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User Interaction Within Online Innovation Communities:
A Social Network Analysis

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ABSTRACT

In the digital era, enterprises have established online innovation communities to attract customers to participate. Presented in this study is user interactions within these communities using social network analysis. By identifying distinct subgroups within the network and comparing the user interactions among these subgroups, this research aims to identify the group diversity of online interactions. The findings indicate that dialogists are more willing to interact and hold a favorable network position, followed by questioners, while answerers have the lowest level of interaction. User subgroups are identified using k-core analysis. The higher the value of the core k, the more interactions between users in the k-core subgroup and the better the network position. By combining both ego-centered and group dimensions of online interaction characteristics, this paper also outlines an investigation into an empirical study on the influence of user interactions on community recognition. The results confirm heterogeneous effects among different subgroups.

KEYWORDS:

Online Interaction, User Community, Social Network, Subgroup, Community Recognition

INTRODUCTION

Recently, there has been a shift toward deriving product ideas from users rather than relying solely on the research and development (R&D) personnel of an enterprise. This pattern has been termed as open innovation by Professor Henry Chesbrough of the University of California (Chesbrough, 2003). Ideas generated by users are often of higher quality in terms of novelty and customer benefits compared to those generated by professionals (Costa et al., 2023). Consumers prefer to purchase products that are developed by other users due to the feeling of being involved vicariously in the

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design process (Dahl et al., 2015). As a result, many enterprises have established online innovation communities to attract a wider customer base to participate in enterprise innovation. Examples of such communities include Microsoft's Power BI Community, LEGO Ideas innovation community, and Xiaomi's MIUI community of China.

User interaction is a critical feature of online innovation communities (Hwang et al., 2019). Users in these online innovation communities share their experiences and ideas on production through proposing, commenting, voting, question and answer (Q&A), and other means. Enterprises achieve the product innovation by listening to users' and adopting their valuable ideas. The social interactions in these communities facilitate social relationships among users. For example, users can follow each other and provide support and comment on interesting ideas. This results in the formation of a complex social network with online users as the nodes (Chen et al., 2021).

The literature suggests that the implementation of interaction tools is a significant driver of online community performance (Chen et al., 2021). Online interaction enables members to communicate ideas with one another and promotes the sharing and production of knowledge (Liang et al., 2020; Masson & Parmentier, 2022). Studies have also shown that online interactions help build trust among users and community reciprocity norms (Pai & Tsai, 2016), and online identification (Panteli & Sivunen, 2019).

Recent studies have used social network analysis to characterize online relations from multiple dimensions and explore their impacts on user innovation (Pyo et al., 2023; Qi et al., 2021; Rishika & Ramaprasad, 2019). As a quantitative method for studying relational data, social network analysis provides methodological support for depicting the whole picture of user online interaction and deconstructing the characteristics of user online interaction. Previous research commonly initiates the ego-centered network to characterizing user interactions such as their direction and frequency (Chen et al., 2021; Wang et al., 2022) or the redundancy measured by the connectivity of neighboring users (Li et al., 2021; Stephen et al., 2016). Few studies have addressed the subgroups of the user network and explored the characteristics among the subgroups formed by certain users with similar interactive patterns.

Our objective is to analyze users' online interactions by establishing a social network, identifying distinct subgroups within the network, and comparing the user interactions among these subgroups. To achieve this, we have selected one typical online user innovation community, Microsoft's Power BI Community, as our sample. We also investigated the impact of user interaction on community recognition, considering interaction characteristics from both the ego-centered and subgroup dimensions. The regression results confirm heterogeneous effects among different subgroups, even though the users have the same number and strength of online interactions, which implies the social contagion effect within the groups.

The primary contribution we present in this paper is the characterization of user interactions for various user groups and the identification of heterogeneous effects on community recognition among these groups. This study inspires future research to focus on the group diversity in user interactions and its impact on user behaviors. Additionally, the findings can guide the development of user interaction guidelines in online communities and enhance user innovation.

