User Roles in Online Communities and Their Moderating Effect on Online Community Usage Intention: An Integrated Approach

Ezgi Akar, Sona Mardikyan & Tevfik Dalgic

INTERNATIONAL JOURNAL OF HUMAN–COMPUTER INTERACTION
2019, VOL. 35, NO. 6, 495–509
https://doi.org/10.1080/10447318.2018.1465325

User Roles in Online Communities and Their Moderating Effect on Online Community Usage Intention: An Integrated Approach

Ezgi Akar [a], Sona Mardikyan [b], and Tevfik Dalgic [c]

[a]Department of Management Information Systems, Bogazici University, Istanbul, Turkey; [b]Department of Management Information Systems, Bogazici University, Istanbul, Turkey; [c]Naveen Jindal School of Management, The University of Texas at Dallas, Dallas, Texas, USA

ABSTRACT

Recently, it has been evident that the analysis of user data and content in online environments allows practitioners to understand how to motivate online community members and keep them frequently involved in the community, and so to manage these communities successfully. In this sense, practitioners should comprehend community members' usage intentions to give a better service and to motivate them. However, different user types engage in such communities, so understanding their diverse needs is also essential for practitioners. In parallel, this article addresses the problem of the different user types existing in online communities, and each of them requires different strategies to be motivated and involved in the community. Thus, unlike previous studies, this study firstly identifies user roles in an online community based on the structural role theory, social network analysis, and community members' contribution behavior. After that, it investigates members' usage intentions based on the technology acceptance model and examines the moderating effect of identified user roles on their usage intentions. The study also guides practitioners to develop motivational strategies to keep each type of member continually satisfied.

1. Introduction

Technological advancements have led to the Internet proliferation and have increased the social media use by societies on the global scale. The statistics indicate that the total population of the world is 7.4 billion and the total number of Internet users is 3.4 billion (Kemp, 2016). Moreover, the emergence of Web 2.0 has also fired the interactivity among the Internet users, and so, social networking sites and online communities have started to show up gradually. They have become very common among the Internet users by inviting them to discuss various socio-economic issues as discussed in traditional media (Baek & Kim, 2015).

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 different needs engage in online communities, so practitioners should develop different managerial and motivational strategies to keep each type of user satisfied. Unfortunately, previous studies fail to understand how factors having any impact on community website usage intention can vary regarding different community member types. Therefore, at the first step, this study explores user roles in an online community based on the structural role theory and applies social network analysis (SNA) to investigate users' interactions in the community. Members' contribution behaviors in the community are also integrated into the analysis to gain a deep understanding of the implication of these members' interactions. In the second step, this study examines the moderating effect of identified user roles on members' community website usage intentions. As a result, this study gives implications and further insights from the theoretical perspective and suggests motivational strategies for practitioners who create and manage online community websites from a managerial standpoint.

As a case study, an online community known as *Inci Sozluk* has been selected to be investigated. *Inci Sozluk* has 918.299 members and has been ranked as a 44th popular website in Turkey by January 2017 (Alexa, n.d.). In this community, members open topics about any subject, add their contents, and share a mutual interest with other community members. On the global basis, Inci Sozluk is regarded as the Turkish version of 4chan (Leyden, 2010; Trend Micro, 2010) and it can be considered as a representative of an online discussion forum.

In the first half of the article, literature review, research model, and hypotheses are introduced. In the second half of the article, the methodology and study results are presented. Lastly, significant study findings are highlighted and discussed to address further research questions from both theoretical and managerial perspectives.

2. Theoretical background and hypotheses

2.1. Online communities and user roles

Online communities can be defined as "social aggregations that emerge from the Net when enough people carry on those

CONTACT Ezgi Akar, ezgi.akar@boun.edu.tr, Yönetim Bilişim Sistemleri Bölümü, Boğaziçi Üniversitesi, Hisar Kampüs B Blok, Bebek, İstanbul 34342, Turkey.
Color versions of one or more of the figures in the article can be found online at www.tandfonline.com/hihc.

public discussions long enough, with sufficient human feeling, to form webs of personal relationships in cyberspace" (Rheingold, 1993, p. 6–7). This definition indicates that online communities involve users who have likely had never met, but they are together for mutual interest or goal.

