	105	122	19	83	0	0	22	9
	D65	0	0	0	73	12	0	0	0	0
	D108	3	4	5	30	63	2	0	0	2
	D17	0	1	0	209	1	0	0	0	0
	D33	1	5	6	46	20	0	0	1	0
	D123	2	19	24	22	22	0	0	0	2
	D301	2	46	35	15	24	0	0	1	1
	D279	1	21	11	22	16	0	0	1	3
	D3	1	12	18	31	13	0	0	1	0
	D26	1	0	10	4	15	0	0	0	0
	D91	9	14	16	10	23	0	0	1	1

Table 31. Frequencies of interactions performed by influential users

Figure 25 represents the frequencies of original posts, outgoing interactions, and incoming interactions of the influential users in each group. Outgoing interactions represented users' contributions to the groups, while incoming interactions represented the attentions users attracted. Across the five groups, there were one or two users in each group who gained tremendous attention from others, such as user a41 and user a23 in Group 1, user B6 and B31 in Group 2, user E4 and user E52 in Group 3, user C2 in Group 4, and user D4 in Group 5.

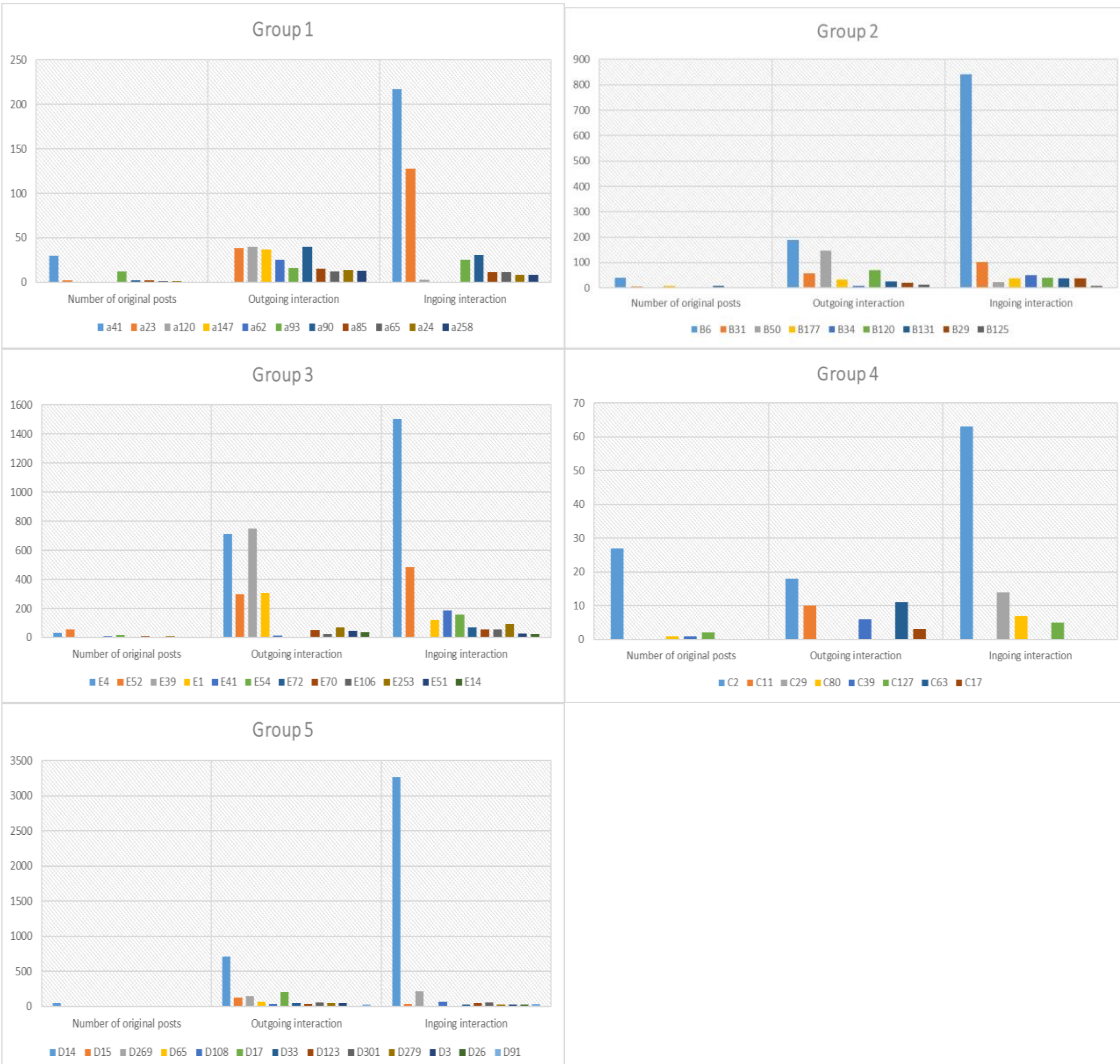

Figure 25. Frequency of outgoing and incoming interactions of influential users in each group

A Kolmogorov-Smirnov test was conducted to examine the normality of the datasets before the parametric tests. In this case, the significance values for the Kolmogorov-Smirnov tests conducted was 0.000, suggesting the violation of the normality assumption in all the five groups. Therefore, in this study, a non-parametric correlation analysis was conducted to test the relationships among the frequncies of the orginal posts, the outgoing interactions, and the incoming interactions. The relationships among orginal post, the outgoing interaction, and the incoming interactions (as measured by the frequency of each activity) were investigated using Spearman correlation coefficient. Cohen (1988) suggested the interpretation of the value of the correlation coefficient as the following guidelines: small (*rho*=0.10 to 0.29), medium (*rho*=0.30 to 0.49), and large (*rho*=0.50 to 1.0). Table 32 shows the Spearman's rho values between each pair of activities. In Table 32, the correlation values with two asterisks (**) are significant at the 0.01 level (2-tailed). The test results demonstrated that significant large correlations were found betweem original post and incoming interaction. The frequencies of posts a user posted were strongly correlated with the interaction he/she received (*rho*=0.838). It suggests that users who posted more messages may acquire more attentions from others.

Pearson Correlation	Original post	Outgoing interaction	Incoming interaction
Original post	1	0.253	**0.838****
Outgoing interaction	0.253	1	**0.357****
Incoming interaction	**0.838****	**0.357****	1

Table 32. Correlations among frequencies of original post, outgoing interaction, and incoming interaction

4.3.4 Summary

To answer RQ 2, social network analysis was employed to identify the influential users based on interactions (or opinion leaders) in each Facebook support group, and to unveil the interaction characteristics of those users. Among the five investigated groups, 53 influential users who occupied top 20 important positions in each group were found based on three centrality measures: degree centrality, betweenness centrality, and closeness centrality. The background characteristics of the key actors were investigated by reviewing their posts and visiting their Facebook profile pages. All of the 53 key actors were individual Facebook users, 32 out of whom were female users while 21 were male users. The *parents* group (Group 3) and the *local support* group (Group 5) were dominated by female opinion leaders, while the majority of the opinion leaders were male users in the *research* group (Group 4).

The in-degree and out-degree, measures the number of incoming ties and outgoing ties, respectively, for an actor in a network. An actor who receives many ties is often said to be prominent, or to have high prestige (Hanneman & Riddle, 2005). With respect to the interactions with other group members, 31 out of 53 influential users reached higher in-degree values than out-degree values, which means they tended to receive relatively more attentions than they sent. That is, many other group members sought to react to the influential users, and this indicated their importance in the groups.

The identified influential users, on average, posted 7.2 original messages in the groups. Significant correlations were found among the frequencies of the orginal post, the outgoing interaction, and the incoming interactions. It suggested that users who posted more messages may acquire more attentions and interact more with others.

As can be seen in Figure 18-22, the group interactions among group members were dominated by a few most influential users who were identified as dominators (shown as the largest one or two nodes in the network). For Group 2, Group 4, and Group 5, only one star actor in each group appeared to be the dominator of the whole group, while two star actors were found in Group 1 and Group 3. As shown in Figure 25, the dominators in each group tended to have much higher incoming interactions, which meant they attracted tremendous attention from others.

4.4 Findings for research questions 3 (RQ3)

Discovering what people talked about in the autism support groups on Facebook is one of the major research questions of this study. RQ3 seeks to generate the discussion topics in each investigated autism support group on Facebook. The LDA model was implemented to discover the topics drawn from group posts and comments.

Modeling evaluation is of importance to the topic modeling methods. To identify the optimal number of topics as the K parameter, which is the number of topics in the model training process, interactive visualization methods (*pyLDAvis* package imported in Python) were employed to evaluate produced models. Using the methods applied in Ellmann, Oeser, Fucci, & Maalej (2017), the number of LDA topics was tuned until it reached a set of non-overlapping clusters that had sufficient distance between each other. The parameter of K was given for a series of descending numbers to train the model until the circles representing the topics became separated without any significant overlapping. For example, given the K parameter as five, three of the five resulted topics represented as the circles in the inter-topic distance map overlapped with each other (see the left part in Figure 26). When the value of K was lowered from five to four, the resulted four topics appeared to be split (see the right part in Figure 27), which means the generated topics were distinctive to each other. The author stopped searching for the optimal number of topics when the circles did not overlap anymore. The size of the circles represents the popularity of the topic within the overall set of topics (Ellmann et al., 2017).

All five investigated groups were explored through the model training and evaluation process. The input datasets for each group consisted of posts and comments generated by group members. Each record (i.e. post or comment) was processed by text preparation procedures including tokenization, punctuation removal, lowercase correction, stop-word removal, stemming, and manual cleansing.

After producing the appropriate LDA models, the revealed topics in each group were labeled manually according to the top terms in the topic-term distributions. Labelling topics makes it possible to interpret the corpus to see which concepts are prevalent (Saeidi, Hage, Khadka, & Jansen, 2015). The interpretation of a topic can be achieved by examining a ranked list of the most probable terms in that topic (Sievert & Shirley, 2014). Therefore, the interpretation of the topics is subjective in nature.

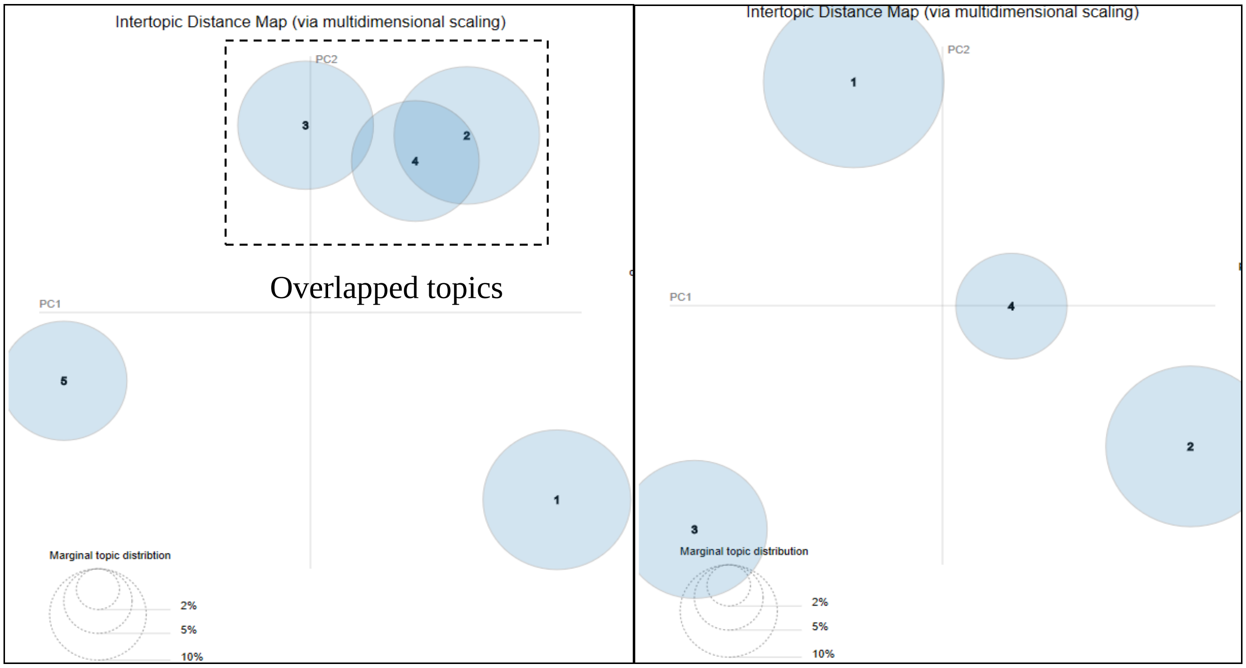

Figure 26. Topic visualization results given different values of k parameter

4.4.1 Discussion topics of Group 1 (Awareness group)

The modeling evaluation process indicated that four topics emerged from the posts and comments in Group 1. The inter-topic distance map of the four topics (represented by the four circles) is visualized in Figure 27. By using *pyLDAvis* package, each individual topic can be explored by clicking on its corresponding circle.

After the text preparation process, there were 314 records and 1424 unique terms which remained in Group 1. Table 33 lists the top 20 terms and the associated probabilities of the terms to each topic. Results indicated that the trained LDA model was meaningful, where topics were interpretable based on their terms. The four topics emerged from the discussions in Group 1 were *parenting, behavioral traits, diagnosis, and video sharing*. The parenting topic was related to discussions on parents of autistic children sharing their children’s daily life. People shared their children's accomplishments and sometimes expressed the frustrated issues which happened with their children. One example post was "*My son [name] who has autism has always seen Woody and Buzz Lightyear as his best friends. When he saw them yesterday at Disney, it was a beautiful sight to see.*" Along with talking about the parenting challenges, group members also shared their own behavior traits as patients or their kids' behaviors. There was a post saying, "*Can anyone tell me if this lining up of toys is a trait of Autism Spectrum Disorder?*" This question raised a number of replies from other group members. Some comments expressed similar observations: "*Our son who has autism LOVES to line up his toys.*" Some stated other opinions: "*Not in of itself. It depends on the age of the child and how the child uses these toys and other toys in other play activities.*" Since autism often appears in early ages of children, parents sometimes struggled with the diagnosis process: "*We keep pushing but the paediatrician just won't commit to a diagnosis and it's been 2 1/2 to 3 years now*." Sometimes they received specific informational suggestions from other group members: "*Please take your child to a developmental pediatrician with expertise in autism. There is an assessment tool called the ADOS that is very accurate in diagnosing ASD. If your regular Dr won't refer you, seek a referral through the school or a different Dr. It's important to have an accurate diagnosis so your son can receive the appropriate interventions ASAP.*" Video sharing topics were contributed mainly by one of the group member, user a41, who was identified as the most influential user in Group 1. User a41 is a professional speaker with autism. He regularly uploaded videos regarding stories about real autism patients and their parents, basic knowledge about autism, how to communicate with people who have autism, school bulling problems for children with autism, etc.

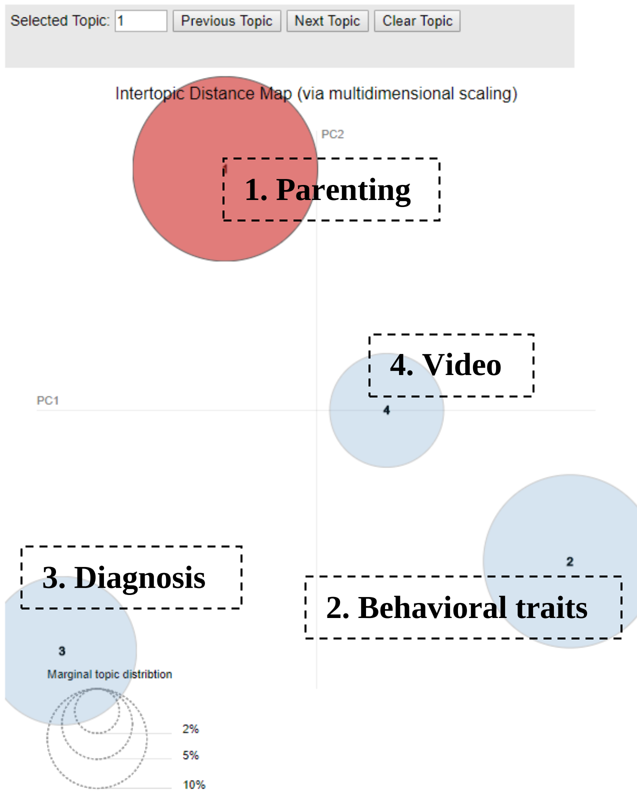

Figure 27. Visualization of the topics in Group 1

Topic 1 Parenting		Topic 2 Behavioral traits		Topic 3 Diagnosis		Topic 4 Video sharing	
autism	0.02	autism	0.046	well	0.009	autism	0.014
son	0.013	son	0.015	happy	0.009	get	0.013
need	0.009	like	0.008	like	0.008	autist	0.01
thank	0.008	autist	0.007	son	0.008	vlog	0.009
children	0.007	vlog	0.007	look	0.008	go	0.008
get	0.007	thing	0.006	need	0.007	like	0.007
time	0.007	people	0.006	feel	0.007	son	0.007
use	0.006	help	0.006	get	0.007	well	0.006
thing	0.006	look	0.006	year	0.006	new	0.006
keep	0.006	year	0.006	autism	0.006	great	0.006
take	0.006	see	0.006	people	0.006	kid	0.006
well	0.005	know	0.005	birthday	0.006	help	0.006
child	0.005	toy	0.005	person	0.006	got	0.006
ashley	0.005	love	0.004	sometime	0.006	thing	0.005
see	0.005	disorder	0.004	know	0.005	time	0.005
way	0.005	line	0.004	autist	0.005	work	0.005
someone	0.005	life	0.004	parent	0.005	hope	0.005
good	0.005	today	0.004	skill	0.005	want	0.005

great	0.005	say	0.004	pediatrician	0.005	come	0.005
autist	0.005	differ	0.004	read	0.005	every	0.005

Table 33. Top 20 terms and the associated probabilities of the terms to each topic in Group 1