LITERATURE REVIEW

Online User Interaction

In the context of online innovation communities, scholars attend more to the effect of online interactions on user innovation. Online user interaction facilitates the tacit knowledge embedded in the individuals to be transformed into explicit knowledge and spread to other users, which inspires users with new ideas (Stephen et al., 2016). An abundance of empirical studies confirm that online interactions between users promote innovation through social influence and learning (Riedl & Seidelc,

2019) such as inspiring users to contribute more ideas and comments (Kosonen et al., 2013; Qi et al., 2021), improving the quality of users' ideas (Chan et al., 2015; Yang & Li, 2016), and increasing users' participation in the community (Guo et al., 2017).

Several studies have demonstrated that online interactions among users can facilitate the development of trust and reciprocity norms within a community (Pai & Tsai, 2016). This, in turn, strengthens users' sense of identification (Panteli & Sivunen, 2019) and fosters collaboration among them (Kumi & Sabherwal, 2018). When reciprocity is perceived as high, it has a positive impact on participation and contribution (Haas et al., 2021; Jahan & Kim, 2021).

Social Network Analysis in Online Communities

The social network analysis methodology combines social theory with mathematical, statistical, and graphical techniques, enabling the clear expression and measurement of social structural attributes through mathematical methods (Wasserman & Faust, 1994). Recent research has employed social network analysis to characterize online interactions from various aspects such as number, direction, strength, and redundancy, among others, to investigate their diverse impacts on user behavior (Li et al., 2021; Qi et al., 2021). Other studies calculated indicators that describe certain network attributes to measure social capital in online user communities from three dimensions (i.e., structural, relational, and cognitive capital) (Pyo et al., 2023; Wang et al., 2022).

Chen et al. (2015) consider online interactions in one crowdsourcing community from the direction, size, and frequency of interactions, find positive effects of interactive relations on individuals' idea generation. Chen et al. (2021) collect user interaction data from LEGO Ideas and empirically assess the effects of relational and structural characteristics of online social networks on users' idea contributions. The relational characteristics (i.e., number and strength of ties, neighbors' characteristics) is qualified by the ego-centered network, while the structural characteristics (i.e., centrality, bridge location) is qualified by the entire network.

Hwang et al. (2019) study one specific dimension of user interaction—whether users interact with others on broad topic domains and find that generalists are more likely to create novel ideas than nongeneralists. Focusing on the ego-centered network, Stephen et al. (2016) study the redundancy of online interactions in terms of the connectedness characteristics of neighbor users interacting with focal users. They find that the redundancy of online interaction would reduce the innovation performance of online users. The higher the connectivity of neighbor users, the higher the redundancy of online interactions of focal users, which is positively related to the novelty of the ideas focal users proposed. Taking the LEGO Ideas platform as an example, Li et al. (2021) calculate the information redundancy of users' online interaction and also confirmed the negative effect of information redundancy on the number of ideas the user proposed.

Previous studies have examined online interactions from various aspects. They have primarily focused on the ego-centered network perspective, however, calculating interaction indicators for individual users and exploring their impact on user innovation behavior. Few studies have analyzed the structural position of the user in the entire interaction network. Furthermore, only a few studies have identified user groups within the network and analyzed interaction patterns for these groups, rather than individual users. Therefore, in this paper, we explored the identification of user groups and the characterization of their interactions.