Previous studies including consumer communities (Lorenzo-Romero, Constantinides, & Alarcón-del-Amo, 2011), health communities (Han et al., 2012), innovation contest communities (Füller et al., 2014), enterprise online communities (Hacker, Bodendorf, & Lorenz., 2017; Muller, Shami, Millen, & Feinberg, 2010), and social networking sites (Brandtzæg & Heim, 2011; Çiçek & Eren-Erdogmus, 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. (2011) developed 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) identified social roles in an ideological and a nonideological online community by using the Reader-to-Leader model, and they investigated the importance of each user role in each type of community. Choi et al. (2015) also examined user roles in an online community based on their behavioral types, and they identified *initiators, commentators, attractors*, and *translators* in Reddit. Additionally, Füller et al. (2014) analyzed user types in an innovation contest community and found 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-Erdogmus (2013) focused on social networking sites and categorized users based on their social media usage preferences by conducting cluster and factor analyses, and Analysis of Variance (ANOVA). As a result, they identified social media users consisting of *inactives, sporadics, entertainment users, debaters*, and *advanced users*. Also, Brandtzæg and Heim (2011) collected data from social networking sites in Norway and identified five user roles including *sporadics, lurkers, socializers, debaters*, and *actives* based on cluster analysis and qualitative techniques. Additionally, Lee, Yang, Tsai, and Lai (2014) extracted 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) tried 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 considered online social networking sites, but they developed a semantic approach to model user profiles in social networking sites based on the raw data of the user activities in online communities.

Furthermore, Welser et al. (2011) collected posted comments in Wikipedia and tried to analyze user roles by considering users' patterns in their edit histories in these comments, and they found four user roles including substantive *experts, technical editors, vandal fighters*, and *social networkers*. Also, Arazy et al. (2015) focused 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) adapted role typology based on the findings from social media and literature to find worker's roles in enterprise social networks. Additionally, Muller et al. (2010) identified 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) identified user roles in an online network of teachers by examining their usage patterns and found five clusters consisting of *newbies, inbound participants, full participants, celebrities*, and *peripheral participants*. Wu, Zhou, Jin, Lin, and Leung (2017) introduced a three-layer model to investigate user roles hierarchically and developed an integrated framework to benefit from the identification of user roles to support the collective decision making. Golder and Donath. (2004) analyzed social roles derived from sociolinguistics, social psychology, and the ethnography of communication in speech communities and they identified *celebrities, newbies, lurkers, flamers, trolls*, and *ranters* in a speech community. Lastly, Chan, Hayes, and Daly (2010) used distinctive features to profile the user roles in a medium-sized bulletin board and applied 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; Martino & 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) benefited from SNA to visualize ego networks of user types. Additionally, Füller et al. (2014) utilized from SNA and calculated degree centralities of user types. Risser and Bottoms. (2014) also calculated network centralities of all types of users. Also, Angeletou, Rowe, and Alani (2011) integrated SNA into a semantic model to categorize users' behaviors over time in an online community, and Pfeil, Svangstu, Ang, and Zaphiris (2011) combined 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 and Brendan Murphy (2015) developed an 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) analyzed user posting behaviors in Reddit and found the presence of an *answer-person* role. Additionally, Hecking, Chounta, and Hoppe (2015) investigated network analysis methods for the analysis of emergent themes and user types in discussion forums. Lastly, White, Chan, Hayes, and Murphy (2012) developed 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 toward 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., Füller et al., 2014; Yeh, Chuan-Chuan Lin, & Lu, 2011), this study applies a community detection algorithm to identify user roles in an online community across a different context and considers members' contribution behavior to identify these roles in a more meaningful way (Gleave, Welser, Lento, & Smith, 2009).

2.2. Technology acceptance model

The technology acceptance model (TAM), which 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) (Please see Table A2 for all abbreviations used in the study). 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, 1989; 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 skeptical about 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 the UI.

H2: PEOU has a significant impact on the UI.

H3: PEOU has a significant impact on the PU.

There are also other factors that have impacts 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, p. 75). Online community sites offer entertaining contents and services for their members (Shin, 2010). Thus, members want to experience pleasure or joy, and they become intrinsically motivated to be a part of the online community (Agrifoglio, Black, Metallo, & Ferrara., 2012). Parallel to the previous research, members having pleasure or fun are more likely to continue to use online community sites (Agrifoglio et al., 2012; Moon & Kim., 2001; Shin, 2010; Sledgianowski & Kulviwat., 2009). 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, Rawski, Yang, & Johnson, 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). Parallel to the previous studies, the following hypotheses are suggested:

H4: PP has a significant impact on the UI.

H5: PP has a significant impact on the PU.

H6: PEOU has a significant impact on the PP.