4.4.2 Discussion topics of Group 2 (Treatment group)

Text preparation procedures generated 259 records and 1566 terms in Group 2. Figure 28 gives the global overview of the relationship between the topics based on the established topic-document relationship. Similar to Figure 27, in Figure 28, the right panel reveals the most dominant topics in Group 2 while the left panel gives the global overview of the relationship between the topics based on the established topic-document relationship. Three distinct topics emerged from the discussions in Group 2, including *EMF (Electromagnetic Field) pollution*, *home decoration*, and *wireless safety* (as shown in Table 34). The main discussion topic was about the EMF pollution, since the group founder described this group as following: "*Exploring the emerging link between autism and EMF/wireless, and helping ASD families to heal their children by providing information and resources for reducing their exposure.*" On several occasions, group members shared their advocacy of reducing the EMF pollution, such as the following post: "*URGENT!!! PLEASE Call Gov. Jerry Brown NOW @ (916) 445-2841 and ask him to VETO Senate Bill 649 — which would allow telecom corporations to install cell towers wherever they want — even in front of OUR homes and schools.*" Another discussion theme was regarding home decorations that may reduce or enlarge the EMF pollution. For example, one of the group members raised a question about the bedroom painting: "*Ok, so just making sure I'm reading all of the old threads correctly... EMF paint is a bad idea for a child's bedroom.*" In addition, a number of posts and comments were related to smart meters, including how to install smart meter shields and specific products that can replace the smart meters. Wireless (wifi) networks are one type of sources of EMF according to the National Institute of Environmental

Health Sciences (“Electric & Magnetic Fields,” n.d.). People discussed concerns about a variety of wireless products in the group, such as “*Does anyone still have a child using a Fitbit, Apple watch or location tracker? Those are all big wireless emitters and can really increase stimming in the kids.*”

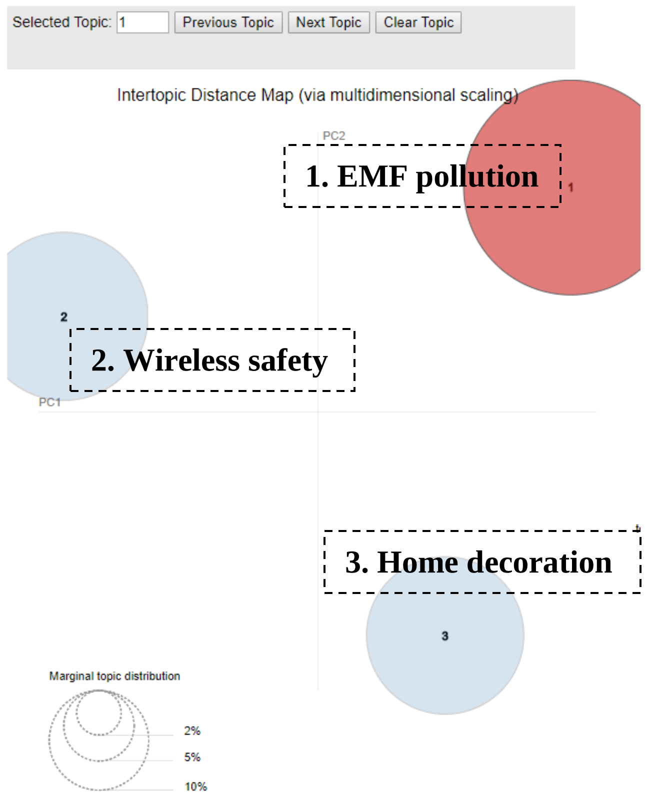

Figure 28. Visualization of the topics in Group 2

Topic 1 EMF pollution		Topic 2 Home decoration		Topic 3 Wireless safety	
thank	0.011	meter	0.01	thank	0.014
emf	0.009	smart	0.009	emf	0.012
like	0.005	like	0.007	help	0.009
use	0.005	emf	0.006	school	0.007
school	0.005	live	0.006	meter	0.006
comment	0.005	get	0.005	new	0.005
make	0.005	cell	0.005	wireless	0.005
next	0.004	area	0.005	radiate	0.005
time	0.004	autism	0.005	use	0.005
home	0.004	group	0.005	want	0.005
work	0.004	make	0.004	folk	0.004

feel	0.004	people	0.004	know	0.004
meter	0.004	thank	0.004	share	0.004
field	0.004	home	0.004	wire	0.004
share	0.004	video	0.004	phone	0.004
liability	0.003	tower	0.004	wifi	0.004
health	0.003	solute	0.004	electric	0.004
educate	0.003	great	0.004	group	0.004
state	0.003	hope	0.004	thing	0.004
write	0.003	find	0.004	like	0.004

Table 34. Top 20 terms and the associated probabilities of the terms to each topic in Group 2

4.4.3 Discussion topics of Group 3 (Parents group)

The resulted dataset for Group 3 consisted of 924 records and 2334 words. The five discussion topics drawn from Group 3 are shown in Figure 29, while the top terms associated with each topic are listed in Table 35. As a group created for parents, *family support* and *parenting* were not unexpected to be two of the major discussion themes. Group members shared the stories and experiences about their family members (e.g. brother, son, daughter) in the group, such as "*I was brought to this group because I wanted to connect with people whose lives have been affected by autism. The person in the photo is my baby brother….*" People also brought up specific questions in being parents of autistic children, such as "*R there any summer camp for my 11 year old son with autism that in Memphis TN please I need help*". Another topic, *experiences*, included posts and comments regarding some videos shared by group members. These videos explained the way people on the autism spectrum saw the world and the social difficulties they experienced in real life. Another aspect of experiences shared in the group was related to school issues, such as "*Morning - the Bad News is we are on the countdown for the children going back to school and all the new dramas that will bring when the routine changes again and new teachers!*" With respect to the fourth topic, *education*, people asked questions about how to educate autistic children, such as "*I'm in need of a provider for my 17 year old girl. She has* *learning problems and autism. I live in [name of city]. I need someone who can deal with autism. Please help.*" The comments they received provided informational support with methods that might work for their kids, such as "*As a person who has a hyperactive body type, I can emphatically state that heavy work, stretching, and music are all helpful in regulating me. I have also seen and used many of these activities to support kids on the spectrum with success.*" In addition to all the discussions regarding specific information needs, both group administrators and other group members posted *welcome messages* (the fifth topic), which showed the welcoming environment of the group to new members.

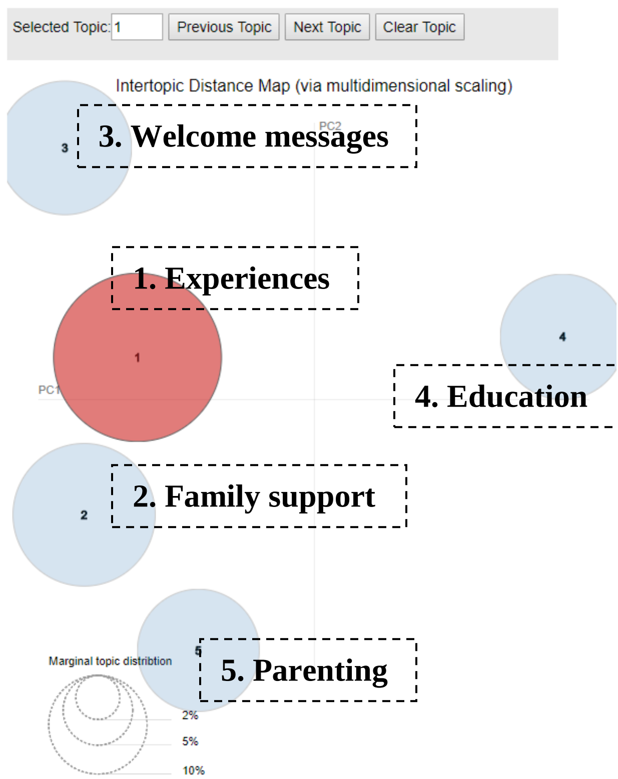

Figure 29. Visualization of the topics in Group 3

Topic 1 Experiences		Topic 2 Family support		Topic 3 Welcome messages		Topic 4 Education		Topic 5 Parenting	
autism	0.026	thank	0.014	welcome	0.023	welcome	0.025	know	0.009
thank	0.02	day	0.011	group	0.011	thank	0.014	like	0.008
welcome	0.015	like	0.008	help	0.011	need	0.012	welcome	0.008

people	0.012	know	0.007	good	0.01	son	0.011	parent	0.008
son	0.011	year	0.006	thank	0.008	help	0.01	right	0.007
get	0.01	make	0.006	get	0.008	autism	0.008	old	0.007
help	0.01	people	0.006	want	0.008	child	0.008	year	0.007
like	0.008	help	0.005	parent	0.008	look	0.007	son	0.007
group	0.007	son	0.005	autism	0.008	group	0.006	group	0.007
love	0.007	call	0.005	time	0.008	like	0.006	study	0.007
school	0.006	good	0.005	go	0.008	see	0.006	good	0.007
want	0.005	think	0.005	big	0.007	work	0.005	go	0.007
video	0.005	time	0.005	like	0.006	share	0.005	get	0.007
feel	0.005	brother	0.005	thing	0.006	want	0.005	want	0.006
know	0.005	well	0.005	join	0.005	old	0.005	autism	0.006
share	0.005	got	0.005	everyone	0.005	learn	0.005	comic	0.006
kid	0.005	parent	0.004	share	0.005	day	0.005	thing	0.005
need	0.005	family	0.004	day	0.005	right	0.004	child	0.005
give	0.004	guy	0.004	know	0.005	kid	0.004	need	0.005
say	0.004	hope	0.004	love	0.004	autist	0.004	u	0.004

Table 35. Top 20 terms and the associated probabilities of the terms to each topic in Group 3

4.4.4 Discussion topics of Group 4 (Research group)

There were 88 remaining records and 444 remaining terms in Group 4. As described on the group main page, Group 4 was described as "*plays a leading role — locally, nationally and internationally — in developing an improved understanding of the biological and psychosocial basis of autism.*" Figure 30 shows that three distinct topics emerged from Group 4, while Table 36 lists the top 20 terms associated with each topic. The three major topics which appeared in Group 4 were related to the *therapies*, the *trainings and workshops*, and the *events and visits*. Group members talked about various types of therapy for autism patients, such as "*Play therapy builds on the natural way that children learn about themselves and their relationships in the world around them. Through play therapy, children learn to communicate with others, express feelings, modify behaviour, develop problem-solving skills, and learn a variety of ways of relating to others.*" Information regarding trainings and workshops was also shared in the group, such as "*We are excited to announce that our new Online Certification Programme on Play*

Therapy for Children with Special Needs will launch this August!" The trainings and workshops discussed in the group were not only for professional therapists but also for parents of autism kids. The most influential user in Group 4, user C2, contributed to the topic of events and visits. User C2 is the group administrator and serves as an occupational therapist. He often uploaded updated his professional visits at different places and events he and his colleagues arranged. One of the posts was "*Today my first day #occupationaltherapy professional visit at #Mumbai went well heavy rains but parents managed to come for #OccupationalTherapy assessment and guidance.....*"

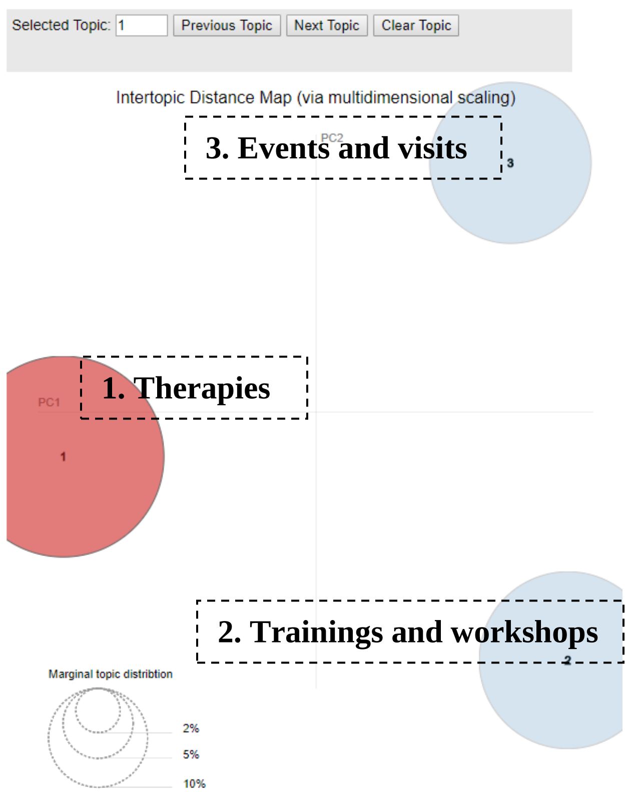

Figure 30. Visualization of the topics in Group 4

Topic 1 Therapies		Topic 2 Trainings and workshops		Topic 3 Events and visits	
therapy	0.022	share	0.017	autism	0.021
learn	0.014	autism	0.013	children	0.018
autism	0.014	parent	0.01	therapy	0.013
children	0.012	program	0.01	karthikeyan	0.013

center	0.011	special	0.008	visit	0.011
toy	0.011	respect	0.008	minister	0.011
occupation	0.011	workshop	0.008	day	0.011
seat	0.011	early	0.008	tamilnadu	0.011
visit	0.011	id	0.008	special	0.011
therapist	0.009	like	0.008	parent	0.011
special	0.009	dear	0.007	therapist	0.011
today	0.009	learn	0.006	occupationaltherapi	0.01
play	0.009	aware	0.006	occupation	0.008
online	0.009	friend	0.006	iotg	0.008
support	0.009	educate	0.006	participate	0.008
good	0.006	day	0.006	sai	0.008
time	0.006	child	0.006	dr	0.008
experience	0.006	sensory	0.006	respect	0.008
make	0.006	research	0.006	expense	0.006
early	0.006	children	0.006	social	0.006

Table 36. Top 20 terms and the associated probabilities of the terms to each topic in Group 4

4.4.5 Discussion topics of Group 5 (Local support group)

The input dataset for the LDA model for Group 5 consisted of 756 records and 2001 words. The posts and comments in Group 5 focused on four topics as shown in Figure 31. These were *greetings, support, conferences,* and *help requests.* The theme of each topic was labeled based on the top words listed in Table 37. The word "Mia" appeared to be among the top words for both the first and the third topic. "MM" is the name of the group founder's daughter who has autism. A pseudonym was used to protect the privacy of subject. The group founder, user D14, was the most central person in the group interaction network. He posted photos and daily updates about his daughter. Those posts usually received compliments like "*She is so beautiful love u mia grace!!!*" As shown in Figure 31, the first two topics were comparatively close to each other. People posted greetings on special days such as on Mother's Day and someone' birthday. Such messages included "*Love this poem! Happy Mother's Day to all you wonderful moms! You work very hard, I hope your day is as wonderful as you are!*" and "*Happy Birthday! You guys are a* *beautiful couple, and have a beautiful family!*" Other support information were expressed as "*Pm me! I'm happy to help!!!*" The third discussion topic was related to an adult autism conference. One of the group members kept posting information regarding the conference, such as the call for presentation flyers, the conference agendas, and the photos of conference presentations. Another discussion topic was questions and answers regarding specific help inquiries, such as "*I am new to this group. I have an amazing 3 year old son who has recently been given an ASD diagnosis… So I ask, what has been other mom's or family's experience with obtaining SSI Disability benefits?*" Such specific help request tended to receive informational replies from others, such as "*I filed with copy of diagnosis and 4 weeks later start getting payments on child*"

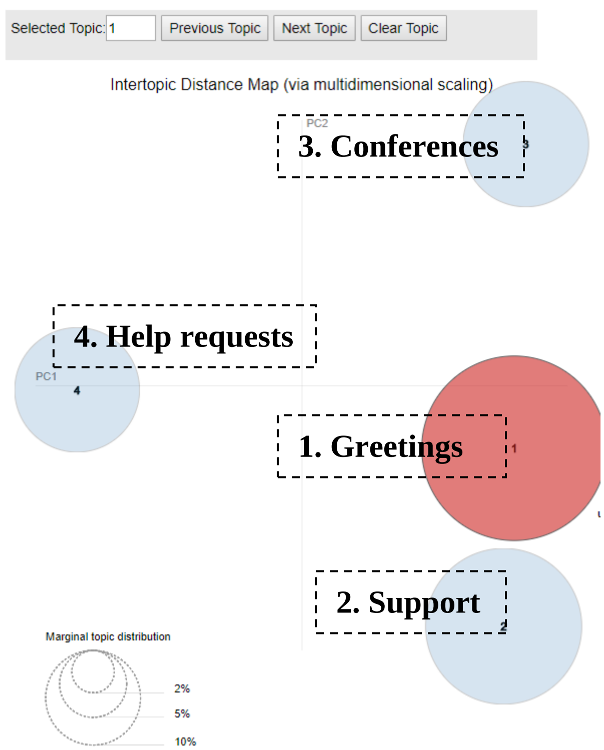

Figure 31. Visualization of the topics in Group 5

Topic 1 Greetings		Topic 2 Support		Topic 3 Conferences		Topic 4 Help requests	
love	0.016	get	0.014	autism	0.015	autism	0.021
autism	0.013	thank	0.013	get	0.015	help	0.011
go	0.009	like	0.013	try	0.008	son	0.008

work	0.008	autism	0.011	take	0.008	autist	0.007
like	0.008	go	0.009	true	0.008	make	0.006
get	0.008	know	0.008	love	0.007	child	0.006
mia	0.008	son	0.007	conference	0.006	share	0.006
help	0.007	help	0.007	MM	0.006	love	0.006
great	0.007	month	0.006	adult	0.006	year	0.006
child	0.006	sure	0.006	thank	0.005	try	0.006
day	0.006	need	0.006	day	0.005	give	0.005
know	0.006	time	0.006	think	0.005	get	0.005
good	0.006	everyone	0.006	that	0.005	old	0.005
take	0.006	beauty	0.006	kid	0.005	new	0.005
need	0.005	look	0.005	keep	0.004	family	0.005
thank	0.005	great	0.005	always	0.004	free	0.005
want	0.005	happy	0.005	he	0.004	people	0.005
time	0.005	make	0.005	need	0.004	hope	0.004
children	0.005	year	0.005	go	0.004	asd	0.004
start	0.004	work	0.005	know	0.004	he	0.004

Table 37. Top 20 terms and the associated probabilities of the terms to each topic in Group 5

4.4.6 Summary

Inspired by Griffiths and Steyvers (2004), the LDA model was implemented to discover the topics drawn from group posts and comments. An interactive visualization method (*pyLDAvis*) was employed to evaluate produced models and visualize the inter-topic distance maps. As a result, distinct discussion topics were summarized and labeled in each group. The discussion topics in Group 1 included *parenting*, *behavioral traits*, *diagnosis*, and *video sharing*. The three topics which emerged from Group 2 were *EMF pollution*, *home decoration*, and *wireless safety*. Group members talked about the following five topics in Group 3: *experiences*, *family support*, *welcome messages*, *education*, and *parenting*. In Group 4, the three major topics which appeared were related to *therapies*, *trainings and workshops*, and *events and visits*. Posts and comments in Group 5 mainly focused on *greetings*, *support*, *conferences*, and *help requests*. Each group had certain distinctive discussion topics that related to the purposes of the groups. Parenting was a common theme in Group 1 and Group 3.

