THE ANATOMY OF AN ONLINE SOCIAL COMMUNITY NETWORK

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- this thesis contains no material that has been submitted or accepted for a degree or diploma in any other educational institution;
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ABSTRACT

The Anatomy of an Online Social Community Network

The emergence of Web 2.0 has revolutionized the ways of communication on the Internet and has allowed people to form their virtual worlds involving online communities and social networks. People have started to generate their contents, share them, and communicate with each other in these communities and networks. In parallel to the generation of huge amount of contents in these platforms, these communities and networks have become valuable data sources for businesses. It is the fact that analysis of user content in online communities and social networks allows businesses to enhance their business value and achieve their goals. In this sense, to create and manage these communities successfully, managers need to understand how to motivate community members and keep them frequently involved. Therefore, this study employs social network analysis to map and understand the network structure of an online community and to detect sub-communities in it. Additionally, it explores and identifies user roles in an online community and proposes a research model that investigates members' usage intentions of the community. The research model also analyzes the moderating effect of these investigated user roles on members' usage intentions of the community. In this manner, this study combines various theories for a better understanding of what roles exist in online communities, what roles members prefer to adopt, what usage intentions members have by presenting a four-phase methodology. Additional to theoretical implications, the study also guides managers to develop motivational strategies to keep their members continually satisfied in online communities.

ÖZET

Bir Çevrimiçi Sosyal Ağ Topluluğunun Anatomisi

Web 2.0'ın ortaya çıkışı İnternetteki iletişim yollarını değiştirdi ve insanların çevrimiçi sosyal topluluklar ve sosyal ağlar içeren sanal dünyalarını kurmasına izin verdi. İnsanlar, bu topluluk ve ağlarda kendi içeriklerini üretmeye, bunları paylaşmaya ve birbirleri ile iletişim kurmaya başladılar. Bu platformlardaki büyük miktardaki içerik üretimine paralel olarak, bu topluluklar ve ağlar işletmeler için değerli bir veri kaynağı haline geldiler. Gerçek şu ki çevrimiçi topluluklardaki ve sosyal ağlardaki kullanıcı içeriklerinin analiz edilmesi işletmelerin, işletme değerlerini artırmalarına ve hedeflerine ulaşmalarına olanak vermektedir. Bu bağlamda, bu toplulukları başarıyla oluşturmak ve yönetmek için, yöneticiler topluluk üyelerini nasıl motive edeceklerini ve onları nasıl sıklıkla topluluk içerisine dahil edeceklerini anlamalıdırlar. Bu sebeple bu tez çalışması çevrimiçi bir topluluğun ağ yapısını ortaya çıkarmak ve anlamak ve bu topluluktaki alt toplulukları tespit etmek için sosyal ağ analizini kullanmaktadır. Ayrıca bu tez çalışması, çevrimiçi bir topluluktaki kullanıcı rollerini araştırmakta ve üyelerin çevrimiçi topluluğunun kullanım niyetlerini araştıran bir araştırma modeli önermektedir. Bu araştırma modeli aynı zamanda ortaya çıkarılan kullanıcı rollerinin kullanım niyeti üzerindeki moderatör etkisini de analiz etmektedir. Bu çalışma, çevrimiçi topluluklarda yer alan rollerin neler olduğunu, üyelerin hangi rolleri benimsemeyi tercih ettiğini, üyelerinin nasıl bir kullanım niyetlerini bulunduğunu daha iyi anlamak için çeşitli teorileri birleştirmekte ve dört aşamadan oluşan bir metodoloji sunmaktadır. Teorik çıkarımlara ek olarak, bu çalışma da aynı zamanda ilgili yöneticilere, üyelerini mutlu etmek için her kullanıcı rolüne ilişkin motivasyon stratejileri sunulmaktadır.

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Akar, E., & Akar, S. (2017). Data Never Sleep: A Marketing Perspective. *Journal of Marketing and Strategic Management*, 11, 31-43.

Akar, E., & Mardikyan, S. (2016). Factors Affecting the Adoption of Cloud Computing: A Case of Turkey. *KSII Transactions on Internet and Information Systems*, 10 (1), 18-37.

Ozturan, M., Basarir-Ozel, B., & Akar, E. (2015). A Review on Methods for the Assessment of Information System Projects. *Journal of Information Technology and Applications*, 5 (2), 117-128.

Akar, E., & Nasir, V.A. (2015). A Review of Literature on Consumers' Online Purchase Intentions. *Journal of Customer Behaviour*, 14 (3), 215-233.

Ozturan, M., Bozanta, A., Basarir-Ozel, B., Akar, E., & Çoşkun, M. (2015). A roadmap for an integrated university information system based on connectivity issues: Case of Turkey. *The International Journal of Management Science and Information Technology*, Jul-Sep 2015(17), 1-22.

Akar, E., & Mardikyan S. (2014). Factors Affecting Users' Behavior Intention to Use Social Media: Twitter Case. *International Journal of Business and Social Science*, 5 (11-1), 85-95.

Books and Book Chapters

Akar, E. (2018). Blockchain Technology. In *Bitcoin Devrimi* (Bitcoin Revolution). (pp. 36-52). Istanbul, Turkey: Elma Publishing.

Unal, S., Dalgic, T., & Akar, E. (2018). Avatars as the Virtual World's Personality. In *Virtual Worlds and Marketing* (pp. 33-53). Lady Stephenson Library, Newcastle upon Tyne, NE6 2PA, UK: Cambridge Scholars Publishing.

Conference Proceedings and Presentations

Akar, E., & Dalgic, T. (2017). Analyzing Online Consumers' Purchase Intentions: The Perspectives for International E-Marketers. Presented in *the 26th Annual Consortium for International Marketing Research Conference*, June 20-23, Florence, Italy.

Unal, S., Dalgic, T. & Akar, E. (2017). How Avatars Help Enhancing Self-Image Congruence: Implications for International Marketers. Presented in *the 26th Annual Consortium for International Marketing Research Conference*, June 20-23, Florence, Italy.

Ari, E., & Nasir, V.A. (2014). A Critical Review of Online Consumers' Purchase Intentions. In *Advances in Business-Related Scientific Research Conference (ABSRC-2014), Venice/Italy*.

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ABBREVIATIONS

AARS	Average Adjusted R Squared
AFVIF	Average Full Collinearity
APC	Average Path Coefficients
ARS	Average R Squared
AVE	Average Variance Extracted
AVIF	Average Block Variance Inflation Factors
GOF	Goodness of Fit
LISREL	Linear Structural Relations
PCM	Perceived Critical Mass
PEOU	Perceived Ease of Use
PLS	Partial Least Squares
PP	Perceived Playfulness
PU	Perceived Usefulness
SEM	Structural Equation Modeling
SNA	Social Network Analysis
TAM	Technology Acceptance Model
TW	Trustworthiness
UI	Usage Intention
VIF	Variance Inflation Factors

CHAPTER 1

INTRODUCTION

Technological advancements have led to the Internet proliferation and have increased the Internet adoption and social media use by societies on the global scale. Statistics indicate that the total population of the world is 7.593 billion, the total number of the Internet users is 4.021 billion, and 79.48% of them are active social media users (Digital in 2018, 2018). Additionally, the emergence of Web 2.0 has fired the interactivity among the Internet users, and online communities and social networks have started to show up gradually and become very common among the Internet users by inviting people to discuss various socioeconomic issues as discussed in traditional media (Baek & Kim, 2015). Now, they serve as platforms to exchange and share personal information, knowledge, and opinions.

Online communities can be defined as “social aggregations that emerge from the Net when enough people carry on those public discussions long enough, with sufficient human feeling, to form webs of personal relationships in cyberspace” (Rheingold, 1993, pp. 6-7). In parallel to this definition, the success of online communities depends on the members’ willingness to share their opinions, to communicate with other members, and to contribute to the community by generating contents (Füller, Hutter, Hautz, & Matzler, 2014). In this sense, a better understanding of the users’ community website intentions is essential for the community managers. But, different user types with diverse needs engage in online communities, so practitioners should develop different managerial and motivational strategies to keep each kind of users satisfied.

Therefore, at the first step, this study analyzes the topography of an online community network and detects sub-communities by the perspective of social network analysis (SNA). After that, this study explores user roles in a community based on the detected sub-communities and members’ contribution behavior in the given community. The integration of structural data and members’ contribution behavior allows us to identify the roles in a more meaningful way (Gleave, Welser, Lento, & Smith, 2009) and to gain a more comprehensive understanding of user roles in the context of online communities. Lastly, this study proposes a research model to understand the factors affecting the members’ usage intention of community website and to test the moderating effect of user roles on members’ usage intentions by extending the technology acceptance model (TAM).

In parallel, the aims of the paper can be broken down into the following objectives:

- To analyze whole network topology,
- To detect influential users in the online community,
- To detect sub-communities in the online community,
- To identify user roles in the online community,
- To investigate the impacts of factors on online community members’ website usage intentions,
- To examine the moderating impact of distinct user roles on online community members’ website usage intentions,
- To give implications and further insights from theoretical perspective,

- To suggest motivational strategies for practitioners who create and manage online community websites to satisfy community members.

A local online community has been selected to be investigated. This community can be considered as a discussion forum in where members open topics about any subject, add contents, and share a mutual interest with each other.

The study results are beneficial for practitioners who manage online community websites to understand behaviors of their members and to identify appropriate motivational strategies for them. Thereby they can increase their members’ satisfaction and gain a competitive advantage in the digital environment. The findings also complement other studies on the topic of social network analysis, online user roles, and online community website usage intention and provide them with different perspectives that can lead to further research.

In the first half of the study, literature review, social network analysis, community, and research methodology are described. In the second half of the study, research model and hypotheses, and the study results are presented. In the last part, highlighting significant findings are discussed.

CHAPTER 2

LITERATURE REVIEW

This chapter introduces brief information and history about online social networks and communities, and then it presents previous research focusing on the analysis of network structure, the identification of user roles, and the investigation of online community usage intention.

2.1 Online social networks and communities

The advances in communication technologies and the Internet proliferation have changed the way that the Internet users behave, interact, and communicate. They have started to share, create, and modify the content on the Internet (Kietzmann, Hermkens, McCarthy & Silvestre, 2011) and they have also become more connected with each other. All these developments have led to the emergence of online social networks and online communities.

Boyd and Ellison (2008) define social network sites as

> web-based services that allow individuals (1) to construct a public or semi-public profile within a bounded system, (2) articulate a list of other users with whom they share a connection, and (3) view and traverse their list of connections and those made by others within the system. (p. 211)

Also, Mislove (2009) defines social networks as

> a system where (a) users are first class entities with a semi-public profile, (b) users can create explicit links to other users or content items, and (c) users can navigate the social network by browsing the links and profiles of other users. (p. 11)

Mislove (2009) indicates that classmates.com was the first website in where users connected to other users in 1995. Though, users only linked to each other if they were studied at the same school or college. They could not create user profiles and friend list, and they could not connect to others if they studied at different schools or colleges. In this sense, SixDegrees.com, which was launched in 1997 and closed in 2000, was the first website that met the definition of social network site (Boyd & Ellison, 2008). Users started to create their profiles, list their friends, and connect with others. After that new social network sites began to emerge such as Friendster in 2002, Orkut in 2004, LinkedIn and Myspace in 2003, Flickr and Facebook in 2004, Yahoo! 360, Cyworld, and YouTube in 2005, Windows Live Space and Twitter in 2006, Foursquare in 2009, Instagram in 2010, and Snapchat in 2011.

Furthermore, Koçak (2014) says that the emergence of social network sites has also led to the advancement of online or virtual communities. Online communities can be defined as "social aggregations that emerge from the Net when enough people carry on those public discussions long enough, with sufficient human feeling, to form webs of personal relationships in cyberspace" (Rheingold, 1993, pp. 6-7). Moreover, Lee, Cheung, Lim, and Ling (2006) describe online communities as "socio-technical" systems. In the social context, these systems deal with the attributes of users, the relationships among users, the culture and the structure of user groups. In the technical context, these systems manage tasks, processes, and technology needed.

There are some conditions that online communities should meet (Christian Franklin, Mainelli, & Pay, 2014). Firstly, online communities require an adequate number of members who engage in the community and communicate with other community members actively. Secondly, community members should share a mutual interest or concern to interact with other members, and a collection of rules should govern the behavior of community members (Bagozzi & Dholakia, 2002; Christian

Franklin et al., 2014). In this sense, online communities can be categorized as communities of mind in where people cooperate, and coordinate based on a mutual or a similar interest (Tonnies, 1995; Zhou & Amin, 2014). Thirdly, online communities should involve a participation mechanism for its both new and old members (Toral, Rocío Martínez-Torres, Barrero, & Cortés, 2009). Lastly, community members should experience a sense of community which is "a feeling that members have of belonging, a feeling that members matter to one another and to the group, and a shared faith that members' needs will be met through their commitment to be together" (McMillan & Chavis, 1986, p. 9).

Although online social networks and communities look like having a similar social structure, they differ from each other. In online social networks, people connect mainly to individuals who share some offline connections (Boyd & Ellison, 2008). For example; friendship, kinship, classmates, or colleagues. The primary goal of online social networks is allowing people to communicate with individuals who have already been a part of their offline network instead of looking to meet new people. In other words, people want to maintain their existing relationships and expand their network (Wu, 2011). Additionally, in social networks, people have a profile, and their friends can identify them. On the other hand, online communities involve individuals who share a common goal or interest. People can share a hobby, profession, geographic location, or similar lifestyle. For example; Wikipedia is an online community in where people communicate with each other due to the cause of the Internet encyclopedia project. Moreover, it is not required that people should have a previous relationship with their connections and anyone can be part of the community. Wu (2011) also states that online communities can be nested and overlap. For example; YouTube is a nested community involving video enthusiasts, and it can include sub-communities such as friends and family members, and people interested in time-lapse videos.

It is evident that online social networks and communities are important parts of Web and studying them can include some benefits. For example; Benevenuto, Rodrigues, Cha, and Almeida (2009) state that modeling user behaviors in online social networks and communities can play a significant role. They say that understanding user behaviors allows us to evaluate the performance of existing systems and make a better website and system design. It is also essential to understand the workload of social networks for better design of next-generation Internet infrastructure and content distribution systems. Also, Mislove, Marcon, Gummadi, Druschel, and Bhattacharjee (2007) give an example that understanding the structure of online social networks and communities can be helpful to detect trusted or influential users, to improve the Internet search, and to defend against Sybil attacks. Additionally, they imply that understanding the structure of online social networks and communities provides numerous benefits not only for computer science but also for other disciplines such as marketing and sociology. For example; analyzing social networks and communities can help to explain the improvement in marketing campaigns, viral marketing, and theory testing.

2.2 Network structure

Studies analyzing network structures focus on Facebook, Twitter, YouTube, blogs, and other popular social network sites. Facebook, which was launched in 2007, is one of the most popular online social networks. Lewis, Kaufman, Gonzalez, Wimmer, and Christakis (2008) study tastes, ties, and time by using Facebook dataset. In this study, they collect Facebook profile details of the freshman students of a private college in

Northeast U.S. by the permission of Facebook. They analyze the social structure of the network by examining network size, network density, network heterogeneity, and betweenness centrality. As a method, they use ordinary least squares regression to see the association of gender, race/ethnicity, and socioeconomic status in the network. They use UCINET's node-level regression to generate significant levels based on permutations of the dependent vector. As a result, they find that students sharing social relationships as well as demographic traits tend to share a considerable number of cultural preferences.

Furthermore, Mayer and Puller (2008) gather both administrative and Facebook data together. They use a large dataset from ten public and private universities to form social networks. For this purpose, they use student data to describe the structure of those networks. Additionally, they measure segmentation of social links by race, socioeconomic background, and ability. Then, authors develop a model of network formation and balance the model to their data and perform experiments of university policies that promote student diversity. They state that two students having similar characteristics are more likely to be a friend. The results of the study reveal that if two students share same major or political orientation or same cohort, they are moderately more likely to form a friendship. Also, students living in the same dorm, two black students, and two Asian students are 13 times, 17 times, and 5 times more likely to be friends, respectively. Although socioeconomic background and academic achievement have some smaller effects on the formation of friendship, they also have significant effects on it. The results also indicate that students from families with similar income levels are more likely to be friends.

Catanese, De Meo, Ferrara, Fiumara, and Provetti (2011) also focus on Facebook. They collect data by examining two large networks to describe the connections between participants of online social networks. They apply two different sampling methods to get subgraph of Facebook: breadth-first search sampling and uniform sampling. They compare the results of these two sampling methods. After that, they describe the network by considering degree distribution, diameter and hops, clustering coefficient, connected components, and eigenvector centralities. The results indicate that Facebook network can be regarded as just about a connected network. In another study, Catanese, De Meo, Ferrara, Fiumara, and Provetti (2012) analyze the friendship relations on Facebook. In this study, they focus on node similarity detection, community detection, and influential user detection. They use the same two sampling methods to gather data from Facebook.

Moreover, Park, Lee, and Kim (2012) investigate the personal network characteristics which also known as egocentric network and patterns of Facebook use. In their study, they measure time spent on Facebook, message posting, photo posting, and reading postings or viewing photos without posting messages, comments, or photos. They employ an online survey in the Southwestern United States. The sample includes 292 students out of 1500 students. They state that aspects of individuals' relationships can be better understood by examining the match between personal network characteristics and patterns of Facebook use. They indicate that there is not a parallel relationship between the existing personal relationships and Facebook usage.

Ugander, Karrer, Backstrom, and Marlow (2011) also study the social graph of active Facebook users. They analyze a subgraph of Facebook including 149 million users and compute the number of users and friendships, degree distribution, clustering coefficient, and mixing patterns. They find that the social network is about fully connected, has short average path length, and high clustering coefficient. They observe the substantial effects of age and nationality on friendship preferences. However, they do not find any effect of gender homophile.

Twitter, which is a popular microblogging platform, is studied in many research. Morales, Borondo, Losada, and Benito (2014) investigate the efficiency of human activity on information spreading on Twitter. They consider Venezuelan political protest on Twitter. They find that while some influential users efficiently lead to exceptional collective reactions by their messages on Twitter, most users must apply excessively larger efforts to reach similar impacts. Cheong and Cheong (2011) also focus on the dissemination of information about vital cases and try to identify the valuable online resources that are disseminated on Twitter. They take Australian 2010-2011 floods as a case. They use two types of networks. The first one is a network of Twitterer. When a Twitter user gives a response to a tweet, it creates a network. The second network includes the resources. It consists of tweets including links to web pages. They apply ego analysis and find that local authorities including mainly Queensland Police Services, political personalities involving Queensland Premier, Prime Minister, Opposition Leader, Member of Parliament, social media volunteers, traditional media reporters, and people from not-for-profit, humanitarian, and community associations play an active role in the information dissemination.

Yoon and Park (2014) also investigate Twitter data from the political perspective. They analyze Twitter-network pattern of South Korean politicians. They examine following and mention relationships of politicians. They gather data of 189 South Korean politicians from Twitter. They conduct exponential random graph model and a regression model. They find that the politicians tended to mention popular politicians on Twitter who belonged to the same political group and there is a social pressure to follow other politicians.

Blogs have also attracted the attention of many researchers. Chin and Chignell (2007) identify, measure, and evaluate communities in blogs. They select an independent music blog. They ask questions to visitors of this blog to collect data from them. They find several types of communities. Also, Warmbrodth, Sheng, and Hall (2008) investigate the video bloggers' network. They examine the degree, closeness, and betweenness centralities. They find video bloggers' community is highly decentralized and exhibits a core/periphery structure. In another study, Ko (2011) questions that why A-list bloggers are continuously popular. A-list bloggers have more readers when they are compared with other bloggers. The results indicate that many users frequently visit A-list blogs, so dissemination of information promote A-list bloggers' reputations and build social capital. In return, it increases the popularity of bloggers.

Furthermore, there are researchers focusing on Wikipedia which is an online encyclopedia. Users add, browse, and search any encyclopedic information and edit their own and others' information. Capocci et al. (2006) analyze the statistical things and growth of Wikipedia. They present a directed graph including topics as actors and hyperlinks as links. They collect 500.000 Wikipedia pages of the English version. They find that Wikipedia graph has a bow-tie-like structure which means a strongly connected network.

It is evident that users collaborate by adding and editing encyclopedic information in Wikipedia. Brandes, Kenis, Lerner, and Van Raaij (2009) form models and algorithms to describe and analyze the collaboration among Wikipedia authors.

They present an edit network including authors as actors. They encode how the author edits the page and how he responds to edits of others. They try to encode that whether the authors are a provider of the content or a deleter. They use weighted attributes on nodes and edges how much text users add, delete, or restore and compute bipolarity and visualize the network. As a result, the structural network indicators are correlated with quality labels of the associated Wikipedia articles. Iba, Nemoto, Peters, and Gloor (2010) also analyze the creative editing behavior of Wikipedia editors. They develop a tool which converts the edit flow of among editors into a temporal, social network. In this respect, they try to identify most active users. In their study, they analyze 2,580 featured Wikipedia articles of the English version. Study results show that they find two types of editors: the mediators and the zealots. While the first group tries to harmonize the different attitudes of users, the second group add fuel to a heated discussion on questionable topics. Also, they also look for the authors who are egoists. These people use Wikipedia to advertise themselves. They state that understanding the patterns of different authors gives crucial insights into the cultural norms of online creators.

Other than these digital platforms, some researchers apply SNA on different platforms. Abbasi, Altmann, and Hossain (2011) study the correlation between a social network of scholars in informatics and their success to get a citation. They form a network including scholars as actors. If authors have co-authors, a link occurs between them. They reveal that researchers having strong co-authorship relationships with only one author of a group of linked co-authors achieve better than researchers with links to many co-authors of a group of linked co-authors.

In the study of Swamynathan, Wilson, Boe, Almeroth, and Zhao (2008), they analyze an online market network known as Overstock like e-Bay. Overstock consists of two types of networks. The first network includes users who can be friends with other users and then become the part of social network. On their profiles, they share their characteristics, shopping preferences, and tax policies. The second network consists of users who sell or buy something. Then, these users become the part of the business network. Researchers analyzed a dataset including data of more than 400,000 users. They find that social network consists of 85,200 users and business network consist of 398,989 users. It indicates that 86% of a business network of users do not have a social network. In other words, the majority is interested in financial shopping or is not aware of the presence of a social network. Different results of the study indicate that users have fewer business relations with their friends in their social network. However, the business relationships between partners who have connected in the social network result in high user satisfaction.

2.3 User roles

Role theory has provided academics with numerous opportunities in the field of sociology, psychology, anthropology, etc. (Biddle, 1986). Role theory can be concerned as “the study of behaviors that are characteristics of persons within the context and various processes that presumably produce, explain, or are affected by those behaviors” (Biddle, 2013, p. 4). Furthermore, this theory posits that “all forms of social behaviors are an ‘expression of some social role’”(Markel, 1998 as cited in Pfeil, Svangstu, Ang, & Zaphiris, 2011, p. 324). A role can be defined as a set of behaviors, beliefs, and norms that are characterized and expected by individuals in a social situation (Biddle 1986; Goffman, 1959).

Previous studies including consumer communities (Lorenzo-Romero, Constantinides, & Alarcón-del-Amo, 2010), health communities (Han et al., 2012), innovation contest communities (Füller et al., 2014), enterprise online communities (Muller, Shami, Millen, & Feinberg, 2010; Hacker, Bodendorf, & Lorenz, 2017), and social networking sites (Brandtzæg & Heim, 2011; Çiçek & Eren-Erdoğmuş, 2013), distributed collaboration systems such as Wikipedia (Arazy, Ortega, Nov, Yeo, & Balila, 2015; Welser et al. 2011), and social news aggregations such as Reddit (Choi et al., 2015), figure out that understanding the existence of several user roles in the communities is crucial for the successful management of these communities.

Previous research gives valuable insights into the identification of these several user roles in online communities. For example; Lorenzo-Romero et al. (2010) develop a classification of Web 2.0 consumers by considering users' socio-demographic features and involvement, their level of the Internet usage, online purchasing behaviors, personality characteristics, and their degree of the use of social websites. As a result, authors identify three types of 2.0 users including embryonic, amateur, and expert. In another study, Pluempavarn et al. (2011) identify social roles in an ideological and a non-ideological online community by using the Reader-to-Leader model, and they investigate the importance of each user role in each type of community. Choi et al. (2015) also examine user roles in an online community based on their behavioral types, and they identify initiators, commentators, attractors, and translators in Reddit. Additionally, Füller et al. (2014) analyze user types in an innovation contest community and find six user types including socializers, idea generators, masters, efficient contributors, and passive idea generators based on both qualitative and quantitative techniques.

On the other hand, Çiçek and Eren-Erdoğmuş (2013) focus on social networking sites and categorize users based on their social media usage preferences by conducting cluster and factor analyses, and ANOVA. As a result, they identify social media users consisting of inactives, sporadics, entertainment users, debaters, and advanced users. Also, Brandtzæg and Heim (2011) collect data from social networking sites in Norway and identify five user roles including sporadics, lurkers, socializers, debaters, and actives based on cluster analysis and qualitative techniques. Additionally, Lee, Yang, Tsai, and Lai (2014) extract user-generated contents and behavior patterns in social networks to identify user roles and explore their change patterns in a social network and Gong, Lim, and Zhu (2015) try to characterize lurkers in Twitter and profile them by examining the tweets generated by distinct types of communities. In addition to these studies, Fernandez, Scharl, Bontcheva, and Alani (2014) also consider online social networking sites, but they develop a semantic approach to model user profiles in social networking sites based on the raw data of the user activities in online communities.

Additionally, Welser et al. (2011) collect posted comments in Wikipedia and try to analyze user roles by considering users' patterns in their edit histories in these comments, and they find four user roles including substantive experts, technical editors, vandal fighters, and social networkers. Also, Arazy et al. (2015) focus on Wikipedia and try to find the structure of functional roles in this community. On the other hand, there are also some studies concentrating on enterprise online communities. For example; Hacker et al. (2017) adapt role typology based on the findings from social media and literature to find worker's roles in enterprise social networks. Additionally, Muller et al. (2016) identify lurking behaviors of uploaders and contributors in an enterprise file sharing.

There are also other studies considering role identification in several types of online communities. Risser and Bottoms (2014) identify user roles in an online network of teachers by examining their usage patterns and find five clusters consisting of newbies, inbound participants, full participants, celebrities, and peripheral participants. Wu, Zhou, Jin, Lin, and Leung (2017) introduce a three-layer model to investigate user roles hierarchically and develop an integrated framework to benefit from the identification of user roles to support the collective decision making. Golder and Donath (2004) analyze social roles derived from sociolinguistics, social psychology, and the ethnography of communication in speech communities and they identify celebrities, newbies, lurkers, flamers, trolls, and ranters in a speech community. Lastly, Chan, Hayes, and Daly (2010) use distinctive features to profile the user roles in a medium-sized bulletin board and apply a two-stage clustering to categorize the users of the forums into several groups and roles.

Some previous studies also apply SNA to examine user roles in communities. SNA enables researchers to characterize social structure of networks at the level of both individual and population (Borgatti, Mehra, Brass, & Labianca, 2009; Krause, Croft, & James, 2007), and it allows researchers not to focus on only individuals but also focus on relationships among them (Marin & Wellman, 2011; Martiono & Spoto, 2006). Some studies apply SNA additional to other analysis techniques to identify user roles in online communities. For example; Welser et al. (2011) and Füller et al. (2014) benefit from SNA to visualize ego networks of user types. Additionally, Füller et al. (2014) utilize from SNA and calculate degree centralities of user types. Risser and Bottoms (2014) also calculate network centralities of all types of users. Also, Angeletou, Rowe, and Alani (2011) integrate SNA into a semantic model to categorize users' behaviors overtime in an online community, and Pfeil et al. (2011) combine SNA and content analysis to identify social roles in an online support community for older people. Authors find six roles including passive members, visitors, technical experts, active members, central supporter, and moderating supporter in an online support community.

Additionally, some of the previous studies only apply SNA to identify user roles. For example; Salter-Townshend & Brendan Murphy (2015) develop ego-exponential-family random graph model, which is a flexible framework, to investigate the roles within a network. In another study, Buntain and Golbeck (2014) analyze user posting behaviors on Reddit and find the presence of answer-person role. Additionally, Hecking, Chounta, and Hoppe (2015) investigate network analysis methods for the analysis of emergent themes and user types in discussion forums. Lastly, White, Chan, Hayes, and Murphy (2012) develop mixed membership models to identify user roles in online discussion forums by benefiting from SNA.

It is evident that several types of users exist in different online communities based on the previous studies. In this manner, this study employs the structural role theory that focuses on social positions of users “who share the same patterned behaviors (roles) that are directed towards other sets of persons in the structure” (Biddle, 1986, p. 73), and applies SNA to find the structural positions of the online community members. Unlike previous studies (Pfeil et al., Yeh, Chuan-Chuan Lin, & Lu, 2011; Füller et al., 2014), this study applies a community detection algorithm to identify a user across a different context. Additionally, this study also considers members’ contribution behavior in the community to identify these roles in a more meaningful way (Gleave et al., 2009).

2.4 Technology acceptance model

TAM was developed to demonstrate the impacts of perceived ease of use and perceived usefulness on users' attitude toward the adoption of recent technologies (Davis, 1989). Perceived usefulness is defined as "the degree to which a person believes that using a particular system would enhance his/her job performance" (Davis 1989, p. 320) and perceived ease of use refers to "the degree to which the prospective user expects the target system to be free of effort" (Davis 1989, p. 320). The model states that perceived usefulness influences only usage intention and perceived ease of use impacts both perceived usefulness and usage intention. After that, TAM was extended by Venkatesh and Davis (2000), and new determinants involving subjective norm, image, job relevance, output quality, and result demonstrability were added to predict perceived usefulness. This new extended model is called TAM2. Additionally, the model was also expanded by Venkatesh and Bala (2008) to predict the impact of computer self-efficacy, the perception of external control, computer anxiety, computer playfulness, perceived enjoyment, and objective usability on perceived ease of use. This new model is called TAM3.

In previous studies, TAM is used to test individuals' intentions to do online shopping (Koufaris, 2002; Vijayasarathy, 2004), to use web-based information systems (Mun & Hwang, 2003), world wide web (Lederer, Maupin, Sena, & Zhuang, 2000), and e-government website (Wangpipatwong, Chutimaskul, & Papasratorn, 2008), and to adopt mobile commerce (Wu & Wang, 2005), electronic commerce (Klopping & McKinney, 2004; Pavlou, 2003), e-learning systems (Park, 2009; Roca, Chiu, & Martínez, 2006), and hedonic information systems (Van der Heijden, 2004).

Additionally, in the most recent studies, TAM is used to analyze individuals' behaviors to adopt sports brands app (Byun, Chiu, & Bae, 2018), e-procurement (Brandon-Jones & Kauppi, 2018), e-service technology (Taherdoost, 2018), crowdfunding (Mohd Thas Thaker, Mohd Thas Thaker, & Allah Pitchay, 2018), mobile health services (Ebrahimi, Mehdipour, Karimi, Khammarnia, & Alipour, 2018), smart in-store technology (Kim, Lee, Mun, & Johnson, 2017), smart phone credit card (Ooi & Tan, 2016), social media sites (Akar & Mardikyan, 2014; Howell, 2016), quick response code (Kim & Woo, 2016), and social network games (Park, Baek, Ohm, & Chang, 2014).

Furthermore, in the context of online communities, Agag and El-Masry (2016) try to understand consumers' intentions to participate in online travel community based on TAM. Zhu, Chang, and Luo (2016) also focus on marketing perspective, and they try to understand the influence of consumer-to-consumer communication on purchase decision in online communities. Additionally, Nistor et al. (2014) examine the participation in virtual academic communities.

CHAPTER 3

SOCIAL NETWORK ANALYSIS

This chapter presents a general overview about SNA. After that, it explains some key principals and concepts and presents some calculations for the analysis of a network structure. Lastly, it introduces community detection algorithms used in SNA.

3.1 A general overview

SNA is a widely used approach in various fields such as social science, psychology, economics, sociology, and information science. Martino and Spoto (2006) state that SNA was born with the collaboration of sociologists, mathematicians, economists, anthropologists, and physicians. Borgatti et al. (2009) state that SNA was perceived as a field within the social science by 1980s. In the 1990s, SNA was begun to be used in other areas including physics and biology.

Feicheng and Yating (2014) define SNA as a “quantitative method of analysis developed by sociologists, based on mathematical models and graph theory” (p. 232). Furthermore, Martínez-Torres, Toral, Palacios, and Barrero (2011) say that SNA emerged from “using mathematical models of graphs applied in the analysis of social relationships among actors” (p. 107).

Focusing on relationships among individuals and even things makes SNA different from other analysis methods (Marin & Wellman, 2011; Martino & Spoto, 2006). Because it is stated that these relationships are motivated by social influence (Li, Cui, & Ma, 2015). They illustrate that social influence happens when an individual’s feelings or thoughts are influenced by other individuals in psychology. Moreover, Muldoon (2013) emphasizes that thinking only about people is sometimes not satisfactory because social norms are influenced by individuals' choices and behaviors. SNA helps to understand them well.

In the simplest terms, a social network consists of a set of people or things known as actors and links among them (Koçak, 2014). Marin and Wellman (2009) define a social network as "a set of socially-relevant nodes connected by one or more relations" (p. 12). Also, Wasserman and Faust (1994) say that "a social network consists of a finite set or sets of actors and the relation or relations defined on them" (p. 20). In a social network, nodes also called vertices represent individual actors, links also called edges or ties, describe relationships among nodes. Nodes can be a person, firm, country, journal article, department, position, web page, etc. and edges can be friendship, competition, etc. (Borgatti & Li, 2009; Marin & Wellman, 2011). Figure 1 shows an example of a social network.

Designing a social network can have some challenges. One of them is the identification of which nodes will be included in a network. Marin and Wellman (2011) point out that it is a significant problem. Laumann, Marsden, and Prensky (1989) state three different approaches to specify network boundaries: position-based, event-based, and relation-based approaches. Position-based approach determines nodes as members of an organization or nodes belong to positions. For example; lecturers employed in the departments of management information systems. The second approach, event-based, refers to the definition of the network boundary based on who had participated in critical events. For example; researchers who had attended at least one management information systems conference in the past two years.