The second factor is the perceived critical mass (PCM). PCM is one of the critical variables that must be considered in 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 significant 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 affects usage intention of computer-mediated technologies such as instant messaging, groupware acceptance, social media networks, and virtual communities (Lim, 2014; Lou, Luo, & 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 about 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 a 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 willing to share their experience which may decrease any learning curve associated with an online community site. In light of the previous research, the following hypotheses are proposed:

H7: PCM has an impact on the UI.

H8: PCM has an impact on the PU.

H9: PCM has an impact on the 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 parallel, online communities' ability to take responsibilities to provide a secure platform for their members will influence members' usage intentions. In other words, members must feel that their privacy is protected and they must trust 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 the 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 (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 et al., 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 the 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' online community usage intentions. Figure 1 also shows related hypotheses on the proposed research model.

3. Methodology

The methodology of the study involves two phases. The first phase introduces how data are collected and cleaned to form an online community network and to identify user roles. The second phase presents how online questionnaire is developed, distributed, and collected and how online community members' usage intentions are analyzed.

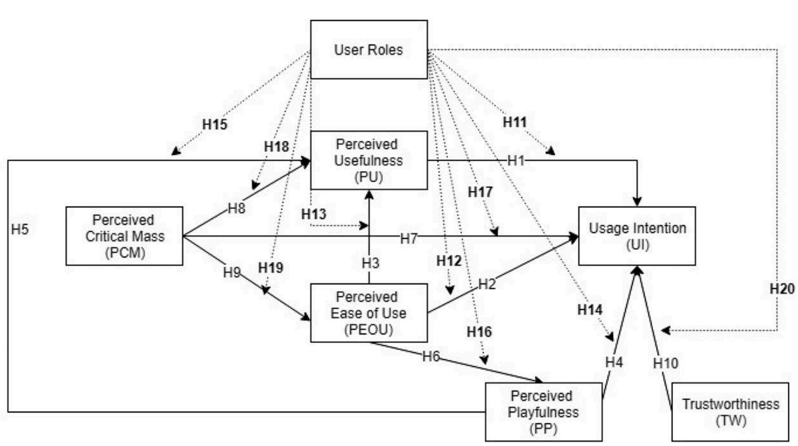

Figure 1. The proposed research model and hypotheses.

3.1. Data collection, cleaning, and network preparation

On the 27 October 2016, data were extracted from the address of www.incisozluk.com.tr directly by using an application programming interface provided by the community administration. In this respect, measurement errors such as interviewer effects, failure in the recall, and other errors, arising from survey research were avoided (Brewer, 2000; Brewer & Webster, 2000; Marsden, 2003). Additionally, from the ethical perspective, the data were publicly available, and the 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 in accordance with the terms of use and privacy policy of the community by protecting each member's anonymity in the community.

In detail, data collection, cleaning, and network preparation follow these steps:

(1) Topics that were opened in the last 30 days were specified to focus on active users of the community. Totally, 11,609 topics were collected. After that 387,418 relationships between topics and members who added any content including pictures, video, or text to the given topic were extracted. Topics including only one content were deleted because they could not start an interaction between members.
(2) A member can add more than one content to any given topic. For this reason, a relationship weight is calculated by counting the relationships between the same member and the same topic. For example; if a member added three contents to the same topic, it was formed as there was a relationship between this member and the given topic, and the relationship weight was three. This weight shows the strength of the relationship (Haythornthwaite, 1996). As a result, 288,898 unique relationships were obtained.
(3) A two-mode network, including topics and members, was transformed into the one-mode network by a projection method (Borgatti & Everett, 1997). Bipartite projection function in the igraph package of R was used. Members were selected as the primary node set. It means that if two members add content to the same topic, a relationship occurs between them. Finally, the function formed a weighted and one-mode network including 28,715 members and 21,739,690 relationships among them. It is crucial that two members can add contents under one or more same topics, so this function calculated relationship weights. These three steps summarize how the community network is formed.
(4) The relationship list was stored in a text file to be analyzed with 0.99.896 version of R-Studio, and the fast greedy community detection algorithm was used to detect sub-communities (Clauset, Newman, & Moore, 2004) due to its calculation speed (Mislove, 2009).
(5) To interpret and to label the detected sub-communities, members' contribution to the community was analyzed by collecting each member's attributes. The attributes that were available for each member by the administration were selected:
    - his or her membership age,
    - the total number of topics opened by him or her in the last 30 days,
    - the total number of contents added by him or her in the last 30 days,
    - the total number of his or her community website visits.