As presented above, user a41 in Group 1 contributed most in the discussion topic of *video sharing*. User C2 in Group 4 shared most of the posts related to the topic of *events and visits*. Part of the posts and comments of the *greetings* topic and the *support* topic were generated by user D14 in Group 5. Based on the group interactions, the above three users served as the influential users in their respective group. This suggests that influential users took significant roles in controlling or leading the discussions in their groups.

In addition, several time-sensitive topics appeared during the group discussions. Group members greeted about Mother's Day during May. For example, group members in Group 5 posted "*Hope all you mothers have a blessed mother's day.*"

4.5 Findings for research questions 4 (RQ4)

RQ4: What are the sentiment characteristics of discussions in autism support groups on Facebook?

The last research question aims to unveil the sentiment characteristics of the group discussions which appeared within autism support groups on Facebook. RQ 4.1 and RQ 4.2, respectively, examined the gender differences and group differences expressed by group members.

4.5.1 RQ 4.1 & Hypothesis group 3

RQ 4.1 was answered by hypothesis group 3, which consisted of a series of hypotheses and sub-hypotheses. To test the gender differences of the sentiment characteristics, a series of inferential analyses were applied. The parametric tests (e.g. t-tests, analysis of variance) require assumptions that the shape of the population distribution is normally distributed, while non-parametric tests do not include assumptions about the underlying population distribution (Pallant 2013).

H_{04} stated that *there are no significant differences between male group members and female group members in terms of the sentiment in autism support groups on Facebook.* A Kolmogorov-Smirnov test was conducted to examine the normality of the datasets before proceeding with the parametric tests. A non-significant result (significance value of more than .05) indicates normality (Pallant, 2010). In this case, the significance values for the Kolmogorov-Smirnov tests conducted in each group were 0.000 (Group 1), 0.000 (Group 2), 0.000 (Group 3), 0.001 (Group 4), and 0.000 (Group 5), suggesting violation of the assumption of normality in all five groups. Therefore, in this study, a series of non-parametric tests (e.g. Mann-Whitney U test, Kruskal-Wallis H test) were performed to examine the null hypotheses.

The significance level (α) for all tests was equal to 0.05. If the resultant *p*-value of a null hypothesis test was smaller than 0.05, the null hypothesis was rejected. Otherwise, the null hypothesis failed to be rejected. In the Kruskal-Wallis H test, the results included both χ^2-value and *p*-value. The χ^2-value is presented as $\chi^2(df, n)$ where the *df* stands for the degrees of freedom and the *n* stands for the sample size. Effect size indicates the influence of the independent variable (Pallant, 2013). In this study, the effect size statistic was reported as the *r*- value, and the median was reported as the *Md* value.

The Mann-Whitney U test is used to test for differences between two independent groups on a continuous measure (Pallant, 2010). A series of Mann-Whitney U tests was conducted to test the hypotheses under hypothesis group 3. For H_{04}, Mann-Whitney U-value was found to be statistically significant (U= 664450.5, Z= -2.056, $p=0.04<0.05$). The resultant effect size *r* was 0.04, indicating a very small effect size using Cohen (1988) criteria of 0.1=small effect, 0.3=medium effect, 0.5=large effect (Pallant 2013). It suggests that male group members and female group members expressed significantly different sentiment in the autism support groups on Facebook, but the effect size would be considered very small.

Figure 32 displays the boxplots of the sentiment scores for the male group members and female group members. It compared the medians and spread of the data by the gender groups. In Figure 32, each box plot represents a gender (i.e. male and female). The crosses correspond to the means. The lower and upper limits of the box are the first and third quartiles, respectively. Points above or below the whiskers' upper and lower bounds may be considered as outliers. The median score of the sentiment presented by females (Md=0.201) was higher than by males (MD=0.148). The spread of the sentiment scores for males and females were similar. As can be seen from Figure 32, more outliers appeared for females. It suggested that the females tended to convey emotions that were more intensive. Examples of very positive messages posted by women included "*I would really love to connect locally!*" and "*That is so very true... We shouldn't give up*". The intensively negative posts included "*This is ridiculous!!*"

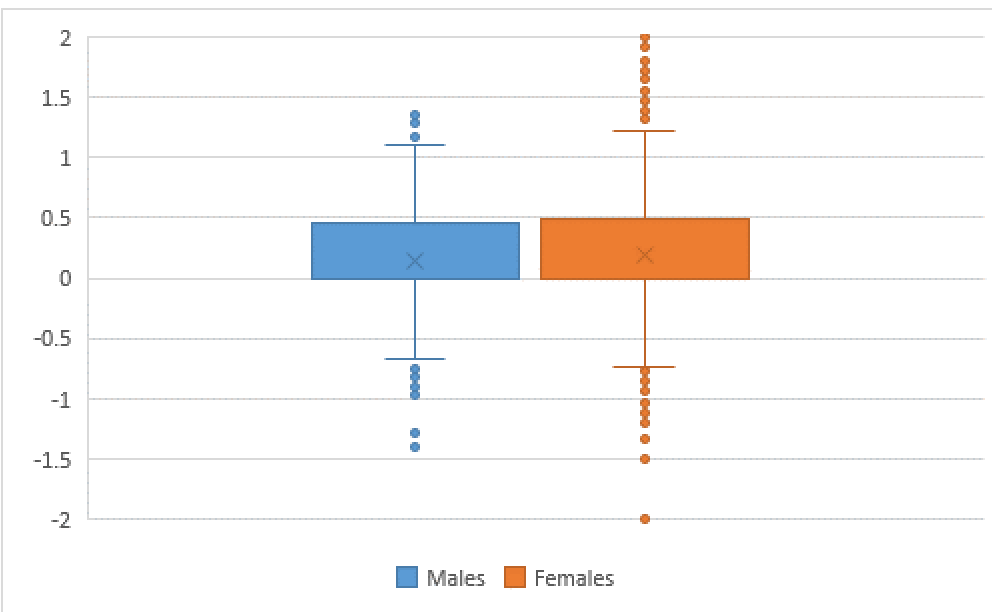

Figure 32. Boxplots of the sentiment scores for males and females

Table 38 shows the statistical results of the Mann-Whitney U tests of the gender differences in each group. As a result, all five sub-hypotheses (i.e. $H_{05(a)}$, $H_{05(b)}$, $H_{05(c)}$, $H_{05(d)}$, $H_{05(e)}$) failed to be rejected. It suggests that there were no significant gender differences in sentiment characteristics were found in all five groups.

	Group 1	Group 2	Group 3	Group 4	Group 5
Mann-Whitney U	11076.5	57420	74657	573	64268.5
Z	-1.002	-1.729	-0.418	-0.85	-0.081
p-value	0.317	0.084	0.676	0.395	0.936
r	0.057	0.066	0.013	0.098	0.003

Table 38. Statistical results for H_{05}

Figure 33 displays the means and standard deviations of the sentiment scores of the male group members and female group members in each group. The means of sentiment scores of males and females in all groups were slightly above zero, which means the average sentiment appeared to be positive in each group. Female group members and male group members reached similar sentiment scores in Group 1, Group 3, and Group 5. Female group members expressed lower sentiment scores in Group 2 than male group members did, while female group members were more positive in Group 4 than male group members were. The standard deviations showed that the male group members in Group 1 and Group 5 addressed emotions that varied more than in the other groups. The variations of the emotions expressed by the female group members were quite close in all groups. Group 2 focused on the discussions of the treatment. In this group, female group members sometimes expressed extremely negative emotions such as "*Very scary!!*" and "*Holy shit!*". In Group 4, which was created for research focus, 24 out of 26 messages posted by female group members were positive or neutral. Most of the females expressed enthusiasm to share the workshop information and videos with other group members, such as “*This workshop focuses on some of the most widely used IQ Assessments used in field of Child & Clinical Psychology*” and “*Hello friends I'd like to share this amazing story with you.*”

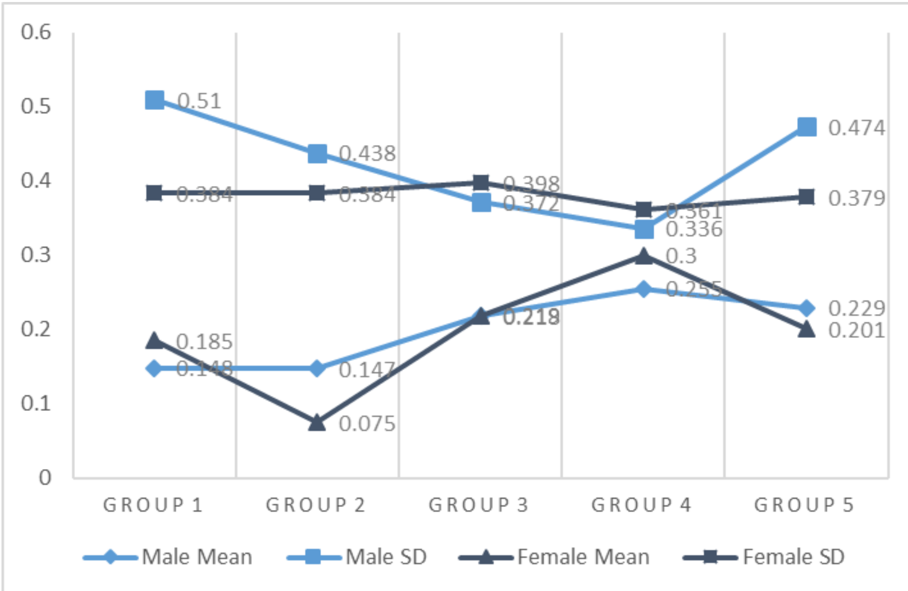

Figure 33. Distributions of means and standard deviations of sentiment scores of males and females in each group

4.5.2 RQ 4.2 & Hypothesis group 4

RQ4.2 addresses the following: “Are there any significant differences among the defined categories in terms of sentiment characteristics in autism support groups on Facebook?” It concerns the comparison of sentiment characteristics in autism support groups that focused on different topics.

Hypothesis group 4 consisted of three hypotheses H_{06}, $H_{07(a)}$, and $H_{07(b)}$. In contrast to hypothesis group 3, the independent variable for each hypothesis under hypothesis group 4 was the defined category of the group. A series of non-parametric Kruskal-Wallis H tests were conducted to examine the three hypotheses.

The results of the Kruskal-Wallis H test revealed that there were statistically significant differences among the five groups in terms of the expressed sentiment (χ^2 (4, n=2798)= 47.302, $p=0.000<0.05$). In other words, hypothesis H_{06} was rejected. This suggests that the sentiment which appeared in each group differed significantly. Table 39 summarizes the number of records and the medians of the sentiment scores in each group.

	Group 1	Group 2	Group 3	Group 4	Group 5
N	310	695	942	76	775
Median	0.008	0.000	0.13	0.368	0.000

Table 39. Descriptive statistics of the group sentiment comparisons

To find out which of the groups were significantly different from one another, statistically speaking, a Dunn-Bonferroni test between pairs of groups (e.g. between Group 1 and Group 2) was carried out as a *post-hoc* test. Table 40 shows the statistical results for the Dunn-Bonferroni test. In Table 40, the p-values smaller than the significance level (0.05) are in bold and have the asterisks. The results indicate that a very strong evidence of sentiment differences occurred between the following pairs of groups: Group 2 vs. Group 3, Group 2 vs. Group 4, Group 2 vs. Group 5, and Group 1 vs. Group 4. There was no evidence of a significant difference between the other pairs.

	Group 1	Group 2	Group 3	Group 4	Group 5
Group 1		0.178	0.461	**0.045***	1.000
Group 2	0.178		**0.000***	**0.000***	**0.000***
Group 3	0.461	**0.000***		0.508	1.000
Group 4	**0.045***	**0.000***	0.508		0.268
Group 5	1.000	**0.000***	1.000	0.268	

Table 40. Statistical results for the Dunn-Bonferroni test for H_{06}

Figure 34 displays the boxplot of the sentiment scores in each group. It compares the medians and spread of the data by group. The central horizontal bar within a box is the median. Posts and comments in Group 4 appear to have higher median sentiment scores. The sentiment scores in Group 2 were less spread out than the other groups. This suggested that 50% of the messages which appear in the *treatment* group fall into a smaller sentiment range (0 to 0.366).

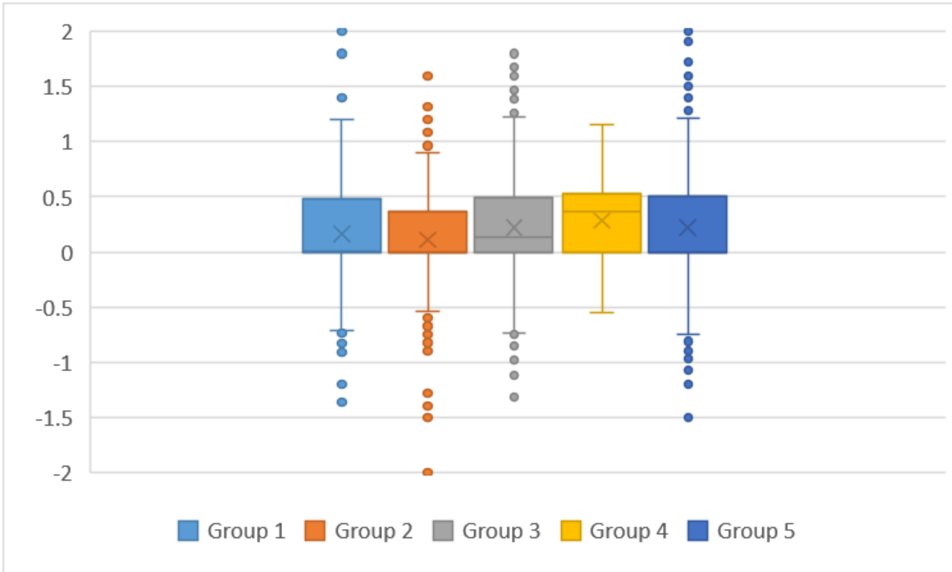

Figure 34. Boxplot of the sentiment scores in each group

H_{07} was proposed to examine if there are significant differences among the defined categories in terms of the sentiment of group members with the same gender in autism support groups on Facebook. H_{07} was then divided into two associated sub-hypotheses based on the gender of group members (i.e. male and female). The results of the two Kruskal-Wallis H tests revealed that there were statistically significant differences across the five groups in terms of the sentiment expressed by males (χ^2 (4, n=986)= 36.504, p=0.000<0.05) and by females (χ^2 (4, n=1821)= 15.006, p=0.005<0.05). In other words, hypothesis $H_{07(a)}$ and $H_{07(b)}$ were rejected. It suggests that both male group members and female group members expressed significantly different sentiment in different groups. Table 41 summarizes the number of records and the medians of the sentiment scores generated by male and females in each group.

		Group 1	Group 2	Group 3	Group 4	Group 5
Male	N	137	350	207	50	242
	Median	0.200	0.000	0.164	0.385	0.000
Female	N	173	345	735	26	533
	Median	0.000	0.000	0.105	0.251	0.000

Table 41. Descriptive statistics of the group sentiment comparisons for males and females

Two Dunn-Bonferroni tests (one for males and one for females) between pairs of groups were then carried out. Table 42 shows the statistical results for the two post-hoc tests. In Table 42, the p-values smaller than the significance level (0.05) are in bold and have the asterisks. There was strong evidence of differences between the following pairs of male groups: Group 1 vs. Group 2, Group 2 vs. Group 3, Group 2 vs. Group 4, and Group 2 vs. Group 5. In terms of the content generated by female group members, the emotions varied significantly in Group 2 and Group 3.

		Group 1	Group 2	Group 3	Group 4	Group 5
Male	Group 1		**0.032***	1.000	0.266	1.000
	Group 2	**0.032***		**0.000***	**0.000***	**0.001***
	Group 3	1.000	**0.000***		0.834	1.000
	Group 4	0.266	**0.000***	0.834		0.344
	Group 5	1.000	**0.001***	1.000	0.344	
Female	Group 1		1.000	0.398	1.000	0.954
	Group 2	1.000		**0.008***	0.940	0.057
	Group 3	0.398	**0.008***		1.000	1.000
	Group 4	1.000	0.940	1.000		1.000
	Group 5	0.954	0.057	1.000	1.000	

Table 42. Statistical results for the Dunn-Bonferroni tests for $H_{07(a)}$ and $H_{07(b)}$

Figure 35 displays the boxplots of the sentiment score distributions for male group members and female group members across the five groups. For males, the median of the sentiment scores in Group 2 was lower than those in Group 1, Group 3, and Group 4. In addition, the spread of the sentiment scores in Group 2 was smaller than all the other four groups. In the *treatment* group, the male group members were more likely to convey intensive emotions than they did in the other groups. Sample messages included “*Hey guys, thanks for letting me join, wrote this article and thought youd all appreciate it !!*” and “*Blocking by using 2 reflectors - stupid!*” For the female group members, the median scores of the sentiment were similar in

Group 1, Group 2, and Group 5, while the spread of the sentiment scores was slightly smaller for Group 2 than for the other four groups.

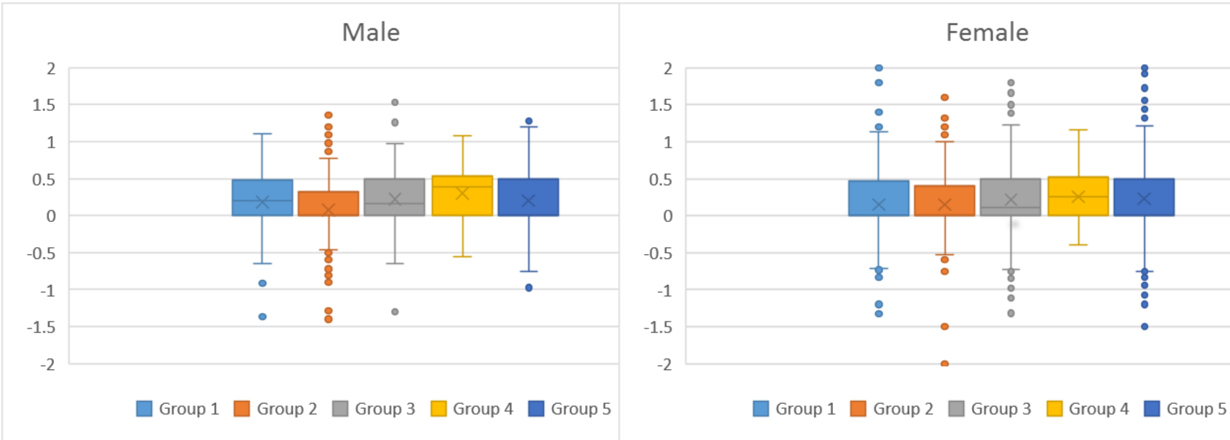

Figure 35. Boxplots of the sentiment score distributions for males and females

4.5.3 Summary

The fourth research question concerned the sentiment expressed within autism support groups on Facebook. RQ4.1 examined the gender differences in the presented sentiment, while RQ4.2 investigated the differences in the presented sentiment across groups that belong to various categories. Table 43 summarizes the associated hypotheses, independent variables (IV), measurements of dependent variables (DV), statistical tests, and generated test results with respect of RQ 4.