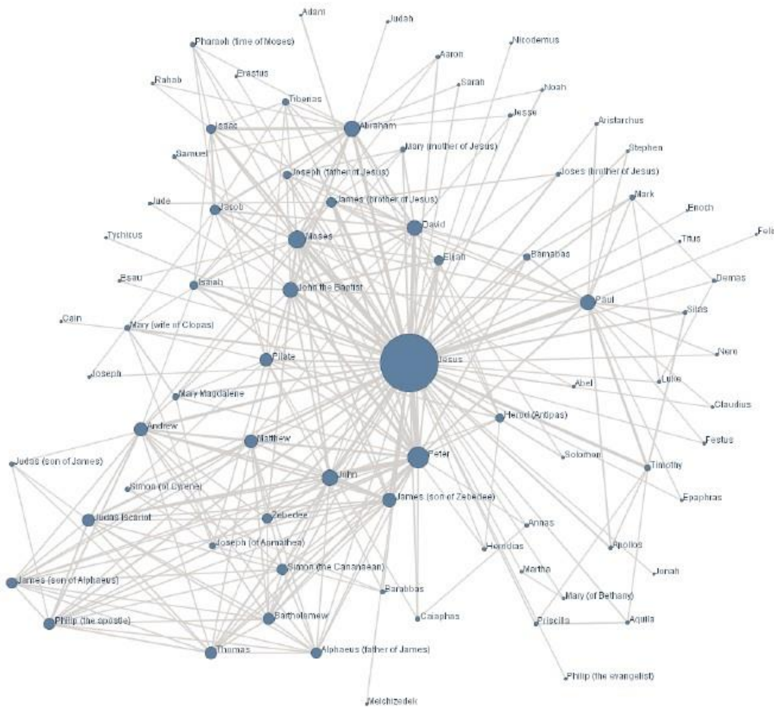

Figure 1. An example of a social network

Source: [Muldoon, 2013]

Finally, relation-based approach starts with a small set of vertices and then develops by including others' sharing specific types of relations. For example; a network can start with scholars publishing in key management information systems journals and then expand by adding their co-authors and collaborators, and then their co-authors and collaborators and so on. Marin and Wellman (2011) highlight that these approaches are not mutually exclusive. Studies can use a combination of them to define network boundaries.

The second challenge is the identification of relationships. Haythornthwaite (1996) says that a relationship is an interaction between individuals, groups, and organizations, etc. Borgatti and Li (2009) divide ties into two categories: continuous and discrete. Continuous ties always appear for the duration of the relationship. For example; being a spouse of someone. On the other hand, discrete ties occur in a series of discrete events. For example; the number of times A sends e-mail to B. These two categories are also divided into subcategories. The continuous group is divided into similarities and social relations, and the discrete category is divided into interactions and flows. Figure 2 describes the structure of these categories.

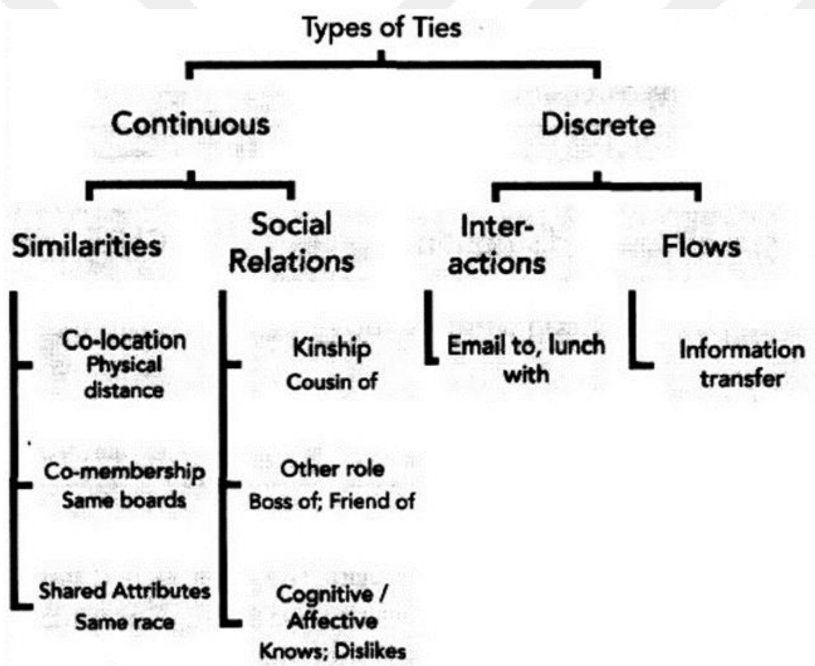

Figure 2. Types of ties

Source: [Borgatti & Li, 2009]

Similarities refer to co-membership, co-locations, and shared attributes in groups. For example; in Silicon Valley, CEO of Company A is next-door neighbor of CEO of Company B. Social relations refers to kinship relations or role-based relations. On the other hand, interactions are discrete events such as sending an e-mail to someone and having lunch with someone. For example; an employee of Company A goes dancing with an employee of Company B. Lastly, Borgatti and Li (2009) define flows as “content that (potentially) moves between actors when they interact, such as ideas or money or stocks of inventory” (p. 7). For example; an employee of Company A disseminates information to an employee of Company B. Furthermore; Figure 3 involves more examples of ties regarding their similarities, social relations, interactions, and flows.

Similarities			Social Relations				Interactions	Flows
Location	**Membership**	**Attribute**	**Kinship**	**Other role**	**Affective**	**Cognitive**	e.g.,	e.g.,
e.g.,	e.g.,	e.g.,	e.g.,	e.g.,	e.g.,	e.g.,	Sex with	Information
Same spatial and temporal space	Same clubs Same events etc.	Same gender Same attitude etc.	Mother of Sibling of	Friend of Boss of Student of Competitor of	Likes Hates etc.	Knows Knows about Sees as happy etc.	Talked to Advice to Helped Harmed etc.	Beliefs Personnel Resources etc.

Figure 3. Examples of ties

Source: [Borgatti et al., 2009]

Haythornthwaite (1996) identifies the three attributes of a relationship: content, direction, and strength. Relationships can be characterized by their content because they can include sharing, exchange, or delivery of various resources. For example; friend of, a co-worker of, likes, or hates, etc. Additionally, information flows in a particular direction from one actor to another actor. In this sense, direction can be undirected or directed. If A talks to B and B talks to A, it is an undirected direction. These types of networks are called undirected networks. A can follow B on Twitter but it is not necessary that B must also follow A on Twitter, so it is a directed link from A to B.

These types of networks are called directed networks. Although the direction of a relationship cannot be measured, its strength can be measured. Strength or weight refers to the intensity of a relationship or frequency of the communication between two nodes. For example; if the information is frequently exchanged in a relationship, then it can be said that it is a stronger relationship than a relationship including rarely information exchange. If ties among nodes have a strength, these types of networks are called weighted networks. If ties do not have a strength and equal, these types of networks are called unweighted networks.

Koçak (2014) also states that there are other core concepts related to social networks: one-mode network, dyad, triad, and subgroup. Most of the social networks focus on the same type of actors. This type of networks is called a one-mode network. For example; people in a workgroup. Whereas Figure 4 shows a one-mode undirected network, Figure 5 depicts a one-mode directed network.

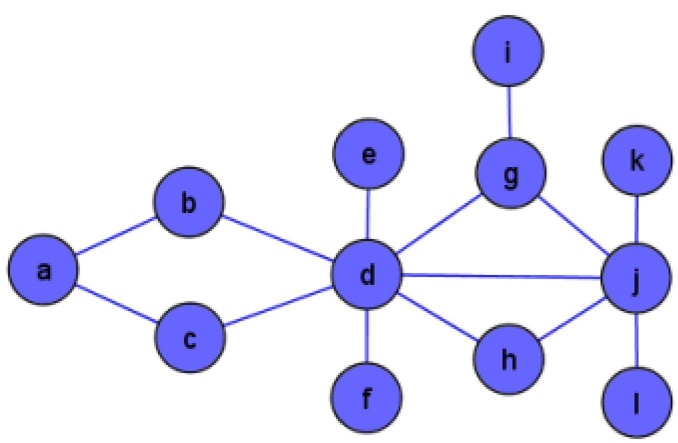

Figure 4. One-mode network with undirected ties

Source: [NetworkAnalyzer Online Help, n.d.]

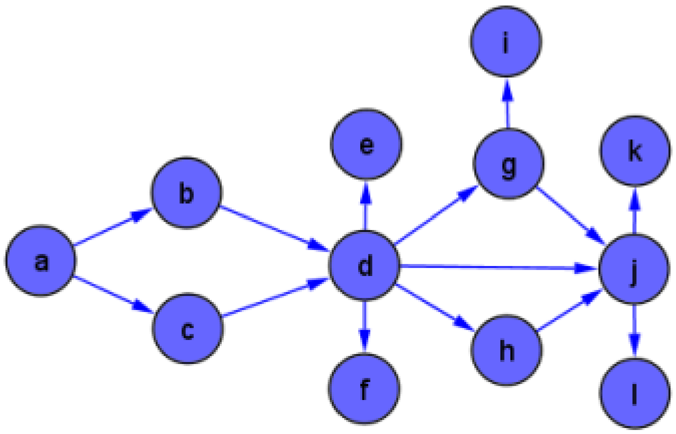

Figure 5. One-mode network with directed ties

Source: [NetworkAnalyzer Online Help, n.d.]

It is mentioned that a relationship forms a tie between two actors. This tie becomes the property of this pair. In other words, this property does not belong to just an individual actor who is known as a dyad. Dyad consists of a pair of actors and the ties between them. Additionally, a subgroup includes any subset of actors and all relationships among them. In this sense, a triad includes a subset of three actors and the relationships among them.

Figure 6 shows an example of dyad and triad. In Figure 6, the green actor represents Moe, blue and brown ones represent Larry and Curly. The first network shows that Moe knows Larry and Curly, so there is a dyad between Moe and Larry; and Moe and Curly. In the second network, Moe introduces Larry to Curly and helps them build a relationship between them. Then, in the third network, the relationship between Larry, Curly and Moe becomes a triad.

Tsvetovat and Kouznetsov (2011) indicate that there can be two several types of nodes in a network which is called a two-mode network. For example; movies and movie stars. Borgatti and Everett (1997) emphasize that analysis of two-mode networks involves transformation.

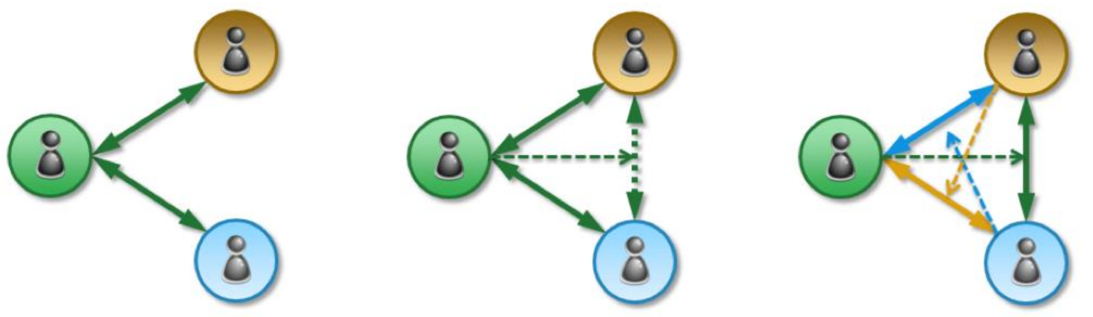

Figure 6. Example of a dyad and triad

Source: [An Introduction to Triads, n.d.]

Transformation of a two-mode network to a one-mode network is done by using a method called projection. Firstly, one node set is selected. This node often is called the primary node set. Then, nodes from that set are linked if they are connected to at least one common node in the other set. Figure 7 shows a two-mode network and its transformation to one-mode network. The primary node set includes the blue nodes. It is seen that there is one common orange node between A and C, so there is a relationship between A and C and the strength of the tie is calculated as 1. There are two common orange nodes between A and B, so there is a tie having the strength of 2 between A and B. Additionally, as mentioned before, it is called a weighted network. In this sense, in Figure 7, the first network is an unweighted, two-mode, and undirected network. The second network represents a weighted, one-mode, and undirected network.

Furthermore, Haythornthwaite (1996) state that social network analysts approach networks in two separate ways: egocentric and whole network

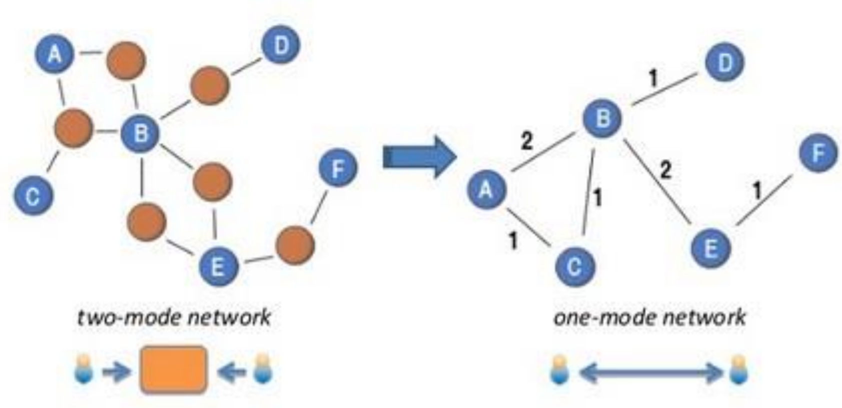

Figure 7. Two-mode network and its transformation to one-mode network

Source: [Projection of Two-Mode Networks, n.d.]

While egocentric networks provide a view from the perspective of one actor, the whole network provides a view of whole structure of the network. An egocentric network consists of a focal actor known as ego, set of actors (alters) having a link with ego or neighbors of ego, and links between alters (Borgatti & Li, 2009). Figure 8 shows an ego network and shows its components involving ego, alter, and ties.

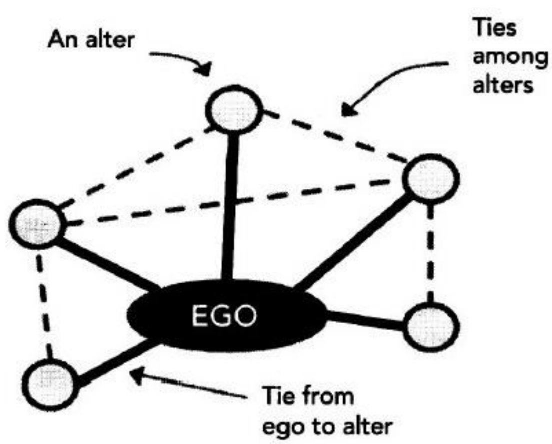

Figure 8. An ego network

Source: [Borgatti & Li, 2009]

3.2 Key principals, concepts, and calculations

Before introducing some calculations to analyze the structure of the network, a graph consists of a set of nodes and edges among nodes. It is denoted as G = {V, E} in where G is a graph, V is vertices, and E is an edge (Mislove, 2009). In a network, data are represented as either adjacency matrix, edge list, or adjacency list. An adjacency matrix represents edges as a n*n square matrix. If there is an edge between C and B, then A_{cb} equals to 1. If there is not an edge between C and B, then A_{cb} equals to 0. A node can also have a self-loop. In such a situation, A_{cc} equals to 1.

If data are represented in edge list, neighboring node pairs are listed as E = {(A, B), (B, C), (A, C), (B, D)} in where E is the edge list, and A, B, C, and D are nodes. On the other hand, in an adjacency list, data are represented as:

A: B, C

B: A, C, D

D: B

In SNA, the widely used calculations and discussed topics are a degree, degree distribution, joint degree distribution, assortativity, density, the geodesic path including average path length and diameter, connectivity, transitivity, reciprocity, centralities including degree, closeness, betweenness, and eigenvector, small world phenomena, power-law and scale-free networks.

The degree is a property of a node. Mislove (2009) states the degree of a node is calculated as the number of nodes connected directly to the given node. For undirected networks, the degree of node i is calculated as $k_i = \sum_{j=1}^{i} A_{ij}$ in where A is adjacency matrix. For directed networks, out-degree and in-degree values are calculated separately.

Whereas out-degree includes outgoing edges from the given node, in-degree includes incoming edges to the given node. Out-degree of node i is calculated as $k_i^{out} = \sum_{j=1}^{n} A_{ij}$. Additionally, in-degree of node i is calculated as $k_i^{in} = \sum_{i=1}^{n} A_{ij}$.

Mislove (2009) states that degree distribution shows how the edges are distributed among the nodes in the network. It shows a frequency count of the occurrence of each degree. In addition to degree distribution, some researchers also focus on joint degree distribution. It shows "how often nodes of different degrees connect to each other" (Mislove 2009, p. 25). It is calculated as a k_{nn} function. This function maps between out-degree and the average in-degree of all nodes connected to nodes of that out-degree. An increasing k_{nn} indicates that high-degree nodes tend to follow high-degree nodes (Mislove et al., 2007; Mislove, 2009). It means that a high-degree node touches other high-degree nodes quickly. A decreasing k_{nn} shows an opposite trend. It means that a high-degree node does not touch high-degree nodes very fast.

Another metric that identifies the tendency of nodes to connect to other nodes with similar degrees is assortativity coefficient. Mislove (2009) states that "the assortativity is defined as the Pearson correlation coefficient between the degrees of all pairs of nodes connected by an edge" (p. 26). In this sense, it ranges from -1 to 1. When it closes to 1, it indicates that nodes tend to connect to nodes of similar degree. Otherwise, a negative coefficient shows that nodes likely connect to nodes with a different degree from their own. However, it is stated that assortativity cannot be advisable to compare the structure of networks because it does not consider the possible configurations of networks with properties including connectedness and no self-loops (Li, Alderson, Doyle, & Willinger, 2005).

Another calculation is density, and it is one of the properties of a network. Haythornthwaite (1996) mentions that density "indicates the degree to which members are connected to all other members. It is calculated as the ratio of the number of actual links in a population to the number of possible links in the population" (p. 332). In parallel to its definition, density for undirected networks is calculated as $m_{max} = \frac{n*(n-1)}{2}$ in where m stands for the number of edges and n stands for the number of nodes, and density is calculated as $\Delta = \frac{m}{m_{max}} = \frac{2*m}{n*(n-1)}$. Furthermore, density for directed networks is calculated as $m_{max} = n*(n-1)$ and density is calculated as $\Delta = \frac{m}{m_{max}} = \frac{m}{n*(n-1)}$. When the density closes to 1, it indicates that the network is a highly dense network, otherwise the network is considered as sparse.

A geodesic path is one of the widely used calculations in SNA. A path can be defined as any sequence of nodes such that every connected pair of nodes in the sequence is connected by an edge (Acemoglu & Ozdaglar, 2013). Path length is calculated as the total number edges visited along the path and more than one path can be possible. Furthermore, the path includes distinct nodes and edges. In a network, geodesic path gives the shortest path that is the shortest sequence of nodes connecting two edges. Although in undirected networks the direction is not important, in directed networks, the direction of edges plays a significant role in the calculation of geodesic path. Another related topic about the network structure is the average path length and diameter. While average path length is defined as "the average distance between any two nodes in the network," diameter refers to "the largest distance between any two nodes in the network" (Acemoglu & Ozdaglar, 2013, p. 14). Average path length is calculated as $L = \frac{1}{n*(n-1)} \sum_{i,j} l\,(i,j)$ in where n stands for the number of nodes, and l(i, j) stands for the length between any given node i and node j.

Connectivity is also part of the SNA. It identifies that it is a connected network if every node can reach every other node by a path (Easley & Kleinberg, 2010). In other words, there is a path between each pair node. However, the network cannot also be fully connected. Then, each component is analyzed in the network. The groups of nodes that are fully connected are found. These subsets of groups called connected components. If the network is directed, components can be analyzed as either strongly or weakly connected components. In strongly connected components, each node can be reached from other nodes in the component by following the directed links. On the other hand, in weakly connected components, each node can be reached from other nodes by following links in either direction. Additionally, if a connected component includes a significant portion of all the nodes, then it is called a giant component. If the number of components in the network that includes the node v is fewer than the number of components in the subgraph that results from deleting v from the network, then this node v is called cutpoint (Kolaczyk & Csardi, 2014).

Additionally, if the network including a particular edge has fewer components than the subgraph has when this edge is deleted, then this edge is called a bridge (Kolaczyk & Csardi, 2014). Moreover, vertex-connectivity of a network indicates the minimum number of nodes that must be removed to make the graph disconnected and edge-connectivity indicates the minimum number of edges that must be removed to disconnect the network.

Tang and Liu (2010) emphasize that people in a group interact with each other more than others who are outside of the group. It is known as transitivity, and it is measured by clustering coefficient. It refers to “the probability of connections between one vertex's neighboring friends” (p. 492). For example; Ross knows Monica and Monica knows Rachel, so there is a possibility that Ross also knows Rachel. Clustering coefficient is calculated as $\mathrm{cc} = \frac{\text{\#of closed paths of length 2}}{\text{\# of paths length 2}}$. Clustering coefficient ranges between 0 and 1. A high clustering coefficient indicates high transitivity. If a pair of nodes at random are picked, the probability that they are connected is calculated as $\mathrm{p} = \frac{\text{\# of edges}}{\mathrm{n}*(\mathrm{n}-1)}$ in where n stands for the number of nodes. Additionally, if a pair of nodes with a common connection is selected at random, then the probability that they are connected gives the clustering coefficient. It can be concluded that if clustering coefficient is greater than p, then the network has high clustering coefficient. Moreover, clustering coefficient is calculated by not assuming the directions of edges in directed networks.

Another important topic is the reciprocity, and it refers to “the fraction of directed edges (u, v) such that (v, u) also exists in the graph” (Kumar, Novak, & Tomkins, 2010, p. 613). In this sense, reciprocity is a measure for directed networks, because all edges have already been reciprocated in undirected networks.

Centrality is also one of the crucial topics in the SNA because it measures the access to other nodes in the network and information dissemination through the network (Freeman, 1979; Haythornthwaite, 1996). Centrality aims the identification of most important actors within the given network (Haythornthwaite, 1996; Wasserman & Faust, 1994). Wasserman and Faust (1994) define the centrality as “actors who are the most important or the most prominent are usually located in strategic locations within the network" (p. 169). Most frequently used centralities are degree, closeness, betweenness, and eigenvector centralities (Valente, Coronges, Lakon, & Costenbader, 2008). Degree, closeness, and betweenness centralities are proposed by Freeman (1979), and eigenvector centrality is proposed by Bonacich (1972).

Degree centrality indicates the influence of an individual in the network by counting the number of edges that an individual has (Baek & Kim, 2015). It shows how active or popular an individual is. An individual having high degree centrality states that he or she can be the leader or the hub in the network. Additionally, that individual can easily access more information and be reached by other individuals easily. Degree centrality of nodes is calculated as degree calculation mentioned above. For node b, is calculated as $C_D\,(b) = k_b$ and it is normalized as $C_D^N(b) = k_b(n-1)$ in where n stands for the number of nodes. If the network is a directed network, there are two types of degree centrality involving in-degree and out-degree centralities. If an individual receives many messages from other individuals due to his or her popularity in the network, it can be concluded that this individual has a higher in-degree centrality. However, if an individual starts his or her interactions by posting messages to other individuals in the network, it can be determined that this individual has high out-degree centrality. While in-degree centrality of an individual indicates the popularity of the individual and his or her accessibility to information, out-degree shows the control of an individual over the network and the dependence of the network upon him or her (Loosemore, 1998).

Furthermore, closeness centrality measures the length of paths of nodes to other nodes within the network, and it finds "how close an actor is to all the other actors in the network" (Catanese et al., 2012, p. 312; Jamali & Abolhassani, 2006). Freeman (1979) states that if a node is in the closest position to all other nodes, it accesses the information efficiently and instantly. In other words, an individual having high closeness centrality may disseminate information and ideas to other individuals in the network quickly, and he or she may control most individuals in the network directly (Baek & Kim, 2015). Simply, higher closeness allows us to find the shortest, less expensive, and more efficient path in each network to receive and send information (Song, Nerur, & Teng, 2007). In other words, closeness centrality pays attention to the economic dimension of the communication in the network (Wasserman & Faust, 1994). Furthermore, it is also implied that individuals having high closeness centrality may employ influence on more individuals than the individuals having high degree centrality (Dogan, Arditi, Gunhan, & Erbasaranoglu, 2013 as cited in Baek & Kim, 2015). The main reason is that individuals having high closeness centrality have lots of direct and indirect links with other individuals in the network.

If the network is a directed one, out-closeness and in-closeness centralities should be calculated separately. While an individual with high in-closeness centrality may listen to most individuals through direct or indirect connections in the network, an individual with high out-closeness centrality send messages to most individuals in the network through direct or indirect connections (Baek & Kim, 2015). Closeness of a given node p_k is calculated as $C_c(P_k) = \sum_{i=1}^{n} d(p_i, p_k)^{-1}$ where n is the number of nodes in the network and $d(p_i, p_k)$ is a distance between p_i and p_k (Abbasi et al., 2011). The crucial point is that making comparisons among other nodes in the network with varied sizes requires normalization. The normalized closeness is calculated as $C_{c'}(P_k) =$

$\frac{\sum_{i=1}^{n} d(p_i, p_k)^{-1}}{n-1}$. For directed networks, the formula remains as the same. Only the direction of edges is considered.

Another centrality is betweenness centrality. Catanese et al. (2012) say that betweenness centrality is the most appropriate measure to identify the critical actors in the network. Wasserman and Faust (1994) define it as "how important an actor is at bridging the gap between other actors in the network." In other words, it implies "the number of times that a participant needs another given actor to reach any other participant by the shortest path" (Baek & Kim, 2015, p. 667). Individuals having high betweenness centrality has the power to control the information between two non-adjacent points (Latora & Marchiori, 2007). The difference of betweenness centrality from degree and closeness centralities is that an individual having high betweenness can reach weakly connected subgroups (Baek & Kim, 2015). In this sense, these individuals play the role of gatekeeper (Freeman, 1979). If a node having high betweenness is removed from the network, it disturbs the flow of information through the network (Lewis et al., 2008; Warmbrodth et al., 2008). Betweenness of a given node p_k is calculated as $C_B(p_k) = \sum_{i<}^{n} \sum_{j}^{n} \frac{g_{ij}(p_k)}{g_{ij}}$, $i \neq j \neq k$ where g_{ij} is the number of geodesics linking node p_i and p_j and $g_{ij}(p_k)$ is the number of geodesics linking node p_i and p_j that contains p_k . (Abbasi et al., 2011). The normalized betweenness centrality is calculated as $C_{B'}(p_k) = \frac{2 * C_B(p_k)}{n^2 - 3n + 2}$. For directed networks, only the directions of edges are considered.

The last centrality measure is eigenvector centrality. It states that the centrality of a node does not only depend on the number of its adjacent nodes (Abbasi et al., 2011).

The values of the centrality of these adjacent nodes also have important roles on the centrality of a given node. If a node is connected to many other nodes that are also well-connected, then it means that this node has a high eigenvector centrality (Lu, Luo, Polgar, & Cao, 2010 as cited in Abbasi et al., 2011). It is calculated as for a given node p_k as $\lambda * C_E(p_k) = \sum_{k=1}^{n}(a_{ik} * C_E(p_k)) \quad \forall i$ where c (p_k) of a node p_k as positive multiple of the sum of adjacent centralities (Abbasi et al., 2011).

Additional to these types of centralities, centralization of the network is also analyzed. It looks at the centrality measures at a network-wide level (Warmbrodth et al., 2008). In other words, it indicates if there are nodes that dominate all other nodes in degree, closeness, and betweenness. It is calculated as $NC_x = \frac{\sum_{i=1}^{n}(\max_i(C_i) - C_i)}{\max \sum_{i=1}^{n}(\max_i(C_i) - C_i)}$ where C_i represents the centrality of node i for degree, closeness, betweennes, and eigenvector (Freeman, 1979).

In SNA, there are also other important topics to be discussed. One of them is small world phenomenon. It is also known as six degrees of separation (Easley & Kleinberg, 2010). The starting point of this phenomenon is that Stanly Milgram who was a professor at Harvard at that time wanted to know the probability that two randomly selected individuals would know each other in 1967 (Van Steen, 2010). In other words, Milgram wanted to measure the average path length. Milgram measured it by asking individuals who were randomly selected to send letters to target individuals. The letters were sent from places in the Mid-West of the United States to the targets living in Massachusetts. The result of the experiment indicated that letters were received by targets by taking an average of only 5.5 hops and it leads to the emergence of famous phrase six degrees of separation. The idea behind the experiment is that if an individual who is the source does not know the target individual, then the source must send the letter to one of his or her connections by assuming that his or her connection knows the target better than him or her. In social networks, more evidence can be found how people connect in larger structures (Easley & Kleinberg, 2010). It allows the process of search for distant individuals. Additionally, individuals tend to group into small clusters in social networks, and an individuals' connections also know each other (Van Steen, 2010). In this sense, most of the social networks tend to have high clustering coefficient and small diameter, and they can be considered as small worlds (Cheng, Dale, & Liu, 2008; Mislove et al., 2007).

Furthermore, the other relevant topics are power-law networks and scale-free networks. Mislove (2009) defines power-law networks as "where the probability that a node has degree k is proportional to $k^{-\alpha}$, for large k >1" (p. 30). It implies that the degrees in a power-law network are exponentially distributed. The parameter α is called a power-law coefficient. For example; World Wide Web shows a structure that includes a few high degree nodes, but the number of nodes with high degree decreases exponentially (Van Steer, 2010). Scale-free networks indicate that they have the characteristics of power-law networks where the high degree nodes tend to be connected to other high degree nodes (Mislove, 2009).

3.3 Community detection

Communities are a subset of individuals who are more closely interconnected than the overall network (Mislove, 2009). To find these communities, there are various community detection algorithms serving different purposes. The first community detection algorithm that does not assume previous knowledge of the community structure is suggested by Girvan and Newman (2002). In this algorithm, betweenness centrality is used as a calculation (Mislove, 2009). In other words, edge betweenness score that indicates the number of shortest paths passing through a given edge, are calculated. After that the most important edges are removed, and they continue to be removed by decreasing order of their edge betweenness scores. The algorithm stops after the network becomes partitioned. The main idea behind the algorithm is that edges connecting different subgroups are more likely to be included in multiple shortest paths basically because they are the only option to go from one group to another. On the other hand, the algorithm works slowly due to the complexity of edge betweenness calculation. Because after an edge is removed, the algorithm recalculates edge betweenness scores for the whole graph again. Additionally, the algorithm does not give researchers any guidance to obtain the final communities. It only gives you a full dendrogram. For this purpose, modularity score can be used, and dendrogram can be cut where the highest value of modularity is obtained.

Modularity is a quality metric to evaluate "how 'good' a particular division of the network into communities is" (Mislove, 2009, p. 28). This metric is proposed by Newman and Girvan (2004). Modularity can be defined as a "measure of the fraction of intra-community edges minus the expected value of the same quantity in a network with the same community divisions, but with edges placed without regard for communities" (Mislove, 2009, pp. 28-29). It ranges from -1 to 0 and positive modularity represents the presence of community structure. Fast greedy, multi-level, and spin-glass algorithms are developed based on modularity maximization (Orman, Labatut, & Cherifi, 2011).

The fast-greedy algorithm is developed by Clauset, Newman, and Moore (2004). It is a hierarchal approach like edge betweenness. However, this algorithm is a bottom-up approach instead of a top-down approach like edge-betweenness. This algorithm optimizes the modularity in a greedy manner (Mislove, 2009). At the first step, each node belongs to a separate community, and then communities are merged iteratively if the merge yields the largest increase in the current value of the modularity. The algorithm stops when the highest modularity is obtained. As a result, the algorithm gives the groupings and a dendrogram. The main advantage of the algorithm is that it is fast.

After that Wakita and Tsurumi (2007) enhance the algorithm developed by Clauset et al. (2004). It is stated that the first algorithm presented by Clauset et al. (2004) works for only networks that size up to 500,000 nodes. Wakita and Tsurumi (2007) also present a metric known as consolidation ratio, and they try to balance the sizes of the communities being merged. As a result, their algorithm works for networks including 5.5 million nodes, and it indicates an improvement in the execution efficiency of the algorithm introduced by Clauset et al. (2004).

The multi-level algorithm also known as Louvain is proposed by Blondel, Guillaume, Lambiotte, & Lefebvre (2008) for large networks. It is a simple method based on modularity optimization, and it improves the computation time regarding fast greedy algorithm (Orman et al., 2011). The algorithm consists of two phases. At the first phase, it applies a greedy optimization to detect communities in the network. At the second step, it develops a new network including the nodes detected at the first stage. It stops when only one community remains.

Additionally, spin-glass algorithm is proposed by Reichardt and Bornholdt (2006). It is developed as based on a statistical mechanics model called Potts spin glass (Orman et al., 2011). The algorithm works as “the simulated annealing optimization technique on this model to optimize the modularity” (Orman et al., 2011, p. 3).

In the literature, there are also spectral algorithms that benefit from various matrix representations of networks. These methods concentrate on the eigenvectors of the Laplacian matrix. These types of algorithms detect the communities by minimizing the links lying in-between node groups. Leading eigenvector is one of the spectral community detection algorithms developed by Newman (2006). This algorithm utilizes from "so-called modularity matrix instead of Laplacian" (Orman et al., 2011, p. 3). It can be considered as a hierarchical and top-down approach. The algorithm divides the network into two parts in a way that the division yields an increase in the modularity. The algorithm decides to separation by evaluating the leading eigenvector of the modularity matrix. It also includes a stopping condition that does not allow further separation of closely connected groups.

There are also random walk-based algorithms to detect the communities. One of them is Walktrap introduced by Pons and Latapy (2005). Although it is a hierarchical bottom-up approach like fast greedy, it focuses on a different merging criterion (Orman et al., 2011). It calculates a node-to-node distance based on the concept of random walk. The main idea behind the algorithm is that if an individual performs random walks in the network, "the walks are more likely to stay within the same community because there are only a few edges that lead outside a given community" (Stackoverflow, 2012, p. 1). The algorithm calculates short random walks of 3-4-5 steps based on its parameters and determines to merge separate communities based on these random walks. To determine the number of communities, the modularity score can be used to cut the dendrogram.

Furthermore, there are also information-based algorithms derived from the information theory (Orman et al., 2011). These types of algorithms benefit from using less information than the adjacency matrices to find the communities. One of them is

Infomap introduced by Rosvall, Axelsson, and Bergstrom (2009). This algorithm embraces the problem of finding the optimal separation of a graph from a distinct perspective (Emmons, Kobourov, Gallant, & Börner, 2016). This algorithm focuses on the "finding a description of minimum information of a random walk on the graph. The algorithm maximizes an objective function called the Minimum Description Length" (Emmons et al., p. 5). This algorithm runs for up to 100,000 nodes.

Moreover, there is also a simple approach called label propagation developed by Raghavan, Albert, and Kumara (2007). This algorithm assigns each node of unique labels (Emmons et al., 2016). Then the algorithm reassigns labels to nodes. The main idea behind reassigning process is that each node takes the most common label of its neighbors synchronously. It stops when the label of each node is one of the most common labels in its neighborhood. Although it is a fast approach, it yields different results based on initial configuration. Table 1 shows the summary of community detection algorithms and their appropriateness for different network models. Table 1 shows that there are two suitable algorithms for directed networks: edge betweenness and Infomap.

Table 1. Summary of Community Detection Algorithms

Community Detection Algorithm	Unweighted Network	Weighted Network	Undirected Network	Directed Network
Edge Betweenness	Yes	Yes	Yes	Yes
Fast-Greedy	Yes	Yes	Yes	No
Multi-Level	Yes	Yes	Yes	No
Spinglass	Yes	Yes	Yes	No
Leading Eigenvector	Yes	Yes	Yes	No
Walktrap	Yes	Yes	Yes	No
Infomap	Yes	Yes	Yes	Yes
Label Propagation	Yes	Yes	Yes	No

Other algorithms can also be used for directed networks, but the algorithm neglects the direction of edges. If the direction of edges is neglected, the results can be partial or mislead (Lancichinetti & Fortunato, 2009).