3.2. Questionnaire development

An online questionnaire including seven descriptive questions and 20 items for related factors were used to test the proposed research model. As shown in Table A1, it was mainly adapted from the previous studies (Moore & Benbasat., 1991; Rauniar et al., 2014; Yeh et al., 2011). Each 20 item was measured on a seven-point Likert scale, ranging from "strongly disagree" (1) to "strongly agree" (7). The descriptive question asking members' roles in the community was designed based on the results obtained after the fifth step mentioned above. Each member was asked which user role identifies his or her behavior in the community.

The questionnaire was shared on the announcement board and the Twitter profile of the online community. In a 1-month period, 843 responses were collected. The response rate was 74.27%. After the deletion of incomplete or unsuitable responses, 783 replies were gathered. Study hypotheses were tested with partial least squares (PLS) by using WarpPLS 6.0, and each type of member usage pattern was analyzed by conducting a multi-group analysis with WarpPLS 6.0. The partial least squares approach allows researchers to work with nonnormal data, minimizes the effect of measurement error, tests, and validates exploratory models (Goodhue, Thompsun, & Lewis, 2013; Moqbel, 2012).

4. Study results

4.1. Social network analysis

Table 1 shows members' contribution behaviors in the community across each subcommunity. The fast greedy algorithm has divided the community network into four subcommunities with 0.1952174 modularity. Table 1 describes that the first subcommunity consists of 4,611 members, the second

Table 1. Members' contribution behaviors across subcommunities.

	Community 1 $N = 4{,}611$		Community 2 $N = 17{,}444$		Community 3 $N = 6{,}594$		Community 4 $N = 66$	
Criteria	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
Content	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
Visit	6.67	14.58	10.10	30.54	5.18	14.31	3.77	6.49

Table 2. The summary of user roles.

Subcommunities	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, he fires other community members to communicate and adds his contents by opening topics.
Community 3	Content 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.

one includes 17,444, the third one involves 6,594 members, and the last sub-community comprises only 66 members.

Table 1 also shows that members in the second subcommunity have submitted the most contents and opened the most topics. They visit the website more than other subcommunity members do. These subcommunity members are called *socializers* (Füller et al., 2014) who are the most social members of the community based on their contribution to the community. Socializers very actively participate in the communication and interaction activities. They generate an enormous amount of content, and they fire other community members to communicate and add their contents by opening topics.

Furthermore, Table 1 indicates that members in the first subcommunity usually visit the website, they open fewer topics, and they add fewer contents than other subcommunity members do. Thus, they are called *visitors* (Füller et al., 2014). Additionally, members of the third subcommunity often visit the website, they open few topics, but they generate lots of contents, so they are called content generators. This type of users is also called efficient contributors in the literature (Füller et al., 2014). Lastly, members of the fourth subcommunity visit the community seldom, they do not open any topic, and they produce the fewest content. Thus, they are called *passive members*. This type of users is also identified as lurkers who make fewer contributions regarding other subcommunities (Füller et al., 2014; Füller, Jawecki, & Mühlbacher., 2007). Table 2 also summarizes these user roles in the online community.

4.2. Test of the proposed model

Table 3 includes the descriptive statistics collected by the questionnaire. It shows that respondents mainly consist of males. About 61.8% of the members are equal or less than 18 years old, and 26.8% of the members are between 19 and 25 years old. Additionally, 24.8% of the members are high school students, 47.4% of them are university students, and most of the community 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. Furthermore, 41.0% of the members identify themselves as *visitors*, 23.8% of them as content *generators*, 18.5% of them as *socializers*, and 16.7% of as *passive members*.

Table 3. 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%
	Content 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%

Results of the measurement model analysis

The individual item reliability of the measurement model is measured by Cronbach's alpha. Table 4 shows that Cronbach's alpha values of all constructs range from 0.616 to 0.908. Although Cronbach's alpha coefficients should be equal to or greater than 0.7 (Cronbach, 1971), this threshold can be set at 0.6 (Nunnally, 1978; Nunnally & Bernstein.,

Table 4. Results of measurement model analysis.