Research questions	Hypothesis	IV	Measurement of DV	Test	Result
RQ4.1	H_{04}	Gender	Sentiment scores	Mann-Whitney U test	Reject
	$H_{05(a)}$	Gender	Sentiment scores	Mann-Whitney U test	Not reject
	$H_{05(b)}$	Gender	Sentiment scores	Mann-Whitney U test	Not reject
	$H_{05(c)}$	Gender	Sentiment scores	Mann-Whitney U test	Not reject
	$H_{05(d)}$	Gender	Sentiment scores	Mann-Whitney U test	Not reject
	$H_{05(e)}$	Gender	Sentiment scores	Mann-Whitney U test	Not reject
RQ4.2	H_{06}	Category	Sentiment scores	Kruskal-Wallis H test	Reject
	$H_{07(a)}$	Category	Sentiment scores	Kruskal-Wallis H test	Reject
	$H_{07(b)}$	Category	Sentiment scores	Kruskal-Wallis H test	Reject

Table 43. Summary of the findings for RQ 4

Through a series of inferential analyses, it was revealed that female group members tended to express more positive emotions in the group discussions. In addition, it was found that the female group members were more likely to convey intensive emotions in their posts. However, no significant gender differences in the expressed sentiment were found in all five groups. Interestingly, female group members expressed more negative emotions in the *treatment* group than male group members did, while male group members were more positive in the *research* group than female group members were.

Within the groups focused on various topics, the group members appeared to express significantly different sentiment. Emotions that were more negative occurred in the *treatment* group. Males especially seemed to address significantly more negative opinions in the *treatment* group.

4.6 Results summary

Research questions 1 and 4 were addressed by a series of statistical analyses. Table 44 summarizes the statistical findings for RQ 1 and RQ4.

Research questions	**Sub-questions**	**Hypothesis**	**Results**
RQ1: How do users interact with each other in autism support groups on Facebook based on social network analysis?	RQ1.1: Are there any differences between male group members and female group members in terms of interactions in autism support groups on Facebook?	$H_{01(a)}$	Reject
		$H_{01(b)}$	Reject
		$H_{01(c)}$	Reject
		$H_{02(a)}$	Group 1: Reject
			Group 2: Reject
			Group 3: Not reject
			Group 4: Reject
			Group 5: Reject
		$H_{02(b)}$	Group 1: Reject
			Group 2: Reject
			Group 3: Not reject
			Group 4: Reject
			Group 5: Reject
		$H_{02(c)}$	Group 1: Not reject
			Group 2: Not reject
			Group 3: Not reject
			Group 4: Not reject
			Group 5: Not reject
	RQ1.2: Are there any differences	$H_{03(a)}$	Reject

	among the defined categories in terms of online interactions in autism support groups on Facebook?	$H_{03(b)}$ $H_{03(c)}$	Reject Reject
RQ4: What are the sentiment characteristics of discussions in autism support groups on Facebook?	RQ4.1: Are there any differences between male group members and female group members in each of the defined categories in terms of sentiment characteristics in autism support groups on Facebook?	H_{04} $H_{05(a)}$ $H_{05(b)}$ $H_{05(c)}$ $H_{05(d)}$ $H_{05(e)}$	Reject Not reject Not reject Not reject Not reject Not reject
	RQ4.2: Are there any differences among the defined categories in terms of sentiment characteristics in autism support groups on Facebook?	H_{06} $H_{07(a)}$ $H_{07(b)}$	Reject Reject Reject

Table 44. Statistical findings for RQ 1 and RQ4

RQ2 and RQ3 discovered the influential users based on interactions and the discussion topics within the autism support groups on Facebook. To answer RQ2, social network analysis was employed to identify the influential users based on interactions in each Facebook autism support group, and to unveil the interaction characteristics of those users. As a result, 53 influential users were identified. They occupied the top 20 important positions in each group based on three centrality measures: degree centrality, betweenness centrality, and closeness centrality. It was noticed that group members tended to react more to the influential users. RQ3 was answered by applying *Latent Dirichlet Allocation* (LDA) to the posts and comments appearing in the groups. As a result, the distinct discussion topics were revealed within each sampled group.

Chapter 5. Discussion and Implications

The following paragraphs include a discussion of unique, irregular, and unexpected findings, and a comparison of this study's findings with previous studies. In addition, the theoretical and practical implications of the findings from this study are discussed.

5.1 Discussion

5.1.1 Interactions in online health communities

In comparison to face-to-face groups, the "Reaction" or "Like" buttons are exclusive to the Facebook groups. As shown in Figure 17, giving reactions to posts, which includes the like function, were the most popular interaction behaviors in comparison to commenting, sharing out, and tagging in this study. The prevalence of giving reactions (or likes) was also found in a Facebook stutter support group where the number of likes was three times the number of replies. Such quantitative finding can be confirmed by the qualitative findings from a prior study (Raj, 2015). Various participants involved in a Facebook stutter support group explained that they believed the "Like" button's role within the Facebook group was a form of support (Raj, 2015).

Among the five investigated groups, there were 53 influential users occupying the top 20 important positions in each group in terms of three centrality measures: degree centrality, betweenness centrality, and closeness centrality. A correlation analysis was conducted to examine if there were significant correlations among the following nine detailed interaction behaviors: post, comment, received comment (re_comment), reaction, received reaction (re_reaction), share, being shared (re_share), tag, and being tagged (re_tag). The relationships among different activities were investigated using Spearman correlation coefficient. As mentioned before, Cohen (1988) suggested the interpretation of the value of the correlation coefficient as the following guidelines: small (*rho*=0.10 to 0.29), medium (*rho*=0.30 to 0.49), and large (*rho*=0.50 to 1.0). Table 45 shows the Spearman's *rho*-values between each pair of activities. In Table 45, the correlation values with two asterisks (**) are significant at the 0.01 level (2-tailed). The test results demonstrate that significant medium to large correlations were found between the post activity and all four types of received activities: received comment (*rho*=.589), received reaction (*rho*=.869), being shared (*rho*=.488), and being tagged (*rho*=.351). The frequencies of posts that a user posted were significantly correlated with the interactions he/she received. Moreover, significant large correlations were also revealed between the following three pairs of behaviors: comment and received comment (*rho*=.832), share and being shared (*rho*=.520), and tag and being tagged (*rho*=.647). That is, the more a group member engaged in the group, the more support he/she obtained from the group. This finding is consistent with previous studies of other health-related online support groups. In online support groups for distressed adolescents, the number of reply messages posted and the number of messages received by participants were significantly correlated (Barak Azy & Dolev-Cohen Michal, 2007).

Pearson Correlation	Post	Comment	Re_comment	Reaction	Re_reaction	Share	Re_share	Tag	Re_tag
Post	1	.410**	.589**	.167	.869**	.372**	.488**	.199	.351**
Comment	.410**	1	.832**	.388**	.455**	.418**	.347**	.613**	.685**
Re_comment	.589**	.832**	1	.202	.673**	.410**	.444**	.603**	.678**
Reaction	.167	.388**	.202	1	.199	.371**	.203	.199	.235
Re_reaction	.869**	.455**	.673**	.199	1	.469**	.543**	.222*	.419**
Share	.372**	.418**	.410**	.371**	.469**	1	.520**	.057	.474**
Re_share	.488**	.347*	.444**	.203	.543**	.520**	1	.166	.407**
Tag	.199	.613**	.603**	.199	.222	.057	.166	1	.647**
Re_tag	.351**	.685**	.678**	.235	.419**	.474**	.407**	.647**	1

Table 45. Correlation results of detailed interaction behaviors

In addition to the correlations between the interaction behaviors, the findings of previous studies showed that active involvement in a support group was conversely related to a participants' later level of distress, which means the more involved a participant, the lower her or his distress level becomes over time (Barak Azy & Dolev-Cohen Michal, 2007). Along with previous research, it suggests that group members should be encouraged to post more messages in the online communities, since it might result in gaining more replies and feeling better.

5.1.2 Interaction networks of online health communities

Network density relates directly to the availability of social support (Marsden, 1987). Table 46 summarizes the network measures from previous studies (Chang, 2009) and the present study. Compared to the network measures reported in six previous studies, the five investigated autism support groups on Facebook in this study were comparative large but sparsely interconnected. It has been suggested in the traditional social support literature that the density of the network is dependent on the types of social support provided (Chang, 2009). Wellman (1992) argued that greater service for chronical diseases tended to be more widely offered in high-density networks, whereas more companionship was offered in low-density networks. Chang (2009) claimed later that emotional aid was forthcoming in low-density networks. Thus, in this study the network measures show that more companionship and emotional support were provided in the investigated autism support groups on Facebook than other service.

Studies	Support group	Sampling period	Size	Number of messages	Density
Bjornsdottir, 1999	Heart disease	4 weeks	30	69	.08
Braithwaite et al., 1999	Disabilities	1 month	42	1,472	.85
Coulson, 2005	Irritable bowel syndrome	8 months	132	572	.03
Eichhorn, 2008	Eating disorder	Longitudinal	N/A	490	N/A
Galegher et al., 1998	Arthritis	3 weeks	119	200	.01
	Attention deficit	3 weeks	274	5,520	.07
	Depression	3 weeks	733	39,864	.07
Chang, 2009	Psychosis	30 months	344	689	0.005
Present study	Autism group 1 (Awareness group)	6 months	325	314	0.006
	Autism group 2	6 months	301	259	0.017

	(Treatment group)				
	Autism group 3 (Parents group)	6 months	525	924	0.011
	Autism group 4 (Research group)	6 months	184	88	0.014
	Autism group 5 (Local support group)	6 months	438	756	0.009

Table 46. Summary of network measures from previous studies and present study

5.1.3 Influential users in support groups on Facebook

As shown in Figures 18 to 22, the five investigated autism support groups were highly centralized. This network pattern was also found with the communication patterns within a psychosis social support group (Chang, 2009). It was reported that about 1% of group members within the online psychosis support group contributed almost 20% of the overall communication (Chang, 2009).

Previous studies have explored the functions and emergence of the influential users in a network. Bambina (2007) revealed that a star user played the key function in linking together a highly-distributed network in an online cancer discussion forum. In this study, 53 out of 1773 group members (3%) were identified as influential users across the five autism groups. These identified influential users dominated the group communications and attracted more attentions from other group members. Across Group 2, Group 3, Group 4, and Group 5, the most central users in each group appeared to be the group administrators. It demonstrated that group administrators tended to have intensive impact on other group members.

Raj (2015) reported that one of the co-leaders of the stuttering support group regularly kept posting new stuttering-related questions to the Facebook group. It turned out that many of these questions generated replies and “Like” button clicks. In this study, it was also found that influential users attracted many attentions from other group members. It might suggest that questions posted by the influential users might trigger more discussions and help other group members engage in the group.

5.1.4 Gender difference in Facebook group behaviors

Gender differences were unveiled from previous studies in other support groups on Facebook. A high male prevalence was found in groups for concussion (Ahmed, Sullivan, Schneiders, & McCrory, 2010), while a high female prevalence was found in self-harm groups (Niwa & Mandrusiak, 2012), pre-term infants groups (Thoren, Metze, Bührer, & Garten, 2013), and thoracic outlet syndrome group (Walker, 2014). In this study, the prevalence of female group members was found among the five investigated autism support groups. It confirmed findings from previous research (Yang, 2015) that females were better prepared to seek, acquire, and offer support than their male counterparts.

With respect to people with autism, Baio (2012) reported that the prevalence of autism among males was significantly ($p<0.01$) higher than among females. In this study, it was noticed that although more female group members engaged in the group interactions in the autism support groups, male group members had significantly more central positions in the groups than the female group member did in terms of degree centrality and betweenness centrality. Given the fact that autism affects more males (Baio, 2012), male users can potentially benefit from online communication by increasing social connectedness and well-being (Valkenburg & Peter, 2009; Ko, 2014).

Significant gender differences were found in four out of the five investigated groups in terms of degree centrality and betweenness centrality in this study. This finding was consistent with conclusions from Ko (2014), which showed that males and females with autism socialized differently on social media.

5.1.5 Social and informational exchange in support groups on Facebook

Through interviews with 14 participants who used support groups on Facebook for weight loss and diabetes management, Newman, Lauterbach, Munson, Resnick, and Morris (2011) unveiled that participants used Facebook support groups in pursuit of emotional support, motivation, accountability, and advice. Sugimoto (2014) identified informational and emotional supports as the common type of support exchanged in depression online support groups. Sugimoto (2014) then summarized findings from previous studies that informational and emotional supports occupied a significant proportion of the total interaction among users (Alexander, 2002; Alexander et al., 2003; Fekete, 2002; Lamerichs & Molder, 2003; Macias et al., 2005; Muncer et al., 2000a; Muncer et al., 2000b; Salem et al., 1997; Witt, 2000).

Similar with other support groups on Facebook, social support was also found in the investigated autism support groups. Group members often received comments from others with similar situations and experiences (e.g. "*I can relate entirely and feel this way every day i drop my brave boy at pre-school. Xx*"). Although people may not receive actual information regarding their information needs, the social support they acquired may help with emotional relief.

In addition to general social support, disease-specific information was also exchanged in the support groups on Facebook. For individuals in Facebook support groups for presumed ocular histoplasmosis syndrome (POHS), issues regarding diagnosis, treatment, adjustment, and emotional distress were discussed. In the five investigated autism support groups of this study, the following autism-related topics were shared in the Facebook groups: "parenting", "behavior traits", "diagnosis", "home decorations", "education", and "therapies".

As a beneficial result of membership, collective coping strategies were identified as well as timely medical advice based on personal experience, research resources, linkage to services, compassionate support, camaraderie, and social interaction (Thompson, 2015). In this study, it was noticed that group members brought up questions regarding the coping strategies and received multiple suggestions from others with the similar experiences. For example, a mother asked in one of the investigated autism groups: "*what has been other mom's or family's experience with obtaining SSI Disability benefits?*" The post obtained 11 comments including information from others with similar experiences, e.g. "*I filed with copy of diagnosis and 4 weeks later start getting payments on child*" and "*For SEVERAL years (ages 3-9) we got SSI for our son. It helped tremendously. And was not hard at all to get. It was a couple months when we got it. It was a life saver!*" Another group member replied to the post and expressed the willingness to provide personal help: "*Pm me! I'm happy to help!!!*" As demonstrated by a previous study, such health communities provide access to experience-based information about particular situations, which many users find more relevant or accessible than information obtained from professionals (Newman et al., 2011).

Previous studies argued that, unlike face-to-face support groups, instrumental or tangible support was either absent or very rare in online depression support groups (Alexander et al., 2003; Muncer et al., 2000; Sugimoto, 2014). However, it was noticed that group members offered tangible responses when people asked specific questions in the autism support groups in this study. For example, one group member brought up a question: "*I am thinking of purchasing this emf meter for our home. …Are any of you familiar with this product or have a recommendation for a different meter?*" Several instrumental and tangible comments replied by others included "*For about the same price, you can get this one: http://www.electricsense.com/10786/cornet-ed88t-emf-meter*/" and "*I second the recommendation. Tue Cornet is way better for a similar price.*" In this case, the product recommendations can be considered as informational and useful support for people who did not have such experiences.

Disseminating information with others about upcoming events was identified as one of the most popular things to do on Facebook (Cheung, Chiu, & Lee, 2011). In both Group 4 (research group) and Group 5 (local support group), there was information about a variety of events and conferences shared in the groups. These types of information were also noticed in other Facebook support groups. Raj (2015) unveiled that leaders of support groups used their Facebook groups to post numerous messages that promoted upcoming meetings. It suggested that one of the benefits of being involved in support groups on Facebook is to gain access to beneficial information like available events and conferences. It helps group members feel connected and supported, since they could stay current and up-to-date with the groups they choose to be a part of (Raj, 2015).

5.1.6 Emotional exchange in Facebook support groups

Previous studies identified that venting is one of the purposes for people who use Facebook groups to fulfill a need to share information without an expectation of responses (Niwa & Mandrusiak, 2012b). As shown in Figure 36, for all of the five investigated autism support groups on Facebook, negative messages appeared in the groups less than positive and neutral messages. A prominent theme of the messages that conveyed negative emotions can be classified into the venting category (e.g. "*Yes its a very scaring feeling my son is 3 an he takes off on me...My heart sinks*"). It suggested that Facebook groups could serve as not only a place to seek informational and emotional help but also a venue people could feel free to speak of the bad feelings.

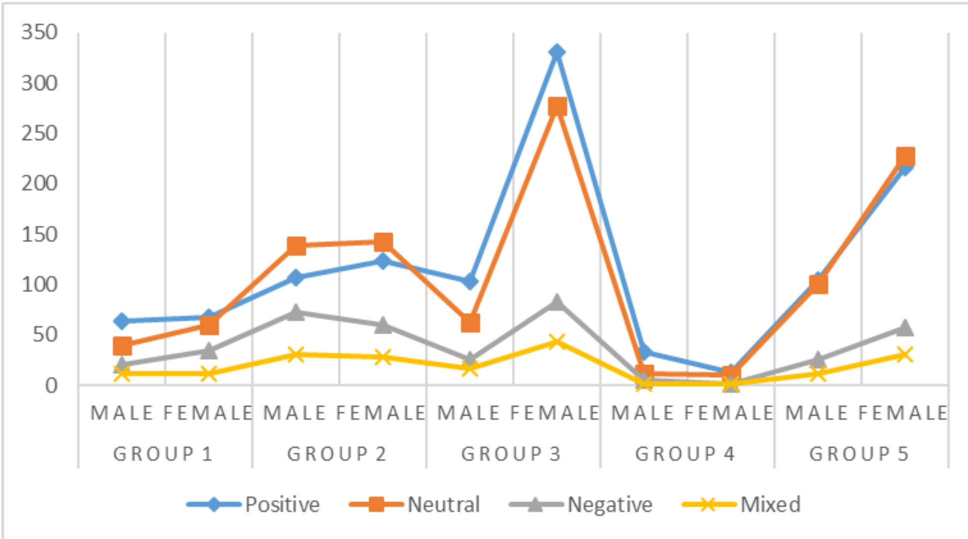

Figure 36. Gender differences of sentiment distributions in each group

There are contrasting and possibly conflicting views on the pros and cons to participating in online support communities (Niwa & Mandrusiak, 2012b). In 4 self-injury groups on Facebook, Niwa and Mandrusiak (2012b) revealed that 3.6% of the total posts were praising or thanking in the group. In contrast to the self-injury groups, as shown in Table 34, 35, and 37, "thank" appeared to be one of the most frequently occurring keywords in three of the five autism support groups. It implied that autism support groups offered a more supportive emotional atmosphere for group members than those of the self-injury groups.