DATA COLLECTION AND NETWORK CONSTRUCTION

Sample Selection

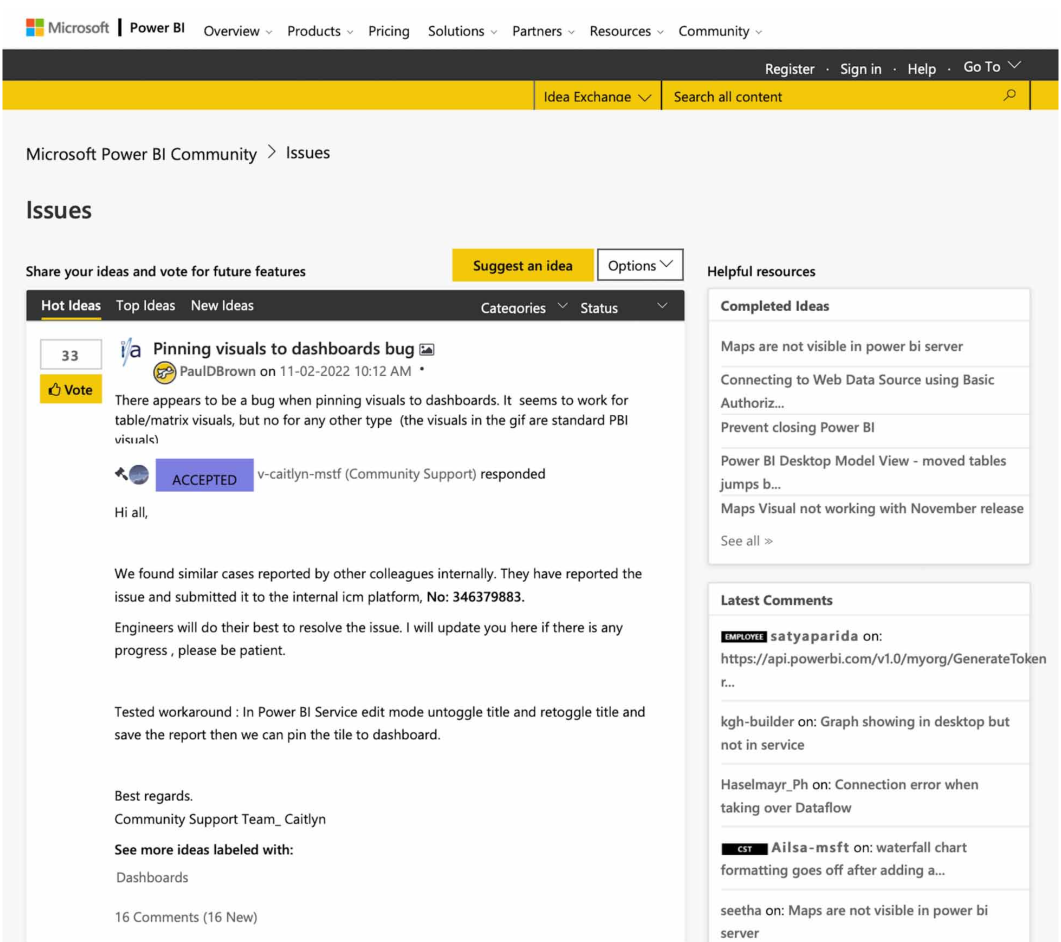
Considering the data availability and typicality, we selected Microsoft's Power BI Community (https://community.powerbi.com) as the research sample. Power BI is a set of business intelligence software launched by Microsoft, which can connect hundreds of data sources and transform complex data to allow for a concise and clear view, thus providing a reference for enterprise decision-making. Power BI Community, initiated by Microsoft Group, was officially launched on December 1, 2016. Users can register as a member of the community and posting and reply to other members. By March 2022, the number of posts on the Power BI Community exceeded 1.8 million.

The community consists of 13 sections including instructions for the usage of Power BI software (Get Help with Power BI), Q&A among users (Issues), and social development sections (Galleries). Because we focused on the kind of interaction behaviors referring to knowledge sharing among users, rather than the instructions for usage or social development, we selected the Q&A section—issues to analyze the characteristics of the users' interaction behaviors. As shown in Figure 1, in the "Issues" section, users exchange their problems and experiences with using Power BI software and put forward suggestions for improvement of performance.