Construct	Item	Factor loading	AVE	Item reliability (Cronbach's a)	Composite reliability	VIFs
PCM	PCM1	0.830	0.489	0.644	0.789	1.555
	PCM2	0.769				
	PCM3	0.606				
	PCM4	0.555				
TW	TW1	0.775	0.600	0.776	0.857	1.278
	TW2	0.761				
	TW3	0.836				
	TW4	0.721				
PU	PU1	0.809	0.569	0.618	0.797	1.402
	PU2	0.662				
	PU3	0.783				
PEOU	PEOU1	0.855	0.636	0.703	0.837	1.090
	PEOU2	0.883				
	PEOU3	0.629				
UI	UI1	0.828	0.568	0.616	0.797	1.703
	UI2	0.757				
	UI3	0.668				
PP	PP1	0.907	0.844	0.908	0.942	1.126
	PP2	0.941				
	PP3	0.908				

Table 5. Results of 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*

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

1994). The internal consistency of the measurement model is considered by composite reliability. Composite reliabilities of each construct are at least 0.7 that implies a high internal consistency of scales.

Construct validity of the model is measured by factor loading analysis. Factor loadings should be at least 0.5 and ideally should be greater than 0.7 (Hair, Anderson, Babin, & Black, 2010). Table 4 displays that all factor loadings for each construct are at least 0.5 and it implies adequate construct validity. Also, average variance extracted (AVE) values greater than 0.5 suggest adequate convergent validity.

Furthermore, AVE values for two constructs should be greater than the square of the correlation between these two factors to provide evidence for discriminant validity. Table 5 shows the correlations and squared correlations between constructs. The values above the diagonal are less than AVE values, and it provides the proof of discriminant validity. Lastly, all constructs are derived from the literature that indicates a high content validity.

Also, a full collinearity test is conducted to investigate if there is multicollinearity among the latent variables. This test relies on the variance inflation factors (VIFs) calculated for each latent variable about the other latent variables (Kline, 2016). In Table 4, the results show that VIF values for all latent variables are less than the threshold of 5.0 and do not imply any multicollinearity among the latent variables (Hair et al., 2010).

Results of the structural model analysis

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; $p \le 0.001$; H1 supported), PP (β = 0.162; $p \le 0.001$; H4 supported), TW (β = 0.192; $p \le 0.001$; H10 supported), and PCM (β = 0.334; $p \le 0.001$; H7 supported) significantly affect the UI (R^2 = 0.446). Furthermore, PEOU (β = 0.189; $p \le 0.001$; H6 supported) has a significant impact on the PP (R^2 = 0.036). PEOU (β = 0.093; $p \le 0.01$; H3 supported), PP (β = 0.098; $p \le 0.01$; H5 supported), and PCM (β = 0.435; $p \le 0.001$; H8 supported) have also a significant impact on the PU (R^2 = 0.240). Lastly, PCM (β = 0.174; $p \le 0.001$; H9 supported) has a significant impact on the PEOU (R^2 = 0.030). Figure 2 shows the path estimations and their significance levels.

Furthermore, Table 6 shows model fit and quality indices. The table indicates that the model is robust based on the significance of average path coefficients (APC), average R squared (ARS), and average adjusted R-squared (AARS). Additionally, average block VIF (AVIF) and average full collinearity VIF (AFVIF) values should be ideally less than or equal to 3.3 (Kock, 2011). Lastly, Tenenhaus goodness–of-fit (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 6 shows that the explanatory power of the structural model is medium.

Moreover, age, gender, education, economic level, daily visiting frequency, and hourly visiting frequency are added as control variables to the model to remove other possible explanations for the relationships between UI and PCM, TW, PU, PP, and PEOU. It can be concluded that path estimations shown in Figure 2 are significantly associated with UI regardless of the control variables. Additionally, Table 7 shows the effects of control variables on the UI. It is stated that it is not important whether the impacts associated with control variables are significant or not (Kock, 2011).

Path analysis results for usage patterns

The sample is split into four subsamples for further PLS analysis to understand the different usage patterns regarding four user roles. Table 8 includes path estimations for regarding each user role. The results show that PCM has a more significant effect than TW, PP, and PU on the UI for visitors. On the other hand, PU has a more significant impact than

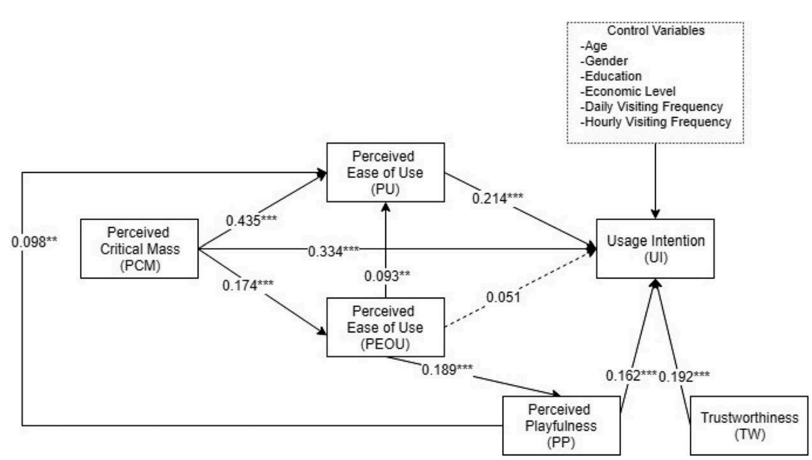

Figure 2. Path estimation results.