As can be seen from Figures 34 and 36, the overall sentiment, appearing in all five investigated groups, was positive and the positive and neutral messages outnumbered the negative messages. Moreover, from Tables 33 to 37, many positive words (e.g. "well", "like", "thank", "happy", "love", "good", and "great") appeared to be the most relevant terms to the discussion topics revealed in the groups. These findings were consistent to a reported healthy and continuous communication loop uncovered in a stutter support group on Facebook (Raj, 2015). Raj (2015) identified that the sense of family which came from the Facebook group helped to diminish feelings of loneliness or isolation for people who had communication barriers.

5.1.7 Manual annotation of sentiment categories

Accuracy of the sentiment classification is one of the most significant issues for sentiment analysis research (Baccianella, Esuli, & Sebastiani, 2010). In order to evaluate the performance of the adopted sentiment detection technique, which was the lexicon-based sentiment analysis conducted by Lexalytics, the author annotated the sentiment categories (i.e. positive, neutral, negative) of a randomly sampled sub-dataset. It was investigated whether the human judged sentiment polarities for the sampled records matched to the automatically obtained sentiment categories using Lexalytics. The sub-dataset contained 10 records randomly extracted from each of the selected groups. Thus, the performance was assessed based on 50 records annotated by both human and automatic sentiment detection technique. Cohen's kappa was run to determine if there was agreement between human and automatic sentiment annotations. The resultant inter-coder reliability (Cohen's kappa) was 0.505. Cohen's kappa results can be interpreted as follows: values ≤ 0 as indicating no agreement and 0.01-0.20 as none to slight, 0.21-0.40 as fair, 0.41-0.60 as moderate, 0.61-0.80 as substantial, and 0.81-1.00 as almost perfect agreement (McHugh, 2012). In this case, the human judgements and the automatic annotations achieved a moderate agreement in the sentimental category assignments.

5.1.8 Normalization impact

As shown in Table 25, the five sub-hypotheses associated with $H_{02(c)}$ failed to be rejected. It meant that no significant gender differences were found in the group interactions in terms of closeness centrality. To further explore whether these results were caused by the normalization method of the closeness centrality measure, the author conducted an experiment that used the square roots of the numbers of nodes instead of using the numbers of nodes directly to normalize the closeness centrality measures. As a result, the five sub-hypotheses associated with $H_{02(c)}$

remained as fail to be rejected, which meant that the insignificant results were not caused by the normalization method. It suggested that the abilities to instantly communicate and interact with others without going through many intermediaries were not significantly different between male group members and female group members.

5.2 Implications

5.2.1 Theoretical implications

The theoretical implications lie in the uncovering of emerging patterns and information exchange among autism support groups on Facebook. Previous studies on the information need of autism-affected consumers applied qualitative research methods such as interviews and focus groups to gather their opinions of online support groups. This study collected user-generated content from real support groups on social media. Computer-mediated methods, including topic modeling and sentiment analysis, were applied to the content gathered from autism support groups on Facebook. The analysis of the interactions and communications appearing in the groups revealed users' information needs and communication patterns.

Theoretically, the results of this study align with previous studies that demonstrated the significance of social media for autism users. The unique implication of this study is to identify autism support groups on Facebook as a source of informational, social, and emotional support for autism-related users. This observation suggested new opportunities of using Facebook help users who suffer from autism.

The findings regarding discussion topics appearing in the autism support groups on Facebook revealed the information needs of autism-related users. In addition, it examined that the informational support, such as specific strategies to deal with autistic kids, was provided in those support groups on Facebook.

A key finding of this study offers important implications for health communication in the social media era. The overall positive climate reflected by the discussions in autism support groups on Facebook suggest that support groups on social media promised to be a way to provide social and emotional support for autism-related users.

5.2.2 Methodological implications

Social network analysis has been widely applied in social media research. Social network analysis offers a unique way to draw insights from communications among community members. This study employed social network analysis to identify the communication patterns in Facebook groups, and discovered the influential users among group members. The way that social network analysis was applied in this study can be adopted to investigate social communities on other social media platforms.

Multiple methods were used to address how autism-affected users sought health information through social media. This study synthesized four distinct methods (social network analysis, topic modeling, sentiment analysis, and inferential analysis) to seek the patterns of health behaviors of autism-affected users. Visualization methods were also utilized to present the results from social network analysis and topics modeling. The methodology applied in this study developed a mixed method to evaluate the information exchange in health-related support groups on social media. The methodology proposed in this study can be employed to explore online social support communities focusing on other health concerns.

5.2.3 Practical implications

This study was designed to explore how autism-affected users engaged in autism support groups on Facebook. The results of autism-related Facebook groups identified in this study and the active interactions observed in the investigated groups supported the findings from previous clinical study that people with autism has an affinity towards computer and technology (Ko, 2014). These findings suggest that online communities might be used as an effective platform for social skills intervention to help autism patients handle and recognize their difficulties with socialization.

The overall positive group environment observed in this study advocates for the potential role of information technology in the social lives of autism-related users. The findings help people understand how health consumers are supporting each other and reveal new capabilities of online intervention programs that can be designed to offer social supports in a timely and effective manner. Moreover, the outcomes unveiled in this study can provide useful input to aid the development of online intervention programs for autism users.

This study examined topics derived from messages posted to the autism support groups on Facebook. The revealed topics (e.g. parenting, education, behavior traits) identify the issues that individuals with autism were concerned about on a daily basis and how they addressed such concerns in the form of group communication. These topics can also be used as the road map for the design of autism websites and the creation of subject directories for social media information organization. In addition, the revealed topics help professionals understand autism from users' perspectives. The keywords can be used to assist the thesaurus and subject headings. In addition, the symptom-related content (e.g. lining toys, reading comic books) which emerged from the group discussions aids the screening for parents who wonder whether their children show autism symptoms. The relationships between keywords and topics identified through topic modeling may also be used to build recommendation mechanisms for the Facebook group platform and social Q&A websites. For example, when a user posts a message in a Facebook group or on a social Q&A website, the systems can automatically suggest related topics in which the user might be interested.

Identifying influential users in a support group can assist the group administrators in recognizing group members' contributions and reinforce positive behaviors within the group. The analysis of the characteristics of influential users also helps train health providers who offer health services and consultations to autism-affected users. For example, caregivers are recommended to more frequently start conversations with autism patients and their relatives. The more support caregivers provide through communications, the more responses they may receive from care-recipients.

Strong correlations found among the interaction behaviors (e.g. posting, making reactions, commenting) suggest that appropriate instructions, such as posting welcoming messages and regularly raising discussion questions in groups, should be delivered to group administrators in order to encourage their active involvement in the group. Likewise, group administrators should be instructed and trained accordingly to play a major role in encouraging group members' active involvement.

5.3 Summary

The results from this study were compared to findings from previous studies. Similar with the prior studies on other health-related support groups on Facebook, preferences to giving reactions (e.g. likes) over replies and strong correlations between contributions to the group and gaining from the group were also found in this study. Sparse interaction networks revealed from this study demonstrate that autism support groups on Facebook offer companionship and emotional support to autism-affected users. In addition, social, informational, and emotional support found in this study were consistent with interactions which appeared in other online health communities. Especially, in contrast to other support groups for psychological conditions, the investigated autism support groups on Facebook appear to provide a supportive and grateful atmosphere for group members.

The theoretical and practical implications of this study were discussed. The methods applied in this study were found to be not only a sound methodology but also a foundation for research on other health-related communities on social media. The practical implications of the findings revealed from this study can assist clinical practitioners, support group administrators, and online autism intervention designers.

Chapter 6. Conclusions

This final chapter summarizes the research questions and associated major findings in this study. The limitations of this study are also discussed. Finally, a few research directions are proposed for future works.

6.1 Summary of research questions and major findings

The primary research problem of this study was to investigate how users interact within autism support groups on Facebook. The interactions appearing in groups consist of two primary facets of characteristics: behavior-based characteristics and content-based characteristics. Specifically, the behavior-based characteristics represent the interaction patterns among group members including preferences to different interaction behaviors (e.g. liking, commenting, etc.,); characteristics of interaction networks, gender differences appearing in the interaction networks, and influential users among the group members. Content-based characteristics were composed by the topics of group discussions and the sentiment characteristics drawn from the group discussions.

After screening hundreds of autism-related groups on Facebook, five public Facebook autism support groups (an *awareness* group, a *treatment* group, a *parents* group, a *research* group, and a *local support* group) were selected in this study. Data collection for this study centered on the extraction of the interactions and content that appeared in each group. The time window for the data collection was set as 6 months. Social network analysis, topic modeling, sentiment analysis, and inferential analysis method were employed to analyze the collected data.

RQ1: How do users interact with each other in autism support groups on Facebook based on social network analysis?

The first research question explored how users communicate with each other within the autism support groups on Facebook. The significance of RQ1 was the investigation of group interactions from the network perspective. RQ1.1 examined the gender differences in the group interactions, while RQ1.2 investigated the differences in the group interactions across the groups that belong to various categories. As a result, it was examined that group members favored giving comments and making reactions more than tagging someone or sharing others' posts out of the groups. Although more female group members engaged in the group interactions, male group members held significantly more central positions in the groups than the female group members did based on degree centrality and betweenness centrality. Significant gender differences were found in the four investigated groups (the *awareness* group, the *treatment* group, the *research* group, and the *local support* group) in terms of degree centrality and betweenness centrality. The exception was in the *parents* group.

RQ2: Who are the influential users based on interactions in autism support groups on Facebook?

The second research question discovered the influential users based on interactions within the autism support groups on Facebook. The significance of RQ2 was quantifying the detection of major players in each investigated autism support group. To answer RQ2, social network analysis was employed to identify the influential users based on interactions in each Facebook support group, and to unveil the interaction characteristics of those users. There were 53 influential users who occupied the top 20 important positions in each group. They were found based on three centrality measures: degree centrality, betweenness centrality, and closeness centrality. It was noticed that group members tended to react more to the influential users. A strong correlation was found between the frequencies of the orginal post and the incoming interactions. It suggests that users who contribute more to the group may receive more support from others in the group.

RQ3: What are the discussion topics that emerged from the discussions in autism support groups on Facebook?

RQ3 sought to understand the discussion topics appearing in each autism support group on Facebook. This question was answered by applying one of topic modeling methods, *Latent Dirichlet Allocation* (LDA), to the posts and comments appearing in the groups. As a result, distinct discussion topics were revealed as follows: the awareness group (parenting, behavioral traits, diagnosis, and video sharing), the treatment group (EMF pollution, home decoration, and wireless safety), the parents group (experiences, family support, welcome messages, education, and parenting), the research group (therapies, trainings and workshops, and events and visits), and the local support group (greetings, support, conferences, and help requests). This modeling method suggested that each group had certain distinctive discussion topics that related to the purposes of the groups.

RQ4: What are the sentiment characteristics of discussions in autism support groups on Facebook?

The last research question aimed to unveil the sentiment characteristics of the group discussions which appeared within autism support groups on Facebook. The significance of RQ4 is the quantitative evaluations of the sentiment aspect of group communications. RQ4.1 examined the gender differences in the presented sentiments, while RQ4.2 investigated the differences in the presented sentiments across the groups that belong to various categories. Through a series of inferential analyses, it was revealed that the female group members tended to express more positive emotions in the group discussions than the male groups members did. No significant gender differences in the expressed sentiment were founded in all five groups. Group members appeared to express significantly different sentiments within the groups focused on various topics. More negative emotions were conveyed by group members in the *treatment* group, especially by the male group members.

6.2 Limitations

Like most of scientific studies, there are certain limitations in this study. The limitations include, but are not limited to: the use of only Facebook groups, the absent access to closed groups and secret groups, limited timeframe, lack of qualitative interviews with group members, and a relatively small sample.

The first and most obvious of all the limitations to this study concerns the sampling and data collection. Facebook groups were the only social communities on social media addressed in this research. There are dozens of social communities and discussion forums regarding autism. In addition, due to ethical considerations, only public Facebook groups were investigated in this study. Furthermore, the sampled Facebook groups might not be representative of all autism-related support groups on Facebook. Also, this data collection period was set as 6 months. The limited time window might be unable to provide a whole picture of the group interactions.

Another limitation is related to the research methods adopted in this study. This study identified and examined only the quantitative aspect of the autism support groups on Facebook. Understanding the motivations behind the group interactions and group posts could shed more insights on the meanings and purposes of the autism-related social communities on social media. However, this study did not interview group members that participated in the support groups on Facebook. The inclusion of interviews or questioners was not considered in this study, but should be conducted in the future.

6.3 Future directions

As mentioned above, this study focused on the observation and interpretation of interactions within the autism support groups on Facebook and involved no direct interaction with individual group members. While this was beneficial in terms of observing natural situations of the group interactions, without consulting the group members the interpretation of the interaction activities and the content were limited. A future study that involves interviewing group members on their motivations and experiences within the groups may bring depth to the findings that this study did not capture.

Additionally, larger scale quantitative studies should be conducted to validate results by examining other online autism communities on social media. A larger study would enhance the reliability of the findings generated from this study. Results from larger studies may further examine how social media could function as a training context for promoting social skills for autism patients.

References

Acquisti, A., & Gross, R. (2006). Imagined Communities: Awareness, Information Sharing, and Privacy on the Facebook. In G. Danezis & P. Golle (Eds.), *Privacy Enhancing Technologies* (pp. 36–58). Springer Berlin Heidelberg.

Agichtein, E., Castillo, C., Donato, D., Gionis, A., & Mishne, G. (2008). Finding High-quality Content in Social Media. In *Proceedings of the 2008 International Conference on Web Search and Data Mining* (pp. 183–194). New York, NY, USA: ACM. https://doi.org/10.1145/1341531.1341557

Ashton, D. (2015, June 1). *Analysing the Twitter Mentions Network*. Retrieved from http://www.r-bloggers.com/analysing-the-twitter-mentions-network/

Asur, S., & Huberman, B. A. (2010). Predicting the Future with Social Media. In *2010 IEEE/WIC/ACM International Conference on Web Intelligence and Intelligent Agent Technology (WI-IAT)* (Vol. 1, pp. 492–499). https://doi.org/10.1109/WI-IAT.2010.63

Autism Community Forum. (n.d.). Retrieved from http://wrongplanet.net/forums/

Barney, L. J., Griffiths, K. M., & Banfield, M. A. (2011). Explicit and implicit information needs of people with depression: a qualitative investigation of problems reported on an online depression support forum. *BMC Psychiatry*, *11*, 88. https://doi.org/10.1186/1471-244X-11-88

Baym, N. K., Zhang, Y. B., & Lin, M.-C. (2004). Social Interactions across Media Interpersonal Communication on the Internet, Telephone and Face-to-Face. *New Media & Society*, *6*(3), 299–318. https://doi.org/10.1177/1461444804041438

Beaudoin, C. E., & Tao, C.-C. (2007). Benefiting from social capital in online support groups: an empirical study of cancer patients. *Cyberpsychology & Behavior: The Impact of the*

Internet, Multimedia and Virtual Reality on Behavior and Society, *10*(4), 587–590. https://doi.org/10.1089/cpb.2007.9986

Benetoli, A., Chen, T. F., Spagnardi, S., Beer, T., & Aslani, P. (2015). Provision of a Medicines Information Service to Consumers on Facebook: An Australian Case Study. *Journal of Medical Internet Research*, *17*(11), e265. https://doi.org/10.2196/jmir.4161

Blei, D., & Lafferty, J. (2006). Correlated topic models. *Advances in Neural Information Processing Systems*, 18, 147.

Blei, D. M., Ng, A. Y., & Jordan, M. I. (2003). Latent Dirichlet Allocation. *Journal of Machine Learning Research*, 3, 993–1022.

Board, A. (2012, May 16). *Autism*. Retrieved from http://www.ncbi.nlm.nih.gov/pubmedhealth/PMH0002494/

Bollen, J., Mao, H., & Zeng, X. (2011). Twitter mood predicts the stock market. *Journal of Computational Science*, *2*(1), 1-8. https://doi.org/10.1016/j.jocs.2010.12.007

Borgatti, S. P. (2005). Centrality and network flow. *Social Networks*, *27*(1), 55-71.

Borgatti, S. P., Everett, M. G., & Johnson, J. C. (2013). *Analyzing Social Networks*. Los Angeles: SAGE Publications Ltd.

Borgatti, S. P., Mehra, A., Brass, D. J., & Labianca, G. (2009). Network Analysis in the Social Sciences. *Science*, *323*(5916), 892–895. https://doi.org/10.1126/science.1165821

Bosomworth, D. (2012). *The 6 types of social media user (infographic)*. Retrieved from http://www.smartinsights.com/digital-marketing-strategy/customer-segmentation-targeting/the-6-types-of-social-media-user/

Bradley, R. (2013). Social Media Comes to Health Care. *Fortune*, *167*(6), 52.

Brown, B. B. (1990). Peer groups and peer cultures. In S. S. Feldman & G. R. Elliott (Eds.), *At the threshold: The developing adolescent* (pp. 171–196). Cambridge, MA, US: Harvard University Press.

Bryant, E. M., & Marmo, J. (2012). The rules of Facebook friendship: A two-stage examination of interaction rules in close, casual, and acquaintance friendships. *Journal of Social and Personal Relationships*, *25*, 1-23. https://doi.org/10.1177/0265407512443616

Bryman, A. (2012). *Social Research Methods*. New York, NY: Oxford University Press.

Budak, C., Agrawal, D., & El Abbadi, A. (2011). Structural Trend Analysis for Online Social Networks. *Proceedings of the VLDB Endowment*, *4*(10), 646–656. https://doi.org/10.14778/2021017.2021022

Cataldi, M., Di Caro, L., & Schifanella, C. (2010). Emerging Topic Detection on Twitter Based on Temporal and Social Terms Evaluation. *Proceedings of the Tenth International Workshop on Multimedia Data Mining* (p. 4:1–4:10). New York, NY, USA: ACM. https://doi.org/10.1145/1814245.1814249

Catlin, J. (2011). Question and answers with Lexalytics. In G. Mitra & L. Mitra (Eds.), *The Handbook of News Analytics in Finance* (pp. 323–325). Chichester, UK: John Wiley & Sons, Ltd.