CHAPTER 4

DESCRIPTION OF THE ONLINE COMMUNITY

Inci Sozluk is an online platform serving as an online discussion forum in where users share various contents including texts, images, photographs, and videos about any topics. Inci Sozluk has 1,071,641members by January 2018, and the number of members continues to rise tremendously. Statistics of Google Analytics indicate that approximately 350,000 users visit Inci Sozluk daily and daily page view is about 2,556,000 by January 2018.

Inci Sozluk has the characteristics of an online community. The community members have a mutual interest or concern, and they have their jargon. They get organized when a common concern exists. For example; they have found bugs in the algorithms of Twitter and Facebook, they marched against the laws to prevent the Internet censorship in Turkey, and they also have done lots of charity works as a community. This social community also has made considerable impacts not only in the digital environment but also in real life by organizing and pioneering different activities. They have been reported in the public news many times.

In this community, if a user wants to share something such as text, video, or image, he or she opens a topic. After that, if they want, members start to add their contents to the opened topics. For example; a user opens a topic titled as Boğaziçi University and adds a video about that university. Then, other members start to view this topic and add their contents. Each added content on a topic is called entry. There are 17,215,902 topics by January 2018. Furthermore, each topic belongs to a topic category such as politics, movies, philosophy, etc. For example; Boğaziçi University belongs to category of schools. There are 69 topic categories by January 2018. The topics are started to be categorized in 2015, so only 6,802,591 out of 17,215,902 topics are categorized by January 2018.

Any Internet user can be a member of this community. After you sign up, you can start to open topics and add entries. Additionally, there is a collection of rules in the community, and some user types are responsible for setting regulations and controlling the behaviors of the community members. Figure 9 describes the hierarchy among community members.

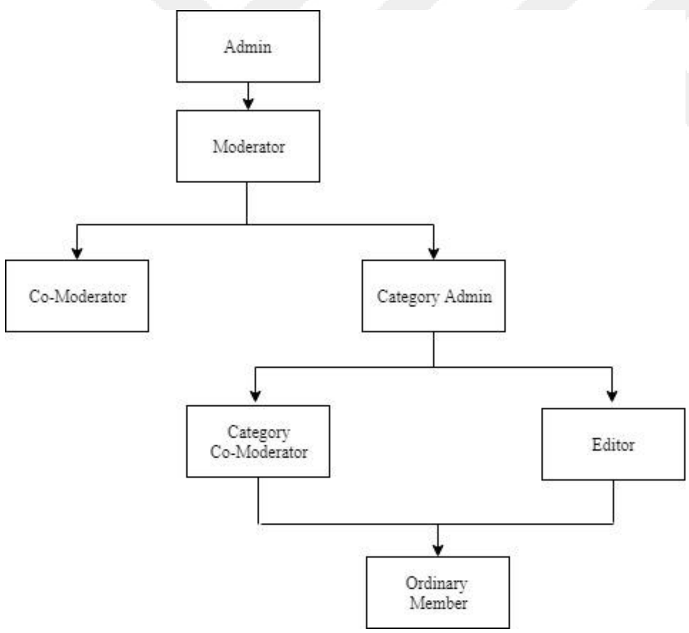

Figure 9. The hierarchy among members in inci sozluk

At the top of the hierarchy, there is an admin. In fact, he is the owner of the community, and so, only one admin exists in the community. At the bottom of the admin, there are moderators. Co-moderators and category admins are responsible to these moderators. Each topic category has its category admin. Lastly, category co-moderators and editors are responsible to their category admins. Furthermore, if a member does not have any duty to the community, he or she is called an ordinary member.

Also, Table 2 explains authorization of each type of special members. Additionally, admin, moderators, co-moderators, category admins, category co-moderators, and editors also can do what an ordinary member does.

Table 2. User Types and Their Authorization

User Type	Authorization
Admin	• Suspend or ban community members. • Edit or delete categories of topics. • Edit or delete entries. • View all details of community members. • Assign or disqualify moderators. • Assign or disqualify co-moderators. • Assign or disqualify category admin. • Assign or disqualify category co-moderator. • Assign or disqualify editor.
Moderator	• Suspend or ban community members. • Edit or delete categories of topics. • Edit or delete entries. • View community members' details limitedly. • Assign or disqualify co-moderators. • Assign or disqualify category admins.
Co-Moderator	• Suspend community member. • Edit categories of topics.
Category Admin	• Edit or delete titles of topics in the given topic category. • Edit the categories of topics which do not belong to the given category. • Edit or delete entries in topics in the given category. • Move topics to popular ones in the given category. • Suspend user from only the given category. • Assign or disqualify co-moderators for the given category. • Assign or disqualify editors for the given category.
Category Co-Moderator	• Edit titles of topics in the given category. • Edit categories of topics which do not belong to the given category.
Editor	• Edit topic titles in the given category.
Ordinary Member	• Open or edit own topic. • Add or edit own entries. • Edit own entries. • Like or unlike entries of other community members.

Although it is not the primary purpose of the community, there is a feature that a member can also follow other members and can be followed by them. A member can also view his or her followers and followings from his or her profile page.

When the dataset is viewed from the perspective of SNA, it is evident that when a member follows any other member, he or she establishes a connection with him or her. Moreover, when a member adds an entry under an existing topic, he or she creates a connection with that topic. Figure 10 shows the network representation of the community. In fact, two networks exist in the community involving follower-following and topic-member networks. The follower-following network is a directed and unweighted network including only one type of actor (members). On the other hand, the topic-member network is an undirected, weighted, and two-mode network including two types of actors (topics and members).

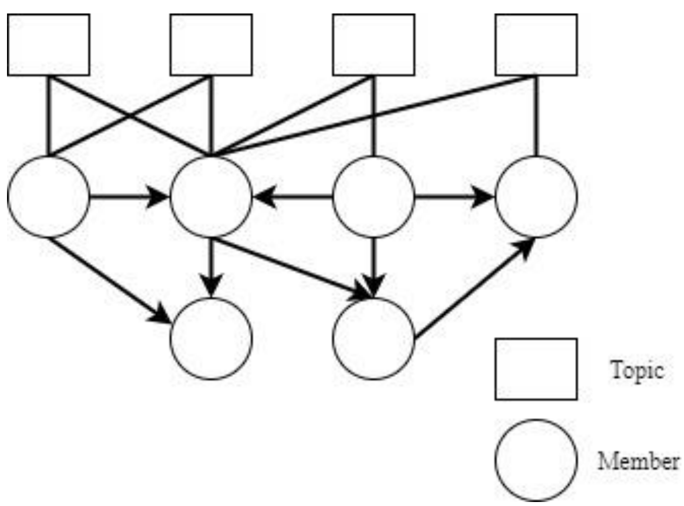

Figure 10. Network representation

CHAPTER 5

RESEARCH METHODOLOGY

This chapter firstly introduces how data are collected, cleaned, and prepared for network formation. After that, this chapter presents four phases of the research methodology including analysis of network structures, detection of sub-communities, identification of user roles, and analysis of research model of the study.

5.1 Data collection, cleaning, and network preparation

Data were downloaded directly from the address of www.incisozluk.com.tr. Direct download avoids measurement errors such as interviewer effects, failure in the recall, and other errors arising from survey research (Brewer, 2000; Brewer & Webster, 2000; Marsden, 2003). Additionally, from the ethical perspective, the data were publicly available, and registration was not required for a user to see related content. Thus, data collection cannot require any consent from the community members (Eysenbach & Till, 2001; Frankel & Siang, 1999 as cited Pfeil et al., 2011). On the other hand, personal data regarding community members were collected with the consent from the administration and accordance with the terms of use and privacy policy of the community administration by protecting each member's anonymity.

5.1.1 The follower-following network

The dataset of the follower-following network was gathered on 23rd March 2016.

1. In the database of Inci Sozluk, the table of spot_soz_uyeler_takip stores only source and target members (see Appendix A). It made it easy to extract an edge

list to form the follower-following network. The edge list was including 87,000 edges.

2. Members' membership ages were obtained from the table of spot_soz_uyeler to find out whether they were active members or not. Their user types were also extracted from that table for further analysis. As a result, 1,314 inactive users since 1st January 2015 were excluded from the network and 83,801 edges were included in the edge list.
3. 156 self-loops that were not indicating a friendship activity were also deleted from the edge list. As a result, the final dataset of the follower-following network, which is an unweighted and directed network, includes 83,645 edges and 34,076 nodes.

5.1.2 The topic-member network

The dataset of the topic-member network was collected on 27th October 2016.

1. Topics, which were opened in the last 30 days (26th September 2016 – 26th October 2016), were extracted from the table of spot_soz_basliklar to focus on active members. Totally 11,609 topics were collected. Topics including only one entry were deleted because they could not start an interaction among members.
2. Secondly, the number of entries added to those topics by each member was obtained from the table of spot_soz_entry. As a result, 387,418 edges were obtained between topics and members. The weights of each edge were 1.
3. A member can add more than one content to any given topic. For this reason, a relationship weight was calculated by counting the relationships between the

same member and the same topic. Finally, a two-mode, weighted, and undirected network including 288,898 edges was obtained.

4. The two-mode network was transformed it into the one-mode network by the projection method (Borgatti & Everett, 1997). igraph package of R and bipartite.projection function were used for the projection. Members were selected as the primary node set. It meant that if two members add an entry to the same topic, a relationship occurred between them. Two members can add entries to one or more same topics, so this function also calculates edge weights. Thus, a weighted and one-mode network including 28,715 nodes and 21,739,690 edges is obtained.
5. Lastly, for the members of the topic-member network, their attributes including age, gender, and membership date were extracted from the table of spot_soz_uyeler. Their membership age was calculated based on their membership date. Furthermore, the total number of topics opened in the last 30 days and the total number of entries added in the last 30 days were calculated for each member of the topic-member network. Additionally, their total number of logins in the last 30 days were calculated based on the data in the table of spot_soz_uyeler_log. These calculations are used to measure members' degree of content contribution for further analysis.

5.2 The first phase of the methodology

In the first phase, the network structures of the follower-following and the topic-member networks were analyzed. Degree, degree distribution, joint degree distribution, assortativity, density, geodesic path, centralities including degree, closeness, betweenness, and eigenvector were examined. Additionally, small world phenomena, power-law, and scale-free network features were investigated for these networks. R-Studio (version 1.0.136) and igraph package were used to conduct the analysis.

5.3 The second phase of the methodology

In the second phase, sub-communities in the topic-member network were detected by the fast-greedy algorithm. Sub-communities were detected only for the topic-member network. As it mentioned in Chapter 4, the community's main purpose is opening topics and adding entries. Additionally, the follower-following feature of the community is a new service and is not preferred so much by the online community members. R-Studio (version 1.0.136) and igraph package were used to conduct the analysis.

5.4 The third phase of the methodology

In the third phase, the roles were identified based on community detection results, literature, and members' degree of content contribution. Sub-communities were discriminated based on members' degree of content contribution, and they were labeled based on both literature and members' degree of content contribution.

5.5 The fourth phase of the methodology

In the fourth phase, the research model of the study is tested. Table 3 also summarizes all the phases. An online questionnaire including 23 items to investigate the research model and hypotheses were used. Each item of the constructs was modified somewhat from the literature to fit the context of the online communities (Moore & Benbesat, 2011; Rauniar, Rawski, Yang, & Johnson, 2014; Yeh et al., 2011).

Table 3. Summary of Research Methods Concerning Research Objectives

Phase	Research Objectives	Method of Analysis	Analyzed Network/Model	Analysis Tool
Network Structure	• To analyze whole network topology. • To detect influential users in the online community.	• Degree, degree distribution, joint degree distribution, assortativity, density, geodesic path, centralities. • Investigation of small world phenomena, power-law, and scale-free network features.	• The follower-following network • The topic-member network	• R-Studio Version 1.0.136 • Gephi 0.9.1
Community Detection	• To detect sub-communities in the online community.	• Fast-greedy algorithm	• The topic-member network	• R-Studio Version 1.0.136
Role Identification	• To identify user roles in the online community	• Community detection results • Literature • The degree of content contribution: • membership age • total opened topics • total added entries • total logins	• The topic-member network	• MS Excel 2016
Research Model Analysis	• To investigate the impacts of factors on online community members' website usage intention. • To examine the moderating impact of distinct user roles on online community members' website usage intention. • To give implications and further insights from a theoretical perspective. • To suggest motivational strategies for practitioners who create and manage online community websites to satisfy community members.	• Partial Least Squares • Multi-group Analysis	• The proposed research model in Figure 11	• WarpPLS 6.0

Each item was measured on a seven-point Likert scale, ranging from “strongly disagree” (1) to “strongly agree” (7). The descriptive question regarding members’ roles in the community was designed based on the results obtained after the third phase mentioned above. Each member was asked which user role identifies his or her behaviors in the community. Appendix B includes the questionnaire and lists all measurement items used in this study.

The questionnaire was shared on the announcement board and Twitter profile page of the online community. In a one-month period, 843 responses were received from the community members. The response rate was 74.27% regarding questionnaire views and replies. After deletion of useless responses, 783 responses were obtained. WarpPLS 6.0 was used as an analysis tool. Hypotheses were tested with PLS, the moderating effect of user roles was analyzed with multi-group analysis.

Structural equation modeling (SEM) purposes to test hypothesized research models involving relationships among variables (Schumacker & Lomax, 2004 as cited in Moqbel, 2012). SEM can be variance-based as in partial least squares (PLS) path modeling or covariance-based as in linear structural relations (LISREL) (Moqbel, 2012). The main difference between variance-based and covariance-based SEM is that covariance-based models have some limitations. Covariances-based techniques require a theoretical base, support confirmatory types of research unlike exploratory ones.

Also, covariance-based techniques require large sample size usually more than 100 cases, normal distribution, and they include only reflective variables. PLS which is variance-based path modeling was developed by Herman World in the 1960s and 1970s (Rönkkö & Evermann, 2013). PLS can be defined as a method that models “relations between sets of observed variables by means of latent variables” (Rosipal & Kramer, 2006, p. 34). Additionally, the assumption behind the PLS methods is that "the observed data is generated by a system or processes which is driven by a small number of latent (not directly observed or measured) variables" (Rosipal & Kramer, 2006, p. 34). When the model is shown in equations, it includes an inner model equation and an outer model equation (Rönkkö & Evermann, 2013). The inner model equation is formulated as $n_j = \beta_{j0} + \sum_i \beta_{ji} n_i + \gamma_j$ and the outer model equation is formulated as $\theta_{kj} = \pi_{kj}0 + \pi_{kj} n_{kj} + \epsilon_{kj}$. In these equations n shows latent variables, θ represents the indicator variables, π and β designate regression coefficients, and γ and ϵ show random errors.

After that, latent variables are replaced with composites which are weighted sums of their indicators as in the equation of $Y_j = \sum_{k_j} \omega k_j \, \theta_{k_j}$ and a separate ordinary least squares regression is run for each dependent variable in the model to estimate all path coefficients and factor loadings. These calculations can be considered as like ordinary least squares. However, PLS differs from that method. In PLS, weights are estimated iteratively including inner and outer estimation steps.

In the inner estimation step, new latent variable scores are calculated. On the other hand, in the outer estimation step, new indicator weights are calculated, and these weights are used to estimate new latent variable scores.

Although there are criticisms in the literature, PLS path modeling also has some flexibilities for researchers (Gefen, Rigdon, & Straub, 2011). PLS path modeling allows researchers to work with small sample sizes. Additionally, it does not require normality, so it allows researchers to work with non-normal data (Goodhue, Thompson, & Lewis, 2013). Although there are contrasts in the literature, it enables researchers to deal with both formative and reflective constructs, it provides researchers with useful model fit statistics, it minimizes the effect of measurement error, it estimates complex models with several latent variables, and it tests and validates exploratory models (Goodhue et al., 2013; Moqbel, 2012). Whereas a reflective construct includes highly correlated indicators with each other and with the construct itself, a formative construct does not involve highly correlated indicators with each other and with the latent variable itself (Kock, 2011).

CHAPTER 6

RESEARCH MODEL AND HYPOTHESES

This chapter includes research model to test online community members' website usage intention and the moderating effect of user roles on it.

TAM that was developed by Davis (1989) is one of the most frequently used and cited models to explain technology acceptance and adoption in the literature (Tarhini, Hone, & Liu, 2014). This model describes a user's motivation to accept a technology by two constructs: perceived usefulness (PU) and perceived ease of use (PEOU). Perceived usefulness (PU) is defined as "the degree to which a person believes that using a particular system would enhance his/her job performance" and perceived ease of use (PEOU) refers to "the degree to which the prospective user expects the target system to be free of effort" (Davis, 1989, p. 320). The causal relationship between PU and PEOU on usage intention (UI) is supported by a significant number of studies (Davis, Bagozzi, & Warshaw, 1992; Venkatesh & Davis, 2000) and is confirmed in the context of online communities and social networks (Fetscherin & Lattemann, 2008; Hartzel, Marley, & Spangler, 2016; Liao, To, Liu, Kuo, & Chuang, 2011; Lin, 2007; Tamjidyamcholo, Kumar, Sulaiman, & Gholipour, 2016; Yeh et al., 2011). In this sense, it is predicted that if community members think that an online community system is useful and easy to use, then they are more likely to use the system. However, they can resist such technologies if they are doubtful of the value of online community and if they find it hard to use. Therefore, the following hypotheses are proposed:

H1: PU has a significant impact on UI.

H2: PEOU has a significant impact on UI.

H3: PEOU has a significant impact on PU.

There are also other factors that have an impact on the usage intention and are analyzed by previous research in the context of online communities. In the following paragraphs, these factors and related studies are investigated.

One of these factors is perceived playfulness (PP). PP can be defined as “the degree to which a current or potential user believes that online community social network will bring him/her a sense of enjoyment and pleasure” (Sledgianowski & Kulviwat, 2009). Online community sites offer entertaining contents and services for their members (Shin, 2010). Thus, members experience pleasure or joy, and they become intrinsically motivated to be part of the online community continually (Agrifoglio, Black, Metallo, & Ferrara, 2012). In parallel with previous research, members having pleasure or fun are more likely to continue to use online community sites (Agrifoglio et al., 2012; Shin, 2010; Sledgianowski & Kulviwat, 2009; Moon & Kim, 2001). Furthermore, previous studies have also revealed that users who perceive technology as easy to use are more likely to enjoy using it (Agrifoglio et al., 2012; Davis, Bagozzi, & Warshaw, 1992; Rauniar et al., 2014). It is also noted that online communities provide members with interactivity and entertaining features; thus, such features and interactivity involving enjoyment or pleasure can improve the tangible benefits of online communities (Childers, Carr, Peck, & Carson, 2001; Rauniar et al., 2014). Consistent with the previous studies, the following hypotheses are suggested:

H4: PP has a significant impact on UI.

H5: PP has a significant impact on PU.

H6: PEOU has a significant impact on PP.

The second factor is perceived critical mass (PCM). PCM is one of the critical variables for recent technology acceptance, and it is supported by theories in psychology, economics, and diffusion innovations (Rauniar et al., 2014). It refers to "the idea that in some threshold of participants or actions has to be crossed before a social movement explodes into being" (Oliver, Marwell, & Teixeira, 1985, p. 523). In the context of online communities, it can be defined as "the point where adopter perceives that the site has a considerable number of members that he or she can associate with due to common interests, friendship" (Sledgianowski & Kulviwat, 2009, p. 76). Previous studies show that PCM has empirically an effect on usage intention of computer-mediated technologies such as instant messaging, groupware acceptance, social media networks, virtual communities (Lim, 2014; Lou, Lou, & Strong, 2000; Rauniar et al., 2014; Sledgianowski & Kulviwat, 2009). Additionally, these studies revealed the effect of PCM on the PU (Lou et al., 2000; Rauniar et al., 2014). It is stated that early adopters can be affected by the decisions of later adopters. If they feel that later adopters will not adopt the recent technology, they can decide to reject the previously adopted one (Lou et al., 2000). In this sense, PCM can be a crucial determinant that strengthens user views of the technology usefulness. In the context of the study, when a user has more friends in the given online community, the user will perceive this community as more useful and thus would be more motivated to use it (Qin, Kim, Hsu, & Tan, 2011). Lastly, the effect of PCM on the PEOU has also been empirically tested, so in this study, it is also expected that PCM influences PEOU. The reason can be that if many users become the part of the community, it may indicate that it is relatively easy to use (Söllner, Hoffmann, & Leimeister, 2016). Another reason can also be that users who have already adopted that community may be ready to share their experience, so it decreases any learning curve related to an online community site. In the light of previous research, the following hypotheses are proposed:

H7: PCM has an impact on UI.

H8: PCM has an impact on PU.

H9: PCM has an impact on PEOU.

The research on technology acceptance shows that trustworthiness (TW) is also a vital determinant supporting the use of recent technologies (Biddle, 1986; Lingyun & Li, 2008). In this study, the institutional TW is taken into consideration. In this sense, TW refers to "a member's perception that effective mechanisms are in place to assure that the social network sites service will behave consistently with the member's favorable expectations" (Sledgianowski & Kulviwat, 2009, p. 76). In this sense, TW can be a significant impact on members' intention to remain loyal to the online community. Online communities' ability to take responsibilities to provide a secure platform for its members will influence members' usage intentions. In other words, members must feel that their privacy is protected and they must trust to the site while engaging in the community (Rauniar et al., 2014). Therefore, it is hypothesized as:

H10: TW of online social network community has an impact on UI.

In addition, there are previous studies considering the moderating effect of perceived risk (Belanche, Casaló, & Guinalíu, 2012) and user experience on website use (Castañeda, Muñoz-Leiva, & Luque, 2007); e-purchasing experience (Hernández, Jiménez, & Martín, 2010) and customer characteristics (age, education, income) (Cooil, Keiningham, Aksoy, & Hsu, 2007) on online consumer purchase intention; public/private consumption on the adoption of high-tech innovations (Kulviwat, Bruner, & Al-Shuridah, 2009); usage experience on instant messaging usage (Shen, Cheung, Lee, & Chen, 2011); subjective norms on the adoption of cloud computing (Chi, Yeh, & Hung, 2012); membership duration (De Valck, Langerak, Verhoef, & Verlegh, 2007), member types involving lurkers and posters (Liao & Chou, 2012), age (Chung, Park, Wang, Fulk, & McLaughlin, 2010), and social roles involving habitual, active, personal, and lurker (Yeh et al., 2011) on online communities; technology readiness and sex on social networking sites use (Borrero, Yousafzai, Javed, & Page, 2014); and age and gender on the adoption of e-learning systems (Tarhini et al., 2014) regarding various constructs. It is evident that each online community is unique, has its own structure, involves different user roles, and its users' behaviors vary concerning these user roles (Yeh et al., 2011). In parallel, the following hypotheses are proposed: In an online community, user roles have a moderating effect on,

H11: PU and UI.

H12: PEOU and UI.

H13: PEOU and PU.

H14: PP and UI.

H15: PP and PU.

H16: PEOU and PP.

H17: PCM and UI.

H18: PCM and PU.

H19: PCM and PEOU.

H20: TW and UI.

Based on previous studies, this study presents a unique combination of factors that have not been combined previously and expands TAM to determine factors which mostly influence members' usage intention of online communities. Figure 11 also shows related hypotheses on the proposed research model.

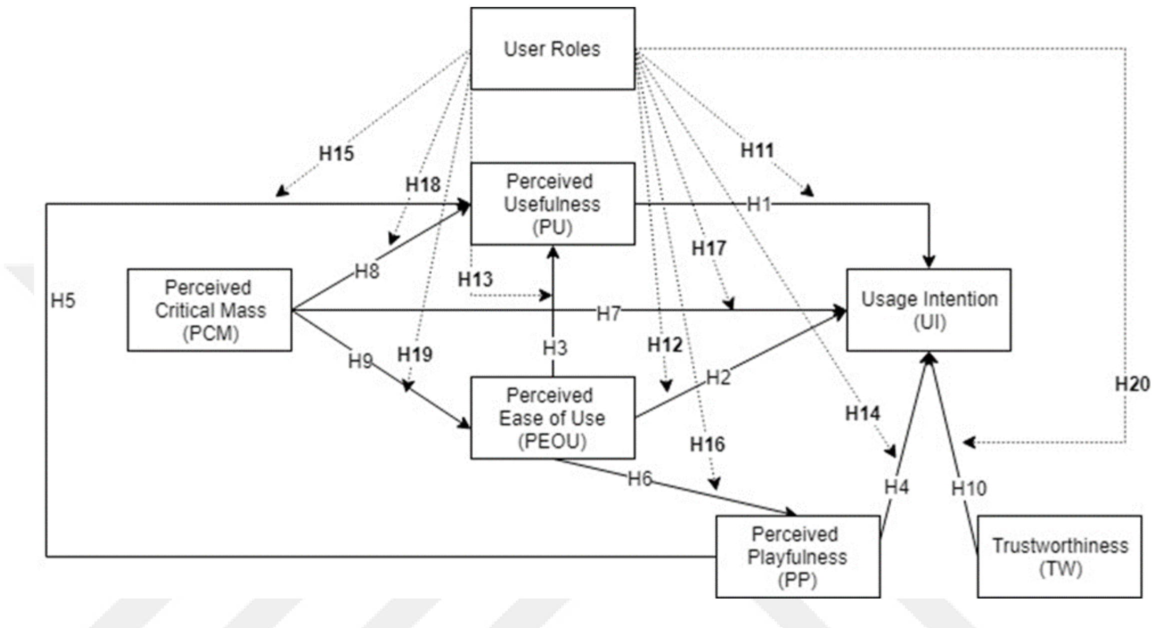

Figure 11. Research model of the study

CHAPTER 7

RESULTS

This chapter includes the analysis results of the network structure, community detection, role identification, and research model testing.

7.1 Network structure

In this part, the descriptive analyses of the follower-following and topic-member networks are presented. The follower-following network includes 83,645 edges and 34,076 nodes. Figure 12 shows the follower-following network. In the network, only 1,003 nodes having degree greater than 20 and 13,233 edges are shown for a better visualization and node sizes are proportional to the degree of a given node. On the other hand, the topic-member network involves 28,715 nodes and 21,739,690 edges. Figure 13 shows the topic-member network after the projection and Figure 14 shows the topic-member network before the projection. In Figure 14, this network only includes topic and member relationships in one day (21st October 2016). It includes 4,217 unique topics (pink nodes) and 1,895 unique members (blue nodes). On the other hand, Figure 13 shows that the network includes 1,283 edges and 400 nodes having degree greater than 4. Node sizes are proportional to the degree of a given node, and edge thickness is proportional to the edge weight. Additionally, Figure 12 and Figure 13 shows that while the follower-following network is directed and unweighted, the topic-member network is undirected and weighted.

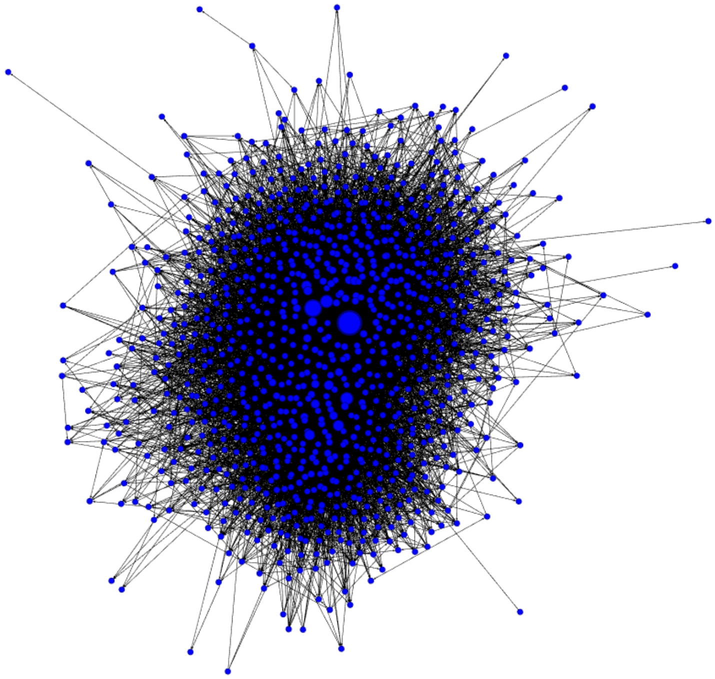

Figure 12. The follower-following network

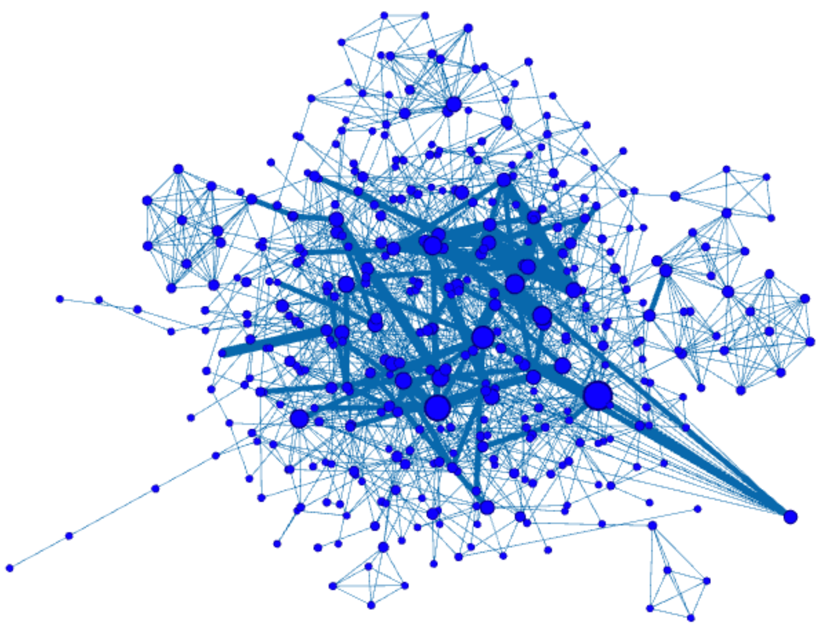

Figure 13. The topic-member network

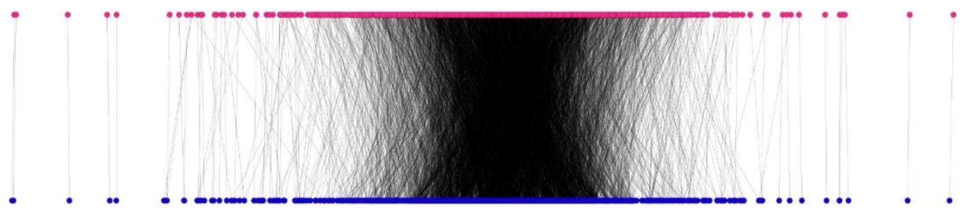

Figure 14. Bipartite network

Firstly, the degree distributions of both networks are analyzed. The follower-following network is a directed network, so in-degree and out-degree distributions are analyzed separately. Figure 15 shows in-degree distribution and Figure 16 presents the out-degree distribution of it.

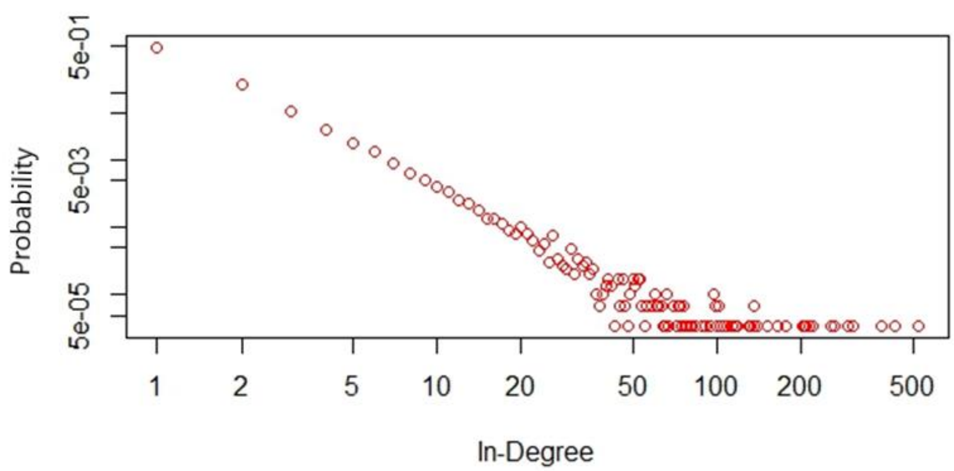

Figure 15. Follower-following network log-log in-degree distribution

Figure 15 indicates that while in-degree values increase, the frequency decreases. Additionally, in Appendix C, Table C1 shows that 28.56% of the nodes are not followed by any other member of the network. It means that 9,733 members have zero in-degree value. Furthermore, approximately half of the members (42.31%) are followed by only one member.

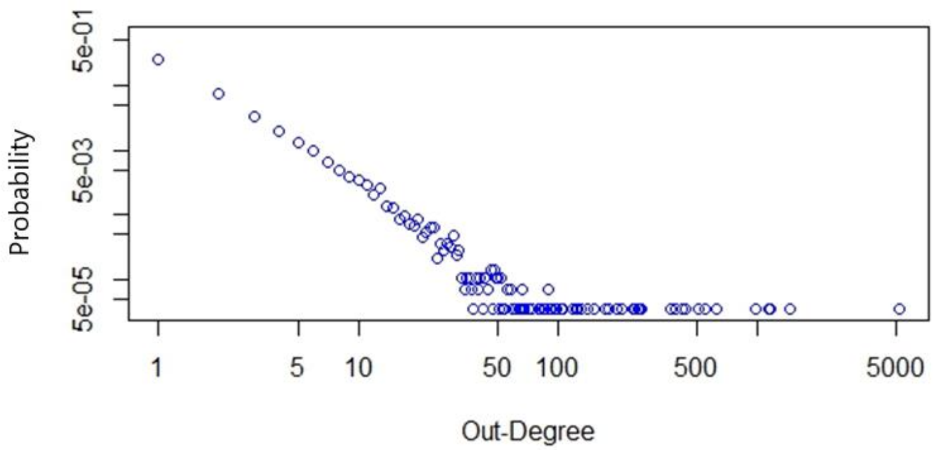

Figure 16. Follower-following network log-log out-degree distribution

Figure 16 also shows that while out-degree values increase, the frequency decreases. Furthermore, in Appendix C, Table C2 shows that 15,122 (44.38%) members do not follow any other members, and 11,001 members (32.29%) follow only one member of the community.

Figure 17 shows the degree distribution of the topic-member network. It is evident that this network does not show a similar path as in the follower-following network. While degree values increase, frequency decreases and in some cases, it also increases. In the network, each node has at least one edge. The member having the highest degree value is an ordinary member, and he or she has 18,351 edges. It indicates that this member has added entries to 18,351 common topics along with the other community members. The second and the third highest degree values are 16,749 and 16,438, respectively. In Appendix C, Table C3 also indicates that 0.731% of the nodes have the degree of 1,533.