Table 6. Model fit.

Quality index	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	

Table 7. The 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

**$p \le 0.01$

PCM, TW, and PP on the UI for socializers. For the group of content 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.

Moreover, Table 9 shows that factors in Table 8 are significantly associated with UI regardless of the control variables. Table 10 also shows that all structural models are fit, and the explanatory power of each model is also large (Kock, 2011).

After that, a multi-group analysis is performed to evaluate the moderating effect of user roles and to test whether path coefficients significantly differ across each user role (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" (Kock, 2014, p. 4).

WarpPLS 6.0 makes a pair-wise comparison across each type of user. For this purpose, it calculates a critical ratio based on a pooled standard and presents p-values to check the significance of the path estimates. The program calculates the pooled standard as in Figure 3 (Keil et al., 2000) in where 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.

Table 9. The effect of control variables on UI concerning user roles.

	Visitors	Socializers	Content 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

**$p \le 0.01$

Table 10. Model fit for each user role model.

	Visitors		Socializers		Content 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	

After that, it calculates a critical ratio as $T_{12} = (\beta_1 - \beta_2)/S_{12}$ (Kock, 2014), where β_1 and β_2 are path coefficients of group one and group two, respectively. Lastly, it uses T_{12} to calculate p-values related to the difference between the path coefficients. WarpPLS 6.0 gives the results of pair-wise comparisons, T-values, and their significance levels. Table 11 shows these T-values. The results indicate that only H11, H14, H15, H16, H17, H18, and H20 are supported.

5. Discussion

5.1. Online community members' usage intentions

This study is conducted to understand the effects of the factors contributing to online community usage intention. The results point out that PCM, PU, TW, and PP play a key role in the determination of online community members' usage intention, respectively, in the context of online discussion forums. The importance of PCM can be

Table 8. Path coefficients regarding user roles.

	User roles			
Hypotheses	Visitors (N = 321)	Socializers (N = 145)	Content 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*

***$p \le 0.001$; **$p \le 0.01$, *$p \le 0.05$

Table 11. Multigroup 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

***$p \leq 0.001$; **$p \leq 0.01$, *$p \leq 0.05$

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

Figure 3. The calculation of pooled standard.

explained like that the value of an online community increases for users when more users are involved and communicated with each other in the community, because they tend to adopt online communities when a sufficient number of other members are already using the same community (Qin et al., 2011). Additionally, the results indicate that PCM also affects the usage intention indirectly through perceived ease of use (PEOU) and PU, while its impact on PU is greatly stronger than its effect on PEOU. This result indicate that if nonmembers perceive that many of their friends are members of the community, they tend to think that using that community is useful (Lou et al., 2000) and if community members want to share the benefit of their experience with the potential members, it eases any learning curve effects associated with that community use and it increases ease of use of the community site (Van Slyke, Ilie, Lou, & Stafford, 2007).

The study results also highlight that PU is more important than PP for community members. This result can indicate that members use online communities serving as online discussion forums to satisfy their utilitarian purposes rather than hedonic ones (Davis et al., 1992; Venkatesh & Davis, 2000). In other words, the importance of extrinsic motivations is higher than intrinsic motivations in such communities. Furthermore, PP also impacts usage intention (UI) independently through PU. It shows that if members perceive hedonic values in the community, they also perceive more utilitarian values in the community (Rauniar et al., 2014). If a member enjoys services in an online community such as texting, adding images, videos, or hyperlinks, this member perceives the community more useful.

Trust to the online community administration also increases the members' usage intentions. It implies that as members create and share contents and information, they should feel that the online community site has a mechanism that fulfills their privacy needs and any third-party cannot use their contents and information without their consent or knowledge (Rauinar et al., 2014).

Finally, although this study does not find a significant effect of PEOU on the UI, it indirectly has an impact on UI. This result highlights that if the online community is easy to use, members perceive more usefulness and they are more likely to feel playful during their engagement in the community (Agrifoglio et al., 2012).