Cha, M., Benevenuto, F., Haddadi, H., & Gummadi, K. (2012). The World of Connections and Information Flow in Twitter. *IEEE Transactions on Systems, Man and Cybernetics, Part A: Systems and Humans*, *42*(4), 991–998. https://doi.org/10.1109/TSMCA.2012.2183359

Cha, M., Haddadi, H., Benevenuto, F., & Gummadi, P. K. (2010). Measuring User Influence in Twitter: The Million Follower Fallacy. *Proceedings of the Fourth International AAAI Conference on Weblogs and Social Media, 10*, 10-17.

Cheong, F., & Cheong, C. (2011). Social Media Data Mining: A Social Network Analysis of Tweets during the 2010-2011 Australian Floods. *Proceedings of PACIS*, *11*, 46–46.

Chou, W. S., Hunt, Y. M., Beckjord, E. B., Moser, R. P., & Hesse, B. W. (2009). Social Media Use in the United States: Implications for Health Communication. *Journal of Medical Internet Research*, *11*(4). https://doi.org/10.2196/jmir.1249

Cohen, J. (1988). Statistical power analysis for the behavioral sciences. *Statistical Power Analysis for the Behavioral Sciences*. doi:10.1234/12345678

Cole, J., Watkins, C., & Kleine, D. (2016). Health Advice from Internet Discussion Forums: How Bad Is Dangerous? *Journal of Medical Internet Research*, *18*(1), e4. https://doi.org/10.2196/jmir.5051

Dean, A., & Lin, N. (1977). The stress-buffering role of social support. Problems and prospects for systematic investigation. *The Journal of Nervous and Mental Disease*, *165*(6), 403–417.

Deering, M. J., & Harris, J. (1996). Consumer health information demand and delivery: implications for libraries. *Bulletin of the Medical Library Association*, *84*(2), 209–216.

Duggan, M. (2015, August 19). *Mobile Messaging and Social Media 2015*. Retrieved from http://www.pewinternet.org/2015/08/19/mobile-messaging-and-social-media-2015/

Eckler, P., Worsowicz, G., & Rayburn, J. W. (2010). Social Media and Health Care: An Overview. *PM&R*, *2*(11), 1046–1050. https://doi.org/10.1016/j.pmrj.2010.09.005

Ellison, N. B., Steinfield, C., & Lampe, C. (2007). The Benefits of Facebook “Friends:” Social Capital and College Students’ Use of Online Social Network Sites. *Journal of Computer-Mediated Communication*, *12*(4), 1143–1168. https://doi.org/10.1111/j.1083-6101.2007.00367.x

Entis, L., & Advisor. (2015, May 2). *How Facebook "Likes" Could Be Used to Make Personality-Based Hiring Decisions*. Retrieved from http://www.entrepreneur.com/article/242274

European Commision. (2014). *Flash Eurobarometer 404: European citizens' digital health literacy survey*. Retrieved from http://ec.europa.eu/commfrontoffice/publicopinion/flash/fl_404_en.pdf

Eysenbach, G. (2008). Medicine 2.0: Social Networking, Collaboration, Participation, Apomediation, and Openness. *Journal of Medical Internet Research*, *10*(3), e22. https://doi.org/10.2196/jmir.1030

Eysenbach, G., & Köhler, C. (2002). How do consumers search for and appraise health information on the world wide web? Qualitative study using focus groups, usability tests, and in-depth interviews. *BMJ*, *324*(7337), 573–577. https://doi.org/10.1136/bmj.324.7337.573

Friending. (n.d.). Retrieved from https://www.facebook.com/help/1540345696275090/?helpref=hc_fnav

Facebook users worldwide 2016. (2016). Retrieved from https://www.statista.com/statistics/264810/number-of-monthly-active-facebook-users-worldwide/

Feldman, R. (2013). Techniques and applications for sentiment analysis. *Communications of the ACM*, *56*(4), 82–89.

Flick, U. (2009). *An Introduction to Qualitative Research*. London, UK: SAGE Publications Ltd.

Fox, S. (2006). *Online Health Search 2006*. Retrieved from http://www.pewinternet.org/2006/10/29/online-health-search-2006/

Fox, S. (2008, February 11). *Health Information-Seeking on a Typical Day*. Retrieved from http://www.pewinternet.org/2008/02/11/health-information-seeking-on-a-typical-day/

Fox, S. (2011a, May 20). *The Social Life of Health Information, 2011*. Retrieved from http://www.pewinternet.org/2011/05/12/the-social-life-of-health-information-2011/

Fox, S. (2011b, October 18). *Who Doesn't Gather Health Information Online?* Retrieved from http://www.pewinternet.org/2011/10/18/who-doesnt-gather-health-information-online/

Fox, S. (2013a, August 3). *Peer-to-peer health care is a slow idea that will change the world*. Retrieved from http://susannahfox.com/2013/08/03/peer-to-peer-health-care-is-a-slow-idea-that-will-change-the-world/

Fox, S. (2013b). After Dr Google: peer-to-peer health care. *Pediatrics*, *131*(4), s224-s225.

Fox, S., & Duggan, M. (2013, January 15). *Health Online 2013*. Retrieved from http://www.pewinternet.org/2013/01/15/health-online-2013/

Gilbert, E., & Karahalios, K. (2009). Predicting Tie Strength with Social Media. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (pp. 211–220). New York, NY, USA: ACM. https://doi.org/10.1145/1518701.1518736

Gilbert, E., Karahalios, K., & Sandvig, C. (2008). The network in the garden: an empirical analysis of social media in rural life. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (pp. 1603–1612). ACM. Retrieved from http://dl.acm.org/citation.cfm?id=1357304

Goldberg, L., Lide, B., Lowry, S., Massett, H. A., O'Connell, T., Preece, J., … Shneiderman, B. (2011). Usability and accessibility in consumer health informatics current trends and future challenges. *American Journal of Preventive Medicine*, *40*(5), S187-197. https://doi.org/10.1016/j.amepre.2011.01.009

Golder, S. A., Wilkinson, D. M., & Huberman, B. A. (2007). Rhythms of Social Interaction: Messaging Within a Massive Online Network. In C. Steinfield, B. T. Pentland, M. Ackerman, & N. Contractor (*Eds*.), *Communities and Technologies 2007* (pp. 41–66). Springer London.

Gravetter, F. J., & Forzano, L.-A. B. (2011). *Research Methods for the Behavioral Sciences*. Australia; Belmont, CA: Wadsworth Publishing.

Gray, N. J., Klein, J. D., Noyce, P. R., Sesselberg, T. S., & Cantrill, J. A. (2005). Health information-seeking behaviour in adolescence: the place of the internet. *Social Science & Medicine*, *60*(7), 1467–1478. https://doi.org/10.1016/j.socscimed.2004.08.010

Greene, J. A., Choudhry, N. K., Kilabuk, E., & Shrank, W. H. (2010). Online Social Networking by Patients with Diabetes: A Qualitative Evaluation of Communication with Facebook. *Journal of General Internal Medicine*, *26*(3), 287–292. https://doi.org/10.1007/s11606-010-1526-3

Griffin, R. J., Dunwoody, S., & Neuwirth, K. (1999). Proposed Model of the Relationship of Risk Information Seeking and Processing to the Development of Preventive Behaviors. *Environmental Research*, *80*(2), S230–S245. https://doi.org/10.1006/enrs.1998.3940

Griffiths, T. L., & Steyvers, M. (2004). Finding scientific topics. *Proceedings of the National Academy of Sciences of the United States of America*, *101* (Suppl 1), 5228–5235. https://doi.org/10.1073/pnas.0307752101

Groups. (n.d.). Retrieved from https://www.facebook.com/help/1629740080681586/?helpref=hc_fnav

Gruhl, D., Guha, R., Kumar, R., Novak, J., & Tomkins, A. (2005). The Predictive Power of Online Chatter. *Proceedings of the Eleventh ACM SIGKDD International Conference on Knowledge Discovery in Data Mining* (pp. 78–87). New York, NY, USA: ACM.

Hanneman, R. A., & Riddle, M. (2005). *Introduction to Social Network Methods*. Riverside, CA: University of California.

Hansen, D., Shneiderman, B., & Smith, M. A. (2010). *Analyzing Social Media Networks with NodeXL: Insights from a Connected World*. Burlington, MA: Morgan Kaufmann.

Hawn, C. (2009). Take Two Aspirin and Tweet Me in the Morning: How Twitter, Facebook, and Other Social Media Are Reshaping Health Care. *Health Affairs*, *28*(2), 361–368. https://doi.org/10.1377/hlthaff.28.2.361

Haythornthwaite, C. (1996). Social network analysis: An approach and technique for the study of information exchange. *Library & Information Science Research*, *18*(4), 323–342. https://doi.org/10.1016/S0740-8188(96)90003-1

Hether, H. J., Murphy, S. T., & Valente, T. W. (2014). It's Better to Give Than to Receive: The Role of Social Support, Trust, and Participation on Health-Related Social Networking Sites. *Journal of Health Communication*, *19*(12), 1424–1439.

Hofmann, T. (1999). Probabilistic Latent Semantic Indexing. In *Proceedings of the 22Nd Annual International ACM SIGIR Conference on Research and Development in Information Retrieval* (pp. 50–57). New York, NY, USA: ACM.

Hong, L., & Davison, B. D. (2010). Empirical Study of Topic Modeling in Twitter. *Proceedings of the First Workshop on Social Media Analytics* (pp. 80–88). New York, NY, USA: ACM.

Houston, T. K., Cooper, L. A., & Ford, D. E. (2002). Internet support groups for depression: a 1-year prospective cohort study. *The American Journal of Psychiatry*, *159*(12), 2062-2068.

Hu, Y., Boyd-Graber, J., Satinoff, B., & Smith, A. (2014). Interactive topic modeling. *Machine Learning*, 95(3), 423–469.

Huberman, B. A., Romero, D. M., & Wu, F. (2009). Social networks that matter: Twitter under the microscope. *First Monday*, *14*, 1-5.

IBM - SPSS Text Analytics for Surveys. (2014, February 22). Retrieved from http://www-03.ibm.com/software/products/en/spss-text-analytics-surveys/

Jadad, A. R., Enkin, M. W., Glouberman, S., Groff, P., & Stern, A. (2006). Are virtual communities good for our health? *BMJ (Clinical Research Ed.), 332*(7547), 925–926. https://doi.org/10.1136/bmj.332.7547.925

Jansen, B. J., Sobel, K., & Cook, G. (2011). Classifying ecommerce information sharing behaviour by youths on social networking sites. *Journal of Information Science*, *37*(2), 120–136. https://doi.org/10.1177/0165551510396975

Java, A., Song, X., Finin, T., & Tseng, B. (2007). Why We Twitter: Understanding Microblogging Usage and Communities. *Proceedings of the 9th WebKDD and 1st SNA-KDD 2007 Workshop on Web Mining and Social Network Analysis* (pp. 56–65). New York, NY, USA: ACM.

Join and Interact with Groups. (2016). Retrieved from https://www.facebook.com/help/1210322209008185/?helpref=hc_fnav

Kao, A., & Poteet, S. R. (2007). *Natural Language Processing and Text Mining*. London, UK: Springer Science & Business Media.

Kaplan, A. M., & Haenlein, M. (2010). Users of the world, unite! The challenges and opportunities of Social Media. *Business Horizons*, *53*(1), 59–68. https://doi.org/10.1016/j.bushor.2009.09.003

Kempe, D., Kleinberg, J., & Tardos, É. (2003). Maximizing the Spread of Influence through a Social Network. *Proceedings of the Ninth ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* (pp. 137–146). New York, NY, USA: ACM.

Keselman, A., Browne, A. C., & Kaufman, D. R. (2008). Consumer Health Information Seeking as Hypothesis Testing. *Journal of the American Medical Informatics Association : JAMIA*, *15*(4), 484–495. https://doi.org/10.1197/jamia.M2449

Kietzmann, J. H., Hermkens, K., McCarthy, I. P., & Silvestre, B. S. (2011). Social media? Get serious! Understanding the functional building blocks of social media. *Business Horizons*, *54*(3), 241–251. https://doi.org/10.1016/j.bushor.2011.01.005

Kishimoto, K., & Fukushima, N. (2011). Use of anonymous Web communities and websites by medical consumers in Japan to research drug information. *Yakugaku Zasshi: Journal of the Pharmaceutical Society of Japan*, *131*(5), 685–695.

Klemm, P., Hurst, M., Dearholt, S. L., & Trone, S. R. (1999). Gender differences on Internet cancer support groups. *Computers in Nursing*, *17*(2), 65-72.

Knoke, D., & Yang, S. (2008). *Social Network Analysis*. Los Angeles: SAGE Publications Ltd.

Krippendorff, K. (2012). *Content Analysis: An Introduction to Its Methodology*. Los Angeles: SAGE Publications Ltd.

Kumar, A., & Sebastian, T. M. (2012). Sentiment Analysis: A Perspective on its Past, Present and Future. *International Journal of Intelligent Systems and Applications (IJISA)*, *4*(10), 1.

Kuttschreuter, M., Rutsaert, P., Hilverda, F., Regan, Á., Barnett, J., & Verbeke, W. (2014). Seeking information about food-related risks: The contribution of social media. *Food Quality and Preference*, *37*(Supplement C), 10-18. https://doi.org/10.1016/j.foodqual.2014.04.006

Lai, L. S., & To, W. M. (2015). Content analysis of social media: a grounded theory approach. *Journal of Electronic Commerce Research*, *16*(2).

Lak, P., & Turetken, O. (2014). Star Ratings versus Sentiment Analysis – A Comparison of Explicit and Implicit Measures of Opinions. *2014 47th Hawaii International Conference on System Sciences* (pp. 796–805). https://doi.org/10.1109/HICSS.2014.106

Landro, L. (1999). Alone Together Cancer Patients and Survivors Find Treatment-and Support-Online. It Can Make All the Difference. *The Oncologist*, *4*(1), 59-63.

Lau, T. P., Wang, S., Man, Y., Yuen, C. F., & King, I. (2014). Language Technologies for Enhancement of Teaching and Learning in Writing. In *Proceedings of the 23rd International Conference on World Wide Web* (pp. 1097–1102). New York, NY, USA: ACM.

Lea, M. (1989). Factors Underlying Friendship: An Analysis of Responses on the Acquaintance Description form in Relation to Wright's Friendship Model. *Journal of Social and Personal Relationships*, *6*(3), 275–292. https://doi.org/10.1177/0265407589063003

Leskovec, J. (2011). Social Media Analytics: Tracking, Modeling and Predicting the Flow of Information through Networks. *Proceedings of the 20th International Conference Companion on World Wide Web* (pp. 277–278). New York, NY, USA: ACM.

Lewis, D., Eysenbach, G., Kukafka, R., Stavri, P. Z., & Jimison, H. (2006). *Consumer Health Informatics: Informing Consumers and Improving Health Care*. London, UK: Springer Science & Business Media.

Lewis, K., Kaufman, J., Gonzalez, M., Wimmer, A., & Christakis, N. (2008). Tastes, ties, and time: A new social network dataset using Facebook.com. *Social Networks*, *30*(4), 330–342. https://doi.org/10.1016/j.socnet.2008.07.002

Liang, B., & Scammon, D. L. (2011). E-Word-of-Mouth on health social networking sites: An opportunity for tailored health communication. *Journal of Consumer Behaviour*, *10*(6), 322–331. https://doi.org/10.1002/cb.378

Liddy, E. D. (2000). Text Mining. *Bulletin of the American Society for Information Science and Technology*, *27*(1), 13–14. https://doi.org/10.1002/bult.184

Liu, B. (2012). *Sentiment Analysis and Opinion Mining*. San Rafael, CA: Morgan & Claypool Publishers.

Liu, Y., Huang, X., An, A., & Yu, X. (2007). ARSA: A Sentiment-aware Model for Predicting Sales Performance Using Blogs. *Proceedings of the 30th Annual International ACM SIGIR Conference on Research and Development in Information Retrieval* (pp. 607–614). New York, NY, USA: ACM.

Lu, K., & Wolfram, D. (2012). Measuring author research relatedness: A comparison of word-based, topic-based, and author cocitation approaches. *Journal of the American Society for Information Science and Technology*, *63*(10), 1973–1986. https://doi.org/10.1002/asi.22628

Ma, W. W. K., & Chan, A. (2014). Knowledge sharing and social media: Altruism, perceived online attachment motivation, and perceived online relationship commitment. *Computers in Human Behavior*, *39*, 51–58. https://doi.org/10.1016/j.chb.2014.06.015

Mathews, W. (2011, February 7). *How to effectively use Facebook mentions to engage users, share content*. Retrieved from http://www.poynter.org/news/media-innovation/107150/how-to-effectively-use-facebook-mentions-to-engage-users-share-content/

Mathioudakis, M., & Koudas, N. (2010). TwitterMonitor: Trend Detection over the Twitter Stream. *Proceedings of the 2010 ACM SIGMOD International Conference on Management of Data* (pp. 1155–1158). New York, NY, USA: ACM.

Mazurek, M. O. (2013). Social media use among adults with autism spectrum disorders. *Computers in Human Behavior*, *29*(4), 1709–1714. https://doi.org/10.1016/j.chb.2013.02.004

Mcauliffe, J. D., & Blei, D. M. (2008). Supervised topic models. In *Advances in neural information processing systems* (pp. 121–128). Retrieved from http://papers.nips.cc/paper/3328-supervised-topic-models

McHugh, M. L. (2012). Interrater reliability: the kappa statistic. *Biochemia Medica*, *22*(3), 276–282.

McNab, C. (2009). What social media offers to health professionals and citizens. *Bulletin of the World Health Organization*, *87*(8), 566–566. https://doi.org/10.1590/S0042-96862009000800002

MedlinePlus. (n.d.). *Autism Spectrum Disorder*. Retrieved from https://medlineplus.gov/autismspectrumdisorder.html

Microsoft Research. (2015). *NodeXL - Network Overview Discovery and Exploration in Excel*. Retrieved from http://research.microsoft.com/en-us/projects/nodexl/

Moreland, J., French, T. L., & Cumming, G. P. (2015). The Prevalence of Online Health Information Seeking Among Patients in Scotland: A Cross-Sectional Exploratory Study. *JMIR Research Protocols*, *4*(3), e85. https://doi.org/10.2196/resprot.4010

Myers, S. A., Sharma, A., Gupta, P., & Lin, J. (2014). Information Network or Social Network?: The Structure of the Twitter Follow Graph. *Proceedings of the 23rd International Conference on World Wide Web* (pp. 493–498). Republic and Canton of Geneva, Switzerland: International World Wide Web Conferences Steering Committee.