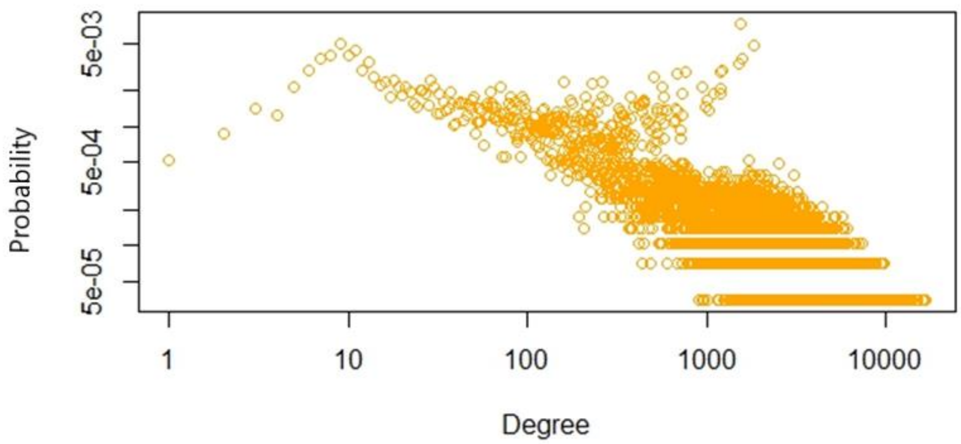

Figure 17. Topic-member network log-log degree distribution

Figure 18 and Figure 19 shows power-law fits regarding in-degree and out-degree distributions of the follower-following network. These Figures indicate that the follower-following network shows properties consistent with power-law distribution. Additionally, Figure 20 designates that the topic-member network also follows a power-law distribution.

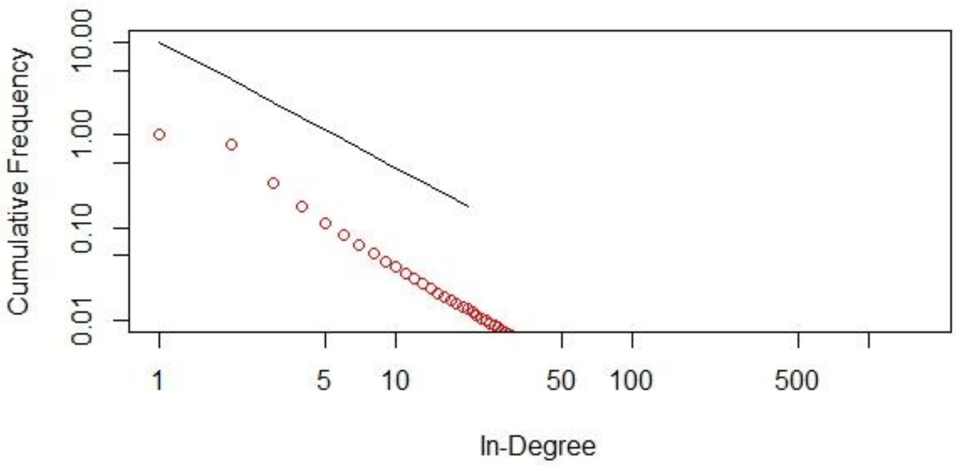

Figure 18. Follower-following network in-degree distribution and power-law fit

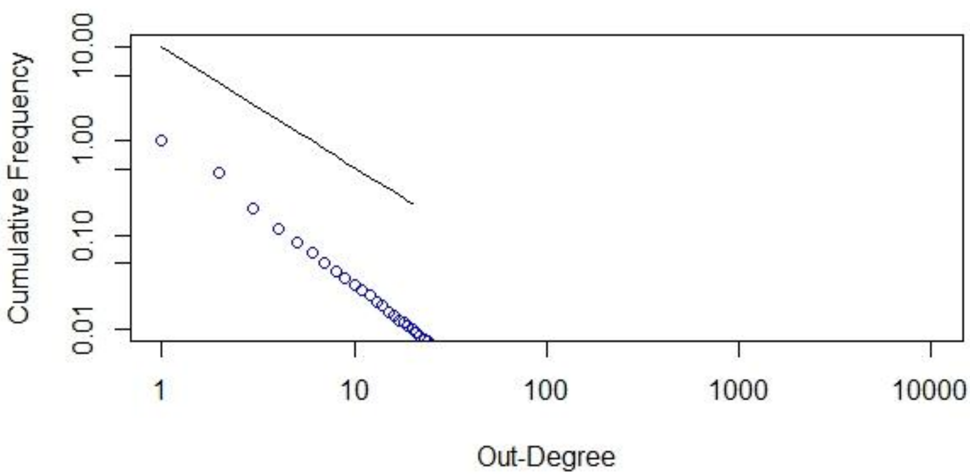

Figure 19. Follower-following network out-degree distribution and power-law fit

However, while the best power-law coefficients approximate the distributions very well for the follower-following network, the topic-member network deviates significantly. The main reason can be that only a part of the topic-member network data is collected so, nodes can be undersampled with a lower degree, and it can explain the flat head of the distribution (Mislove, 2009).

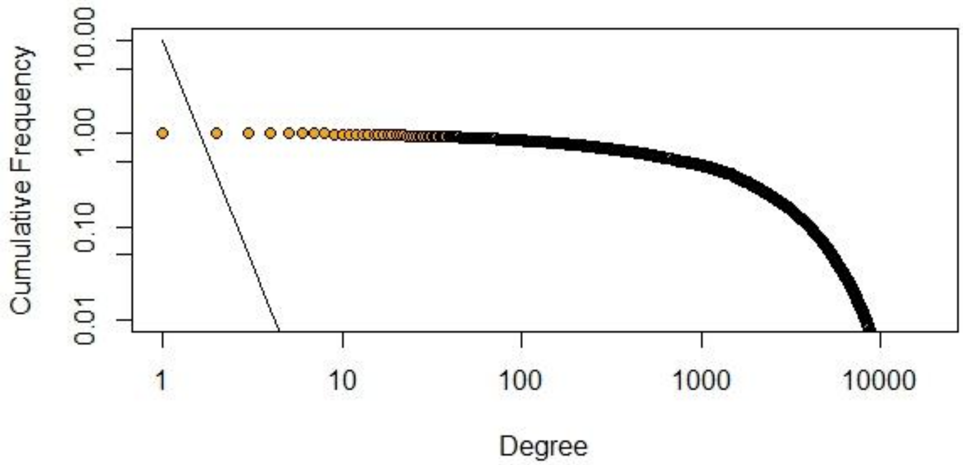

Figure 20. Topic-member network degree distribution and power-law fit

In addition to Figure 18, Figure 19, and Figure 20, the power-law function gives some statistics in R. Table 4 shows these statistics for each network. Alpha is the exponent of the fitted power-law distribution (Nepusz & Csardi, n.d.). Xmin shows the lower bound for fitting the power-law. LogLik shows the log-likelihood of the fitted parameters. Kolmogorov-Smirnov statistic designates the test statistic of a Kolmogorov-Smirnov test that contrasts the fitted distribution with input vector. Lastly, the p-value belongs to the Kolmogorov-Smirnov test.

Clauset, Shalizi and Newman (2009) state that if the p-value is equal to or less than 0.1, the dataset does not come from a power-law distribution. On the other hand, if the p-value is greater than 0.1, it is plausible that the dataset comes from a power-law distribution. According to Table 4, p-values are greater than 0.1 for the follower-following network, and it indicates that the network is well approximated by a power-law. Although the p-value for the topic-member network is a little bit greater than 0.1, it indicates that the network follows the power-law distribution, but it is not well approximated.

Table 4. Power-Law Statistics

Networks	Alpha	Xmin	LogLik	Kolmogorov-Smirnov Statistic	p-value
The follower-following network					
In-degree distribution	2.36	6	-5950.149	0.0094	0.996
Out-degree distribution	2.28	5	-5643.204	0.0224	0.312
The topic-member network					
Degree distribution	5.81	6839	-5673.237	0.0449	0.134

Additionally, it is stated that the scale-free networks are a class of power-law networks (Mislove et al., 2007), so it can be concluded that the follower-following and the topic-member networks show the characteristics of scale-free networks.

In addition to degree distributions, understanding the way of nodes of different degrees are linked with each other can also interesting. For this purpose, joint degree distributions of both networks are analyzed. Figure 21 and Figure 22 show the plots of the average degree versus node degree in the follower-following and topic-member networks, respectively. Figure 21 suggests that there is a tendency for nodes of higher degrees to link with nodes of lower degrees. Moreover, nodes of lower degree tend to link nodes of both lower and higher degrees. The reason can be that there are a few extremely popular members in the community to whom many unpopular members connect.

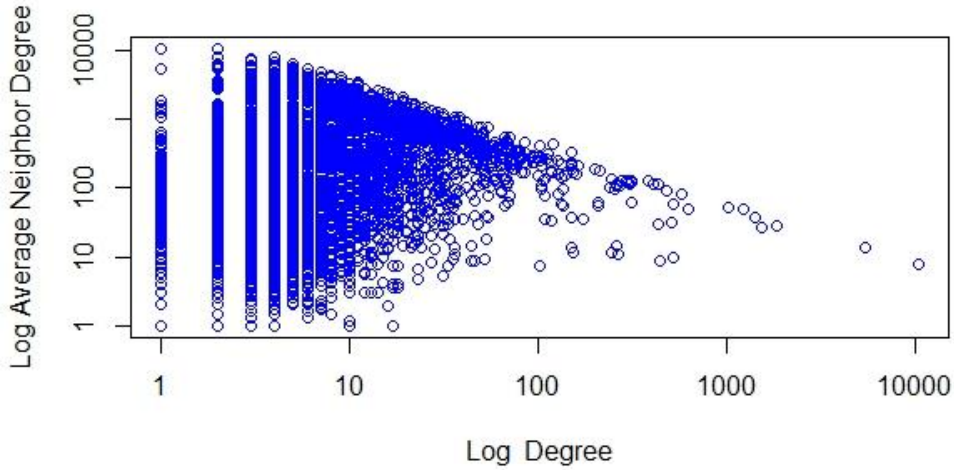

Figure 21. Average neighbor degree versus vertex degree for the follower-following network

Furthermore, Figure 22 suggests that there is a tendency that nodes of higher degree to link with nodes of higher degree.

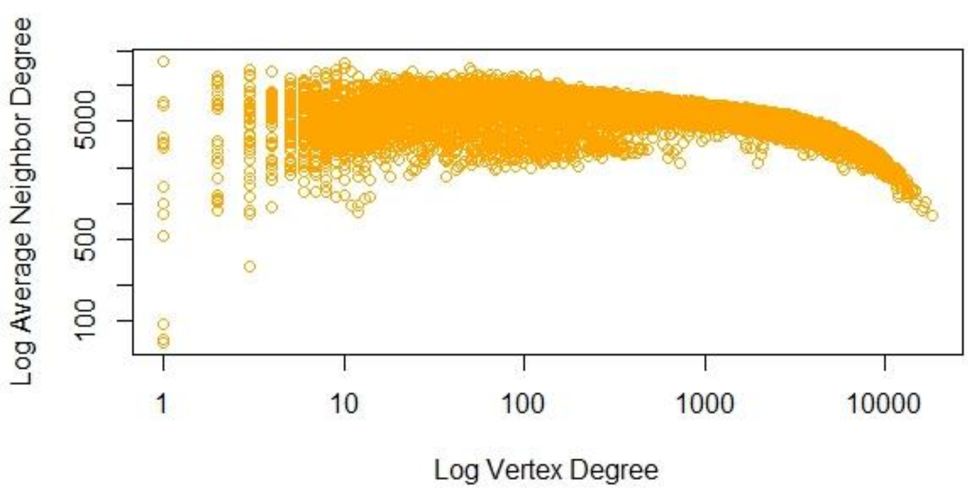

Figure 22. Average neighbor degree versus vertex degree for the topic-member network

However, nodes of lower degree tend to link nodes of both lower and higher degrees. The assortativity coefficient of the follower-following network is -0.152, and it is -0.125 for the topic-member network. The negative assortativity coefficient states that similar nodes do not tend to link to each other (Newman, 2002).

Table 5 includes average path length, diameter, clustering coefficient, reciprocity, and density values of the networks.

Table 5. Geodesic Path, Transitivity, Reciprocity, and Density

Networks	Value
The follower-following network	
Average path length	4.5
Diameter	14
Transitivity – clustering coefficient	0.0024
Reciprocity	0.1629
Density	0.000007204
The topic-member network	
Average path length	2.0169
Diameter	5
Transitivity – clustering coefficient	0.3748
Reciprocity	1
Density	0.0527

The average path length of the follower-following network is 4.5, and it is 2.00169 for the topic-member network. Table 5 also indicates that the diameter of the topic-member network is very smaller than the diameter of the follower-following network. The clustering coefficient of the follower-following network is 0.0024 which is very low. It indicates that the mean probability is 0.24% that two members who have a common friend are also friends together. However, the clustering coefficient of the topic-member network is higher than the follower-following network. It suggests that the mean probability is 37.48% that two members who have a common friend are also friends together. Additionally, the default reciprocity of the follower-following network is

0.1629 which is very low. It indicates that friendship edges are not highly mutual. For example; Kumar et al. (2010) state that reciprocities of Flickr and Yahoo! 360 are around 70.2% and 84%, respectively. The topic-member network is an undirected network, so the reciprocity is 1. Lastly, while the density of the follower-following network is 0.000007204, it is 0.0527 for the topic-member network. It shows that the follower-following network is a very low dense network than the topic-member network.

Mislove et al. (2007) and Cheng et al. (2008) state that small-world phenomena indicate a small diameter and high clustering coefficient. For example; Mislove (2009) finds that the diameters of Flickr, LiveJournal, Orkut, and YouTube are 27, 20, 9, and 21, respectively. Additionally, the clustering coefficients of Flickr, LiveJournal, and YouTube are 0.313, 0.330, 0.171, and 0.136, respectively. Although the diameter of the follower-following network is smaller than the diameters of Flickr, LiveJournal, Orkut, and YouTube, its clustering coefficient is very low. It can be concluded that the follower-following network does not have all the characteristics of small-world networks. On the other hand, the diameter of the topic-member network is very small, and the clustering coefficient is higher than the clustering coefficients of Flickr, LiveJournal, Orkut, and YouTube. It suggests that the topic-member network is a small-world network.

Another principal issue about the networks is the connectivity. The follower-following network is neither a weakly connected nor a strongly connected network. When it is decomposed, Table 6 shows the connected components in it. Table 6 indicates that there is only one giant component involving 32,055 nodes. It means that giant component contains 94% of nodes in the network. Additionally, other components except one of them contain less than 1% of nodes.

Table 6. Census of the Connected Components

The Number of Components	The Number of Nodes	The Percentage of Nodes
774	2	4.5%
91	3	0.8%
22	4	0.25%
9	2	0.053%
2	6	0.035%
1	7	0.021%
1	8	0.024%
2	11	0.065%
1	18	0.053%
1	32,055	94%

Table 7 includes the values of the geodesic path, transitivity, reciprocity, density, and vertex-cut of the giant component.

Table 7. Analysis of the Giant Component

	Values
The average path length	4.5
Diameter	14
Transitivity – clustering coefficient	0.0024
Reciprocity	0.1611
Density	0.00008012
Vertex-cut	4,302

The average path length is 4.5, and the diameter is 14. The clustering coefficient is 0.0024, the reciprocity is 0.1611, and the density is 0.00008012. Additionally, edge connectivity and node connectivity of the giant component are both 0. It indicates that this subgraph cannot be broken into additional components. A single node which disconnects the graph is called a cut vertex or articulation point (Kolaczyk & Csardi, 2014). Table 7 shows that in the giant component, almost 13% of the nodes are cut vertices that can be a candidate to disconnect the network. Furthermore, Table 8 shows that there is only one strongly connected component including 19.02% of the nodes of the whole network.

Table 8. Census of the Strongly Connected Components

The Number of Components	The Number of Nodes	The Percentage of Nodes
26,421	1	77.5%
460	2	2.70%
61	3	0.54%
9	4	0.11%
3	5	0.04%
2	6	0.035%
1	7	0.021%
1	6,482	19.02%

Mislove (2009) states that core should have two properties. The first property is that the core must be necessary for the connectivity of network and the second property is that the core must have an almost small diameter. Table 9 shows that the average path length is 4.11, the diameter is 13, clustering coefficient is 0.015, reciprocity is 0.352, and density is 0.000833 of the strongly connected component. Additionally, Table 9 shows that in the strongly connected component of the network, almost 7.09% of the nodes are cut vertices.

In addition to the connectivity analysis of the follower-following network, the topic-member network is also analyzed regarding connectivity. This network is strongly and fully connected. The vertex connectivity and edge connectivity are both 1. It indicates that only a single well-chosen node or edge is required to decompose this graph into additional components. Additionally, there are 19 vertex cuts that can disconnect the graph.

Table 9. Analysis of the Strongly Connected Component

	Values
Average path length	4.11
Diameter	13
Transitivity – clustering coefficient	0.015
Reciprocity	0.352
Density	0.000833
Vertex-cut	460

After that degree, closeness, betweenness, and eigenvector centralities are investigated. Table 10 shows in-degree values of top ten members in the follower-following network; It indicates that member having the most followers has 2,149 followers, and he is the community admin. Additionally, Table 10 shows that there is another type of members who are popular in the community.

Table 10. In-Degree Centralities of the Top Ten Members of the Follower-Following Network

Number	ID Number	In-Degree	Member Type
1	270	2,149	Admin
2	1220261	673	Ordinary Member
3	39571	580	Moderator
4	1288964	563	Ordinary Member
5	314087	483	Moderator
6	1115128	395	Ordinary Member
7	1149776	391	Ordinary Member
8	251992	361	Moderator
9	31846	354	Moderator
10	1415766	340	Ordinary Member

On the other hand, Table 11 presents out-degree values of top ten members in the same network. It shows that an ordinary member mostly follows 10,110 other community members.

Table 11. Out-Degree Centralities of Top Ten Members of the Follower-Following Network

Number	ID Number	Out-Degree	Member Type
1	1220261	10,110	Ordinary Member
2	1115128	5,159	Ordinary Member
3	1253332	1,459	Ordinary Member
4	1349624	1,163	Ordinary Member
5	1230342	1,143	Ordinary Member
6	1377325	1,014	Ordinary Member
7	1339847	976	Ordinary Member
8	1311650	619	Ordinary Member
9	501760	549	Ordinary Member
10	114303	509	Ordinary Member

Additionally, Table 12 shows degree values of top ten members in the topic-member network. It shows that the most central member regarding degree centrality has 18,351 relationships with other community members.

Table 12. Degree Centralities of the Top Ten Members of the Topic-Member Network

Number	ID Number	Degree	Member Type
1	1525870	18,351	Ordinary Member
2	1529867	16,749	Ordinary Member
3	1403094	16,438	Ordinary Member
4	1569501	16,157	Ordinary Member
5	1584950	15,104	Ordinary Member
6	1499981	14,808	Ordinary Member
7	1659534	14,758	Ordinary Member
8	1516970	14,662	Ordinary Member
9	1153361	14,103	Ordinary Member
10	1650159	13,992	Ordinary Member

Moreover, in-closeness and out-closeness centralities are examined for the follower-following network. While Figure 23 shows the top 1% of nodes ranked by normalized in-closeness centrality values, Table 13 introduces the top ten central members in the follower-following graph.

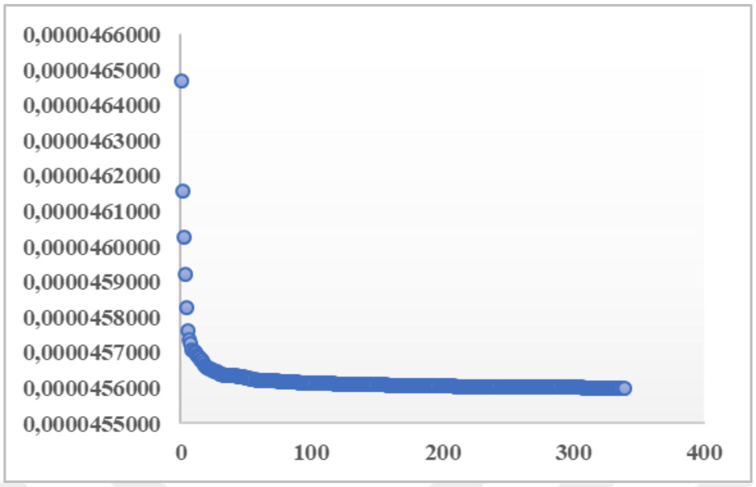

Figure 23. Top 1% of nodes ranked by the normalized in-closeness centrality of the follower-following network

Table 13. In-Closeness Centralities of the Top Ten Members of the Follower-Following Network

Number	ID Number	Normalized In-Closeness	Member Type
1	1288964	0.0000464683	Ordinary Member
2	39571	0.0000461581	Ordinary Member
3	551070	0.0000460257	Ordinary Member
4	18750	0.0000459223	Ordinary Member
5	1415766	0.0000458276	Ordinary Member
6	318487	0.0000457620	Ordinary Member
7	550387	0.0000457371	Ordinary Member
8	1254525	0.0000457268	Ordinary Member
9	1246812	0.0000457077	Ordinary Member
10	218100	0.0000457061	Ordinary Member

Figure 23 and Table 13 show that the most central member, who is an ordinary member, has 0.0000464683 in-closeness centrality value. Figure 23 also states that after a point, in-closeness centralities gets very close to each other. In Appendix D, Table D1 includes the frequency table of in-closeness centrality values of the follower-following network. It shows that 9,733 (almost 29%) of the nodes have 0.0000293 in-closeness centralities.

While 11% of nodes have 0.0000456 in-closeness centrality, 0.063% of nodes have 0.0000293 in-closeness centrality.

On the other hand, Figure 24 and Table 14 present the most central members regarding out-closeness values.

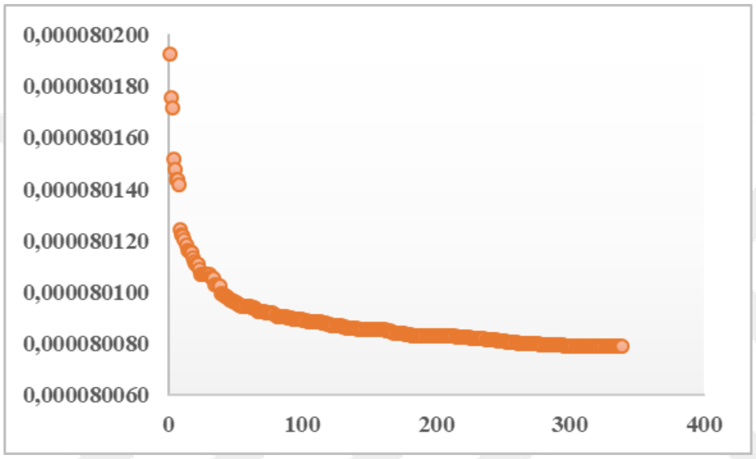

Figure 24. Top 1% of nodes ranked by the normalized out-closeness centrality of the follower-following network

The most central member, who is an ordinary member, has 0.0000801925 out-closeness centrality. Figure 24 also depicts very close out-closeness values. Additionally, in Appendix D, Table D2 presents the frequency table of out-closeness centrality values of the follower-following network. It shows that 15,122 (almost 44%) of nodes have 0.000029346 out-closeness centrality values. While 15% of nodes have 0.000029347 out-closeness centrality values, 0.019% of nodes have 0.000029348 out-closeness centrality values.

Table 14. Out-Closeness Centralities of the Top Ten Members of the Follower-Following Network

Number	ID Number	Normalized Out-Closeness	Member Type
1	1334783	0.0000801925	Ordinary Member
2	1236233	0.0000801755	Ordinary Member
3	883094	0.0000801714	Ordinary Member
4	1371743	0.0000801517	Ordinary Member
5	1286764	0.0000801479	Ordinary Member
6	855588	0.0000801439	Ordinary Member
7	1286558	0.0000801439	Ordinary Member
8	1287985	0.0000801417	Ordinary Member
9	1285708	0.0000801245	Ordinary Member
10	1306691	0.0000801224	Ordinary Member

Figure 25 depicts the top 1% of nodes ranked by normalized closeness centrality value in the topic-member network and Table 15 shows the most central ten members.

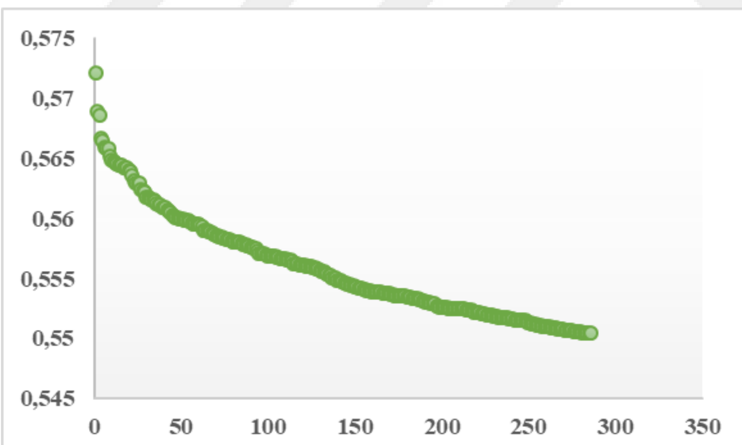

Figure 25. Top 1% of nodes ranked by the normalized closeness centrality of the topic-member network

Table 15 presents that the highest closeness centrality values of the first three members are 0.572128796, 0.568864411, and 0.5685828, respectively. These members are also ordinary members. In Appendix D, Table D3 includes the frequency table of closeness centrality values of the topic-member network. It shows that 0.72%, 0.49%, and 0.37% of nodes have 0.507448971, 0.510480186, and 0.507171118 closeness centrality values, respectively.

Table 15. Closeness Centralities of the Top Ten Members of the Topic-Member Network

Number	ID Number	Normalized Closeness	Member Type
1	1529867	0.5721287957	Ordinary Member
2	1525870	0.5688644108	Ordinary Member
3	1499981	0.5685828003	Ordinary Member
4	1589467	0.5666193070	Ordinary Member
5	1624305	0.5665075169	Ordinary Member
6	1569501	0.5659380728	Ordinary Member
7	1516970	0.5658600032	Ordinary Member
8	1403094	0.5657708071	Ordinary Member
9	1578028	0.5652250940	Ordinary Member
10	1240413	0.5648692778	Ordinary Member

Figure 26 shows the top 1% of nodes ranked by normalized betweenness centrality values for the follower-following network and Table 16 lists the most central members. The node having the highest betweenness (0.1186606) value is an ordinary member, the second most central node (0.0548071) is the community admin, and the third most central node (0.0496570) is also an ordinary member. Figure 23 also states that there are lots of members having 0 betweenness. In Appendix E, Table E1 displays that 79% nodes of the network have 0 betweenness centrality value. The reason is that these nodes do not follow any other nodes and followed by none or only one node. They do not reside between any other nodes.

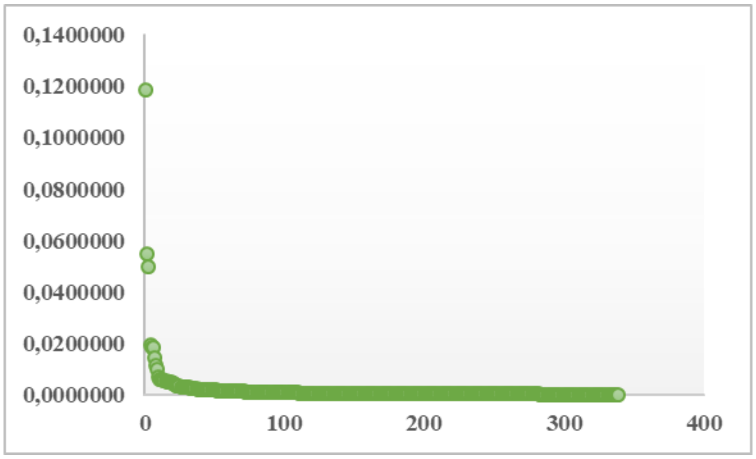

Figure 26. Top 1% of nodes ranked by the normalized betweenness centrality of the follower-following network

Table 16. Betweenness Centralities of the Top Ten Members of the Follower-Following Network

Number	ID Number	Betweenness	Member Type
1	1220261	0.1186605697	Ordinary Member
2	270	0.0548071239	Admin
3	1115128	0.0496570403	Ordinary Member
4	566050	0.0192579486	Co-Moderator
5	1230342	0.0183650354	Ordinary Member
6	894723	0.0182876836	Moderator
7	314087	0.0144535746	Moderator
8	1253332	0.0114592343	Ordinary Member
9	46353	0.0100323816	Moderator
10	1287703	0.0070208530	Ordinary Member

Figure 27 and Table 17 shows that member having the highest betweenness (0.00366354939) value is an ordinary member, the second most central member (0.00338082622) is an ordinary member, and the third most central member (0.00263333342) is also an ordinary member.

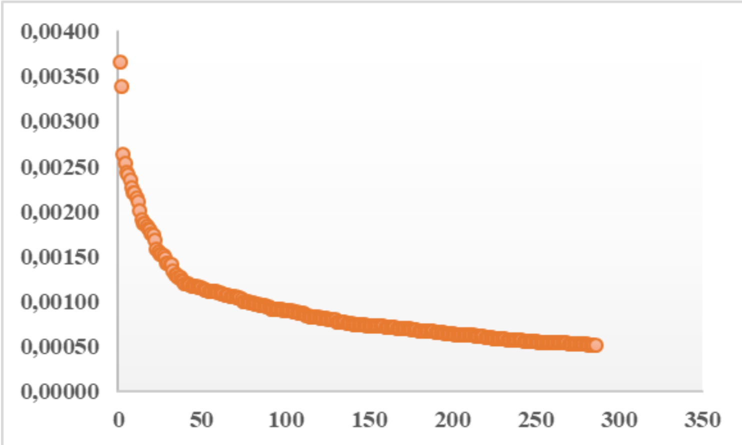

Figure 27. Top 1% of nodes ranked by the normalized betweenness centrality of the topic-member network

Table 17. Betweenness Centralities of the Top Ten Members of the Topic-Member Network

Number	ID Number	Betweenness	Member Type
1	1525870	0.0036635494	Ordinary Member
2	1569501	0.0033808262	Ordinary Member
3	1652435	0.0026333334	Ordinary Member
4	1283163	0.0025294109	Ordinary Member
5	1403094	0.0024384110	Ordinary Member
6	1633555	0.0024060871	Ordinary Member
7	1612526	0.0023450814	Ordinary Member
8	1631708	0.0022570686	Ordinary Member
9	1659534	0.0022114553	Ordinary Member
10	1584950	0.0022041369	Ordinary Member

In Appendix E, Table E2 displays the frequency of betweenness centrality of nodes in the topic-member network. It shows that 0.72%, 0.46%, and 0.35% of the nodes have 0.00000032092, 0.00000069419, and 0.00000058865 betweenness centrality values.

Figure 28 and Table 18 shows that the node having the highest eigenvector (1) value is the community admin, the second most central (0.5704765555) and the third node most central (0.5639855874) nodes are ordinary members.

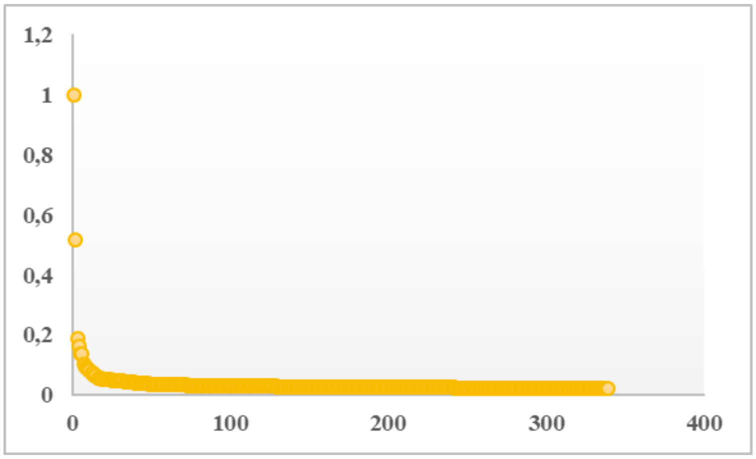

Figure 28. Top 1% of nodes ranked by eigenvector centrality of the follower-following network

Table 18. Eigenvector Centralities of the Top Ten Members of the Follower-Following Network

Number	ID Number	Eigenvector	Member Type
1	270	1.0000000000	Admin
2	314087	0.5704765555	Moderator
3	1220261	0.5639855874	Ordinary Member
4	1115128	0.4399069010	Ordinary Member
5	39571	0.3931320334	Moderator
6	251992	0.3818147611	Moderator
7	46353	0.3589055055	Moderator
8	14243	0.3432693161	Co-Moderator
9	20332	0.3332831222	Co-Moderator
10	517764	0.3071593427	Co-Moderator

Figure 29 also shows that there are many members having 0 eigenvector centrality. In Appendix F, Table F1 states that 35.78%, 13.78%, and 5.35% of the nodes have 0, 0.0172838, and 0.0134813 eigenvector centrality values.

Figure 29 shows the top 1% of nodes ranked by eigenvector centrality in the topic-member network and Table 19 presents the top ten members having the highest eigenvalue centralities. The member having the highest value is an ordinary member.

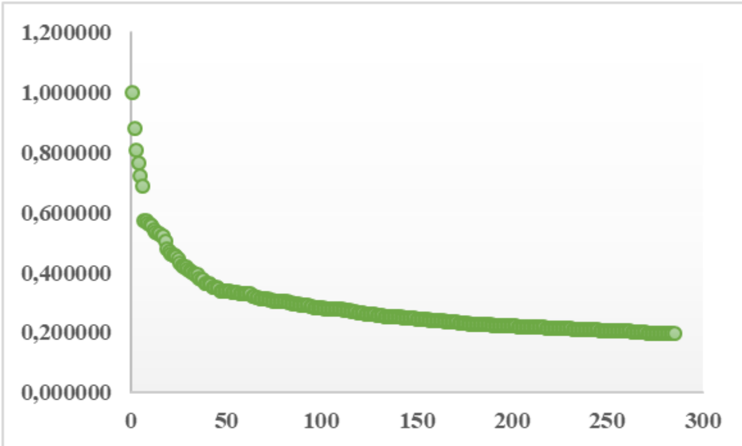

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Figure 29. Top 1% of nodes ranked by eigenvector centrality of the topic-member network

Table 19. Eigenvector Centralities of the Top Ten Members of the Topic-Member Network

Number	ID Number	Eigenvector	Member Type
1	1525870	1.0000000000	Ordinary Member
2	1569501	0.8776278566	Ordinary Member
3	1403094	0.8077224786	Ordinary Member
4	1659534	0.7635436651	Ordinary Member
5	1529867	0.7233311031	Ordinary Member
6	1584950	0.6865625004	Ordinary Member
7	1631708	0.5744648849	Ordinary Member
8	1648477	0.5728500233	Ordinary Member
9	1633555	0.5639402979	Ordinary Member
10	1516970	0.5590424347	Ordinary Member

In Appendix F, Table F2 shows the frequency of eigenvector centrality of nodes in the topic-member network. It shows that 0.72%, 0.46%, and 0.35% of the nodes have 0.014366429, 0.022239416, and 0.019090435 eigenvector centrality values.