5.2. The moderating effect of user roles

The study results indicate that members' behaviors may vary across different user roles. For example; 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 party. It can be crucial to keep socializers continually satisfied and to increase visitors' interactions within the community.

On the other hand, PP is an essential criterion for passive members and especially content generators. Content 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. Lastly, 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 content generators mostly perceive the online communities as useful and easy to use, 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.

6. Conclusion

6.1. Theoretical implications

Consistent with the previous studies, the findings of the study confirm that PP, PCM, PU, and TW except for PEOU act as influential factors in the context of online communities (Lee, Tyrrell, & Erdem., 2013; Lim, 2014; Lou et al., 2000; Qin et al., 2011; Rauniar et al., 2014; Sledgianowski & Kulviwat., 2009; 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 (Lin & Lee., 2006; Sledgianowski & Kulviwat., 2009), hedonic values have been found as the weakest indicator in the study. This result may strengthen the differences between the online communities and social networks and show that members want to gain benefits from the online communities.

Furthermore, the results point out that PCM has the most substantial effect on UI. It can reveal that for the growth of online communities, it is the most driving force for administrators. PP, PCM, and PEOU also have 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 sophisticated skills, therefore, when users perceive it is easy to learn, they tend to explore features and functions which can result in the improvement of PU (Lee et al., 2013). They also found the online communities to be more useful if more users engage in it and feel that it is playful (Rauniar et al., 2014).

Moreover, online communities are based on the commitment of their members (Ren, Kraut, & Kiesler, 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 in the community. After that, this study integrates these identified user roles into 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 study results show that user roles have a 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.

6.2. Managerial implications

One of the main challenges to increase social participation and motivate members in 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 user. For example; they can want to turn visitors and passive members into socializers or content 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 and 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 some passive members increase, 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 convince them to involve in the 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 important 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 the fact that socializers and content generators are core members of the community. These members' experiences play a crucial role in attracting 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 content 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 others and develop healthier relationships (Qin et al., 2011; Yeh

Table 12. Summary of user roles and managerial implications.

User role	Contribution behavior	Usage intention[a]	Managerial implication[a]
Visitors	• Usually visit • Fewer open topics than content generators and socializers • Fewer generate contents than content generators and socializers	• PCM • TW • PU	• Encourage word-of-mouth. • Prove the value that the community offers. • Provide a secure environment. • Provide special 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 special community features or functions to increase more relationship development. • Provide a secure environment, so make them comfortable while posting, communicating, or messaging
Content Generators	• Often visit • Fewer open topics than socializers • Generates a huge amount of content	• PP • PU	• Develop online interactive games, online contests, or entertaining services. • Provide special community features or functions to encourage them to open more topics and add contents.
Passive members	• Seldom visit • Do not open any 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

[a]*In the order of importance*

et al., 2011). Additionally, the platform should be reliable and convenient, and the response time should not be low. Furthermore, 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 they should also 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 return of visitor and passive members (Preece & Shneiderman, 2009).

Although PEOU does not have 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, and search functionalities to promote interactions and contributions of online members in the community (Yeh et al., 2011). Table 12 also summarizes the user roles and motivational strategies for each of them.

7. Limitations

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.

Acknowledgement

We thank Serkan Inci, the founder of Inci Sozluk, for his help and support for data access.

Funding

This study is supported by Bogazici University Research Fund with Grant Number 12751.

ORCID

Ezgi Akar http://orcid.org/0000-0002-1791-8331

References

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.

Alexa. (n.d.). Retrieved from http://www.alexa.com/siteinfo/incisozluk.com.tr

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).

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

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

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

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., 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

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.

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

Chan, J., Hayes, C., & Daly, E. M. (2010). Decomposing discussion forums and boards using user roles. *Icwsm*, *10*, 215–218.

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

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). doi: 10.1145/2817946.2817959.

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

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 neasurement* (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. (1989). User acceptance of computer technology: A comparison of two theoretical models. *Management Science*, *35*(8), 982–1003. doi:10.1287/mnsc.35.8.982

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

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

Fernandez, M., Scharl, A., Bontcheva, K., & Alani, H. (2014). User profile modelling in online communities. *Proceedings of the Third International Conference on Semantic Web Collaborative Spaces*, 1275 (pp. 1–15).

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

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.

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

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.

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*. ICWSM (pp. 140–149).