Naslund, J. A., Aschbrenner, K. A., Marsch, L. A., & Bartels, S. J. (2016). The future of mental health care: peer-to-peer support and social media. *Epidemiology and Psychiatric Sciences*, *25*(2), 113–122. https://doi.org/10.1017/S2045796015001067

National Institute of Mental Health. (NIMH, n.d.). *Autism Spectrum Disorder*. Retrieved from https://www.nimh.nih.gov/health/topics/autism-spectrum-disorders-asd/index.shtml

National Library of Medicine. (NLM, 2014, December 6). *Health Information*. Retrieved from http://www.nlm.nih.gov/hinfo.html

Netlytic. (2014). *System Overview*. Retrieved from https://netlytic.org/home/?page_id=20

Neuendorf, K. A. (2002). *The Content Analysis Guidebook*. Los Angeles: SAGE Publications Ltd.

Niederdeppe, J., Hornik, R. C., Kelly, B. J., Frosch, D. L., Romantan, A., Stevens, R. S., … Schwartz, J. S. (2007). Examining the dimensions of cancer-related information seeking and scanning behavior. *Health Communication*, *22*(2), 153–167. https://doi.org/10.1080/10410230701454189

Otte, E., & Rousseau, R. (2002). Social network analysis: a powerful strategy, also for the information sciences. *Journal of Information Science*, *28*(6), 441–453. https://doi.org/10.1177/016555150202800601

Pak, A., & Paroubek, P. (2010). *Twitter as a Corpus for Sentiment Analysis and Opinion Mining*. Presented at the Proceedings of the Seventh conference on International Language Resources and Evaluation (LREC'10), European Language Resources Association (ELRA). Retrieved from http://www.lrec-conf.org/proceedings/lrec2010/pdf/385_Paper.pdf

Pang, B., & Lee, L. (2008). Opinion Mining and Sentiment Analysis. *Foundations and Trends in Information Retrieval*, *2*(1-2), 1–135. https://doi.org/10.1561/1500000011

Park, H., & Park, M. S. (2014). Cancer Information-Seeking Behaviors and Information Needs among Korean Americans in the Online Community. *Journal of Community Health*, *39*(2), 213–220. https://doi.org/10.1007/s10900-013-9784-8

Pempek, T. A., Yermolayeva, Y. A., & Calvert, S. L. (2009). College students' social networking experiences on Facebook. *Journal of Applied Developmental Psychology*, *30*(3), 227–238. https://doi.org/10.1016/j.appdev.2008.12.010

Pew Research Center. (2013, December 20). *The Internet and Health*. Retrieved from http://www.pewinternet.org/2013/02/12/the-internet-and-health/

Pew Research Center. (2015). *Health Fact Sheet*. Retrieved from http://www.pewinternet.org/fact-sheets/health-fact-sheet/

Porter, M. f. (1980). An algorithm for suffix stripping. *Program*, *14*(3), 130–137. https://doi.org/10.1108/eb046814

Portier, K., Greer, G. E., Rokach, L., Ofek, N., Wang, Y., Biyani, P., … Yen, J. (2013). Understanding Topics and Sentiment in an Online Cancer Survivor Community. *JNCI Monographs*, *2013*(47), 195–198. https://doi.org/10.1093/jncimonographs/lgt025

Prasad, B. (2013). Social media, health care, and social networking. *Gastrointestinal Endoscopy*, *77*(3), 492–495. https://doi.org/10.1016/j.gie.2012.10.026

Preece, J. (1999). Empathic communities: balancing emotional and factual communication. *Interacting with Computers*, *12*(1), 63–77. https://doi.org/10.1016/S0953-5438(98)00056-3

Price, S., Mercer, S. W., & MacPherson, H. (2006). Practitioner empathy, patient enablement and health outcomes: a prospective study of acupuncture patients. *Patient Education and Counseling*, *63*(1–2), 239–245. https://doi.org/10.1016/j.pec.2005.11.006

Proferes, N. (2015). Informational Power on Twitter: A Mixed-methods Exploration of User Knowledge and Technological Discourse about Information Flows. *Theses and Dissertations*. Retrieved from http://dc.uwm.edu/etd/909

Prybutok, G., & Ryan, S. (2015). Social Media: The Key to Health Information Access for 18- to 30-Year-Old College Students. *CIN: Computers, Informatics, Nursing*, *33*(4), 132–141. https://doi.org/10.1097/CIN.0000000000000147

Qiu, B., Zhao, K., Mitra, P., Wu, D., Caragea, C., Yen, J., … Portier, K. (2011). Get Online Support, Feel Better – Sentiment Analysis and Dynamics in an Online Cancer Survivor Community. *2011 IEEE Third International Conference on Privacy, Security, Risk and Trust (PASSAT) and 2011 IEEE Third Inernational Conference on Social Computing (SocialCom)* (pp. 274–281). https://doi.org/10.1109/PASSAT/SocialCom.2011.127

Rasmussen-Pennington, D. M., Richardson, G., Garinger, C., & Contursi, M. L. (2013). “I could be on Facebook by now” : insights from Canadian youth on online mental health information resources. *Canadian Journal of Information and Library Science, 37*(3), 183–200.

Rau, P.-L. P., Gao, Q., & Ding, Y. (2008). Relationship between the level of intimacy and lurking in online social network services. *Computers in Human Behavior*, *24*(6), 2757–2770. https://doi.org/10.1016/j.chb.2008.04.001

Risk, A., & Dzenowagis, J. (2001). Review of Internet Health Information Quality Initiatives. *Journal of Medical Internet Research*, *3*(4), e28. https://doi.org/10.2196/jmir.3.4.e28

Roe, B. E., & Just, D. R. (2009). Internal and External Validity in Economics Research: Tradeoffs between Experiments, Field Experiments, Natural Experiments, and Field Data. *American Journal of Agricultural Economics*, *91*(5), 1266–1271. https://doi.org/10.1111/j.1467-8276.2009.01295.x

Roffeei, S. H. M., Abdullah, N., & Basar, S. K. R. (2015). Seeking social support on Facebook for children with Autism Spectrum Disorders (ASDs). *International Journal of Medical Informatics*, *84*(5), 375–385. https://doi.org/10.1016/j.ijmedinf.2015.01.015

Romero, D. M., Galuba, W., Asur, S., & Huberman, B. A. (2011). Influence and Passivity in Social Media. In D. Gunopulos, T. Hofmann, D. Malerba, & M. Vazirgiannis (*Eds.*), *Machine Learning and Knowledge Discovery in Databases* (pp. 18–33). Springer Berlin Heidelberg.

Rump, K. M., Giovannelli, J. L., Minshew, N. J., & Strauss, M. S. (2009). The Development of Emotion Recognition in Individuals with Autism. *Child Development*, *80*(5), 1434–1447. https://doi.org/10.1111/j.1467-8624.2009.01343.x

Rutsaert, P., Pieniak, Z., Regan, Á., McConnon, Á., & Verbeke, W. (2013). Consumer interest in receiving information through social media about the risks of pesticide residues. *Food Control*, *34*(2), 386–392. https://doi.org/10.1016/j.foodcont.2013.04.030

Saha, A., & Agarwal, N. (2016). Modeling social support in autism community on social media. *Network Modeling Analysis in Health Informatics and Bioinformatics, 5*(1), 8. https://doi.org/10.1007/s13721-016-0115-8

Sarasohn-Kahn, J. (2008, April). *The Wisdom of Patients: Health Care Meets Online Social Media*. Retrieved from http://www.chcf.org/publications/2008/04/the-wisdom-of-patients-health-care-meets-online-social-media

Schnell, M. W., & Heinritz, C. (2006). *Forschungsethik: Ein Grundlagen- und Arbeitsbuch mit Beispielen aus der Gesundheits- und Pflegewissenschaft*. Bern: Verlag Hans Huber.

Scott, J. (2012). *Social Network Analysis*. Los Angeles: SAGE Publications Ltd.

Seale, C., Ziebland, S., & Charteris-Black, J. (2006). Gender, cancer experience and internet use: A comparative keyword analysis of interviews and online cancer support groups. *Social Science & Medicine*, *62*(10), 2577–2590. https://doi.org/10.1016/j.socscimed.2005.11.016

Shannon, C. E. (1948). A Mathematical Theory of Communication. *Bell Labs Technical Journal*, *27*(3), 379–423. https://doi.org/10.1145/584091.584093

Slack, W. V. (2005). *Consumer Health Informatics: Informing Consumers and Improving Health Care*. (D. Lewis, G. Eysenbach, R. Kukafka, P. Z. Stavri, & H. Jimison, Eds.) (2005 edition). New York: Springer.

Smith, A. (2014, February 3). *6 new facts about Facebook*. Retrieved from http://www.pewresearch.org/fact-tank/2014/02/03/6-new-facts-about-facebook/

Smith, M. A., Shneiderman, B., Milic-Frayling, N., Mendes Rodrigues, E., Barash, V., Dunne, C., … Gleave, E. (2009). Analyzing (social media) networks with NodeXL. *Proceedings of the fourth international conference on Communities and technologies* (pp. 255–264). ACM. Retrieved from http://dl.acm.org/citation.cfm?id=1556497

Steyvers, M., & Griffiths, T. (2007). Probabilistic topic models. *Handbook of Latent Semantic Analysis*, *427*(7), 424–440.

Stoll, A. (2015, September 17). *Fast and Accurate Text Analytics*. Retrieved from http://discovertext.com/2015/09/17/fast-and-accurate-text-analytics-with-discovertext/

Stringhini, G., Kruegel, C., & Vigna, G. (2010). Detecting Spammers on Social Networks. *Proceedings of the 26th Annual Computer Security Applications Conference* (pp. 1–9). New York, NY, USA: ACM. https://doi.org/10.1145/1920261.1920263

Suess, S. (2001). Consumer Health Information. *Journal of Hospital Librarianship*, *1*(4), 41–52.

Suh, B., Hong, L., Pirolli, P., & Chi, E. H. (2010). Want to be Retweeted? Large Scale Analytics on Factors Impacting Retweet in Twitter Network. *2010 IEEE Second International Conference on Social Computing* (pp. 177–184). https://doi.org/10.1109/SocialCom.2010.33

Suzuki, L. K., & Calzo, J. P. (2004). The Search for Peer Advice in Cyberspace: An Examination of Online Teen Bulletin Boards about Health and Sexuality. *Journal of Applied Developmental Psychology: An International Lifespan Journal*, *25*(6), 685–698. https://doi.org/10.1016/j.appdev.2004.09.002

Tang, J., Jin, R., & Zhang, J. (2008). A topic modeling approach and its integration into the random walk framework for academic search. In F. Giannotti, D. Gunopulos, F. Turini,

C. Zaniolo, N. Ramakrishnan, & X. Wu (Eds.), Eighth IEEE International Conference on Data Mining ICDM'08. (pp. 1055-1060). IEEE.

Text Analytics. (2016). Retrieved from https://www.lexalytics.com/technology/text-analytics

Thackeray, R., Crookston, B. T., & West, J. H. (2013). Correlates of Health-Related Social Media Use among Adults. *Journal of Medical Internet Research*, *15*(1), e21. https://doi.org/10.2196/jmir.2297

Thackeray, R., Neiger, B. L., Smith, A. K., & Wagenen, S. B. V. (2012). Adoption and use of social media among public health departments. *BMC Public Health*, *12*(1), 242. https://doi.org/10.1186/1471-2458-12-242

Thelwall, M., Buckley, K., & Paltoglou, G. (2011). Sentiment in Twitter events. *Journal of the American Society for Information Science and Technology*, *62*(2), 406–418. https://doi.org/10.1002/asi.21462

Thompson, T. L. (2014). *Encyclopedia of Health Communication*. Los Angeles: SAGE Publications Ltd.

Thorson, K., Driscoll, K., Ekdale, B., Edgerly, S., Thompson, L. G., Schrock, A., … Wells, C. (2013). Youtube, Twitter and the Occupy Movement. *Information, Communication & Society*, *16*(3), 421–451. https://doi.org/10.1080/1369118X.2012.756051

Tu, H. T. (2011). Surprising decline in consumers seeking health information. *Tracking Report*, (26), 1–6.

Twitter. (n.d.-a). What are replies and mentions? Retrieved from https://support.twitter.com/articles/14023

Twitter. (n.d.-b). How are trends determined? Retrieved from https://support.twitter.com/articles/101125

Van de Belt, T. H., Engelen, L. J., Berben, S. A., Teerenstra, S., Samsom, M., & Schoonhoven, L. (2013). Internet and Social Media for Health-Related Information and Communication in Health Care: Preferences of the Dutch General Population. *Journal of Medical Internet Research*, *15*(10). https://doi.org/10.2196/jmir.2607

Vanwynsberghe, H., Boudry, E., Vanderlinde, R., & Verdegem, P. (2014). Experts as facilitators for the implementation of social media in the library? A social network approach. *Library Hi Tech*, *32*(3), 529–545. https://doi.org/10.1108/LHT-02-2014-0015

Viswanath, B., Mislove, A., Cha, M., & Gummadi, K. P. (2009). On the Evolution of User Interaction in Facebook. *Proceedings of the 2nd ACM Workshop on Online Social Networks* (pp. 37–42). New York, NY, USA: ACM.

Volker, M. A., & Lopata, C. (2008). Autism: A review of biological bases, assessment, and intervention. *School Psychology Quarterly*, *23*(2), 258–270. https://doi.org/10.1037/1045-3830.23.2.258

Vygotsky, L. (1978). Interaction between learning and development. *Readings on the Development of Children*, *23*(3), 34–41.

Watts, D. J., & Strogatz, S. H. (1998). Collective dynamics of “small-world” networks. *Nature*, *393*(6684), 440–442. https://doi.org/10.1038/30918

Westbrook, L., & Zhang, Y. (2015). Questioning strangers about critical medical decisions: “What happens if you have sex between the HPV shots?” *Information Research*, *20*(2). Retrieved from http://www.informationr.net/ir/20-2/paper667.html#.WdFHXMh95aQ

Wilson, R. (2012, December). Trending on Twitter: A Look at Algorithms behind Trending Topics. Retrieved October 1, 2017, from https://www.ignitesocialmedia.com/twitter-marketing/trending-on-twitter-a-look-at-algorithms-behind-trending-topics/

Wilson, T., Wiebe, J., & Hoffmann, P. (2005). Recognizing Contextual Polarity in Phrase-level Sentiment Analysis. In *Proceedings of the Conference on Human Language Technology and Empirical Methods in Natural Language Processing* (pp. 347–354). Stroudsburg, PA, USA: Association for Computational Linguistics. https://doi.org/10.3115/1220575.1220619

Winter, G. (2000). A Comparative Discussion of the Notion of "Validity" in Qualitative and Quantitative Research. *The Qualitative Report*, *4*(3), 1–14.

Worrall, A., & Oh, S. (2013). The place of health information and socio-emotional support in social questioning and answering. *Information Research*, *18*(3). Retrieved from http://www.informationr.net/ir/18-3/paper587.html#.WdFavch95aQ

Xiang, Z., & Gretzel, U. (2010). Role of social media in online travel information search. *Tourism Management*, *31*(2), 179–188. https://doi.org/10.1016/j.tourman.2009.02.016

Yamashita, T., Sato, H., Oyama, S., & Kurihara, M. (2013). Classification of twitter users based on following relations. In *Proceedings of the International MultiConference of Engineers and Computer Scientists (IMECS'13)*. Retrieved from http://www.iaeng.org/publication/IMECS2013/IMECS2013_pp341-343.pdf

Yu, L., Asur, S., & Huberman, B. A. (2011). What Trends in Chinese Social Media. *arXiv:1107.3522 [Physics]*. Retrieved from http://arxiv.org/abs/1107.3522

Zeckman, A. (2012, November 5). Social Media User Types: How You Can Better Connect With Each One. Retrieved from http://www.toprankblog.com/2012/11/5-social-media-user-types/

Zhang, J., & Zhao, Y. (2013). A user term visualization analysis based on a social question and answer log. *Information Processing & Management*, *49*(5), 1019–1048. https://doi.org/10.1016/j.ipm.2013.04.003

Zhang, J., Zhao, Y., & Dimitroff, A. (2014). A study on health care consumers' diabetes term usage across identified categories. *Aslib Journal of Information Management*, *66*(4), 443–463. https://doi.org/10.1108/AJIM-01-2014-0008

Zhang, J., Zhao, Y., & Wang, Y. (2016). A study on statistical methods used in six journals of library and information science. *Online Information Review*, *40*(3), 416–434. https://doi.org/10.1108/OIR-07-2015-0247

Zhao, W. X., Jiang, J., Weng, J., He, J., Lim, E.-P., Yan, H., & Li, X. (2011). Comparing Twitter and Traditional Media Using Topic Models. In P. Clough, C. Foley, C. Gurrin, G. J. F. Jones, W. Kraaij, H. Lee, & V. Mudoch (Eds.), *Advances in Information Retrieval* (pp. 338–349). Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-642-20161-5_34

Zhao, Y., & Zhang, J. (2017). Consumer health information seeking in social media: A literature review. *Health Information and Libraries Journal, 34*(4), 268-289.