In summary, the community admin has the most followers and the highest eigenvalue, and he or she also has the second highest betweenness centrality in the follower-following network. Additionally, the node having the highest eigenvector centrality value (1) also has the highest betweenness centrality value, has the most degree, and the second highest closeness centrality value in the topic-member network.

Table 20 and Table 21 show the centralization values of the follower-following network and the topic-member network. These centralization values help us to compare different networks (Aneela, James, & Santiago, 2010). It is stated that when the value gets larger, the more likely is that a single node is relatively central concerning remaining nodes. In other words, centralization values indicate whether a network is organized around its most central nodes (Centrality and Centralization, n.d.). In this sense, Table 20 shows that there is a single node (admin) is a quite central concerning eigenvector centralization. Furthermore, Table 21 also presents that there is a single node having a high eigenvector centrality while remaining nodes have less values.

Table 20. Centralization of the Follower-Following Network

In-degree Centralization	Out-degree Centralization	In-closeness Centralization	Out-closeness Centralization	Betweenness Centralization	Eigenvector Centralization
6.29 %	29.66%	0.00068%	0.0032%	11.86%	99%

The results also suggest that the topic-member network is more centralized than the follower-following network.

Table 21. Centralization of the Topic-Member Network

Degree Centralization	Closeness Centralization	Betweenness Centralization	Eigenvector Centralization
58.64%	47.26%	0.6719%	86.60%

7.2 Community detection

The topic-member network is an undirected and weighted network. The proper community detection algorithms mentioned in Table 1 are edge betweenness, fast-greedy, multi-level, Walktrap, label propagation, spin-glass, leading eigenvector, and Infomap. The spinglass algorithm is very CPU intensive (Orman et al., 2011). This problem limits its use on large networks, and it performs worse when the network size increases. In this sense, spin-glass algorithm is excluded from the scope of the study. Additionally, edge betweenness algorithm is excluded from the scope of the study due to its slow speed (Newman, 2004).

The main idea behind the community detection is that there should be relatively many edges intra communities and there should be few edges between communities (Traag, 2014). Table 22 shows the results obtained by different community detection algorithms. The fast-greedy algorithm divides the whole network into four sub-communities with the modularity of 0.1952174. The first sub-community includes 4,611 members, the second one involves 17,444 members, the third one consists of 6,594 members, and the last sub-community includes only 66 members.

On the other hand, the multi-level algorithm finds out seven sub-communities with the modularity of 0.2313101. The sub-communities include 4, 3788, 4372, 5761, 584, 14212, and 4 members, respectively. Furthermore, Walktrap algorithm divides the whole network into 356 sub-communities with the modularity of 0.13. However, 54.49% of the sub-communities include only one member, and 86.51% of the sub-communities involve less than ten members. Moreover, Infomap algorithm divides the community into 42 sub-communities with the modularity of 0.0011. 73.80% of the sub-communities include less than 20 members, and 28.57% of the sub-communities consist of only two members.

Table 22. Community Detection Results

Community Detection Algorithm	Number of Sub-Communities	Community Sizes	Modularity
Fast-greedy	4	1:4,611 2:17,444 3:6,594 4:66	0.1952174
Multi-level	7	1:4 2:3,778 3:4,372 4:5,761 5:584 6:14,212 7:4	0.2313101
Walktrap*	356	1:8,710 5:4,532 20:3,207 33:2,371 18:2,086 15:1,069 25:988 40:939 36:580 9:506	0.1300
Infomap**	42	1:28,099 2:120 3:74 4:50 5:41 6:38 7:35 8:29 10:26 9:25 11:24	0.0011
Label Propagation	1	1:28,715	0
Leading Eigenvector	1	1:28,715	0

* Sub-communities including at least 500 nodes are shown in the table.
* *Sub-communities including at least 20 nodes are shown in the table.

Lastly, label propagation algorithm cannot divide the network into any sub-communities. The main reasons can be that nodes with different labels tend to be connected, network having clusters with varying densities, the non-uniformity of the number of occurrences of each label across the whole network, and unreliable node labels (Yamaguchi & Hayashi, 2017). Furthermore, Table 22 indicates that the modularity values achieved by label propagation and leading eigenvector algorithms are both zero. It is stated that zero modularity “indicates that the community structure is no stronger than would be expected by random chance” (Newman, 2004, p.327). It can be concluded that if the network is undivided or does not have underlying community structure, the modularity equals to zero.

7.3 Role identification

Table 23 summarizes online community members’ some attributes including their age, membership age, and gender. Additionally, Table 23 presents other attributes involving the total number of topics opened in the last 30 days (26th September 2016 – 26th October 2016), the total number of entries added in the last 30 days, and the total times of logins in the last 30 days that compose online community members’ degree of content contribution.

Table 23 shows that the network involves mostly male members and the average age of the online members is 23.35 year. However, when a member signs up for the community membership, age and gender information are not required during the registration process so that members can leave age and gender information as blank. In this respect, only 5,446 members out of 28,715 members have age information and only 3,812 members out of 28,715 members have gender information. In other words, only

18% of members have age information, and only 13% members have gender information. Due to lack of data, online community members' age and gender attributes are not considered for further analysis.

Table 23. Summary of Community Members' Degree of Content Contribution

Criteria	Sum	Mean	Median	Standard Deviation
Age	-	23.35	23	4.988
Membership Age (Year)	-	1.08	0.60	1.33
Gender				
Female	70	-	-	-
Male	3,675	-	-	-
Entry	387,418	13.49	1	2.78
Topic	11,560	0.40	0	2.46
Times of Login	241,310	8.40	1	25.54

Additionally, Table 23 states that a member submits 14 entries, opens 0.40 topics, and logs into the website eight times in a month on average. Additionally, the median of zero for topic highlights that a significant portion of community members did not contribute to the online community by opening a topic but only through submitting entries. The large standard deviation of login indicates members' login times are more spread regarding other attributes.

These attributes are considered to discriminate sub-communities in a meaningful way. As it mentioned before that the integration of structural data and interpretive techniques allows us to identify the roles in a more meaningful way (Gleave et al., 2009). As a result, it is revealed that the sub-communities generated by the fast-greedy algorithm are discriminated in a more meaningful way than the sub-communities detected by other community detection algorithms by considering these attributes. For example; Table 24 shows the results concerning multi-level algorithm.

Table 24. Degree of Content Contribution Concerning Multi-Level Algorithm

Criteria	Membership Age		Entry		Topic		Session	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Community 1 (N=4)	0.98	0.61	1.50	1.00	0.25	0.50	13	9.06
Community 2 (N=3,778)	1.03	1.26	11.31	19.38	0.23	1.04	6.24	14.74
Community 3 (N=4,372)	0.80	1.05	10.93	20.47	0.27	1.12	5.76	14.29
Community 4 (N=5,761)	0.77	1.08	11.55	20.81	0.19	0.80	5.31	14.78
Community 5 (N=584)	2.52	1.47	1.04	4.38	0.00	0.42	10.09	16.47
Community 6 (N=14,212)	1.07	1.48	16.09	47.67	0.59	3.35	10.98	32.92
Community 7 (N=4)	3.73	2.48	1.00	0.00	0.25	0.50	6.25	5.74

Table 25 shows sub-communities and their distribution of the degree of content contribution. The second sub-community has the highest number of added entries and opened topics. They also visit the website at the most, and they have been members for one year. This sub-community is called socializers who are the most social members of the community. Socializers very actively participate in the communication and interaction activities of the community (Brandtzæg & Heim, 2011; Füller et al., 2014). They generate an enormous amount of content, and they fire other community members to communicate and add their contents by opening topics.

Table 25. Degree of Content Contribution Concerning Sub-Communities

Criteria	Community 1 N=4,611		Community 2 N=17,444		Community 3 N=6,594		Community 4 N=66	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Membership Age	1.08	5.23	1.01	5.09	0.78	4.24	1.70	3.59
Entry	6.66	1.80	16.19	2.79	11.22	3.09	1.95	0.39
Topic	0.15	0.72	0.55	3.09	0.18	0.72	0.00	0.00
Times of Login	6.67	14.58	10.10	30.54	5.18	14.31	3.77	6.49

Although members of the first sub-community usually visit the website, they open fewer topics and add fewer contents than other members do, so the first sub-community is called visitors. On the other hand, members of the third sub-community often visit the website, open fewer topics, but they add more entries than other members do. In this sense, the third sub-community is called entry generators. They are also called efficient contributors in the study of Füller et al. (2014) and commentators in the study of Choi et al. (2015). Lastly, members of the fourth sub-community visit the website seldom, they do not open topics and produce few contents although they have the oldest membership age, so the fourth sub-community is called passive members. These types of users also identified as passive members or lurkers who make fewer contributions regarding other sub-communities (Brandtzæg & Heim, 2011; Füller, Jawecki, & Mühlbacher, 2007; Füller et al., 2014). Table 26 also summarizes user roles regarding sub-communities.

Table 26. Summary of User Roles

Sub-Communities	User Role	Explanation
Community 1	Visitors	Although this type of community member usually visits the community, he opens fewer topics and adds fewer contents than other sub-community member does.
Community 2	Socializers	This kind of community member is the most social member of the community. He generates a huge amount of content and topics.
Community 3	Entry Generators	Although this type of member often visits the community, he opens fewer topics than sub-community member does, but he generates an enormous amount of contents after a socializer.
Community 4	Passive Members	This member visits the community seldom, he does not prefer to open topics, and he produces fewer contents than other sub-community member does.

Furthermore, Figures 30-33 visualize the egocentric networks of randomly chosen members for each user type. In the Figures, green nodes represent visitors, yellow nodes show socializers, blue ones are entry generators, and orange nodes are passive members. Edge widths are visualized based on edge weights. The more edge is wide; the more communication exists between nodes. Additionally, “*” represents the randomly selected node. In Figure 30, the ego network of a random visitor is shown. It shows that the visitor submitted only one entry and opened only one topic, and eight members also added entries to the same topic along with that visitor. Figure 30 also shows that the visitor is in communication with another visitors, socializers, and entry generators.

Figure 31 visualizes the ego network of a random socializer. It shows that the socializer has submitted three entries, opened one topic, and visited the website thirty-four times in the last thirty days. There are also fifteen members who added entries to the same topics along with the socializer. Figure 31 also shows that the socializer is in communication with other socializers, visitors, and entry generators.

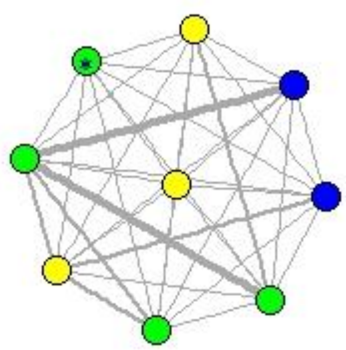


Figure 30. Visitor (id 665235), degree 8, entry 1, topic 1, login 27

Figure 32 visualizes the ego network of a random entry generator. This network is more connected than other networks as expected. It shows that the entry generator submitted fifty entries along with thirty members to the same topic in the last thirty days. Figure 32 also indicates that the entry generator is in communication with other entry generators, visitors, and socializers.

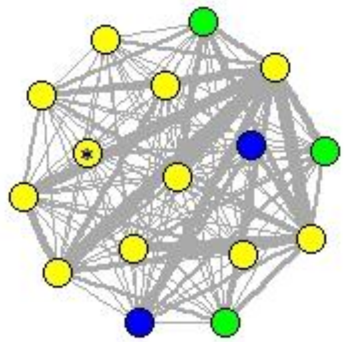


Figure 31. Socializer (id 629286), degree 15, entry 3, topic 1, login 34

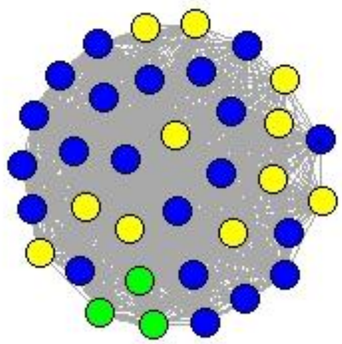


Figure 32. Entry generator (id 1678650), degree 34, entry 50, topic 1, login 17

Lastly, Figure 33 shows the ego network of a random passive member. The passive member has eight relationships, he or she has submitted two entries and visited the website only once in the last thirty days. The passive member communicates with all user groups.

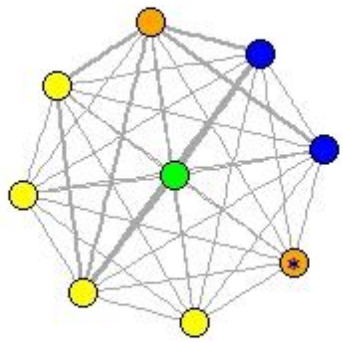


Figure 33. Passive member (id 528551), degree 8, entry 2, topic 0, login 1

7.4 Research model testing

Table 27 includes the descriptive statistics obtained from the online questionnaire. It shows that respondents mainly consist of males. 61.8% of the members are equal or less than 18 years old, and 26.8% of members are between 19 and 25 years old. It can be said that the community has a younger population. In parallel with these statistics, 24.8% of members are high school students, 47.4% of them are university students, and most of the community members earn between 0 and 2,000 Turkish Liras in a month. Furthermore, while 37.4% of the members sometimes visit the community website, 34.0% of them often visit it. Although most of the members spend between 0 and 2 hours in a day on the community website, 23.6% of the members prefer to spend between 3 and 5 hours in a day. Each member also assumes a user role for himself or herself in the community. 41.0% of them state that they are visitors. Entry generators follow them with a percentage of 23.8%. Also, 18.5% of the community members say that they are socializers and 16.7% of them indicate that they are passive members.

Table 27. Descriptive Statistics

Characteristic		Frequency	Percentage
Age	<= 18	484	61.8%
	19 - 25	210	26.8%
	26 - 35	77	9.8%
	>= 36	12	1.53%
Gender	Female	47	6.0%
	Male	736	94.0%
Education	Primary school	11	1.4%
	High school student	194	24.8%
	High school graduate	78	10.0%
	University student	371	47.4%
	University graduate	93	11.9%
	Master/Ph.D. student	18	2.3%
	Master/Ph.D. graduate	18	2.3%
User Roles	Socializer	145	18.5%
	Entry Generator	186	23.8%
	Visitor	321	41.0%
	Passive member	131	16.7%
Daily Visiting Frequency	Never	12	1.5%
	Rarely	118	15.1%
	Sometimes	293	37.4%
	Often	266	34.0%
	Very often	94	12.0%
Hourly Visiting Frequency	0 - 2	500	63.9%
	3 - 5	185	23.6%
	6 - 8	64	8.2%
	>=9	34	4.3%
Economic Level	0 – 2,000 TL	562	71.8%
	2,001 – 3,000 TL	85	10.9%
	3,001 – 5,000 TL	71	9.1%
	>=5,001 TL	65	8,3%

7.4.1 Analysis of the measurement model

The reliability and validity of the proposed model are analyzed in Table 28. The individual item reliability of measurement model is measured by Cronbach's alpha. Table 28 shows Cronbach's alpha values of all constructs ranging from 0.616 to 0.908. Although Cronbach's alpha coefficients should be equal to or greater than 0.7, this threshold can also be set at 0.6 (Nunnally & Bernstein, 1994; Nunnally, 1978). In this respect, it can be accepted that all latent variables are reliable. The internal consistency of the measurement model is considered by composite reliability. Composite reliabilities of each latent variable are at least 0.7, and it implies a high internal consistency of scales (Fornell & Larcker, 1987; Hair, Anderson, Babin, & Black, 2010).

Construct validity of the model is measured by factor loading analysis. Factor loadings of each indicator should be at least 0.5 and ideally should be greater than 0.7 (Hair et al., 2010). Table 28 displays that all factor loadings for each indicator are at least 0.5. Also, AVE values should be 0.5 or greater to suggest adequate convergent validity (Hair et al., 2010). The results imply that the measurement model of the study is adequately valid regarding construct and convergent validities.

Table 28. Measurement Model Testing Results

Construct	Item	Factor Loading	AVE	Item Reliability (Cronbach's α)	Composite Reliability	VIFs
PCM	PCM1	0.830	0.489	0.644	0.789	1.591
	PCM2	0.769				
	PCM3	0.606				
	PCM4	0.555				
TW	TW1	0.775	0.600	0.776	0.857	1.315
	TW2	0.761				
	TW3	0.836				
	TW4	0.721				
PU	PU1	0.809	0.569	0.618	0.797	1.417
	PU2	0.662				
	PU3	0.783				
PEOU	PEOU1	0.855	0.636	0.703	0.837	1.109
	PEOU2	0.883				
	PEOU3	0.629				
UI	UI1	0.828	0.568	0.616	0.797	1.777
	UI2	0.759				
	UI3	0.668				
PP	PP1	0.907	0.844	0.908	0.942	1.150
	PP2	0.941				
	PP3	0.908				

Additionally, AVE values for two latent variables should be greater than the square of the correlation between these two latent variables to provide evidence of discriminant validity. Table 29 shows the correlations and squared correlations among latent variables. The values above the diagonal are less than the AVE values, and it provides the proof of discriminant validity. Lastly, all constructs are derived from the literature which indicates a high content validity (Cronbach, 1971).

Also, a full collinearity test is conducted to explore if there is multicollinearity among the latent variables. This test depends on the variance inflation factors (VIFs) calculated for each latent variable about the other latent variables (Kline, 2016). In Table 28, the results show that VIF values for all latent variables are less the threshold of 5 as suggested by Hair et al. (2010).

Table 29. Discriminant Validity

Construct	PCM	TW	PU	PEOU	UI	PP
PCM	1.000	0.104	0.221	0.030	0.284	0.044
TW	0.322***	1.000	0.086	0.058	0.174	0.040
PU	0.470***	0.294***	1.000	0.028	0.205	0.035
PEOU	0.173***	0.241***	0.167***	1.000	0.044	0.023
UI	0.533***	0.417***	0.453***	0.210***	1.000	0.099
PP	0.210***	0.199***	0.188***	0.152***	0.314***	1.000

***p<=0.001; **p<=0.01; *p<=0.05

Values below the diagonal are correlation estimates among constructs. Diagonal elements are constructed variances. Values above diagonal show the squared correlations.

7.4.2 Analysis of the Structural model

The structural model is tested by using PLS approach. The results are shown in Table 30 and Figure 34. The structural model shows that all hypotheses in the proposed model are supported except the effect of PEOU on the UI. The results show that PU (β= 0.214; p<=0.001; H1 supported), PP (β=0.162; p<=0.001; H4 supported), TW (β=0.192; p<=0.001; H10 supported), and PCM (β=0.334; p<=0.001; H7 supported) significantly affect the UI (R^2=0.446).

Table 30. Path Estimation Results

	Dependents			
Independents	PU	PP	UI	PEOU
PCM	0.435***		0.334***	0.174***
TW			0.192***	
PU			0.214***	
PEOU	0.093**	0.189***	0.051	
PP	0.098**		0.162***	
R^2	0.240	0.036	0.446	0.030

***p<=0.001; **p<=0.01; *p<=0.05

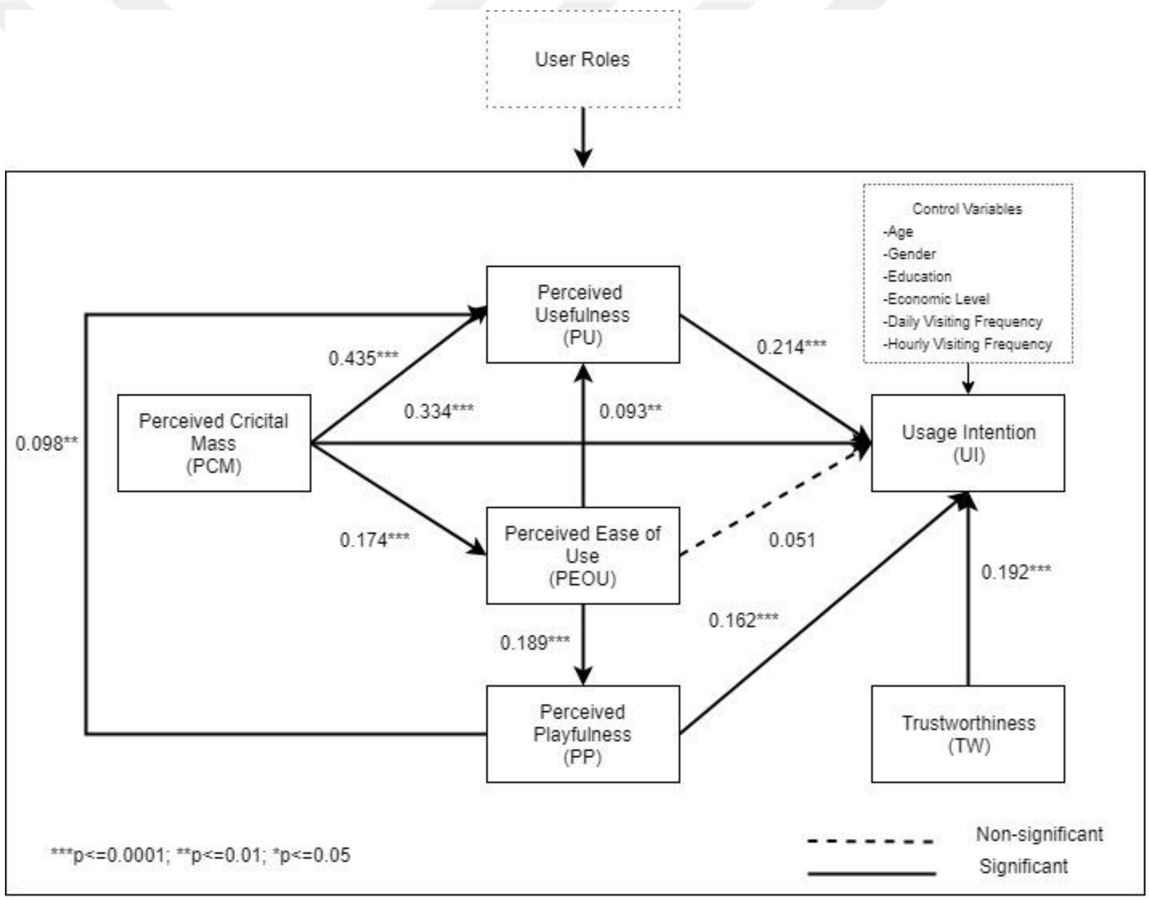


Figure 34. Structural model path estimations

Additionally, PEOU (β=0.189; p<=0.001; H6 supported) has a significant impact on the PP (R^2=0.036). PEOU (β=0.093; p<=0.01; H3 supported), PP (β=0.098; p<=0.01; H5 supported), and PCM (β=0.435; $p<=0.001$; H8 supported) have also a significant impact on the PU (R^2=0.240). Lastly, PCM (β=0.174; $p<=0.001$; H9 supported) has a significant impact on the PEOU (R^2=0.030).

Moreover, age, gender, education, economic level, daily visiting frequency, and hourly visiting frequency are added as control variables to the model. Table 31 introduces that PCM, TW, PU, and PP are significantly associated with UI regardless control variables. Additionally, Table 31 shows that none of the control variables except for daily visiting frequency is significantly associated with UI. However, it does not become important whether the impacts associated with control variables are significant or not (Kock, 2011).

Table 31. Effect of Control Variables on UI

	UI
Control Variables	β
Age	-0,027
Gender	-0,002
Education	0,020
Economic Level	0,011
Daily Visiting Frequency	0,092**
Hourly Visiting Frequency	-0,014

***p<=0.001; **p<=0.01; *p<=0.05

Additionally, the total effects of PCM, TW, PU, PEOU, and PP on UI are shown in Table 32. Table 32 also includes the number of paths used to calculate them, the effect size, and the corresponding p values. Table 32 indicates that all independent variables have a significant positive impact on UI. Moreover, Cohen (1988) states that the effect size of any variable can be determined as small, medium, or large effect size. If the f-squared coefficient is greater than 0.02, then it is determined as small. If it is greater than

0.13 or 0.26, then it is determined as medium and large, respectively. In Table 32, all values in the effect size column are above Cohen’s (1988) effect size threshold and are considered as relevant.

Table 32. Total Effects on UI

	UI		
	Number of Paths	Total Effect	Effect Size
PCM	6	0.445***	0.246
TW	1	0.192***	0.082
PU	1	0.214***	0.099
PEOU	4	0.105**	0.024
PP	2	0.183***	0.060

***p<=0.001; **p<=0.01; *p<=0.05

Additionally, Table 33, Table 34, and Table 35 show the total effects on PP, PU, and PEOU, respectively. In Table 33, only PEOU has a significant positive total effect on PP, and its effect size value is greater than the threshold and is considered as relevant. In Table 34, all latent variables except PP have significant positive total effects on PU. Their effect size value is also considered as relevant. On the other hand, In Table 35, it is seen that PCM does not have a significant total effect on PEOU.

Table 33. Total Effects on PP

	PP		
	Number of Paths	Total Effect	Effect Size
PCM	1	0.033	0.007
PEOU	1	0.189***	0.036

***p<=0.001; **p<=0.01; *p<=0.05

Table 34. Total Effects on PU

	PU		
	Number of Paths	Total Effect	Effect Size
PCM	3	0.454***	0.213
PEOU	2	0.112***	0.020
PP	1	0.098	0.019

***p<=0.001; **p<=0.01; *p<=0.05

Table 35. Total Effects on PEOU

	PEOU		
	Number of Paths	Total Effect	Effect Size
PCM	1	0.174	0.035

***p<=0.001; **p<=0.01; *p<=0.05

Moreover, Table 36 shows sums of indirect effects of PCM, PU, and PEOU on UI and the number of paths used to calculate them, the effect size, and the corresponding p values. Table 36 indicates that the only PCM has a significant positive indirect impact on UI and its effect size is considered as relevant.

Table 36. Sum of Indirect Effects on UI

	UI		
	Number of Paths	Indirect Effect	Effect Size
PCM	5	0.111***	0.062
PEOU	3	0.055	0.012
PP	1	0.021	0.007

***p<=0.001; **p<=0.01; *p<=0.05

On the other hand, In Table 37, it is seen that PCM has an indirect effect on PP, but the results indicate that it is not significant. Also, In Table 38, the results show that the indirect effects of PCM and PEOU on PU are not significant.

Table 37. Sum of Indirect Effects on PP

	PP		
	Number of Paths	Indirect Effect	Effect Size
PCM	1	0.033	0.007

***p<=0.001; **p<=0.01; *p<=0.05

Table 38. Sum of Indirect Effects on PU

	PU		
	Number of Paths	Indirect Effect	Effect Size
PCM	2	0.019	0.009
PEOU	1	0.019	0.003

***p<=0.001; **p<=0.01; *p<=0.05

Furthermore, Table 39 shows model fit and quality indices. The table indicates that the model is robust based on average path coefficients (APC), average R squared (ARS), and average adjusted R-squared (AARS) (Kock, 2017). Additionally, average block VIF (AVIF) and average full collinearity VIF (AFVIF) values should be ideally less than or equal to 3.3, but they are also acceptable if they are less than or equal to 5 in where most variables are single-indicator variables.

Table 39. Model Fit

Quality Indices	Value	p- Value
APC	0.197	<0.001
ARS	0.187	<0.001
AARS	0.184	<0.001
GOF	0.340	
AVIF	1.149	
AFVIF	1.359	

Lastly, Tenenhaus GoF (GOF) indicates the explanatory power of the model. If it is greater than or equal to 0.1, greater than or equal to 0.25, or greater than or equal to 0.36, the explanatory power of the model is considered as small, medium, or large, respectively. Table 39 shows that the explanatory power of the model is medium. Also, there is no multicollinearity; it indicates that the model is fit.

7.4.3 Path analysis results for usage patterns

The sample is split into four sub-samples for further PLS path analysis to understand the different intention behaviors of the four user roles. Table 40 includes path estimations for each user role.

Table 40. Path Coefficients for Each User Role

	User Roles			
Hypotheses	Visitors (N=321)	Socializers (N=145)	Entry Generators (N=186)	Passive Members (N=131)
PU -> UI	0.144**	0.291***	0.210**	0.194*
PEOU -> UI	0.055	0.061	0.083	0.029
PP -> UI	0.074	0.140*	0.412***	0.267***
TW -> UI	0.263***	0.249***	0.040	0.134
PCM -> UI	0.352***	0.177*	0.135*	0.379***
R^2	0.398	0.473	0.464	0.651
PEOU -> PU	0.103*	0.187***	0.105	0.016
PP -> PU	-0.048	0.152*	0.208**	0.421***
PCM -> PU	0.380***	0.450***	0.462***	0.214***
R^2	0.178	0.337	0.358	0.305
PEOU -> PP	0.049	0.224***	0.286***	0.314***
R^2	0.002	0.050	0.082	0.099
PCM -> PEOU	0.201***	0.264***	0.191**	0.252***
R^2	0.040	0.070	0.036	0.063

***p<=0.001; **p<=0.01; *p<=0.05

The results show that PCM has a more significant effect than TW, PP, and PU on the UI for visitors. On the other hand, TW has a more significant impact than PCM and PP on the UI for socializers. For the group of entry generators, PP has a more significant effect than PCM and PU on the UI. Lastly, PCM has a more significant effect than PP and PU on the UI for passive members.

Additionally, PCM and PEOU have significant positive impacts on PU and PCM has a significant positive effect on PEOU for visitors. For socializers, PEOU, PP, and PCM have positive impacts on PU. Also, the impacts of PEOU and PCM are significant on PP and PEOU, respectively. For both entry generators and passive members, PP and PCM effects PU significantly and positively. Also, the effects of PEOU and PCM are significant on PP and PEOU, respectively. Furthermore, UI is explained by all the latent variables together with an R^2 of 0.398. For socializers, entry generators, and passive members, R^2 values are 0.473, 0.464, and 0.651, respectively. Moreover, the results shown in Table 39 are significantly associated with UI regardless control variables. Additionally, Table 41 shows that none of the control variables except for daily visiting frequency is significantly associated with UI for visitors. However, it does not become important whether the impacts associated with control variables are significant or not (Kock, 2011).

Table 41. Effect of Control Variables on UI Concerning User Roles

	Visitors	Socializers	Entry Generators	Passive Members
Control Variables	β	β	β	β
Age	-0.052	0.026	0.029	0.035
Gender	0.012	-.0.004	-0.018	0.041
Education	-0.060	0.002	0.001	-0.064
Economic Level	-0.038	0.009	0.079	0.037
Daily Visiting Frequency	0.130**	0.076	0.047	0.123
Hourly Visiting Frequency	-0,028	-0.094	0.012	0.032

***p<=0.001; **p<=0.01; *p<=0.05

Table 42 also shows all structural models are fit. There is not any multicollinearity and APCs, ARSs, and AARSs are significant for each model. The explanatory power of each model is also large.

Table 42. Model Fit for Each User Role Model

	Visitors		Socializers		Entry Generators		Passive Members	
Quality Indices	Value	p- Value	Value	p- Value	Value	p- Value	Value	p- Value
APC	0.124**	0.006	0.150*	0.016	0.145*	0.011	0.159*	0.015
ARS	0.159***	<0.001	0.232***	<0.001	0.235***	<0.001	0.280***	<0.001
AARS	0.151***	<0.001	0.215***	<0.001	0.221***	<0.001	0.264***	<0.001
GOF	0.357		0.432		0.433		0.482	
AVIF	1.106		1.316		1.228		1.316	
AFVIF	1.451		1.756		1.576		1.730	

***p<=0.001; **p<=0.01; *p<=0.05

Additionally, the multi-group analysis is performed to evaluate whether path coefficients significantly differ across user roles. A comparison between the estimated path coefficients for any two user roles is carried out using a measurement developed by Kock (2014). It is noted that “the main goal of this analysis is the comparison of pairs of path coefficients for identical models but based on different samples” (p. 4).

Firstly, WarpPLS 6.0 calculates a pooled standard using equation shown in Figure 35 (Keil et al., 2000). N_1 and N_2 refer to the sample size of the first group and the sample size of the second group, respectively. Also, S_1 is the standard error of the path coefficient of the first group and S_2 is the standard error of the path coefficient of the second group.

$$S_{12} = \left(\sqrt{\frac{(N_1-1)^2}{(N_1+N_2-2)} \cdot {S_1}^2 + \frac{(N_2-1)^2}{(N_1+N_2-2)} \cdot {S_2}^2}\right) \cdot \left(\sqrt{\frac{1}{N_1} + \frac{1}{N_2}}\right)$$

Figure 35. Pooled standard calculation

Source: [Kock, 2014]

Secondly, it calculates critical ratios as $T_{12}= (\beta_1- \beta_2)/S_{12}$ (Kock, 2014). β_1 and β_2 are path coefficients of group one and group two, respectively. Lastly, T_{12} is used to calculate p values related to the difference between the path coefficients. After that, a multi-group analysis is conducted. Table 43 includes the pairwise comparisons across user roles and T values. The results indicate there are significant differences in all path coefficients except between PEOU and UI, PEOU and PU, and PCM and PEOU. It results as that only H11, H14, H15, H16, H17, H18, H20 are supported because of significant group differences.

Table 43. Multi-Group Analysis

		Pairwise Comparisons (T Values)					
Hypotheses	Result	Visitors/ Socializers	Visitors/ Content Generators	Visitors/ Passive Members	Socializers/ Content Generators	Socializers/ Passive Members	Content Generators/ Passive Members
H11: PU -> UI	Supported	-1.6869*	-5.5692	-0.2667	1.0756	1.2001	0.2205
H12: PEOU -> UI	Not Supported	0.2032	-0.2099	0.3130	-0.3587	0.1008	0.4541
H13: PEOU -> PU	Not Supported	-0.8597	-0.0221	0.8509	0.7624	1.4545	0.7925
H14: PP -> UI	Supported	-0.4282	-3.6818***	-2.1549*	-2.7224**	-1.5206	1.0428
H15: PP -> PU	Supported	-2.0469*	-2.8571**	-4.7093***	-0.5290	-2.3935**	-2.0053*
H16: PEOU -> PP	Supported	-1.7977*	-2.6583**	-2.6437**	-0.5937	-0.7973	-0.2633
H17: PCM -> UI	Supported	1.8270*	3.9220**	-0.3394	1.6025	-1.8316*	-3.5107**
H18: PCM -> PU	Supported	-0.7495	-0.9519	1.6897*	-0.1195	2.1228	2.3482**
H19: PCM -> PEOU	Not Supported	-0.6581	0.1124	-0.5140	0.0196	0.1064	-0.5611
H20: TW -> UI	Supported	0.2961	2.6096**	1.6881*	1.8922*	1.2027	-0.5796

***p<=0.001; **p<=0.01; *p<=0.05

CHAPTER 8

CONCLUSION

This study embeds members' contribution behaviors and structural patterns from the structural role theory perspective along with social network analysis (SNA), and it embraces TAM to find impacts of several factors on members' usage intentions in the context of online communities. In this sense, this study shows how different theories and methods can be integrated. It also presents that the mixture of theories and methods improves the trustworthiness and reliability of the data (Fullerton, Linster, McKee, & Slate, 1991).