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 System Sciences (HICSS), 2013 46th Hawaii International Conference on System Sciences (pp. 4739–4748). doi: 10.1109/HICSS.2013.612

Hacker, J., Bodendorf, F., & Lorenz., P. (2017, February 12–15). *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

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). 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

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

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

Kemp, S. (2016). *Digital Year Book*. Retrieved January 11, 2017, from http://www.slideshare.net/wearesocialsg/2016-digital-yearbook

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

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

Krause, J., Croft, D. P., & James., R. (2007). Social network theory in the behavioural sciences: Potential applications. *Behavirol Econology and Sociobiology*, *62*(1), 15–27. doi:10.1007/s00265-007-0445-8

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

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), 250–261. doi:10.1016/j.dss.2013.12.004

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

Leyden, J. (2010). *Turkish pranksters load Facebook Translate with swears*. Retrieved from https://www.theregister.co.uk/2010/07/29/facebook_translation_turkey_prank/

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

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

Lim, W. M. (2014). Sense of virtual community and perceived critical mass in online group buying. *Journal of Strategic Marketing*, *22*(3), 268–283. doi:10.1080/0965254X.2013.876068

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

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

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

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

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.

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

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.

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

Moon, J. W., & Kim., Y. G. (2001). Extending the TAM for a World-Wide-Web context. *Information & Management*, *38*(4), 217–230. 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 (PhD. Dissertation), Texas A&M International University.

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). doi: 10.1145/1880071.1880106.

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

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

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), 522–556. doi:10.1086/228313

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

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 (pp. 2012), Nicosia, Cyprus, 4.

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

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

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

Ren, Y., Kraut, R., & Kiesler, S. (2007). Applying common identity and bond theory to design of online communities. *Organization Studies*, *28*(3), 377–408. doi:10.1177/0170840607076007

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

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

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

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), 473–495. 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), 274–287. doi:10.1057/ejis.2015.17

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

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

Trend Micro (2010). *Facebook prank, lost in translation*. Retrieved from http://countermeasures.trendmicro.eu/facebook-prank-lost-in-translation/

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), 270–283. doi:10.1057/palgrave.ejis.3000680

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

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).

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

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

About the Authors

Ezgi Akar received her Ph.D. degree in the field of management information systems from Bogazici University in 2018. In the meantime, she is a visiting assistant professor at the University of Texas at Arlington. Her research areas are social networks, social media analytics, marketing research, and data mining.

Sona Mardikyan received her Ph.D. degree in quantitative methods from Istanbul University. She is working in the management information systems department of Bogazici University as an associate professor. Her research areas are statistics, quantitative methods, information systems and technologies, and data mining.

Tevfik Dalgic received his BA and MBA from Middle East Technical University. His Ph.D. is from the Ankara Academy of Economic and Commercial Sciences. He is a professor of Organisation, Strategy and International Management at the University of Texas-Dallas since 2000.

APPENDIX

Table A1. Questionnaire items.

Factors	Items	Questions	References
Perceived Ease of Use	PEOU1	Learning the use inci sozluk is easy for me.	Moore & Benbasat., 1991
	PEOU 2	My interaction with inci sozluk is clear and understandable.	
	PEOU 3	I believe that it is easy to get inci sozluk to do what I want it to do (e.g., sending messages)	
Perceived Usefulness	PU1	I find inci sozluk useful in my personal life.	Rauniar et al., 2014
	PU2	Using inci sozluk enables me to get re-connected with people that matter to me.	
	PU3	Using inci sozluk enhances my effectiveness to stay in touch with others.	
Perceived Critical Mass	PCM1	Inci sozluk is one of the popular social media platform among my friends.	Rauniar et al., 2014
	PCM2	The most of my friends use inci sozluk.	
	PCM3	Using inci sozluk makes me grant privilege among my friends.	
	PCM4	There is a sense of human warmth in inci sozluk.	Yeh et al., 2011
Perceived Playfulness	PP1	I make fun while using inci sozluk.	Rauniar et al., 2014
	PP2	Using inci sozluk is enjoyable.	
	PP3	I found my visit to inci sozluk pleasant.	Yeh et al., 2011
Trustworthiness	TW1	I feel safe while sharing on inci sozluk.	Rauniar et al., 2014
	TW2	Inci sozluk provides required security settings for my profile.	
	TW3	I feel safe while using inci sozluk.	
	TW4	I feel safe while messaging with other members in inci sozluk.	
Usage Intention	UI1	I believe it is worthwhile for me to use inci sozluk.	Yeh et al., 2011
	UI2	Based on my experiences, I will continue to use inci sozluk.	
	UI3	I suggest my friends to use inci sozluk.	Rauniar et al., 2014

Table A2. The alphabetical list of abbreviations.

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