Appendix

Autism support group on Facebook

Group name	Number of members
Autism Parents Support & Discussion Group	53,493
Autism Spectrum Disorder, through my eyes Discussion Group	36,165
Síndrome de Asperger - Autismo infantil	26,441
Autism (A Mothers Support Group)	21,058
Aspergers	19,833
Adults with Asperger's Syndrome	14,697
Asociación Asperger Argentina - AsAAr	14,432
Autisme Malaysia	13,520
AUTISMO/ASPERGER /SÃO PAULO	11,353
Asperger's Syndrome	10,096
ADHD,Asperger's and Autism - Support Network for Families	9,721
Asperger Syndrome Awareness	8,491
Autism Group	8,185
CD Autism	7,524
Families with autism kids	7,081
Asperger's syndrome	6,721
Autism, ADHD and Essential Oils	6,223
Asperger's Syndrome: Raising Awareness!	5,310
Asperger... comunidad en la red.	4,802
Parents Of Autistic Children	4,127
Behavior Analysts for Autism	4,115
Asperger Experts Private Group	4,097
Autism/Asperger's Syndrome awareness wor	4,037
Autism Society of North Carolina	4,022
High Functioning Adults with Asperger Syndrome	3,943
Grupo Integrador "MUNDO AZUL" Tea-Asperger Mar del Plata	3,938
Autistic UK	3,881
Mothers raising a child with Aspergers!!	3,871
Understanding Aspergers	3,808
Aspie Adults - Closed Group	3,796
Autism/Asperger/ADHD Sharing - Indonesia	3,353
Autism Parents Chat	3,347
Always Aspergers	3,234
Aspergers/Autism Young Adults 16-30	3,233
Autism Mommies	3,026

Positively Autistic	3,000
Autism Mamaí	2,959
Parents of children with PDD NOS (Pervasive Developmental Disorder)	2,887
Autism And Aspergers Is Nothing To Be Ashamed Of.	2,861
Autism Friendly UK	2,733
Dyslexia, ADHD, Aspergers Syndrome, Autism Spectrum Disorder Support UK	2,732
Special Needs Educators of Malaysia (Autism, Aspergers, Dyslexia, etc)	2,537
You Might be an Aspie if...	2,164
Support Group for Parents of Severely Autistic Children with LD	2,154
High Functioning Autistic Children Group	2,014
MAPS for Autism - Parent Group	1,892
Somos Asperger y Asperger Temuco	1,882
Autism Society Inland Empire	1,798
Autism Banning Together	1,782
Autism Superfriends	1,766
Autism Parents Australia	1,665
Autistic Society of Trinidad and Tobago	1,606
Adults with Aspergers Syndrome 2	1,605
FAMILIA ASPERGER	1,585
Aspergers Society of Ontario	1,581
Autism in Scotland	1,557
High Functioning Autism	1,506
A.B.A , PECS , Méthodes pour Autistes en Belgique	1,496
Healing and Beating Autism with Natural and Alternative Methods	1,379
Ask me, I'm autistic	1,352
Centre les Colombes des enfants autistes de Monastir	1,323
Asperger's Friendship Network	1,278
Asperger Portugal	1,243
Parents of children with Aspergers UK	1,200
Support Group for moms with kids with ADHD, ADD, Autism and behavior issues	1,190
Autism Spectrum Disorder Famillies in South Australia	1,159
Aspergers, Adhd,ADD, Asd,SPD,and selective mute uk	1,104
Autism Pervasive Developmental Disorder PDD NOS	1,103
Autistic Kidz Rock	1,084
NJ Autism Moms	1,034
USDOJ Protest for All Abused Groups (Autism,GWI,CFIDS,Lyme,Parents,Psych..)	1,024

Algerian National Autistic Forum	1,021
FEAT - Families for Early Autism Treatment	1,011
Autism Pensacola, Inc	973
Autism in New Zealand	969
FACES Autism Support Group	969
Autism Mamaí buy/sell/swap	959
The Autism Sanctuary~ a place for parents	959
PACT Parents of Autistic Children Together	955
Adults with Aspergers	936
Writers on the Autistic Spectrum	910
Down syndrome and autism	909
New Jersey Autism Warriors	896
Asperger Salta	889
Autism Parents Ireland Disneyland info and support group	888
Newcastle & Hunter Autism Support Group	879
Autism - Adelaide Mums Group	876
Autism Bakes	844
WAA (Washington Autism Alliance & Advocacy) Family Supports Network	840
Autism Triage Scotland	835
Aspies: Naughty or Nice (18+)	832
Aspergers dating.	817
Aspies Adulthood	805
Parents of Autistic PreTeens, Teens, and Adults	803
Homeschooling Parents of Children with Asperger's Syndrome	794
Autism and Aspergers buddies :)	783
Vera School For Autistic Learners	777
Columbus Autism Parents	769
Boise Autism Moms (BAM!)	757
Autism Sprinter	734
Connecting Autism Parents, Edmonton	732
Autism Awareness: Severe Non Verbal Autism	727
AUTISM & ASPERGER grupp i Sverige	701
Kansas City Autism Spot	699
Toowoomba Autism Noticeboard	691
HYDERABAD ASSOCIATION OF PARENTS OF AUTISTIC CHILDREN (HAPAC)	682
Autism New Jersey Friends	680
Asperger Moms	664
Autism and SEN Awareness	651
Portland Autism Moms (PAM)	650
Aspergers Support: NT Women Who Love an Adult Aspie	639

Boycott Chlorine dioxide / mms as an Autism Therapy	602
ASD/AUTISM - SUPPORT GROUP FOR AUSSIE MUMS	600
aspies after dark	598
Sunshine Coast ASD Support Group (Autism Spectrum Disorder)	595
ASD (Autism) & SPD Moms: Metro Vancouver	590
M.A.C.S (Merseyside Autistic Children's Society)	582
A support group for Parents (Swindon Autism, ADHD)	577
Autism Rocks (Fife)	571
Autism Parents Hub	556
Down Syndrome-Autism Connection Support	556
Love autism in the north west	553
National Autistic Society Pembrokeshire Branch	550
Autism Families NL (FEAT-NL)	545
Partners of adults with / or suspected of having Aspergers Syndrome	545
Baltimore AUTISM Parents	522
Parents of Children with Classic/Severe Autism	515
Aspergers Safe Room: A Safe Haven for Women on the Spectrum	512
Autism Families Unite for acceptance and understanding	509
Autism Suffolk (NAS)	500
AUTISM MOMS GROUP MEMPHIS TN	496
British Women with Aspergers - UK Connect Group	484
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Radio Aspergers	479
Autism & Asperger Connections	467
Hug Cards for Autism	441
A.D.A.M for Aspergers Malaysia	439
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Afternoon Asperger	427
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Christian Parents of Autistic Kids	423
Female Aspergers/Autism Support Ireland	415
Bristol Autism Support	413
Calgary Moms Autism Support Network	393
Parents of Autistic/Aspergers Teens	387
Parents of Autistic/Aspergers Teens	385
Moreton Bay Region ASD Support Group (Autism Spectrum Disorders)	381
Aspies Being Aspies (Just For Fun)	375
Autism Support Crawley	373

Autism Winnipeg PACE	366
Autistic Artwork	354
AutismUp Parents Group	345
Bendigo Autism (support group)	327
Autism Family	326
Mums & Dads Of Autistic/ Adhd Family Members	326
The National Autistic Society Blaenau Gwent Branch	325
AUTISM SOCIETY Omaha - Autism MomME Time Group	323
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Autism Moms Ontario	311
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Autism/ ASD Chat And Support in the U.K	284
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LGBT Aspergers	282
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Saskatchewan Parents of Children with an Autism Spectrum Disorder	270
Appaws For Autism UK	264
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Stem Cell Therapy for Autism	248
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Fareham Autistic Spectrum Support	246
Autism Page Owners	243
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Autism & ADHD Parents North Down	239
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Autism support aberdeen	228
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Rugby Autism Network Chat	214
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Canadian Autism Family Support	208
Autism ADHD Aspergers Parent Support brisbane	205
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Loved ones of autistic children boycotting 50 cent	190
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Females with Asperger's	87
We love Autistic People ♥♥♥♥	87
Southern Autistic School Victoria	85
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LCC-Loissa college captain orfe [Cesra Anik/Autistic Clg Captain]	84
Redefining Autism - Raising Kids with Asperger's/HFA in BC	84
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Curriculum Vita

Yuehua Zhao

School of Information Studies
University of Wisconsin-Milwaukee

EDUCATION

Ph.D. | 2013-2018 (Expected) | University of Wisconsin-Milwaukee
- Major: Information retrieval
- Minor: Consumer health informatics
- Dissertation: "An Investigation of Autism Support Groups on Facebook"
- Dissertation Committee: Dr. Jin Zhang (chair), Dr. Dietmar Wolfram, Dr. Iris Xie, Dr. Alexandra Dimitroff, Dr. Min Wu

M.A. | 2011-2013 | Wuhan University
- Major: Management science and engineering
- Minor: Information science
- Master's Essay: "Visualization Study on the Development of International Scientometrics"
- Advisor: Dr. Junping Qiu, Wuhan University

B.A. | 2007-2011 | Sichuan University
- Major: Information management and information system

RESEARCH INTEREST

- Data science
- Statistical analysis and text analysis
- Consumer health informatics
- Social media research
- Social network analysis and information visualization
- Informetrics and scholarly communication

PUBLICATIONS

Refereed Journal Articles

1. Zhang, J., Wang, Y., **Zhao, Y.**, & Cai, X. (Accepted). Analysis of statistical methods and their applied areas in research of library and information science. *Data and Information Management*. **(Corresponding author)**
2. **Zhao, Y.,** & Zhang, J. (2017). Consumer health information seeking in social media: A literature review. *Health Information and Libraries Journal, 34*(4), 268-289.
3. Zhang, J., Wang, Y., & **Zhao, Y.** (2017). Investigation on the statistical methods in research studies of library and information science. *The Electronic Library, 35*(6), 1070-1086.

4. **Zhao, Y.,** & Zhao, R. (2016). An evolutionary analysis of collaboration networks in scientometrics. *Scientometrics, 107*(2), 759-772.
5. Zhang, J., **Zhao, Y.**, & Wang, Y. (2016). A study on statistical methods used in six journals of library and information science. *Online Information Review*, *40*(3), 416-434.
6. Yang, S., Han, R., Wolfram, D., & **Zhao, Y.** (2016). Visualizing the intellectual structure of information science (2006–2015): Introducing author keyword coupling analysis. *Journal of Informetrics*, *10*(1), 132–150.
7. Yu, Y., & **Zhao, Y.** (2016). Assessing the journal impact based on twitter popularity: Taking international top-tier journals in the LIS field as examples. *Library and Information Science*, *60*(8), 99-105. (in Chinese)
8. Zhao, R., **Zhao, Y.**, & Guo, F. (2016). Research on scientometrics revolution from the time and space dimensions. *Information and Documentation Services*, *37*(1), 5-10. (in Chinese)
9. Zhao, R., Guo, F., & **Zhao, Y.** (2015). Study of mainstream research fields and hotspots in the field of scientometrics. *Library and Information Science, 59*(2), 66-74. (in Chinese)
10. Zhao, R., Guo, F., & **Zhao, Y.** (2015). Visualization analysis of the evolution of scientometrics: In the view of ISSI conference. *Journal of Intelligence*, *34*(2), 124-130. (in Chinese)
11. Wolfram, D., & **Zhao, Y.** (2014). A comparison of journal similarity across six disciplines using citing discipline analysis. *Journal of Informetrics*, *8*(4), 840–853.
12. Qiu, J., & **Zhao, Y.** (2014). Quantitative analysis of national excellent doctoral dissertations. *Science & Technology Progress and Policy*, *32*(02), 16-20. (in Chinese)
13. Qiu, J., Lou, W., Zeng, Y., **Zhao, Y.**, Sun, D., & Li, C. (2014). An investigation on the situation of electronic book digital libraries in China. *Library and Information Science*, *58*(5), 22-28. (in Chinese)
14. Qiu, J., **Zhao, Y.**, & Zhao, R. (2013). Analysis of foreign information visualization research in the field of library and information. *Information Studies: Theory & Application*, *36*(01), 124-128. (in Chinese)
15. Qiu, J., Wang, F., Lou, W., Wu, S., Zhou, W., & **Zhao, Y.** (2012). Competitive evaluation of world-class universities and research institutions (I). *Chinese University Science & Technology*, 07, 76-78. (in Chinese)

Refereed Journal Articles (In progress)

1. Zhang, J., Chen, Y., **Zhao, Y.**, & Ma, F. (Under revision). Temporal analysis of Zika virus related posts on a public question and answer forum. *Information Processing & Management*.
2. Zhang, J., **Zhao, Y.**, Cai, X., Le, T., Wei, F., & Ma, F. (Under review). A comparison of retrieval result relevance judgement decisions between Chinese and American users. *International Journal of Information Technology & Decision Making*.
3. Lou, W., **Zhao, Y.**, & Chen, Y. (Under revision). Research or management? An investigation of the impact of leadership roles on the research performance of academic administrators. *Scientometrics*. **(Corresponding author)**

Refereed Conference Papers

1. **Zhao, Y.**, Lou, W., & Chen, Y. (2017). Research or management? An investigation of the impact of administrative roles on the research performance of academic administrators. *Proceedings of 16th International conference on Scientometrics & Informetrics*, 1288-1294.
2. **Zhao, Y.**, & Zhao, R. (2015). Evolutionary analysis of collaboration networks in scientometrics. *Proceedings of 15th International conference on Scientometrics & Informetrics*, 1121-1129.
3. Lu, K., **Zhao, Y.**, Ajiferuke, I., & Wolfram, D. (2015). How related is author topical similarity to other author relatedness measures? *Proceedings of 15th International conference on Scientometrics & Informetrics*, 899-908.
4. Zhao, R., & **Zhao, Y.** (2013). Analysis of the development of ISSI and scientometrics and informetrics: A view of ISSI conference papers. *Proceedings of the 8th International Conference on Scientometrics and University Evaluation*, 157-172.

Non-refereed Conference Papers

1. **Zhao, Y.**, Zhao, R., & Yu, H. (2012). Study on the development of informetric tools. *Geomatics and Information Science of Wuhan University*: *Vol*. 37 (pp. 233-236). Wuhan, China.
2. Yu, H., Wang, F., & **Zhao, Y.** (2012). Visualizing science in African union based on SCI papers in 2011. *Geomatics and Information Science of Wuhan University*: *Vol. 37* (pp. 253-257). Wuhan, China.
3. Zhao, R., Xu, L., & **Zhao, Y.** (2010). From the knowledge management to knowledge management science. Proceedings of the 2010 International Conference on Management and Service Science (pp. 1-4), Wuhan, China.

Refereed Conference Posters

1. **Zhao, Y.**, Wang, Y., & Xin, C. (Accepted). *A citation-based review of study on image retrieval*. iConference 2018, Sheffield, UK.
2. **Zhao, Y.**, Zhang, J., & Wang, Y. (2017). *Social media and autism support: Investigation of autism support on Facebook*. Poster presented at the iConference 2017, Wuhan, China.
3. **Zhao, Y.,** & Nambisan, P. (2015). *Social media and autism support: Health information seeking in Facebook by autism patients and caregivers*. Poster presented at the AMIA 2015, San Francisco, CA, USA.
4. **Zhao, Y.,** & Wolfram, D. (2015). *Assessing the popularity of the top-tier journals in the LIS field on Twitter*. Poster presented at ASIST 2015, St. Louis, MO, USA.
5. **Zhao, Y.,** & Zhao, R. (2014). *Evolution of the development of scientometrics*. Poster presented at the iConference 2014, Berlin, Germany.

Non-refereed Conference Posters

1. **Zhao, Y.** (2017). *Investigation on autism support groups on Facebook*. Poster presented at the 17th Association for Library and Information Science Educators Conference, Atlanta, GA, USA. (**Honorable Mention)**

2. Wang, Y., & **Zhao, Y.** (2017). *Explore the topics of big data from journal papers and Wikipedia articles*. Poster presented at the 17th Association for Library and Information Science Educators Conference, Atlanta, GA, USA.
3. Zhang, J., & **Zhao, Y.** (2016). *Social support for autism patients and caregivers: Is the Q&A forum helping users?* Poster presented at the 8th Qualitative and Quantitative Methods in Libraries International Conference, London, England.
4. **Zhao, Y.** (2015). *A qualitative study of the evaluation criteria of health information on different social media: A pilot study*. Poster presented at the 7th Qualitative and Quantitative Methods in Libraries International Conference, Paris, France.
5. Wang, Y., **Zhao, Y.**, & Joo, S. (2014). *Assessment model of academic library productivity using multiple regression*. Poster presented at WAAL 2014. Wisconsin Dells, WI, USA.

AWARDS AND FELLOWSHIPS

Distinguished Dissertation Fellowship 2017
· Highly honorable and competitive fellowship offered by Graduate School at the UWM ($16,500)

Invitation to iConference Doctoral Colloquium 2017
· Registration & lodging wavier, supported by National Science Foundation

Honorable Mention for the ALISE/Jean Tague-Sutcliffe Doctoral Student Poster competition
· Honorable and competitive award 2017

Chancellor's Graduate Student Awards 2013-2014, 2016-2017
Chinese American Librarians Association (CALA) Scholarship 2014
Research Innovation Award at Wuhan University (third-class) 2013
Graduate pacesetter of Wuhan University 2012
Basic Scholarship of Wuhan University 2011-2012
Outstanding Scholarship of Wuhan University (First-class) 2011
Excellent Student Cadre of Wuhan University 2011
Outstanding Student of Sichuan University 2009-2010
Scholarship of Sichuan University 2008-2010

TEACHING EXPERIENCE

Instructor **School of Information Studies, University of Wisconsin-Milwaukee**
· Undergraduate (Online), 230 Organization of Knowledge, Spring 2018

Teaching Assistant **School of Information Studies, University of Wisconsin-Milwaukee**
· Graduate (Online), 571 Information Access and Retrieval, 2017 Spring
· Graduate (Online), 524 Management of Library and Information Services, 2016 Fall
· Graduate (Online), 711 Cataloging and Classification, 2016 Spring
· Graduate (Online), 713 Subject Analysis in Library Catalogs, 2016 Spring
· Undergraduate (On site), 230 Organization of Knowledge, 2015 Fall

Teaching Assistant **School of Information Studies, Wuhan University**
· Undergraduate (On site), Informetrics, 2012 Fall

RESEARCH EXPERIENCE

Graduate Research Assistant ***University of Wisconsin-Milwaukee***

Investigation on the statistical methods in research studies of library and information science

PI: Dr. Jin Zhang Aug. 2013–May 2017

- Collected full-text data for selected journals
- Conducted content analysis and statistical analysis
- Contributed to writing the introduction, literature review, results and discussion sections of three journal papers

How related is author topical similarity to other author relatedness measures?

PI: Dr. Dietmar Wolfram Aug. 2014–May 2017

- Collected bibliographic data from a selected database
- Applied citation analysis and visualized the results
- Contributed to writing the literature review sections of a conference paper

A user-oriented term analysis through mining of social Q&A data

PI: Dr. Jin Zhang Aug. 2013– May 2014

- Collected data from Yahoo! Answers website
- Applied content analysis to reveal the discussion topics
- Wrote a conference poster based on the project

A comparison of journal similarity across six disciplines using citing discipline analysis

PI: Dr. Dietmar Wolfram Aug. 2013–May 2014

- Conducted citation analysis and visualized the results
- Contributed to writing the results and discussion sections of a journal paper

Funded student research project ***Sichuan University***

Development of management information system for industrial carbon emission management

PI: Yuehua Zhao Sept. 2010–Jun. 2011

- Wrote the project proposal and reports
- Organized a group of six students
- Contributed to the design of the system

SERVICE

Scientific Program Committee

- 16th International Conference on Scientometrics & Informetrics, 2017

Reviewer

- Journal of the Association for Information Science and Technology
- Journal of Informetrics
- Scientometrics

· Health Information and Libraries Journal
· American Medical Informatics Association (AMIA) Annual Symposium, 2017
· 16th International Conference on Scientometrics & Informetrics, 2017

Officer

· Doctoral Student Organization (DSO), 2016

Volunteer

· Midwest Interdisciplinary Graduate Conference (MIGC), 2017
· 7th International Conference on Scientometrics and University Evaluation, 2013