In parallel, this study presents a four-phase methodology. In this first phase, the network structures of the follower-following and the topic-member networks are investigated. After that, sub-communities in the topic-member network are detected, and so, user roles are identified by considering both the members' contribution behaviors and sub-community detection results in the third phase. In the last phase, a research model is proposed to test members' online community usage intentions and the moderating effects of user roles on usage intentions. Finally, this chapter introduces a discussion from the theoretical and managerial standpoints.

8.1 Conclusion from the theoretical perspective

The network structures of the follower-following network and the topic-member network shows that members of the follower-following network are farther from each other than the members of the topic-member network. These results indicate that there is a high sparsity and reduced communication among community members of the follower-following network. Furthermore, both networks show the characteristics of power-law and scale-free networks concerning the degree distributions and power-law test statistics. In parallel with the indication that online social networks show power-law degree distribution like offline networks (Mislove, 2009), it can be concluded that online communities also show a similar structure like online social networks. Also, although the follower-following network does not have the characteristics of small-world networks, the topic-member having a small diameter and a high clustering coefficient is considered as a small-world network. It indicates that information can travel more quickly within the topic-member network than the information in the follower-following network (Hanneman & Riddle, 2005).

Additionally, although the topic-member network is a fully connected network, the follower-following network can be decomposed into components. The giant component in the follower-following network comprises almost all nodes, and the strongly connected component includes 19.02% of nodes of the network. The members in the strongly connected component form a well-connected group, and they keep the remainder of the network connected.

In addition to these findings, vital members are determined from different centrality perspectives involving degree, closeness, betweenness, and eigenvector. In the follower-following network, it is obvious that the community admin has the most followers. It indicates that he has control over the network, the network is highly dependent on him (Loosemore, 1998), and he or she receives more information, knowledge, and resources (Li, Liao, & Yen, 2013). Additionally, he has the highest eigenvector centrality and high betweenness centrality. It shows that he or she is the most valuable member who is connected to many other members that are also well-connected (Abbasi et al. 2011). He or she has the highest reputation and considerable influence in the network (Lin, 2002), and he or she plays the role of gatekeeper and acts as bridging the gap between other members (Freeman, 1979; Hanneman & Riddle, 2005). In the topic-member network, it is evident that there is also one member having the highest degree, betweenness, and eigenvector centralities. He or she also has the second closeness centrality. It indicates that he or she is one of the critical members and he or she can reach to other community members and can be reached by other community members at shorter path lengths, and he or she obtains the information efficiently and sooner (Freeman 1979; Hanneman & Riddle, 2005).

Community members also form different types of user roles in such communities. The topic-member network mainly consists of socializers, entry generators, visitors, and passive members, respectively. Socializers flame the contribution and keep the discussion in the community by opening new topics. Entry generators, who are the youngest, prefer submitting entries to opening topics. It indicates that socializers and entry generators are responsible for the flow of information through the topic-member network. On the other hand, visitors visit the website more frequently than entry generators, but they open few topics and add few contents. Additionally, passive members who are the oldest members of the community take up the small part of the whole community, and they make very few contributions to the community.

The result shows that the topic-member network does not include high percentage of passive users who are not actively contributing or communicating in contrast to previous studies (Clauset et al., 2004; Kozinets, 1999; Nolker & Zhou; 2005; Nonnecke & Preece, 2000; Toral et al., 2009; Ye & Kishida; 2003). It can be inferred that this kind of inactive members can be commonly found in online communities rather than in the context of discussion forums.

This study also analyzes the effects of the determinants on online community members' usage intention. Consistent with prior studies, the findings of the study confirm that perceived playfulness (PP), perceived critical mass (PCM), perceived usefulness (PU), perceived playfulness (PP), and trustworthiness (TW) except perceived ease of use (PEOU) generally act as influential determinants on usage intention (UI) in the context of online communities (Lee, Tyrrell, & Erdem, 2013; Lim, 2014; Lou et al., 2000; Rauniar et al., 2014; Sledgianowski & Kulviwat, 2009; Qin et al., 2011; Van Slyke et al., 2007).

Although it is stated that social networks such as Facebook, Twitter, and Instagram are primarily used for hedonic purposes such as chatting, making friends, exchanging ideas, and sharing knowledge rather than utilitarian purposes (Sledgianowski & Kulviwat, 2009; Lin & Lee, 2006), playfulness has found as a weak indicator in the study. This result may strengthen the differences between online communities and social networks and show that members have utilitarian purposes in online communities.

Additionally, the results point out that PCM has the most substantial effect on UI. It proves that the growth of online communities depends on how many members prefer to use it. PP, PCM, and PEOU have also an impact on the PU consistent with the previous studies (Davis, 1989; Rauniar et al., 2014). It can be inferred that online community sites do not require complex skills, therefore, when users perceive it is easy to learn, they tend to explore features and functions. This situation can result in the improvement of PU (Lee et al., 2014), and they find the online communities more useful if more users engage in it and feel that it is a playful platform (Rauniar et al., 2014).

Moreover, online communities are based on the commitment of their members (Ren et al., 2007 as cited in Iskoujina, Ciesielska, Roberts, & Li, 2017), and their behaviors can vary across different user roles. Additionally, each role or each user type perceives online community usage intention in a different way. In this sense, this study also examines the moderating effect of user roles. For this purpose, unlike previous studies (Yeh et al., 2011), this study does not adopt user roles from previous studies in the similar context, it identifies user roles by conducting SNA and considering members' contribution behaviors. After that, this study integrates these identified user roles to the research model to find usage patterns of different community members and shows how community members differ from each other regarding their usage intentions.

The results show that PCM is more important for visitors and especially for passive members. It can be expected that visitors and passive members hesitate to engage in the community if they are not convinced that more users prefer to use online communities. If they perceive that their friends or other social relations engage in online communities, they more tend to be a member of this system.

Additionally, TW is one of the key factors for visitors and socializers to increase their usage intentions. In this sense, these types of users want to stay in a secure environment and feel that all their information is protected and is not open to any third-parties. It can be crucial to keep socializers continually satisfied and to increase visitors' interactions with the community.

On the other hand, PP is an essential criterion for passive members and especially entry generators. Entry generators are the backbone of the community, and their main reason to create such a huge content can be seeking for playfulness. Additionally, lack of playfulness can be a reason for passive members why they do not prefer to add contents to the community. Also, for socializers and content generators PU is also important. They generate the most content in the community, so they can need more useful functions as expected.

Moreover, visitors, socializers, and entry generators mostly perceive the online communities as useful and easy to use platforms, if more users engage in the community. On the other hand, passive members seek for playfulness, and then they perceive the community as more useful than other members do. The study results also indicate that user roles have a significant moderating effect on PU and UI, PP and UI, TW and UI, PCM and UI, PP and PU, PCM and PU, and PEOU and PP.

8.2 Conclusion from the managerial perspective

One of the main challenges to increase social participation and motivate members of online communities is understanding how to design these social systems (Chi, Munson, Fischer, Vieweg, & Parr, 2010). In this sense, this study presents some managerial strategies and actions to be taken by practitioners to motivate each type of users. For example; they can want to turn visitors and passive members into socializers or entry generators. In this manner, they should pay attention to PCM at first sight. These types of users must see that many users are members of this community. For example; practitioners can encourage word-of-mouth communication among both early and later adopters and make the early adopters more visible to the majority (Lim, 2014), and they can add functionalities like sharing buttons or like buttons or follow buttons to increase the critical mass. Additionally, they can clearly prove the value that the community offers while also showing the value that other members get from it. For example; they can allow members to reward or thank members that produce excessive content (Geddes, 2011). The critical point is that practitioners must be aware of that if the number of passive members increases, nobody prefers to be part of a silent community (Füller et al., 2014). Practitioners can also give incentives to both passive members and visitors to involve in a content generation (Pfeil et al., 2011). In this sense, these types of members can gain status in the community, and they feel that they are essential for the community.

For visitors, trust is also another vital concern and practitioners must make them comfortable while posting any content and messaging with other members. To lower their security concerns, for example; practitioners can show that private messages of the members are secured with end-to-end encryption and third parties even the community administrators cannot read or listen these messages. Practitioners can also protect the personal information of their community members from third parties' access and publish a privacy policy and terms of use to assure of security. Additionally, practitioners can provide their contact information; they can prepare a list of frequently asked questions with clear and understandable answers to give confidence to their members (Preece & Shneiderman, 2009). Lastly, for passive members, practitioners cannot miss out the importance of playfulness. They should certify that the community features promote passive members' playfulness and they enjoy these services (Sledgianowski & Kulviwat, 2009). For example; practitioners can develop online interactive games, online contests, or features allowing them to design their avatars (Yeh et al., 2011).

Practitioners should be aware of that socializers, and entry generators are core members of the community. These members' experiences play a crucial role to attract the attention of passive members, visitors, or potential members. In this sense, providing special community features or functions allow them to engage in and interact with the community (Füller et al., 2014). Socializers and entry generators mostly pay attention to the usefulness. For example; practitioners can increase members' performance and effectiveness by providing sociable functions such as instant messaging to contact to others and develop healthier relationships (Qin et al., 2011; Yeh et al., 2011).

Additionally, the platform should be reliable, convenient, and the response time should be low. Furthermore, the recognition of these types of users is important for their motivation (Preece & Shneiderman, 2009). For example; a list of members' usernames who make the most contribution to the community can be published. However, practitioners should not only consider the quantity of the contents but also, they concern for the quality of the contents (Palmer, 2002). In this sense, a rating system can be useful to recognize and evaluate members' contribution. An increase in the quality of contents can also lead to an increase in returns of visitor and passive members (Preece & Shneiderman, 2009).

Although PEOU has not a direct impact on the UI, it indirectly affects it. In this sense, it is vital to present user-friendly or easy-to-use interfaces, easy-to-navigate web layouts, clear and understandable sitemaps, search functionalities to promote interactions and contributions of online members in the community (Yeh et al., 2011). Table 44 also summarizes the user roles and motivational suggestions for each of them.

Table 44. Summary of User Roles and Suggestions

User Role	Contribution Behavior	Usage Intention*	Suggestion*
Visitors	• usually visit • fewer open topics than entry generators and socializers • fewer generate contents than entry generators and socializers	• PCM • TW • PU	• encourage word-of-mouth. • prove the value that the community offers. • provide a secure environment. • provide unique community features or functions to increase topic opening and content adding.
Socializers	• mostly visit • generates the most amount of content • mostly open topics and start the interaction	• PU • TW	• provide unique community features or functions to increase the development of more relationships. • provide a secure environment, so make them comfortable while posting, communicating, or messaging.
Entry Generators	• often visit • fewer open topics than socializers • generates a tremendous amount of content	• PP • PU	• develop online interactive games, online contests, or entertaining services. • provide unique community features or functions to encourage them to open more topics and add contents.
Passive Members	• seldom visit • do not any open topics • the fewest content generation	• PCM • PP • PU	• encourage word-of-mouth. • develop playful activities or festivals to promote them to develop more relationships. • provide interactive games and other playful activities. • provide special community features or functions to encourage them to open topics and contents.

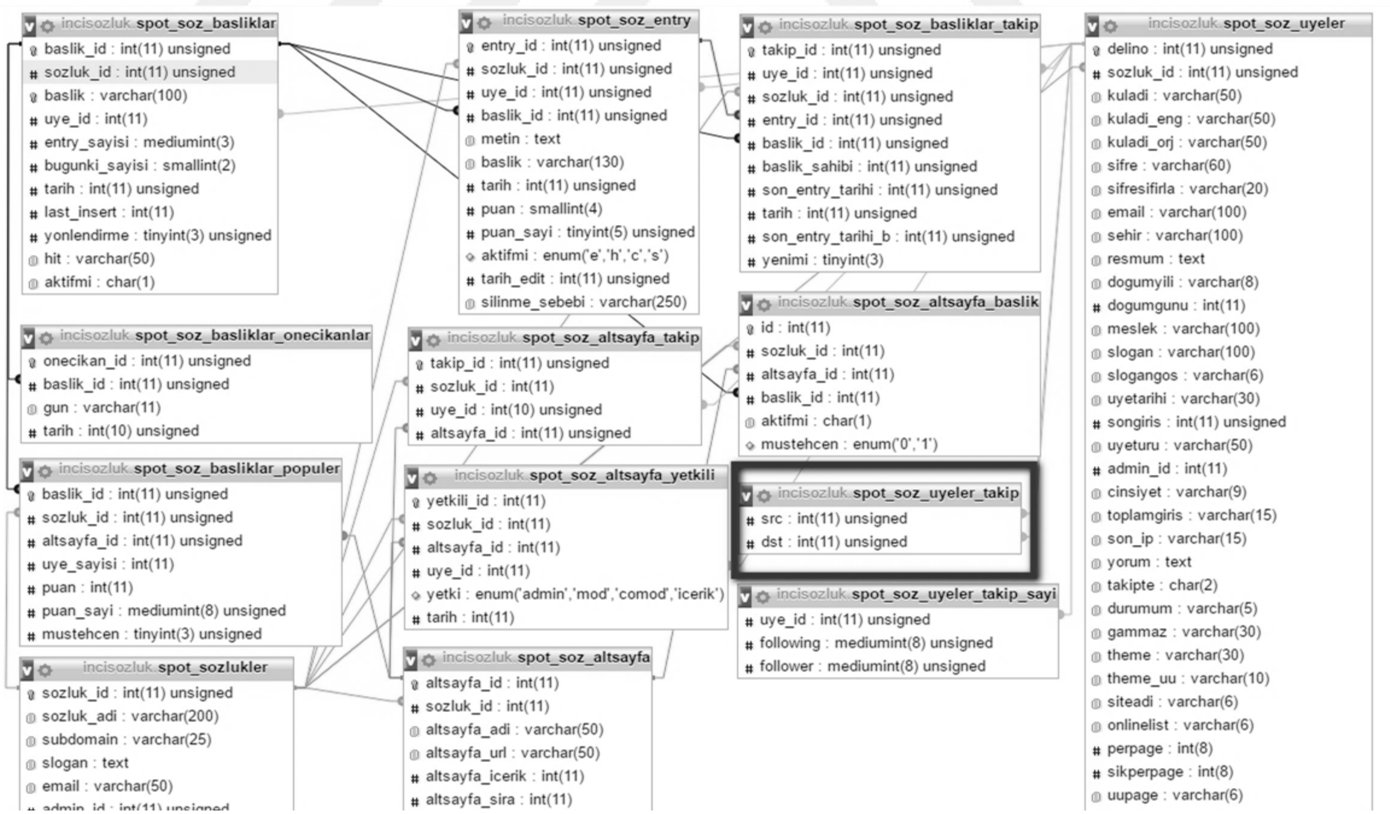
*In the order of importance

8.3 Limitations and future studies

In the scope of the study, some limitations need to be addressed. This study analyzes a Turkish online community, so targeting different samples from different countries can reveal the cultural differences by testing the proposed model. Additionally, this study focuses on an online community serving as a discussion forum, so online communities in different contexts can also be analyzed. This study also identifies four user roles by applying SNA and considering members' contribution behavior; then members are asked to identify themselves across these roles through a questionnaire. However, some members can play multiple roles in the online community, and their roles can change over time. Lastly, further research can analyze the effects of other dimensions by expanding the proposed research model in different contexts.

APPENDIX A

DATABASE STRUCTURE



APPENDIX B

QUESTIONNAIRE

1. Are you a member of Inci Sozluk?

- Yes
- No

2. Gender:

- Female
- Male

3. Age:

- 18 and younger
- 19-25
- 26-32
- 33-38
- 39 and older

4. Educational Status

- Primary/secondary school graduate
- High school student
- High school graduate
- University student
- University graduate
- Graduate / Ph.D. student
- Graduate / Ph.D. Degree

5. Income status:

- 0-2000 TL
- 2001-3000 TL
- 3001-5000 TL
- 5001 TL and more

6. How of the do you visit Inci Sozluk daily?

- Never
- Seldom
- Often
- Usually
- Always

7. How many hours do you spend in Inci Sozluk in a day?

- 0-2
- 3-5
- 6-8
- 9-11
- Greater than 11

8. If you think about your profile and behaviors in Inci Sozluk, which of the following roles do you consider as close to you?

- Socializer: I think that I become mostly online in Inci Sozluk. I open lots of topics and add entries and mostly communicate with other members.
- Entry Generator: I usually visit Inci Sozluk. Although I do not prefer open topics, I usually check for opened topics and add lots of entries while I am online.

- Visitor: Although I often visit Inci Sozluk, I do not prefer open topics and add entries. I prefer to check for opened topics and read entries while I am online.
- Passive Member: I seldom visit Inci Sozluk and I do not prefer open any topics. I only add a few entries while I am online.

9. Please answer the following expressions taking into consideration your behaviors in Inci Sozluk (SD: Strongly Disagree – SA: Strongly Agree):

	SD (1)	(2)	(3)	(4)	(5)	(6)	SA (7)
PEOU							
Learning the use Inci Sozluk is easy for me.							
My interaction with Inci Sozluk is clear and understandable.							
I believe that it is easy to get Inci Sozluk to do what I want it to do (e.g. sending messages)							
PU	SD (1)	(2)	(3)	(4)	(5)	(6)	SA (7)
I find Inci Sozluk useful in my personal life.							
Using Inci Sozluk enables me to get re-connected with people that matter to me.							
Using Inci Sozluk enhances my effectiveness to stay in touch with others.							
Inci Sozluk is useful for information accessing/sharing.							
PCM	SD (1)	(2)	(3)	(4)	(5)	(6)	SA (7)
Inci Sozluk is one of the popular social media platform among my friends.							

The most of my friends use Inci Sozluk.							
Using Inci Sozluk makes me grant privilege among my friends.							
There is a sense of human warmth in Inci Sozluk.							
PP	SD (1)	(2)	(3)	(4)	(5)	(6)	SA (7)
I make fun while using Inci Sozluk.							
Using Inci Sozluk is enjoyable.							
I found my visit to Inci Sozluk pleasant.							
TW	SD (1)	(2)	(3)	(4)	(5)	(6)	SA (7)
I feel safe while sharing on Inci Sozluk.							
Inci Sozluk provides required security settings for my profile.							
I feel safe while using Inci Sozluk.							
I feel safe while messaging with other members in Inci Sozluk.							
UI	SD (1)	(2)	(3)	(4)	(5)	(6)	SA (7)
I believe it is worthwhile for me to use Inci Sozluk.							
Based on my experiences, I will continue to use Inci Sozluk.							
I suggest my friends to use Inci Sozluk.							

APPENDIX C

FREQUENCY OF DEGREE

Table C1. In-Degree Frequency Distribution of the Follower-Following Network

In-Degree	Frequency	Percentage
1	14417	42.308%
0	9733	28.563%
2	3778	11.087%
3	2039	5.984%
4	1010	2.964%
5	622	1.825%
6	420	1.233%
7	303	0.889%
8	291	0.854%
9	187	0.549%
10	133	0.390%
11	132	0.387%
12	109	0.320%
13	84	0.247%
14	76	0.223%
15	70	0.205%
16	50	0.147%
17	46	0.135%
18	44	0.129%
19	40	0.117%
20	33	0.097%
23	31	0.091%
21	29	0.085%
30	20	0.059%
29	19	0.056%
35	19	0.056%
22	17	0.050%
26	17	0.050%
24	16	0.047%
27	16	0.047%
33	16	0.047%
25	14	0.041%
31	14	0.041%

37	9	0.026%
43	9	0.026%
34	8	0.023%
28	7	0.021%
44	7	0.021%
39	6	0.018%
41	6	0.018%
45	6	0.018%
52	6	0.018%
66	6	0.018%
38	5	0.015%
42	5	0.015%
54	5	0.015%
55	5	0.015%
32	4	0.012%
40	4	0.012%
46	4	0.012%
64	4	0.012%
67	4	0.012%
145	4	0.012%
47	3	0.009%
48	3	0.009%
50	3	0.009%
51	3	0.009%
56	3	0.009%
57	3	0.009%
58	3	0.009%
60	3	0.009%
70	3	0.009%
77	3	0.009%
81	3	0.009%
49	2	0.006%
53	2	0.006%
59	2	0.006%
63	2	0.006%
71	2	0.006%
72	2	0.006%
73	2	0.006%
74	2	0.006%
80	2	0.006%
83	2	0.006%

97	2	0.006%
98	2	0.006%
112	2	0.006%
120	2	0.006%
264	2	0.006%
36	1	0.003%
61	1	0.003%
62	1	0.003%
68	1	0.003%
75	1	0.003%
76	1	0.003%
82	1	0.003%
84	1	0.003%
85	1	0.003%
87	1	0.003%
93	1	0.003%
94	1	0.003%
95	1	0.003%
100	1	0.003%
102	1	0.003%
103	1	0.003%
104	1	0.003%
106	1	0.003%
108	1	0.003%
111	1	0.003%
114	1	0.003%
117	1	0.003%
119	1	0.003%
128	1	0.003%
132	1	0.003%
137	1	0.003%
138	1	0.003%
140	1	0.003%
150	1	0.003%
152	1	0.003%
155	1	0.003%
163	1	0.003%
165	1	0.003%
167	1	0.003%
190	1	0.003%
194	1	0.003%

205	1	0.003%
208	1	0.003%
222	1	0.003%
258	1	0.003%
274	1	0.003%
280	1	0.003%
283	1	0.003%
293	1	0.003%
340	1	0.003%
354	1	0.003%
361	1	0.003%
391	1	0.003%
395	1	0.003%
483	1	0.003%
563	1	0.003%
580	1	0.003%
673	1	0.003%
2149	1	0.003%
Total	34.076	100%

Table C2. Out-Degree Frequency Distribution of the Follower-Following Network

Out- Degree	Frequency	Percentage
0	15122	44.377%
1	11001	32.284%
2	3142	9.221%
3	1442	4.232%
4	810	2.377%
5	543	1.593%
6	393	1.153%
7	265	0.778%
8	189	0.555%
9	153	0.449%
10	146	0.428%
11	111	0.326%
13	91	0.267%
12	72	0.211%
14	64	0.188%
15	49	0.144%
17	40	0.117%
16	36	0.106%

20	35	0.103%
19	24	0.070%
23	24	0.070%
18	23	0.067%
24	23	0.067%
21	21	0.062%
22	21	0.062%
26	18	0.053%
30	15	0.044%
27	12	0.035%
29	12	0.035%
28	10	0.029%
25	9	0.026%
31	9	0.026%
32	9	0.026%
34	5	0.015%
36	5	0.015%
45	5	0.015%
46	5	0.015%
48	5	0.015%
41	4	0.012%
50	4	0.012%
52	4	0.012%
33	3	0.009%
35	3	0.009%
37	3	0.009%
39	3	0.009%
40	3	0.009%
43	3	0.009%
49	3	0.009%
55	3	0.009%
38	2	0.006%
42	2	0.006%
56	2	0.006%
58	2	0.006%
66	2	0.006%
74	2	0.006%
89	2	0.006%
99	2	0.006%
123	2	0.006%
47	1	0.003%

51	1	0.003%
53	1	0.003%
54	1	0.003%
59	1	0.003%
61	1	0.003%
62	1	0.003%
64	1	0.003%
65	1	0.003%
67	1	0.003%
68	1	0.003%
69	1	0.003%
72	1	0.003%
80	1	0.003%
81	1	0.003%
82	1	0.003%
84	1	0.003%
87	1	0.003%
91	1	0.003%
93	1	0.003%
94	1	0.003%
96	1	0.003%
97	1	0.003%
105	1	0.003%
107	1	0.003%
109	1	0.003%
115	1	0.003%
120	1	0.003%
126	1	0.003%
130	1	0.003%
141	1	0.003%
151	1	0.003%
170	1	0.003%
174	1	0.003%
175	1	0.003%
181	1	0.003%
191	1	0.003%
199	1	0.003%
203	1	0.003%
209	1	0.003%
240	1	0.003%
242	1	0.003%

251	1	0.003%
255	1	0.003%
259	1	0.003%
262	1	0.003%
287	1	0.003%
320	1	0.003%
371	1	0.003%
389	1	0.003%
421	1	0.003%
435	1	0.003%
507	1	0.003%
509	1	0.003%
549	1	0.003%
619	1	0.003%
976	1	0.003%
1014	1	0.003%
1143	1	0.003%
1163	1	0.003%
1459	1	0.003%
5159	1	0.003%
10110	1	0.003%
Total	34076	100%

Table C3. Degree Frequency Distribution of the Topic-Member Network

Degree	Frequency	Percentage
1533	210	0.731%
9	143	0.498%
1832	139	0.484%
11	124	0.432%
8	114	0.397%
10	112	0.390%
1592	108	0.376%
7	105	0.366%
13	101	0.352%
1519	95	0.331%
1232	86	0.299%
6	84	0.293%
12	84	0.293%
757	83	0.289%
1209	81	0.282%

690	79	0.275%
504	75	0.261%
14	74	0.258%
29	71	0.247%
18	69	0.240%
161	68	0.237%
260	68	0.237%
16	67	0.233%
232	66	0.230%
15	64	0.223%
5	62	0.216%
70	62	0.216%
566	62	0.216%
952	62	0.216%
19	61	0.212%
21	61	0.212%
30	61	0.212%
1210	60	0.209%
25	57	0.199%
26	57	0.199%
22	56	0.195%
37	55	0.192%
62	55	0.192%
27	54	0.188%
32	54	0.188%
729	54	0.188%
1096	54	0.188%
1192	54	0.188%
20	52	0.181%
50	51	0.178%
373	51	0.178%
573	51	0.178%
17	50	0.174%
81	50	0.174%
94	50	0.174%
212	50	0.174%
264	50	0.174%
49	48	0.167%
175	48	0.167%
281	48	0.167%
1009	48	0.167%

95	47	0.164%
447	47	0.164%
34	46	0.160%
42	46	0.160%
85	46	0.160%
446	46	0.160%
23	45	0.157%
38	45	0.157%
41	45	0.157%
43	45	0.157%
45	45	0.157%
63	45	0.157%
79	45	0.157%
249	45	0.157%
451	45	0.157%
60	44	0.153%
178	44	0.153%
28	43	0.150%
47	43	0.150%
91	43	0.150%
215	43	0.150%
422	43	0.150%
429	43	0.150%
24	42	0.146%
59	42	0.146%
64	42	0.146%
67	42	0.146%
83	42	0.146%
390	42	0.146%
983	42	0.146%
36	41	0.143%
48	41	0.143%
53	41	0.143%
326	41	0.143%
673	41	0.143%
3	40	0.139%
97	40	0.139%
123	40	0.139%
529	40	0.139%
35	39	0.136%
56	39	0.136%

121	39	0.136%
570	39	0.136%
599	39	0.136%
692	39	0.136%
1026	39	0.136%
147	38	0.132%
160	38	0.132%
247	38	0.132%
333	38	0.132%
437	38	0.132%
536	38	0.132%
31	37	0.129%
33	37	0.129%
71	37	0.129%
74	37	0.129%
98	37	0.129%
203	37	0.129%
4	36	0.125%
46	36	0.125%
58	36	0.125%
61	36	0.125%
231	36	0.125%
335	36	0.125%
343	36	0.125%
731	36	0.125%
66	35	0.122%
69	35	0.122%
138	35	0.122%
156	35	0.122%
158	35	0.122%
188	35	0.122%
323	35	0.122%
109	34	0.118%
146	34	0.118%
65	33	0.115%
77	33	0.115%
78	33	0.115%
84	33	0.115%
90	33	0.115%
129	33	0.115%
132	33	0.115%

220	33	0.115%
377	33	0.115%
459	33	0.115%
559	33	0.115%
44	32	0.111%
68	32	0.111%
82	32	0.111%
126	32	0.111%
131	32	0.111%
167	32	0.111%
196	32	0.111%
218	32	0.111%
223	32	0.111%
354	32	0.111%
666	32	0.111%
52	31	0.108%
54	31	0.108%
55	31	0.108%
75	31	0.108%
102	31	0.108%
122	31	0.108%
148	31	0.108%
149	31	0.108%
152	31	0.108%
177	31	0.108%
185	31	0.108%
206	31	0.108%
351	31	0.108%
480	31	0.108%
653	31	0.108%
…	>30	70.747%

APPENDIX D

FREQUENCY OF CLOSENESS CENTRALITY

Table D1. In-Closeness Frequency of the Follower-Following Network

In-Closeness	Frequency	Percentage
0.0000293462	9733	28.56%
0.0000455910	3772	11.07%
0.0000293470	2146	6.30%
0.0000455910	1654	4.85%
0.0000455911	487	1.43%
0.0000455908	400	1.17%
0.0000455911	374	1.10%
0.0000455910	297	0.87%
0.0000455889	258	0.76%
0.0000455889	209	0.61%
0.0000293479	190	0.56%
0.0000293479	184	0.54%
0.0000455903	174	0.51%
0.0000455906	159	0.47%
0.0000455889	155	0.45%
0.0000455931	125	0.37%
0.0000455908	115	0.34%
0.0000455903	115	0.34%
0.0000455899	110	0.32%
0.0000455910	108	0.32%
0.0000455896	104	0.31%
0.0000455906	82	0.24%
0.0000455923	78	0.23%
0.0000455905	77	0.23%
0.0000455907	69	0.20%
0.0000455889	68	0.20%
0.0000455889	67	0.20%
0.0000455897	66	0.19%
0.0000455889	62	0.18%
0.0000455905	55	0.16%
0.0000455899	53	0.16%
0.0000455908	52	0.15%
0.0000455902	46	0.13%

0.0000293488	44	0.13%
0.0000455889	43	0.13%
0.0000293488	41	0.12%
0.0000455910	40	0.12%
0.0000455910	39	0.11%
0.0000455889	39	0.11%
0.0000455910	38	0.11%
0.0000455910	38	0.11%
0.0000455889	38	0.11%
0.0000455910	37	0.11%
0.0000455910	37	0.11%
0.0000455903	37	0.11%
0.0000455900	37	0.11%
0.0000455889	37	0.11%
0.0000455903	36	0.11%
0.0000455905	35	0.10%
0.0000455889	35	0.10%
0.0000455888	35	0.10%
0.0000455909	33	0.10%
0.0000455903	33	0.10%
0.0000455902	33	0.10%
0.0000455907	32	0.09%
0.0000293488	32	0.09%
0.0000455910	31	0.09%
0.0000455890	31	0.09%
0.0000455911	29	0.09%
0.0000455889	28	0.08%
0.0000455931	27	0.08%
0.0000455890	27	0.08%
0.0000455910	25	0.07%
0.0000455889	25	0.07%
0.0000455929	24	0.07%
0.0000455911	24	0.07%
0.0000455911	24	0.07%
0.0000455910	24	0.07%
0.0000455889	24	0.07%
0.0000455910	23	0.07%
0.0000455910	22	0.06%
0.0000455890	22	0.06%
0.0000455907	21	0.06%
0.0000455889	21	0.06%

0.0000455889	21	0.06%
0.0000455905	20	0.06%
0.0000455888	20	0.06%
0.0000455911	19	0.06%
0.0000455905	19	0.06%
0.0000455902	19	0.06%
0.0000455901	19	0.06%
0.0000455890	19	0.06%
0.0000455932	18	0.05%
0.0000455910	18	0.05%
0.0000455908	18	0.05%
0.0000455890	18	0.05%
0.0000455887	18	0.05%
0.0000293496	18	0.05%
0.0000455932	17	0.05%
0.0000455910	17	0.05%
0.0000455910	17	0.05%
0.0000455902	17	0.05%
0.0000293488	17	0.05%
0.0000455911	16	0.05%
0.0000455910	16	0.05%
0.0000455910	16	0.05%
0.0000455910	16	0.05%
0.0000455904	16	0.05%
0.0000455903	16	0.05%
0.0000455899	16	0.05%
0.0000293496	16	0.05%
0.0000455922	15	0.04%
0.0000455910	15	0.04%
0.0000455892	15	0.04%
0.0000455888	15	0.04%
0.0000455882	15	0.04%
0.0000455931	14	0.04%
0.0000455911	14	0.04%
0.0000455890	14	0.04%
0.0000455890	14	0.04%
0.0000455890	14	0.04%
0.0000455910	13	0.04%
0.0000455902	13	0.04%
0.0000455899	13	0.04%
0.0000455889	13	0.04%

0.0000455887	13	0.04%
0.0000455951	12	0.04%
0.0000455911	12	0.04%
0.0000455909	12	0.04%
0.0000455906	12	0.04%
0.0000455904	12	0.04%
0.0000455891	12	0.04%
0.0000455891	12	0.04%
0.0000455889	12	0.04%
0.0000455889	12	0.04%
0.0000455882	12	0.04%
0.0000455911	11	0.03%
0.0000455911	11	0.03%
0.0000455911	11	0.03%
0.0000455910	11	0.03%
0.0000455910	11	0.03%
0.0000455903	11	0.03%
0.0000455902	11	0.03%
0.0000455889	11	0.03%
0.0000455889	11	0.03%
0.0000455889	11	0.03%
0.0000455882	11	0.03%
0.0000455925	10	0.03%
0.0000455911	10	0.03%
0.0000455911	10	0.03%
0.0000455910	10	0.03%
0.0000455910	10	0.03%
0.0000455904	10	0.03%
0.0000455902	10	0.03%
0.0000455898	10	0.03%
0.0000455890	10	0.03%
0.0000455889	10	0.03%
0.0000455889	10	0.03%
0.0000455889	10	0.03%
0.0000455888	10	0.03%
0.0000455882	10	0.03%
0.0000455882	10	0.03%
…	<10	29.50%

Table D2. Out-Closeness Frequency of the Follower-Following Network

Out-Closeness	Frequency	Percentage
0.0000293462	15122	44.38%
0.0000293470	5044	14.80%
0.0000293479	631	1.85%
0.0000800702	507	1.49%
0.0000293479	409	1.20%
0.0000293488	154	0.45%
0.0000800638	151	0.44%
0.0000293488	111	0.33%
0.0000800700	111	0.33%
0.0000800661	110	0.32%
0.0000293488	91	0.27%
0.0000800661	61	0.18%
0.0000800665	51	0.15%
0.0000800687	50	0.15%
0.0000800725	48	0.14%
0.0000800583	47	0.14%
0.0000800700	46	0.13%
0.0000800702	45	0.13%
0.0000800662	44	0.13%
0.0000800623	40	0.12%
0.0000800635	39	0.11%
0.0000800698	39	0.11%
0.0000293496	37	0.11%
0.0000800700	36	0.11%
0.0000800661	35	0.10%
0.0000293488	34	0.10%
0.0000800675	33	0.10%
0.0000800702	33	0.10%
0.0000800638	31	0.09%
0.0000800662	31	0.09%
0.0000800664	31	0.09%
0.0000800766	29	0.09%
0.0000293496	28	0.08%
0.0000800702	28	0.08%
0.0000800725	28	0.08%
0.0000293496	25	0.07%
0.0000293496	25	0.07%
0.0000800597	24	0.07%
0.0000800638	24	0.07%

0.0000800638	24	0.07%
0.0000800638	24	0.07%
0.0000800661	24	0.07%
0.0000800669	24	0.07%
0.0000800672	24	0.07%
0.0000800661	23	0.07%
0.0000800700	23	0.07%
0.0000800638	22	0.06%
0.0000800643	21	0.06%
0.0000800661	21	0.06%
0.0000800666	21	0.06%
0.0000800698	21	0.06%
0.0000293505	18	0.05%
0.0000800661	18	0.05%
0.0000800707	18	0.05%
0.0000293505	17	0.05%
0.0000800661	17	0.05%
0.0000800671	16	0.05%
0.0000800702	16	0.05%
0.0000800702	15	0.04%
0.0000800598	14	0.04%
0.0000800638	14	0.04%
0.0000800664	14	0.04%
0.0000800693	14	0.04%
0.0000800693	14	0.04%
0.0000800725	14	0.04%
0.0000293505	13	0.04%
0.0000800519	13	0.04%
0.0000800580	13	0.04%
0.0000800661	13	0.04%
0.0000800683	13	0.04%
0.0000800559	12	0.04%
0.0000800621	12	0.04%
0.0000800637	12	0.04%
0.0000800662	12	0.04%
0.0000800676	12	0.04%
0.0000800684	12	0.04%
0.0000800694	12	0.04%
0.0000293496	11	0.03%
0.0000293496	11	0.03%
0.0000293513	11	0.03%

0.0000800597	11	0.03%
0.0000800597	11	0.03%
0.0000800597	11	0.03%
0.0000800619	11	0.03%
0.0000800638	11	0.03%
0.0000800639	11	0.03%
0.0000800650	11	0.03%
0.0000800655	11	0.03%
0.0000800661	11	0.03%
0.0000800662	11	0.03%
0.0000800687	11	0.03%
0.0000800700	11	0.03%
0.0000293496	10	0.03%
0.0000293505	10	0.03%
0.0000800601	10	0.03%
0.0000800611	10	0.03%
0.0000800621	10	0.03%
0.0000800628	10	0.03%
0.0000800638	10	0.03%
0.0000800638	10	0.03%
0.0000800660	10	0.03%
0.0000800671	10	0.03%
0.0000800684	10	0.03%
0.0000800685	10	0.03%
0.0000800687	10	0.03%
0.0000800690	10	0.03%
0.0000800694	10	0.03%
0.0000800695	10	0.03%
0.0000800700	10	0.03%
0.0000800700	10	0.03%
…	<10	28.25%

Table D3. Closeness Frequency of the Topic-Member Network

Closeness	Frequency	Percentage
0.507448971	208	0.724%
0.510480186	142	0.495%
0.507171118	105	0.366%
0.505101323	95	0.331%
0.503913517	86	0.299%
0.504471266	83	0.289%
0.496258274	79	0.275%
0.494778923	72	0.251%
0.502019337	60	0.209%
0.49973894	56	0.195%
0.505048018	55	0.192%
0.502379453	53	0.185%
0.493410087	51	0.178%
0.474470405	50	0.174%
0.495675741	48	0.167%
0.500767353	46	0.160%
0.48676872	45	0.157%
0.496241121	45	0.157%
0.487454589	44	0.153%
0.489749275	44	0.153%
0.490862779	44	0.153%
0.500636387	42	0.146%
0.491644408	41	0.143%
0.493571232	41	0.143%
0.495162876	41	0.143%
0.486546021	40	0.139%
0.486876017	40	0.139%
0.490217503	40	0.139%
0.491215465	37	0.129%
0.496155375	37	0.129%
0.50119565	37	0.129%
0.49410631	36	0.125%
0.488516111	35	0.122%
0.492386309	35	0.122%
0.475476072	34	0.118%
0.489432058	34	0.118%
0.498506944	34	0.118%
0.492546786	33	0.115%
0.494753347	33	0.115%

0.49524828	33	0.115%
0.494864194	32	0.111%
0.492225936	30	0.104%
0.493079644	30	0.104%
0.486422388	29	0.101%
0.48961566	27	0.094%
0.489824466	27	0.094%
0.490117093	27	0.094%
0.491291106	27	0.094%
0.494821555	27	0.094%
0.479629846	26	0.091%
0.483335578	26	0.091%
0.496335477	26	0.091%
0.489440401	25	0.087%
0.488940351	24	0.084%
0.490091997	24	0.084%
0.49263129	23	0.080%
0.493876849	23	0.080%
0.484060756	22	0.077%
0.490845997	22	0.077%
0.443473157	21	0.073%
0.48820049	21	0.073%
0.484036277	20	0.070%
0.485714769	20	0.070%
0.495427724	20	0.070%
0.497617108	20	0.070%
0.483661232	19	0.066%
0.492192187	19	0.066%
0.492791927	19	0.066%
0.496610169	19	0.066%
0.479541735	18	0.063%
0.479886354	18	0.063%
0.483425089	18	0.063%
0.484346535	18	0.063%
0.489040279	18	0.063%
0.489482118	18	0.063%
0.445212807	17	0.059%
0.452103539	17	0.059%
0.479894374	17	0.059%
0.482442286	17	0.059%
0.482588235	17	0.059%

0.482774854	17	0.059%
0.484518165	17	0.059%
0.486991622	17	0.059%
0.457389531	16	0.056%
0.474540977	16	0.056%
0.483010362	16	0.056%
0.484297521	16	0.056%
0.484853602	16	0.056%
0.486851252	16	0.056%
0.487893565	16	0.056%
0.488291812	16	0.056%
0.517117799	16	0.056%
0.482856038	15	0.052%
0.484199521	15	0.052%
0.484338366	15	0.052%
0.485033784	15	0.052%
0.487537354	15	0.052%
0.488150692	15	0.052%
0.488632496	15	0.052%
0.489473774	15	0.052%
0.489707513	15	0.052%
0.491400407	15	0.052%
0.520124624	15	0.052%
0.444992019	14	0.049%
0.481100462	14	0.049%
0.481245601	14	0.049%
0.483490209	14	0.049%
0.485665477	14	0.049%
0.487446314	14	0.049%
0.487860407	14	0.049%
0.488076014	14	0.049%
0.488965329	14	0.049%
0.490518979	14	0.049%
0.491383589	14	0.049%
0.508644512	14	0.049%
0.432250975	13	0.045%
0.474219653	13	0.045%
0.474776369	13	0.045%
0.475996287	13	0.045%
0.481076281	13	0.045%
0.482945371	13	0.045%

0.484207686	13	0.045%
0.484534517	13	0.045%
0.484796299	13	0.045%
0.48537814	13	0.045%
0.486455351	13	0.045%
0.494940964	13	0.045%
0.512429731	13	0.045%
0.422457297	12	0.042%
0.44214157	12	0.042%
0.444633704	12	0.042%
0.48157652	12	0.042%
0.481907895	12	0.042%
0.48193216	12	0.042%
0.483359987	12	0.042%
0.484968248	12	0.042%
0.486743965	12	0.042%
0.486826489	12	0.042%
0.48755391	12	0.042%
0.489023622	12	0.042%
0.490025087	12	0.042%
0.507646341	12	0.042%
0.467601414	11	0.038%
0.475964726	11	0.038%
0.478670379	11	0.038%
0.479653882	11	0.038%
0.481940248	11	0.038%
0.483205439	11	0.038%
0.484052596	11	0.038%
0.486405909	11	0.038%
0.487330493	11	0.038%
0.487636709	11	0.038%
0.488300116	11	0.038%
0.488549359	11	0.038%
0.490133825	11	0.038%
0.499052783	11	0.038%
0.505804224	11	0.038%
0.511571558	11	0.038%
0.513906289	11	0.038%
0.514578592	11	0.038%
0.42374157	10	0.035%
0.446514376	10	0.035%

0.44780961	10	0.035%
0.451705261	10	0.035%
0.473562688	10	0.035%
0.477008439	10	0.035%
0.477993075	10	0.035%
0.479846257	10	0.035%
0.480995695	10	0.035%
0.481132708	10	0.035%
0.482328832	10	0.035%
0.485575134	10	0.035%
0.486134155	10	0.035%
0.48617531	10	0.035%
0.486760468	10	0.035%
0.487918437	10	0.035%
0.488092607	10	0.035%
0.488341638	10	0.035%
0.489240258	10	0.035%
0.490209134	10	0.035%
0.495299536	10	0.035%
0.496061088	10	0.035%
0.499399969	10	0.035%
0.503957737	10	0.035%
0.50625011	10	0.035%
0.507180076	10	0.035%
0.50756558	10	0.035%
0.509456726	10	0.035%
0.51067084	10	0.035%
0.512091597	10	0.035%
0.512329158	10	0.035%
…	<10	84.416%

APPENDIX E

FREQUENCY OF BETWEENNESS CENTRALITY

Table E1. Betweenness Frequency of the Follower-Following Network

Betweenness	Frequency	Percentage
0.0000000000000	27035	79.337%
0.0000000008613	168	0.493%
0.0000104584425	168	0.493%
0.0000000017225	74	0.217%
0.0000104575812	58	0.170%
0.0000185940307	55	0.161%
0.0000104593037	44	0.129%
0.0000000025838	34	0.100%
0.0000000059046	33	0.097%
0.0000000153532	21	0.062%
0.0000185940307	18	0.053%
0.0000104567199	17	0.050%
0.0000000004306	16	0.047%
0.0000000043064	16	0.047%
0.0000185940307	16	0.047%
0.0000185931694	15	0.044%
0.0000000034451	14	0.041%
0.0000185931694	14	0.041%
0.0000185931694	14	0.041%
0.0000104601650	12	0.035%
0.0000000012919	11	0.032%
0.0000209168849	11	0.032%
0.0000290490280	11	0.032%
0.0000000002871	10	0.029%
0.0000185923081	10	0.029%
0.0000185948919	10	0.029%
…	<10	18.110%

Table E2. Betweenness Frequency of the Topic-Member Network

Betweenness	Frequency	Percentage
0.00000032092	206	0.717%
0.00000069419	131	0.456%
0.00000058865	100	0.348%
0.00000065900	92	0.320%
0.00000055300	81	0.282%
0.00000045149	78	0.272%
0.00000016082	76	0.265%
0.00000012592	70	0.244%
0.00000000000	59	0.205%
0.00000050874	56	0.195%
0.00000038138	55	0.192%
0.00000046161	51	0.178%
0.00000046777	51	0.178%
0.00000001761	50	0.174%
0.00000010788	49	0.171%
0.00000013695	45	0.157%
0.00000005357	44	0.153%
0.00000021441	44	0.153%
0.00000044944	42	0.146%
0.00000006347	41	0.143%
0.00000009606	41	0.143%
0.00000036142	40	0.139%
0.00000007400	38	0.132%
0.00000008268	38	0.132%
0.00000009072	37	0.129%
0.00000017698	36	0.125%
0.00000018419	35	0.122%
0.00000006945	34	0.118%
0.00000018901	34	0.118%
0.00000024368	34	0.118%
0.00000035478	33	0.115%
0.00000017568	31	0.108%
0.00000021466	31	0.108%
0.00000010346	30	0.104%
0.00000024486	30	0.104%
0.00000004577	29	0.101%
0.00000024375	28	0.098%
0.00000005376	27	0.094%
0.00000011589	27	0.094%

0.00000016173	27	0.094%
0.00000006872	26	0.091%
0.00000009715	26	0.091%
0.00000011791	26	0.091%
0.00000012979	26	0.091%
0.00000010881	25	0.087%
0.00000001565	24	0.084%
0.00000004861	24	0.084%
0.00000007271	24	0.084%
0.00000009012	24	0.084%
0.00000014669	23	0.080%
0.00000015060	23	0.080%
0.00000015351	23	0.080%
0.00000026972	22	0.077%
0.00000006010	21	0.073%
0.00000007660	20	0.070%
0.00000014754	20	0.070%
0.00000009378	19	0.066%
0.00000015811	19	0.066%
0.00000027016	19	0.066%
0.00000002605	18	0.063%
0.00000003222	18	0.063%
0.00000000531	17	0.059%
0.00000006346	17	0.059%
0.00000006953	17	0.059%
0.00000000826	16	0.056%
0.00000001110	16	0.056%
0.00000002213	16	0.056%
0.00000002423	16	0.056%
0.00000002908	16	0.056%
0.00000004233	16	0.056%
0.00000004266	16	0.056%
0.00000004549	16	0.056%
0.00000009362	16	0.056%
0.00000009569	16	0.056%
0.00000009638	16	0.056%
0.00000018360	16	0.056%
0.00000002801	15	0.052%
0.00000008649	15	0.052%
0.00000015771	15	0.052%
0.00000000410	14	0.049%

0.00000004212	14	0.049%
0.00000004366	14	0.049%
0.00000005377	14	0.049%
0.00000006115	14	0.049%
0.00000000072	13	0.045%
0.00000001820	13	0.045%
0.00000002822	13	0.045%
0.00000003831	13	0.045%
0.00000003976	13	0.045%
0.00000004037	13	0.045%
0.00000004690	13	0.045%
0.00000005516	13	0.045%
0.00000006119	13	0.045%
0.00000006659	13	0.045%
0.00000008747	13	0.045%
0.00000000423	12	0.042%
0.00000000531	12	0.042%
0.00000000879	12	0.042%
0.00000001230	12	0.042%
0.00000001385	12	0.042%
0.00000001463	12	0.042%
0.00000002296	12	0.042%
0.00000002488	12	0.042%
0.00000002570	12	0.042%
0.00000003331	12	0.042%
0.00000003395	12	0.042%
0.00000003585	12	0.042%
0.00000003848	12	0.042%
0.00000004415	12	0.042%
0.00000004858	12	0.042%
0.00000006309	12	0.042%
0.00000006505	12	0.042%
0.00000006810	12	0.042%
0.00000010018	12	0.042%
0.00000000387	11	0.038%
0.00000000652	11	0.038%
0.00000001881	11	0.038%
0.00000002458	11	0.038%
0.00000002544	11	0.038%
0.00000002964	11	0.038%
0.00000003049	11	0.038%

0.00000003374	11	0.038%
0.00000003731	11	0.038%
0.00000004296	11	0.038%
0.00000004355	11	0.038%
0.00000004956	11	0.038%
0.00000006665	11	0.038%
0.00000007323	11	0.038%
0.00000007583	11	0.038%
0.00000007765	11	0.038%
0.00000008177	11	0.038%
0.00000011299	11	0.038%
0.00000012359	11	0.038%
0.00000016134	11	0.038%
0.00000914803	11	0.038%
0.00000000091	10	0.035%
0.00000000216	10	0.035%
0.00000000649	10	0.035%
0.00000001340	10	0.035%
0.00000002199	10	0.035%
0.00000002581	10	0.035%
0.00000004264	10	0.035%
0.00000004592	10	0.035%
0.00000004950	10	0.035%
0.00000005446	10	0.035%
0.00000005502	10	0.035%
0.00000005715	10	0.035%
0.00000007497	10	0.035%
…	<10	87.320%

APPENDIX F

FREQUENCY OF EIGENVECTOR CENTRALITY

Table F1. Eigenvector Frequency of the Follower-Following Network

Eigenvector Centrality	Frequency	Percentage
0.0000000000	12191	35.78%
0.0172837890	4694	13.78%
0.0134812985	1824	5.35%
0.0307650876	594	1.74%
0.0026748985	513	1.51%
0.0333099142	455	1.34%
0.0082010639	259	0.76%
0.0007848008	209	0.61%
0.0005296755	153	0.45%
0.0082010639	151	0.44%
0.0035686259	142	0.42%
0.0001976663	128	0.38%
0.0001046906	120	0.35%
0.0007085691	111	0.33%
0.0018139081	90	0.26%
0.0009779088	67	0.20%
0.0028200147	66	0.19%
0.0005301734	62	0.18%
0.0024598916	61	0.18%
0.0024598916	59	0.17%
0.0179923581	59	0.17%
0.0178134646	57	0.17%
0.0208524149	55	0.16%
0.0001192162	53	0.16%
0.0173000366	52	0.15%
0.0018501702	51	0.15%
0.0004679674	50	0.15%
0.0173884796	50	0.15%
0.0174814553	47	0.14%
0.0053614153	46	0.13%
0.0170499244	46	0.13%
0.0035686259	45	0.13%
0.0201038038	45	0.13%
0.0012886633	44	0.13%

0.0002196775	40	0.12%
0.0209233854	40	0.12%
0.0369495106	40	0.12%
0.0036395964	38	0.11%
0.0199586876	38	0.11%
0.0021114461	36	0.11%
0.0180685899	34	0.10%
0.0343337135	34	0.10%
0.0000558350	33	0.10%
0.0004525835	33	0.10%
0.0009776925	33	0.10%
0.0044763447	33	0.10%
0.0000558350	32	0.09%
0.0018501702	32	0.09%
0.0190976972	32	0.09%
0.0009779088	28	0.08%
0.0175034665	28	0.08%
0.0000965491	27	0.08%
0.0004679674	27	0.08%
0.0005342072	27	0.08%
0.0009428207	27	0.08%
0.0012869073	26	0.08%
0.0191339592	26	0.08%
0.0018697484	24	0.07%
0.0011291206	23	0.07%
0.0006097223	22	0.06%
0.0007085691	22	0.06%
0.0001007133	21	0.06%
0.0005296755	21	0.06%
0.0004131452	20	0.06%
0.0171208949	20	0.06%
0.0029985967	19	0.06%
0.0173396241	18	0.05%
0.0005497747	17	0.05%
0.0034613115	17	0.05%
0.0036668836	17	0.05%
0.0174030052	17	0.05%
0.0178302101	17	0.05%
0.0026774131	16	0.05%
0.0182614815	16	0.05%
0.0344046840	16	0.05%

0.0002196775	15	0.04%
0.0006097223	15	0.04%
0.0316237080	15	0.04%
0.0002513282	14	0.04%
0.0003023569	14	0.04%
0.0003828030	14	0.04%
0.0010208089	14	0.04%
0.0178179963	14	0.04%
0.0216823625	14	0.04%
0.0307650876	14	0.04%
0.0001709644	13	0.04%
0.0006239679	13	0.04%
0.0023642553	13	0.04%
0.0108759624	13	0.04%
0.0019644649	12	0.04%
0.0021114461	12	0.04%
0.0060791341	12	0.04%
0.0182616979	12	0.04%
0.0254848530	12	0.04%
0.0001862999	11	0.03%
0.0019209495	11	0.03%
0.0182266097	11	0.03%
0.0185706963	11	0.03%
0.0001093634	10	0.03%
0.0001303824	10	0.03%
0.0001315469	10	0.03%
0.0007795626	10	0.03%
0.0009776925	10	0.03%
0.0019644649	10	0.03%
0.0029928358	10	0.03%
0.0034525632	10	0.03%
0.0036528073	10	0.03%
0.0159411901	10	0.03%
…	<10	29.17%

Table F2. Eigenvector Frequency of the Topic-Member Network

Eigenvector	Frequency	Percentage
0.014366429	206	0.717%
0.022239416	131	0.456%
0.019090435	100	0.348%
0.018799577	78	0.272%
0.014416547	71	0.247%
0.006699377	59	0.205%
0.016588060	59	0.205%
0.015916257	56	0.195%
0.013100726	55	0.192%
0.015121468	51	0.178%
0.015362326	51	0.178%
0.001319995	49	0.171%
0.014251647	42	0.146%
0.005230651	41	0.143%
0.007729259	41	0.143%
0.012984727	40	0.139%
0.009562968	39	0.136%
0.005940777	35	0.122%
0.007729259	35	0.122%
0.006709763	34	0.118%
0.009301609	33	0.115%
0.012605640	33	0.115%
0.005693943	29	0.101%
0.003127666	28	0.098%
0.010120714	28	0.098%
0.003599311	27	0.094%
0.003788250	27	0.094%
0.004301061	27	0.094%
0.007752480	27	0.094%
0.006647279	26	0.091%
0.008237006	26	0.091%
0.005937244	25	0.087%
0.001680482	24	0.084%
0.004514712	24	0.084%
0.004645662	24	0.084%
0.007314655	24	0.084%
0.006475862	23	0.080%
0.009468497	23	0.080%
0.004293925	22	0.077%

0.007401358	22	0.077%
0.007508258	22	0.077%
0.016588060	22	0.077%
0.004560374	21	0.073%
0.007515194	21	0.073%
0.003965255	20	0.070%
0.004611817	20	0.070%
0.004711186	20	0.070%
0.006368799	19	0.066%
0.007185531	19	0.066%
0.010611389	19	0.066%
0.002476533	18	0.063%
0.002518961	18	0.063%
0.004711186	18	0.063%
0.005050786	18	0.063%
0.005350594	18	0.063%
0.008347957	18	0.063%
0.003041264	17	0.059%
0.003788250	17	0.059%
0.004482202	17	0.059%
0.004560374	17	0.059%
0.007110547	17	0.059%
0.007682364	17	0.059%
0.010906947	17	0.059%
0.001258808	16	0.056%
0.001439187	16	0.056%
0.002528338	16	0.056%
0.002976329	16	0.056%
0.003564578	16	0.056%
0.005169103	16	0.056%
0.006660035	16	0.056%
0.003038472	15	0.052%
0.004977665	15	0.052%
0.005718142	15	0.052%
0.000343310	14	0.049%
0.002967048	14	0.049%
0.004301061	14	0.049%
0.004331756	14	0.049%
0.004611817	14	0.049%
0.004766515	14	0.049%
0.005940777	14	0.049%

0.018799577	14	0.049%
0.000551914	13	0.045%
0.001918414	13	0.045%
0.002632474	13	0.045%
0.003108422	13	0.045%
0.003157988	13	0.045%
0.003260178	13	0.045%
0.003405773	13	0.045%
0.003509439	13	0.045%
0.004645662	13	0.045%
0.004981452	13	0.045%
0.007515194	13	0.045%
0.001252850	12	0.042%
0.001554690	12	0.042%
0.001967970	12	0.042%
0.002270961	12	0.042%
0.002684044	12	0.042%
0.002710800	12	0.042%
0.002902838	12	0.042%
0.003278070	12	0.042%
0.003285201	12	0.042%
0.003955252	12	0.042%
0.004503492	12	0.042%
0.008347957	12	0.042%
0.001089598	11	0.038%
0.002584244	11	0.038%
0.002728540	11	0.038%
0.002952705	11	0.038%
0.002978658	11	0.038%
0.003220656	11	0.038%
0.003599269	11	0.038%
0.003810567	11	0.038%
0.003975316	11	0.038%
0.004754226	11	0.038%
0.004892901	11	0.038%
0.004939673	11	0.038%
0.005504952	11	0.038%
0.005718142	11	0.038%
0.005954613	11	0.038%
0.006512489	11	0.038%
0.006709763	11	0.038%

0.007314655	11	0.038%
0.028778764	11	0.038%
0.000203541	10	0.035%
0.000397257	10	0.035%
0.000421732	10	0.035%
0.002279877	10	0.035%
0.002349621	10	0.035%
0.002492234	10	0.035%
0.002570515	10	0.035%
0.003224213	10	0.035%
0.003521196	10	0.035%
0.003574865	10	0.035%
0.004124640	10	0.035%
0.004253601	10	0.035%
0.004435340	10	0.035%
0.004498498	10	0.035%
0.004800980	10	0.035%
0.006699377	10	0.035%
0.007682364	10	0.035%
…	<10	88.995%

REFERENCES

Abbasi, A., Altmann, J., & Hossain, L. (2011). Identifying the effects of co-authorship networks on the performance of scholars: A correlation and regression analysis of performance measures and social network analysis measures. *Journal of Informetrics*, *5*(4), 594-607. doi: 10.1016/j.joi.2011.05.007.

Acemoglu, D., & Ozdaglar, A. (2013). *Graph theory and social networks*. Retrieved September 16, 2017, from http://economics.mit.edu/files/4620.

Agag, G., & El-Masry, A. A. (2016). Understanding consumer intention to participate in online travel community and effects on consumer intention to purchase travel online and WOM: An integration of innovation diffusion theory and TAM with trust. *Computers in Human Behavior*, *60*, 97-111. doi: 10.1016/j.chb.2016.02.038.

Agrifoglio, R., Black, S., Metallo, C., & Ferrara., M. (2012). Extrinsic versus intrinsic motivation in continued Twitter usage. *Journal of Computer Information Systems*, *53*(1), 33-41.

Akar, E., & Mardikyan, S. (2014). Analyzing factors affecting users' behavior intention to use social media: Twitter case. *International Journal of Business and Social Science*, *5*(11), 85-95.

An Introduction to Triads (n.d.). Retrieved September 16, 2017, from http://www.culturesync.net/toolbox/an-introduction-to-triads.

Aneela, James, & Santiago (2010). Retrieved April 8, 2018, from https://www.albany.edu/faculty/kretheme/PAD637/ClassNotes/Spring%202010/Week5_Slides.pdf.

Angeletou, S., Rowe, M., & Alani, H. (2011). Modelling and analysis of user behaviour in online communities. *Proceedings of International Semantic Web Conference* (pp. 35-50). Berlin, Heidelberg. doi: 10.1007/978-3-642-25073-6_3.

Arazy, O., Ortega, F., Nov, O., Yeo, L., & Balila, A. (2015). Functional roles and career paths in Wikipedia. *Proceedings of the 18th ACM Conference on Computer Supported Cooperative Work & Social Computing*, (pp.1092-1105). Vancouver, BC, Canada. doi:10.1145/2675133.2675257.

Baek, S. I., & Kim, Y. M. (2015). Longitudinal analysis of online community dynamics. *Industrial Management & Data Systems*, *115*(4), 661-677. doi: 10.1108/IMDS-09-2014-0266.

Bagozzi, R. P., & Dholakia, U. M. (2002). Intentional social action in virtual communities. *Journal of Interactive Marketing*, *16*(2), 2-21. doi: 10.1002/dir.10006.

Belanche, D., Casaló, L. V., & Guinalíu, M. (2012). Website usability, consumer satisfaction and the intention to use a website: the moderating effect of perceived risk. *Journal of Retailing and Consumer Services*, *19*(1), 124-132. doi: 10.1016/j.jretconser.2011.11.001.

Benevenuto, F., Rodrigues, T., Cha, M., & Almeida, V. (2009). Characterizing user behavior in online social networks. *Proceedings of the 9th ACM SIGCOMM Conference on Internet Measurement Conference* (pp. 49-62). Chicago, Illinois, USA. doi: 10.1145/1644893.1644900.

Biddle, B. J. (1986). Recent development in role theory. *Annual Review of Sociology, 12*, 67–92. doi: 10.1146/annurev.so.12.080186.000435.

Biddle, B. J. (2013). *Role theory: Expectations, identities, and behaviors*. New York, NY: Academic Press.

Blondel, V. D., Guillaume, J. L., Lambiotte, R., & Lefebvre, E. (2008). Fast unfolding of communities in large networks. *Journal of Statistical Mechanics: Theory and Experiment*, *10*, 1-12. doi: 10.1088/1742-5468/2008/10/P10008.

Bonacich, P (1972). Technique for analyzing overlapping memberships. *Sociological Methodology*, *4*, 176–185. doi: 10.2307/270732.

Borgatti, S. P., & Everett, M. G. (1997). Network analysis of 2-mode data. *Social Networks*, *19*(3), 243-269. doi: 10.1016/S0378-8733(96)00301-2.

Borgatti, S. P., & Li, X. (2009). On social network analysis in a supply chain context. *Journal of Supply Chain Management*, *45*(2), 5-22. doi: 10.1111/j.1745-493X.2009.03166.x.

Borgatti, S. P., Mehra, A., Brass, D. J., & Labianca, G. (2009). Network analysis in the social sciences. *Science*, *323*, 892-895. doi: 10.1126/science.1165821.

Borrero, J. D., Yousafzai, S. Y., Javed, U., & Page, K. L. (2014). Expressive participation in Internet social movements: Testing the moderating effect of technology readiness and sex on student SNS use. *Computers in Human Behavior*, *30*, 39-49. doi: 10.1016/j.chb.2013.07.032.

Boyd, D. M., & Ellison, N. B. (2008). Social network sites: Definition, history, and scholarship. *Journal of Computer-Mediated Communication*, *13*, 210-230. doi: 10.1111/j.1083-6101.2007.00393.x.

Brandes, U., Kenis, P., Lerner, J., & Van Raaij, D. (2009). Network analysis of collaboration structure in Wikipedia. *Proceedings of the 18th International Conference on World Wide Web* (pp. 731-740). Madrid, Spain. doi: 10.1145/1526709.1526808.

Brandon-Jones, A., & Kauppi, K. (2018). Examining the antecedents of the technology acceptance model within e-procurement. *International Journal of Operations & Production Management*, *38*(1), 22-42. doi: 10.1108/IJOPM-06-2015-0346.

Brandtzaeg, P. B., & Heim, J. (2011). A typology of social networking sites users. *International Journal of Web Based Communities*, *7*(1), 28-51. doi: 10.1504/IJWBC.2011.038124.

Brewer, D. D., & Webster, C. M. (2000). Forgetting of friends and its effects on measuring friendship networks. *Social Networks, 21*(4), 361-373. doi: 10.1016/S0378-8733(99)00018-0.

Brewer, J. (2000). *Ethnography*. Buckingham, England: Open University Press.

Buntain, C., & Golbeck, J. (2014). Identifying social roles in Reddit using network structure. *Proceedings of the 23rd International Conference on World Wide Web* (pp. 615-620). Seoul, Korea. doi: 10.1145/2567948.2579231.

Byun, H., Chiu, W., & Bae, J. S. (2018). Exploring the adoption of sports brand apps: an application of the modified technology acceptance model. *International Journal of Asian Business and Information Management*, *9*(1), 52-65. doi: 10.4018/IJABIM.2018010105.

Capocci, A., Servedio, V. D., Colaiori, F., Buriol, L. S., Donato, D., Leonardi, S., & Caldarelli, G. (2006). Preferential attachment in the growth of social networks: The internet encyclopedia Wikipedia. *Physical Review E*, *74*(3), 1-5. doi: 10.1103/PhysRevE.74.036116.

Castañeda, J. A., Muñoz-Leiva, F., & Luque, T. (2007). Web acceptance model (WAM): Moderating effects of user experience. *Information & Management*, *44*(4), 384-396. doi: 10.1016/j.im.2007.02.003.

Catanese S.A., De Meo P., Ferrara E., Fiumara G., & Provetti A. (2012). Extraction and analysis of Facebook friendship relations. In: A. Abraham (Eds.), C*omputational social networks* (pp. 291-324). London, England: Springer. doi: 10.1007/978-1-4471-4054-2_12.

Catanese, S. A., De Meo, P., Ferrara, E., Fiumara, G., & Provetti, A. (2011). Crawling Facebook for social network analysis purposes. *Proceedings of The International Conference on Web Intelligence, Mining and Semantics* (pp. 1-8). Sogndal, Norway. doi: 10.1145/1988688.1988749.

Centrality and Centralization (n.d.). Retrieved April 8, 2018, from http://www.analytictech.com/mb119/chapter5.htm.

Chan, J., Hayes, C., & Daly, E. M. (2010). Decomposing Discussion Forums and Boards Using User Roles. *Proceedings of the Fourth International AAAI Conference on Weblogs and Social Media* (pp. 215-218). Washington, DC, USA.

Cheng, X., Dale, C., & Liu, J. (2008). Statistics and social network of YouTube videos. *Proceedings of 16th International Workshop on Quality of Service* (pp. 229-238). Enschede, Netherlands. doi: 10.1109/IWQOS.2008.32.

Cheong, F., & Cheong, C. (2011). Social media data mining: A social network analysis of tweets during the 2010-2011 Australian floods. *Proceedings of 5th Pacific Asia Conference on Information Systems: Quality Research in Pacific* (pp. 1-16). Brisbane, Australia.

Chi, E. H., Munson, S., Fischer, G., Vieweg, S., & Parr, C. (2010). Advancing the design of technology-mediated social participation systems. *Computer*, *43*(11), 29-35. doi: 10.1109/MC.2010.304.

Chi, H., Yeh, H., & Hung, W. C. (2012). The moderating effect of subjective norm on cloud computing users' perceived risk and usage intention. *International Journal of Marketing Studies*, *4*(6), 95. doi: 10.5539/ijms.v4n6p95.

Childers, T. L., Carr, C. L., Peck, J., & Carson, S. (2001). Hedonic and utilitarian motivations for online retail shopping behavior. *Journal of Retailing*, *77*(4), 511-535. doi: 10.1016/S0022-4359(01)00056-2.

Chin, A., & Chignell, M. (2007). Identifying communities in blogs: Roles for social network analysis and survey instruments. *International Journal of Web Based Communities*, *3*(3), 345-363. doi: 10.1504/IJWBC.2007.014243.

Choi, D., Han, J., Chung, T., Ahn, Y. Y., Chun, B. G., & Kwon, T. T. (2015). Characterizing conversation patterns in Reddit: From the perspectives of content properties and user participation behaviors. *Proceedings of the 2015 ACM on Conference on Online Social Networks* (pp. 233-243). Palo Alto, CA, USA. doi: 10.1145/2817946.2817959.

Christian Franklin, J., Mainelli, M., & Pay, R. (2014). Measuring the value of online communities. *Journal of Business Strategy*, *35*(1), 29-42. doi: 10.1108/JBS-04-2013-0027.

Chung, J. E., Park, N., Wang, H., Fulk, J., & McLaughlin, M. (2010). Age differences in perceptions of online community participation among non-users: An extension of the technology acceptance model. *Computers in Human Behavior*, *26*(6), 1674-1684. doi: 10.1016/j.chb.2010.06.016.

Çiçek, M., & Eren-Erdogmus, I. (2013). Social media marketing: Exploring the user typology in Turkey. *International Journal of Technology Marketing*, *8*(3), 254-271. doi: 10.1504/IJTMKT.2013.055343.

Clauset, A., Newman, M. E., & Moore, C. (2004). Finding community structure in very large networks. *Physical Review E*, *70*(6), 1-6. doi: 10.1103/PhysRevE.70.066111.

Clauset, A., Shalizi, C. R., & Newman, M. E. (2009). Power-law distributions in empirical data. *SIAM Review*, *51*(4), 661-703. doi: 10.1137/070710111.

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.) New York, NY: Lawrence Erlbaum Association.

Cooil, B., Keiningham, T. L., Aksoy, L., & Hsu, M. (2007). A longitudinal analysis of customer satisfaction and share of wallet: Investigating the moderating effect of customer characteristics. *Journal of Marketing*, *71*(1), 67-83. doi: 10.1509/jmkg.71.1.67.

Cronbach, L.J. (1971). *Educational measurement* (2nd ed.). Washington, DC: American Council on Education.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, *13*(3), 319-340. doi: /10.2307/249008.

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1992). Extrinsic and intrinsic motivation to use computers in the workplace. *Journal of Applied Social Psychology*, *22*(14), 1111-1132. doi: 10.1111/j.1559-1816.1992.tb00945.x.

De Valck, K., Langerak, F., Verhoef, P. C., & Verlegh, P. W. (2007). Satisfaction with virtual communities of interest: Effect on members' visit frequency. *British Journal of Management*, *18*(3), 241-256. doi: 10.1111/j.1467-8551.2006.00499.x.

Digital in 2018 (2018). Retrieved February 7, 2018, from https://hootsuite.com/pages/digital-in-2018.

Dogan, S. Z., Arditi, D., Gunhan, S., & Erbasaranoglu, B. (2013). Assessing coordination performance based on centrality in an e-mail communication network. *Journal of Management in Engineering*, *31*(3), 1-8.

Easley, D., & Kleinberg, J. (2010). *Networks, crowds, and markets: Reasoning about a highly-connected world*. New York, NY: Cambridge University Press. doi: 10.1017/CBO9780511761942.

Ebrahimi, S., Mehdipour, Y., Karimi, A., Khammarnia, M., & Alipour, J. (2018). Determinants of physicians' technology acceptance for mobile health services in healthcare settings. *Journal of Health Management and Informatics*, *5*(1), 9-15.

Emmons, S., Kobourov, S., Gallant, M., & Börner, K. (2016). Analysis of network clustering algorithms and cluster quality metrics at scale. *PloS One*, *11*(7): e0159161. doi: 10.1371/journal.pone.0159161.

Eysenbach, G., & Till., J. (2001). Ethical issues in qualitative research on Internet communities. *British Medical Journal*, *323*, 1103–1105. doi: 10.1136/bmj.323.7321.1103.

Feicheng, M., & Yating, L. (2014). Utilising social network analysis to study the characteristics and functions of the co-occurrence network of online tags. *Online Information Review*, *38*(2), 232-247. doi: 10.1108/OIR-11-2012-0124.

Fernandez, M., Scharl, A., Bontcheva, K., & Alani, H. (2014). User profile modelling in online communities. *Proceedings of Third International Workshop on Semantic Web Collaborative Spaces (SWCS'14) at the 13th International Semantic Web Conference (ISWC 2014)* (pp. 1-15). Riva del Garda, Trentino, Italy.

Fetscherin, M., & Lattemann, C. (2008). User acceptance of virtual worlds. *Journal of Electronic Commerce Research*, *9*(3), 231.

Fornell, C., & Larcker, D. (1987). A second generation of multivariate analysis: Classification of methods and implications for marketing research. *Review of Marketing*, *1*, 407-450.

Frankel, M. S., & Siang., S. (1999). *Ethical and legal aspects of human subjects research on the Internet*. Washington, DC: American Association for the Advancement of Science.

Freeman, L. (1979). Centrality in social networks: Conceptual clarification. *Social Networks*, *1*, 215–239. doi: 10.1016/0378-8733(78)90021-7.

Fullerton, R., Linster, B.G., McKee, M., & Slate, S. (1999). An experimental investigation of research tournaments. *Economic Inquiry*, *37*(4), 624–636.

Füller, J., Hutter, K., Hautz, J., & Matzler, K. (2014). User roles and contributions in innovation-contest communities. *Journal of Management Information Systems*, *31*(1), 273-308. doi: 10.2753/MIS0742-1222310111.

Füller, J., Jawecki, G., & Mühlbacher., H. (2007). Innovation creation by online basketball communities. *Journal of Business Research*, *60*(1), 60–71. doi: 10.1016/j.jbusres.2006.09.019.

Geddes, C. (2011). Achieving critical mass in social networks. *Journal of Database Marketing & Customer Strategy Management*, *18*(2), 123-128. doi: 10.1057/dbm.2011.14.

Gefen, D., Straub, D. W., & Rigdon, E. E. (2011). An update and extension to SEM guidelines for administrative and social science research. *MIS Quarterly*, *35*(2), 3-15.

Girvan, M., & Newman, M. E. (2002). Community structure in social and biological networks. *Proceedings of the National Academy of Sciences*, *99*(12), 7821-7826. doi: 10.1073/pnas.122653799.

Gleave, E., Welser, H. T., Lento, T. M., & Smith, M. A. (2009). A conceptual and operational definition of ‘social role’ in online community. *Proceedings of the 42nd Hawaii International Conference on System Science* (pp. 1530-1605). Big Island, HI, USA. doi: 10.1109/HICSS.2009.6

Goffman, E. (1959). *The presentation of self in everyday life*. Garden City, NY: Guilford Press.

Golder, S. A., & Donath., J. (2004). Social roles in electronic communities. *Internet Research*, 5, 19-22.

Gong, W., Lim, E. P., & Zhu, F. (2015). Characterizing silent users in social media communities. *Proceedings of the Ninth International AAAI Conference on Web and Social Media* (pp. 140-149). University of Oxford, Oxford, UK.

Goodhue, D. L., Thompson, R., & Lewis, W. (2013). Why you shouldn't use PLS: Four reasons to be uneasy about using PLS in analyzing path models. *Proceedings of 46th Hawaii International Conference on System Sciences* (pp. 4739-4748). Wailea, Maui, HI, USA. doi: 10.1109/HICSS.2013.612

Hacker, J., Bodendorf, F., & Lorenz., P. (2017). Helper, sharer or seeker? A concept to determine knowledge worker roles in enterprise social networks. *Proceedings of 13th International Conference on Wirtschaftsinformatik* (pp. 668-682). St. Gallen, Switzerland.

Hair, J. F., Anderson, R. E., Babin, B. J., & Black, W. C. (2010). *Multivariate data analysis: A global perspective* (7th ed.). Upper Saddle River, NJ: Pearson.

Han, J. Y., Kim, J. H., Yoon, H. J., Shim, M., McTavish, F. M., & Gustafson, D. H. (2012). Social and psychological determinants of levels of engagement with an online breast cancer support group: Posters, lurkers, and nonusers. *Journal of Health Communication*, *17*(3), 356-371. doi: 10.1080/10810730.2011.585696.

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

Hartzel, K. S., Marley, K. A., & Spangler, W. E. (2016). Online social network adoption: A cross-cultural study. *Journal of Computer Information Systems*, *56*(2), 87-96. doi: 10.1080/08874417.2016.1117367.

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

Hecking, T., Chounta, I. A., & Hoppe, H. U. (2015). Analysis of user roles and the emergence of themes in discussion forums. *Proceedings of Network Intelligence Conference* (ENIC), 2015 Second European (pp. 114-121). Karlskrona, Sweden. doi: 10.1109/ENIC.2015.24

Hernández, B., Jiménez, J., & Martín, M. J. (2010). Customer behavior in electronic commerce: The moderating effect of e-purchasing experience. *Journal of Business Research*, *63*(9), 964-971. doi: 10.1016/j.jbusres.2009.01.019.

Howell, D. W. (2016). *Social media site use and the technology acceptance model: Social media sites and organization success* (Published PhD thesis). Capella University, Minneapolis, MN, USA.

Iba, T., Nemoto, K., Peters, B., & Gloor, P. A. (2010). Analyzing the creative editing behavior of Wikipedia editors: Through dynamic social network analysis. *Procedia-Social and Behavioral Sciences*, *2*(4), 6441-6456. doi: 10.1016/j.sbspro.2010.04.054.

Iskoujina, Z., Ciesielska, M., Roberts, J., & Li, F. (2017). Grasping the business value of online communities. *Journal of Organizational Change Management*, *30*(3), 396-416. doi: 10.1108/JOCM-02-2016-0023.

Jamali, M., & Abolhassani, H. (2006). Different aspects of social network analysis. *Proceedings of 2006 IEEE/WIC/ACM International Conference on Web Intelligence* (pp. 1-8). Hong Kong, China. doi: 10.1109/WI.2006.61.

Keil, M., Tan, B. C., Wei, K. K., Saarinen, T., Tuunainen, V., & Wassenaar, A. (2000). A cross-cultural study on escalation of commitment behavior in software projects. *MIS Quarterly*, *24*(2), 299–325. doi: 10.2307/3250940.

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. doi: 10.1016/j.bushor.2011.01.005.

Kim, H. Y., Lee, J. Y., Mun, J. M., & Johnson, K. K. (2017). Consumer adoption of smart in-store technology: Assessing the predictive value of attitude versus beliefs in the technology acceptance model. *International Journal of Fashion Design, Technology and Education*, *10*(1), 26-36. doi: 10.1080/17543266.2016.1177737.

Kim, Y. G., & Woo, E. (2016). Consumer acceptance of a quick response (QR) code for the food traceability system: Application of an extended technology acceptance model (TAM). *Food Research International*, *85*, 266-272. doi: 10.1016/j.foodres.2016.05.002.

Kline, R. B. (2016). *Principles and practice of structural equation modeling* (4th ed.). New York, NY: Guilford Press.

Klopping, I. M., & McKinney, E. (2004). Extending the technology acceptance model and the task-technology fit model to consumer e-commerce. *Information Technology, Learning, and Performance Journal*, *22*(1), 35-48.

Ko, H. C. (2012). Why are A-list bloggers continuously popular? *Online Information Review*, *36*(3), 401-419. doi: 10.1108/14684521211241422.

Koçak, N. G. (2014). Social networks and social network analysis. *Journal of Business and Social Science*, *5*(2), 126-135.

Kock, N. (2011). Using WarpPLS in e-collaboration studies: An overview of five main analysis steps. *Advancing Collaborative Knowledge Environments: New Trends in E-Collaboration: New Trends in E-Collaboration* (pp. 180- 191). Hershey, PA: Information Science Reference.

Kock, N. (2014). Advanced mediating effects tests, multi-group analyses, and measurement model assessments in PLS-based SEM. *International Journal of e-Collaboration*, *10*(1), 1-13. doi: 10.4018/ijec.2014010101.

Kock, N. (2017). WarpPLS 6.0 User Manual. Retrieved from http://cits.tamiu.edu/WarpPLS/UserManual_v_6_0.pdf.

Kolaczyk, E. D., & Csárdi, G. (2014). *Statistical analysis of network data with R* (Vol. 65). New York, NY: Springer. doi: 10.1007/978-1-4939-0983-4.

Koufaris, M. (2002). Applying the technology acceptance model and flow theory to online consumer behavior. *Information Systems Research*, *13*(2), 205-223. doi: 10.1287/isre.13.2.205.83.

Kozinets, R. V. (1999). E-tribalized marketing? The strategic implications of virtual communities of consumption. *European Management Journal*, *17*(3), 252-264. doi: 10.1016/S0263-2373(99)00004-3.

Krause, J., Croft, D.P., & James., R. (2007). Social network theory in the behavioural sciences: Potential applications. *Behavioral Econology and Sociobiology*, *62*(1), 15-27.

Kulviwat, S., Bruner, G. C., & Al-Shuridah, O. (2009). The role of social influence on adoption of high tech innovations: The moderating effect of public/private consumption. *Journal of Business Research*, *62*(7), 706-712. doi: 10.1016/j.jbusres.2007.04.014.

Kumar R., Novak J., & Tomkins A. (2010). Structure and evolution of online social networks. In P. Yu, J. Han & C. Faloutsos (Eds.). *Link mining: Models, algorithms, and applications* (pp. 337-357). New York, NY: Springer. doi: 10.1007/978-1-4419-6515-8_13.

Lancichinetti, A., & Fortunato, S. (2009). Community detection algorithms: A comparative analysis. *Physical Review E*, *80*(5), 1-12. doi: 10.1103/PhysRevE.80.056117.

Latora, V., & Marchiori, M. (2007). A measure of centrality based on network efficiency. *New Journal of Physics*, *9*(6), p.188. doi: 10.1088/1367-2630/9/6/188.

Laumann, E. O., Marsden, P. V., & Prensky, D. (1989). The boundary specification problem in network analysis. In L. C. Freeman, D. White & A. K. Romney (Eds.). *Research methods in social network analysis*, (pp. 61- 87). Piscataway, NJ: Transaction Publishers.

Lederer, A. L., Maupin, D. J., Sena, M. P., & Zhuang, Y. (2000). The technology acceptance model and the world wide web. *Decision Support Systems*, *29*(3), 269-282. doi: 10.1016/S0167-9236(00)00076-2.

Lee, A. J., Yang, F. C., Tsai, H. C., & Lai, Y. Y. (2014). Discovering content-based behavioral roles in social networks. *Decision Support Systems*, *31*(59), 250-61. doi: 10.1016/j.dss.2013.12.004.

Lee, M. K., Cheung, C. M., Lim, K. H., & Ling Sia, C. (2006). Understanding customer knowledge sharing in web-based discussion boards: An exploratory study. *Internet Research*, *16*(3), 289-303. doi: 10.1108/10662240610673709.

Lee, W., Tyrrell, T., & Erdem, M. (2013). Exploring the behavioral aspects of adopting technology: Meeting planners' use of social network media and the impact of perceived critical mass. *Journal of Hospitality and Tourism Technology*, *4*(1), 6-22. doi: 10.1108/17579881311302329.

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. doi: 10.1016/j.socnet.2008.07.002.

Li, E. Y., Liao, C. H., & Yen, H. R. (2013). Co-authorship networks and research impact: A social capital perspective. *Research Policy*, *42*(9), 1515-1530. doi: 10.1016/j.respol.2013.06.012.

Li, H., Cui J.T., & Ma, J.F. (2015). Social influence study in online networks: A three-level review. *Journal of Computer Science and Technology*, *30*(1), 184-199. doi: 10.1007/s11390-015-1512-7.

Li, L., Alderson, D., Doyle, J. C., & Willinger, W. (2005). Towards a theory of scale-free graphs: Definition, properties, and implications. *Internet Mathematics*, *2*(4), 431-523. doi: 10.1080/15427951.2005.10129111.

Liao, S., & Chou, E. Y. (2012). Intention to adopt knowledge through virtual communities: Posters vs lurkers. *Online Information Review*, *36*(3), 442-461. doi: 10.1108/14684521211241440.

Liao, C., To, P. L., Liu, C. C., Kuo, P. Y., & Chuang, S. H. (2011). Factors influencing the intended use of web portals. *Online Information Review*, *35*(2), 237-254. doi: 10.1108/14684521111128023.

Lim, W.M. (2014). Sense of virtual community and perceived critical mass in online group buying. *Journal of Strategic Marketing*, *22*(3), 268-83. doi: 10.1080/0965254X.2013.876068.

Lin, H. F. (2007). The role of online and offline features in sustaining virtual communities: An empirical study. *Internet Research*, *17*(2), 119-138. doi: 10.1108/10662240710736997.

Lin, H. F., & Lee., G.H. (2006). Determinants of success for online communities: An empirical study. *Behavioral Information Technology*, *25*(6), 479-488. doi: 10.1080/01449290500330422.

Lin, N. (2002). Social capital: A theory of social structure and action. *Structural Analysis in the Social Sciences*, *19*. New York, NY: Cambridge University Press.

Lingyun, Q., & Li, D. (2008). Applying TAM in B2C E-commerce research: An extended model. *Tsinghua Science & Technology*, *13*(3), 265-272. doi: 10.1016/S1007-0214(08)70043-9.

Loosemore, M. (1998). Social network analysis: Using a quantitative tool within an interpretative context to explore the management of construction crises. *Engineering, Construction and Architectural Management*, *5*(4), 315-326. doi: 10.1108/eb021085

Lorenzo-Romero, C., Constantinides, E., & Alarcón-del-Amo, M. D. C. (2011). Segmenting the web 2.0 market: Behavioural and usage patterns of social web consumers. *Journal of Business Case Studies* (JBCS), *6*(7), 55-66. doi: 10.19030/jbcs.v6i7.1064.

Lou, H., Luo, W., & Strong., D. (2000). Perceived critical mass effect on groupware acceptance. *European Journal of Information Systems*, *9*(2), 91-103. doi: 10.1057/palgrave.ejis.3000358.

Lu, Y., Luo, X., Polgar, M., & Cao, Y. (2010). Social network analysis of a criminal hacker community. *Journal of Computer Information Systems*, *51*(2), 31-41.

Marin, A., & Wellman, B. (2011). Social network analysis: An introduction. In J. Scott & P. J. Carrington (Eds.). *The SAGE handbook of social network analysis* (pp. 11-25). London, England: Sage Publications Ltd.

Markel, N. N. (1998). Semiotic psychology: Speech as an index of emotions and attitudes. *Berkeley Insights in Linguistics and Semiotics*, *26*. Peter Lang Inc., International Academic Publishers.

Marsden, P. V. (2003). Interviewer effects in measuring network size using a single name generator. *Social Networks*, *25*(1), 1-16. doi: 10.1016/S0378-8733(02)00009-6.

Martínez-Torres, M. R., Toral, S. L., Palacios, B., & Barrero, F. (2011). Web site structure mining using social network analysis. *Internet Research*, *21*(2), 104-123. doi: 10.1108/10662241111123711.

Martino, F., & Spoto, A. (2006). Social network analysis: A brief theoretical review and further perspectives in the study of information technology. *PsychNology Journal*, *4*(1), 53-86.

Mayer, A., & Puller, S. L. (2008). The old boy (and girl) network: Social network formation on university campuses. *Journal of Public Economics*, *92*(1), 329-347. doi: 10.1016/j.jpubeco.2007.09.001.

McMillan, D. W., & Chavis, D. M. (1986). Sense of community: A definition and theory. *Journal of Community Psychology*, *14*(1), 6-23. doi: 10.1002/1520-6629(198601)14:1.

Mislove, A. E. (2009). *Online social networks: measurement, analysis, and applications to distributed information systems* (Published PhD thesis). Rice University, Houston, TX, USA.

Mislove, A., Marcon, M., Gummadi, K. P., Druschel, P., & Bhattacharjee, B. (2007). Measurement and analysis of online social networks. *Proceedings of the 7th ACM SIGCOMM Conference on Internet Measurement* (pp. 29-42). San Diego, California, USA. doi: 10.1145/1298306.1298311.

Mohd Thas Thaker, M. A., Mohd Thas Thaker, H., & Allah Pitchay, A. (2018). Modeling crowdfunders’ behavioral intention to adopt the crowdfunding-waqf model (CWM) in Malaysia: The theory of the technology acceptance model. *International Journal of Islamic and Middle Eastern Finance and Management*, *33*(4), 419-440. doi: 10.1108/IMEFM-06-2017-0157.

Moon, J.W., & Kim., Y.G. (2001). Extending the TAM for a world-wide-web context. *Information & Management*, *38*(4), 217-30. doi: 10.1016/S0378-7206(00)00061-6.

Moore, G.C., & Benbasat., I. (1991). Development of an instrument to measure the perceptions of adopting an information technology adoption. *Information Systems Research*, *2*(3), 192-222. doi: 10.1287/isre.2.3.192.

Moqbel, M. (2012). *The effect of the use of social networking sites in the workplace on job performance* (Unpublished PhD thesis). Texas A&M International University, Texas, USA.

Morales, A. J., Borondo, J., Losada, J. C., & Benito, R. M. (2014). Efficiency of human activity on information spreading on Twitter. *Social Networks*, *39*, 1-11. doi: 10.1016/j.socnet.2014.03.007.

Muldoon, R. (2013). Social network analysis. Retrieved September 16, 2017, from: http://www.sas.upenn.edu/ppe/Events/uniconf_2013/documents/Muldoon_SocialNetworkAnalysisppt.pdf.

Muller, M., Shami, N. S., Millen, D. R., & Feinberg, J. (2010). We are all lurkers: Consuming behaviors among authors and readers in an enterprise file-sharing service. *Proceedings of the 16th ACM International Conference on Supporting Group Work* (pp. 201-210). Sanibel Island, Florida, USA. doi: 10.1145/1880071.1880106.

Mun, Y. Y., & Hwang, Y. (2003). Predicting the use of web-based information systems: Self-efficacy, enjoyment, learning goal orientation, and the technology acceptance model. *International Journal of Human-Computer Studies*, *59*(4), 431-449. doi: 10.1016/S1071-5819(03)00114-9.

Nepusz, T., & Csardi, G. (n.d.). Fitting a power-law distribution function to discrete data. Retrieved September 16, 2017, from http://igraph.org/r/doc/fit_power_law.html.

NetworkAnalyzer Online Help (n. d.). Retrieved February 7, 2018, from http://med.bioinf.mpi-inf.mpg.de/netanalyzer/help/2.6.1/.

Newman, M. E. (2002). Assortative mixing in networks. *Physical Review Letters*, *89*(20), 1-5. doi: 10.1103/PhysRevLett.89.208701.

Newman, M. E. (2004). Detecting community structure in networks. *The European Physical Journal B-Condensed Matter and Complex Systems*, *38*(2), 321-330. doi: 10.1140/epjb/e2004-00124-y.

Newman, M. E. (2006). Finding community structure in networks using the eigenvectors of matrices. *Physical Review E*, *74*(3), 1-22. doi: 10.1103/PhysRevE.74.036104.

Newman, M. E., & Girvan, M. (2004). Finding and evaluating community structure in networks. *Physical Review E*, *69*(2), 1-16. doi: 10.1103/PhysRevE.69.026113.

Nistor, N., Baltes, B., Dascălu, M., Mihăilă, D., Smeaton, G., & Trăuşan-Matu, Ş. (2014). Participation in virtual academic communities of practice under the influence of technology acceptance and community factors. A learning analytics application. *Computers in Human Behavior*, *34*, 339-344. doi: 10.1016/j.chb.2013.10.051.

Nolker, R., & Zhou, L. (2005). Social computing and weighting to identify member roles in online communities. *Proceedings of the 2005 IEEE/WIC/ACM International Conference on Web Intelligence* (pp. 87-93). Washington, DC, USA. doi: 10.1109/WI.2005.134.

Nonnecke, B., & Preece, J. (2000). Lurker demographics: Counting the silent. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (pp. 73-80). New York, NY, USA. doi: 10.1145/332040.332409.

Nunnally, J. C., & Bernstein., I.H. (1994). The assessment of reliability. *Psychometric Theory*, *3*(1), 248-292.

Nunnally, J.C. (1978). *Psychometric Theory* (2nd ed.). New York, NY: McGraw-Hill.

Oliver, P., Marwell, G., & Teixeira., R. (1985). A theory of the critical mass. Interdependence, group heterogeneity, and the production of collective action. *American Journal of Sociology*, *91*(3), 522-56. doi: 10.1086/228313.

Ooi, K. B., & Tan, G. W. H. (2016). Mobile technology acceptance model: An investigation using mobile users to explore smartphone credit card. *Expert Systems with Applications*, *59*, 33-46. doi: 10.1016/j.eswa.2016.04.015.

Orman, G. K., Labatut, V., & Cherifi, H. (2011). On accuracy of community structure discovery algorithms. *Journal of Convergence Information Technology*, *6*(11):283-292. doi: 10.4156/jcit.vol6.issue11.32.

Palmer, J. W. (2002). Web site usability, design, and performance metrics. *Information Systems Research*, *13*(2), 151-167. doi: 10.1287/isre.13.2.151.88.

Park, E., Baek, S., Ohm, J., & Chang, H. J. (2014). Determinants of player acceptance of mobile social network games: An application of extended technology acceptance model. *Telematics and Informatics, 31*(1), 3-15. doi: 10.1016/j.tele.2013.07.001.

Park, N., Lee, S., & Kim, J. H. (2012). Individuals’ personal network characteristics and patterns of Facebook use: A social network approach. *Computers in Human Behavior*, *28*(5), 1700-1707. doi: 10.1016/j.chb.2012.04.009.

Park, S. Y. (2009). An analysis of the technology acceptance model in understanding university students' behavioral intention to use e-learning. *Journal of Educational Technology & Society*, *12*(3), 150-162.

Pavlou, P. A. (2003). Consumer acceptance of electronic commerce: Integrating trust and risk with the technology acceptance model. *International Journal of Electronic Commerce*, *7*(3), 101-134.

Pfeil, U., Svangstu, K., Ang, C. S., & Zaphiris, P. (2011). Social roles in an online support community for older people. *International Journal of Human-Computer Interaction*, *27*(4), 323-347. doi: 10.1080/10447318.2011.540490.

Pluempavarn, P., Panteli, N., Joinson, A., Eubanks, D., Watts, L., & Dove, J. (2011). Social roles in online communities: Relations and trajectories. *Proceedings of 6th Mediterranean Conference on Information Systems*, *47*, (pp. 1-14). Nicosia, Cyprus.

Pons, P., & Latapy, M. (2006). Computing communities in large networks using random walks. *Journal of Graph Algorithms and Applications*, *10*(2), 191-218. doi: 10.7155/jgaa.00124.

Preece, J., & Shneiderman, B. (2009). The reader-to-leader framework: Motivating technology-mediated social participation. *AIS Transactions on Human-Computer Interaction*, *1*(1), 13-32. doi: 10.17705/1thci.00005.

Projection of Two-Mode Networks (n.d.). Retrieved January 15, 2016, from http://www.toreopsahl.com.

Qin, L., Kim, Y., Hsu, J., & Tan, X. (2011). The effects of social influence on user acceptance of online social networks. *International Journal of Human-Computer Interaction*, *27*(9), 885-899. doi: 10.1080/10447318.2011.555311.

Raghavan, U. N., Albert, R., & Kumara, S. (2007). Near linear time algorithm to detect community structures in large-scale networks. *Physical Review E*, *76*(3), 1-12. doi: 10.1103/PhysRevE.76.036106.

Rauniar, R., Rawski, G., Yang, J., & Johnson, B. (2014). Technology acceptance model (TAM) and social media usage: An empirical study on Facebook. *Journal of Enterprise Information Management*, *27*(1), 6-30. doi: 10.1108/JEIM-04-2012-0011.

Reichardt, J., & Bornholdt, S. (2006). Statistical mechanics of community detection. *Physical Review E*, *74*(1), 1-16. doi: 10.1103/PhysRevE.74.016110.

Rheingold, H. (1993). *The virtual community: Finding commection in a computerized world*. Boston, MA: Addison-Wesley Longman Publishing.

Risser, H. S., & Bottoms., S. (2014). "Newbies" and "Celebrities": Detecting social roles in an online network of teachers via participation patterns. *International Journal of Computer-Supported Collaboration Learning*, *9*(4), 433-450. doi: 10.1007/s11412-014-9197-4.

Roca, J. C., Chiu, C. M., & Martínez, F. J. (2006). Understanding e-learning continuance intention: An extension of the Technology Acceptance Model. *International Journal of Human-Computer Studies*, *64*(8), 683-696. doi: 10.1016/j.ijhcs.2006.01.003.

Rönkkö, M., & Evermann, J. (2013). A critical examination of common beliefs about partial least squares path modeling. *Organizational Research Methods*, *16*(3), 425-448. 10.1177/1094428112474693.

Rosipal, R., & Krämer, N. (2006). Overview and recent advances in partial least squares. *Lecture Notes in Computer Science*, *3940*, 34-51.

Rosvall, M., Axelsson, D., & Bergstrom, C. T. (2009). The map equation. *The European Physical Journal-Special Topics*, *178*(1), 13-23. doi: 10.1140/epjst/e2010-01179-1.

Salter-Townshend, M., & Brendan Murphy, T. (2015). Role analysis in networks using mixtures of exponential random graph models. *Journal of Computational and Graphical Statistics*, *24*(2), 520-538. doi: 10.1080/10618600.2014.923777.

Schumacker, R. E., & Lomax, R. G. (2004). *A beginner's guide to structural equation modeling*. Mahwah, NJ: Lawrence Erlbaum Associates.

Shen, A. X., Cheung, C. M., Lee, M. K., & Chen, H. (2011). How social influence affects we-intention to use instant messaging: The moderating effect of usage experience. *Information Systems Frontiers*, *13*(2), 157-169. doi: 10.1007/s10796-009-9193-9.

Shin, D.H. (2010). Analysis of online social networks: a cross-national study. *Online Information Review*, *34*(3), 473-95. doi: 10.1108/14684521011054080.

Sledgianowski, D., & Kulviwat., S. (2009). Using social network sites: The effects of playfulness, critical mass and trust in a hedonic context. *Journal of Computer Information Systems*, *49*(4), 74-83.

Söllner, M., Hoffmann, A., & Leimeister., J.M. (2016). Why different trust relationships matter for information systems users. *European Journal of Information Systems*, *25*(3), 274-87. /doi: 10.1057/ejis.2015.17.

Song, S., Nerur, S., & Teng, J. T. (2007). An exploratory study on the roles of network structure and knowledge processing orientation in work unit knowledge management. *ACM SIGMIS Database: the DATABASE for Advances in Information Systems*, *38*(2), 8-26. doi: 10.1145/1240616.1240620.

Stackoverflow (2012). What are the differences between community detection algorithms in igraph? Retrieved September 25, 2017, from https://stackoverflow.com/questions/9471906/what-are-the-differences-between-community-detection-algorithms-in-igraph.

Swamynathan, G., Wilson, C., Boe, B., Almeroth, K., & Zhao, B. Y. (2008). Do social networks improve e-commerce? A study on social marketplaces. *Proceedings of The First Workshop on Online Social Networks* (pp. 1-6). Seattle, WA, USA. doi: 10.1145/1397735.1397737.

Taherdoost, H. (2018). Development of an adoption model to assess user acceptance of e-service technology: E-Service technology acceptance model. *Behaviour & Information Technology*, *37*(2), 173-197. doi: 10.1080/0144929X.2018.1427793.

Tamjidyamcholo, A., Kumar, S., Sulaiman, A., & Gholipour, R. (2016). Willingness of members to participate in professional virtual communities. *Quality & Quantity*, *50*(6), 2515-2534. doi: 10.1007/s11135-015-0274-1.

Tang, L., & Liu, H. (2010). Graph mining applications to social network analysis. In C. Aggarwal & H. Wang (eds.). *Managing and Mining Graph Data. Advances in Database Systems*, 40 (pp. 487-513). Boston, MA: Springer.

Tarhini, A., Hone, K., & Liu, X. (2014). Measuring the moderating effect of gender and age on e-learning acceptance in England: A structural equation modeling approach for an extended technology acceptance model. *Journal of Educational Computing Research*, *51*(2), 163-184. doi: 10.2190/EC.51.2.b

Tonnies, F. (1995). *Community and association* (C. P. Loomis, Trans.). London, England: Routledge and Paul.

Toral, S. L., Rocío Martínez-Torres, M., Barrero, F., & Cortés, F. (2009). An empirical study of the driving forces behind online communities. *Internet Research*, *19*(4), 378-392. doi: 10.1108/10662240910981353.

Traag, V. (2014). *Algorithms and dynamical models for communities and reputation in social networks*. Springer. doi: 10.1007/978-3-319-06391-1.

Tsvetovat, M., & Kouznetsov, A. (2011). *Social network analysis for startups*. Sebastopol, CA: O'Reilly Media.

Ugander, J., Karrer, B., Backstrom, L., & Marlow, C. (2011). The anatomy of the Facebook social graph. Retrieved September 16, 2017, from https://arxiv.org/pdf/1111.4503.pdf.

Valente, T. W., Coronges, K., Lakon, C., & Costenbader, E. (2008). How correlated are network centrality measures? *Connection*, *28*(1), 16-26.

Van der Heijden, H. (2004). User acceptance of hedonic information systems. *MIS Quarterly*, *28*(4), 695-704. doi: 10.2307/25148660.

Van Slyke, C., Ilie, V., Lou, H., & Stafford, T. (2007). Perceived critical mass and the adoption of a communication technology. *European Journal of Information Systems*, *16*(3), 270-83. doi: 10.1057/palgrave.ejis.3000680.

Van Steen, M. (2010). *An introduction to graph theory and complex networks*. Retrieved from http://pages.di.unipi.it/ricci/book-watermarked.pdf.

Venkatesh, V., & Bala, H. (2008). Technology acceptance model 3 and a research agenda on interventions. *Decision Sciences*, *39*(2), 273-315. doi: 10.1111/j.1540-5915.2008.00192.x.

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science*, *46*(2), 186-204. doi: 10.1287/mnsc.46.2.186.11926.

Vijayasarathy, L. R. (2004). Predicting consumer intentions to use on-line shopping: The case for an augmented technology acceptance model. *Information & Management*, *41*(6), 747-762. doi: 10.1016/j.im.2003.08.011.

Wakita, K., & Tsurumi, T. (2007). Finding community structure in mega-scale social networks. *Proceedings of the 16th International Conference on World Wide Web* (pp. 1275-1276). Banff, Alberta, Canada. doi: 10.1145/1242572.1242805.

Wangpipatwong, S., Chutimaskul, W., & Papasratorn, B. (2008). Understanding citizen's continuance intention to use e-government website: A composite view of technology acceptance model and computer self-efficacy. *Electronic Journal of e-Government*, *6*(1), 55-64.

Warmbrodt, J., Sheng, H., & Hall, R. (2008). Social network analysis of video bloggers' community. *Proceedings on Hawaii International Conference on System Sciences* (pp. 1530-1605). Waikoloa, HI, USA. doi: 10.1109/HICSS.2008.402.

Wasserman, S., & Faust, K. (1994). Social network analysis: Methods and applications. *Structural Analysis in the Social Sciences, 8*. Cambridge, England: Cambridge University Press. doi: 10.1017/CBO9780511815478.

Welser, H. T., Cosley, D., Kossinets, G., Lin, A., Dokshin, F., Gay, G., & Smith, M. (2011). Finding social roles in Wikipedia. *Proceedings of the 2011 iConference* (pp. 122-129). Seattle, Washington, USA. doi: 10.1145/1940761.1940778.

White, A. J., Chan, J., Hayes, C., & Murphy, T. B. (2012). Mixed membership models for exploring user roles in online fora. *Proceedings of the Sixth International AAAI Conference on Weblogs and Social Media* (pp. 1-4). Dublin, Ireland.

Wu, B., Zhou, X., Jin, Q., Lin, F., & Leung, H. (2017). Analyzing social roles based on a hierarchical model and data mining for collective decision-making support. *IEEE Systems Journal*, *11*(1), 356-365. doi: 10.1109/JSYST.2014.2386611.

Wu, J. H., & Wang, S. C. (2005). What drives mobile commerce? An empirical evaluation of the revised technology acceptance model. *Information & Management*, *42*(5), 719-729. doi: 10.1016/j.im.2004.07.001.

Wu, M. (2011). Social networks vs online communities: The important distinctions to know. Retrieved September 16, 2017, from http://www.mycustomer.com/marketing/technology/social-networks-vs-online-communities-the-important-distinctions-to-know.

Yamaguchi, Y., & Hayashi, K. (2017). When does label propagation fail? A view from a network generative model. *Proceedings of the Twenty-Sixth International Joint Conference on Artificial Intelligence* (pp. 3224-3230). Melbourne, Australia. doi: 10.24963/ijcai.2017/450.

Ye, Y., & Kishida, K. (2003). Toward an understanding of the motivation of open source software developers. *Proceedings of the 2003 International Conference on Software Engineering* (pp. 419-729). Portland, OR.

Yeh, N. C., Chuan-Chuan Lin, J., & Lu, H. P. (2011). The moderating effect of social roles on user behaviour in virtual worlds. *Online Information Review*, *35*(5), 747-769. doi: 10.1108/14684521111176480.

Yoon, H. Y., & Park, H. W. (2014). Strategies affecting Twitter-based networking pattern of South Korean politicians: Social network analysis and exponential random graph model. *Quality & Quantity, 48*(1), 409-423. doi: 10.1007/s11135-012-9777-1.

Zhou, Y., & Amin, M. (2014). Factors affecting online community commitment in China: a conceptual framework. *Journal of Technology Management in China, 9*(1), 24-36. doi: 10.1108/JTMC-08-2013-0033.

Zhu, D. H., Chang, Y. P., & Luo, J. J. (2016). Understanding the influence of C2C communication on purchase decision in online communities from a perspective of information adoption model. *Telematics and Informatics, 33*(1), 8-16. doi: 10.1016/j.tele.2015.06.001.