Data Collection

Using Python crawler programs, we collected data of the latest one thousand hot posts released in the Issue section. The data includes information about who replied to a post and when, that is, the interactive data among users referring to posting and replying behavior. In addition, we collected data referring to user attributes including user ID, registration time, total number of messages the

Figure 1. Issues section in Microsoft Power BI community



user released, and total number of praise and badges the user received, which can be obtained on the user homepage as shown in Figure 2.

Construction of the User Social Network

We constructed a user social network using the online interaction data collected. In the network, the nodes represent online users in the community, and the edges represent the replies from one user to another. After a series of data processes, the social network is transformed into a simple directed graph, and the weights of the edges represent the total number of replies between two users. The steps of constructing the social network are shown in Figure 3, derived from the Python NetworkX tool.

Visualization of the User Social Network

Figure 4 is a visualization of the user social network. The size of the node refers to the node degree, the number of online interactive relations of the user. Most of the users are concentrated in the core location and its surroundings, where there are relatively close connections between users. A smaller number of users are scattered in the periphery, where there are relatively few connections between users. Table 1 shows the main network indicators for the user social network. The network contains

Figure 2. User homepage

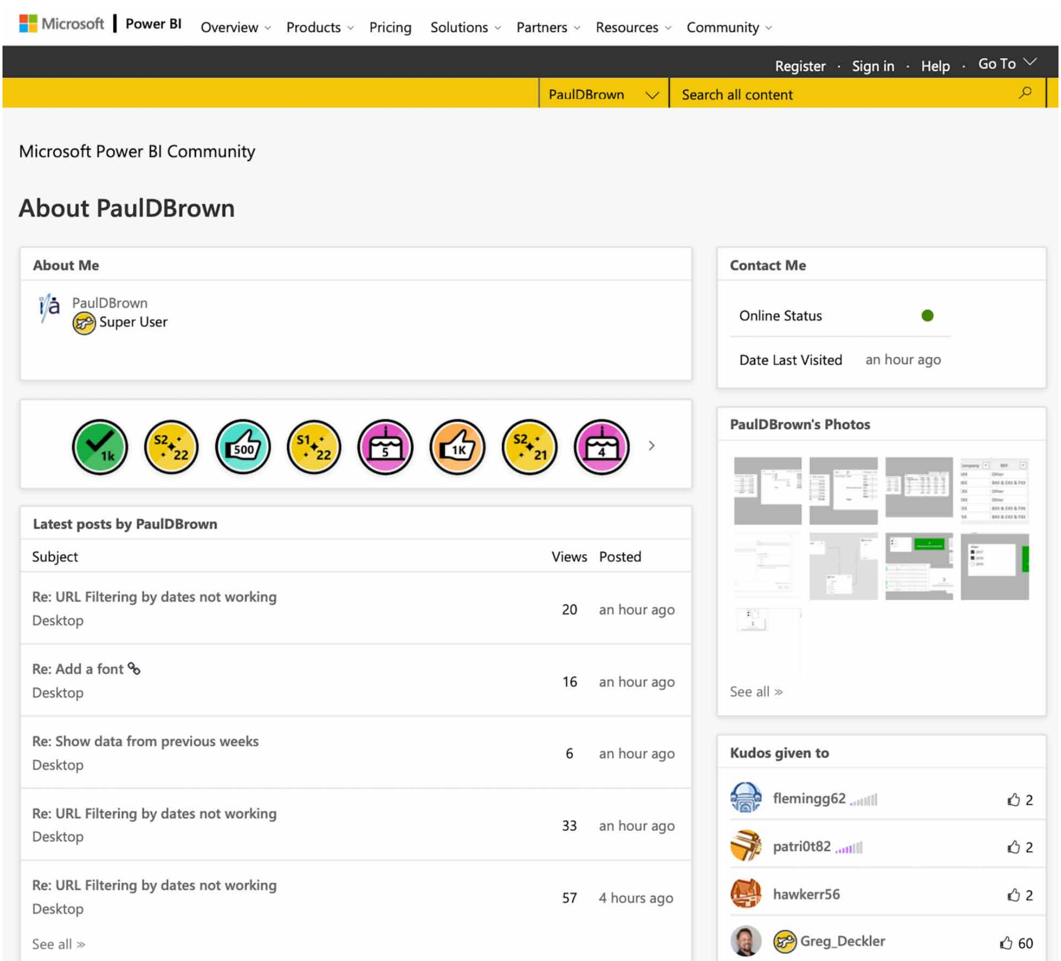


Figure 3. Steps to construct the user social network

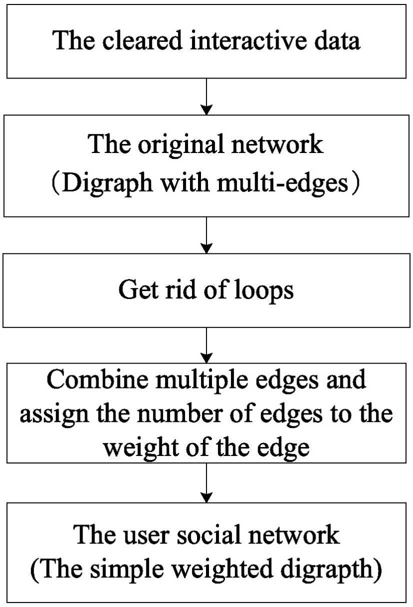
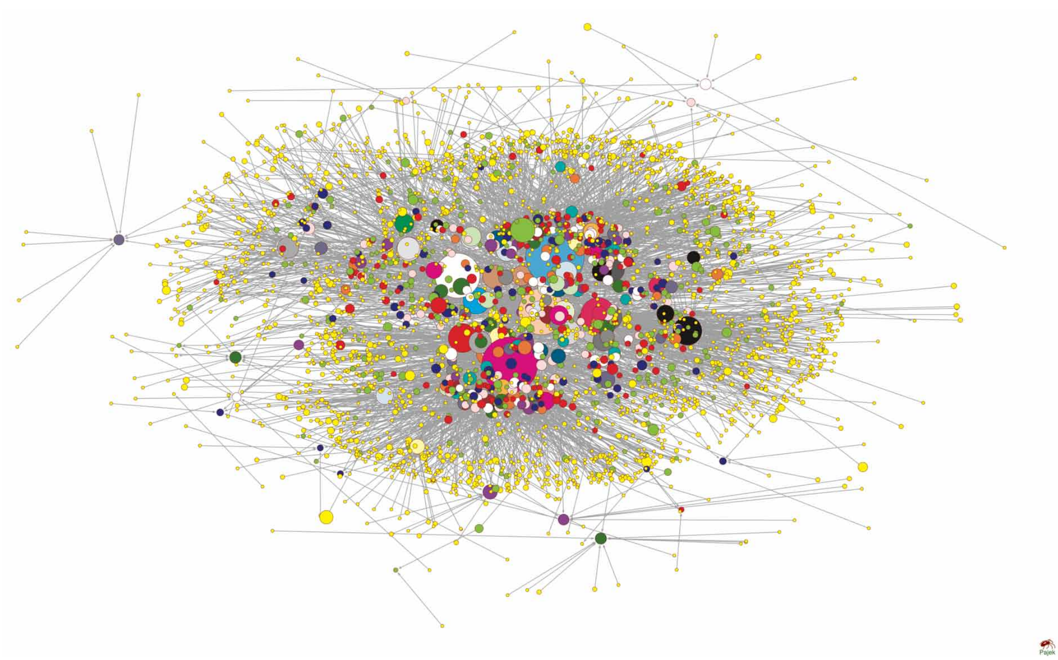


Figure 4. Visualization of online user interaction network



3,150 nodes, or online users. And the weighted total degree is 8,981, which represents the total number of user interactions among users. The average degree of the user social network is 2.3873, which represents that one user interacts with more than two users on average. The average distance is 2.4936. Generally, one user finds any other user in the network passing by three users. The Internet

Table 1. Overall characteristics of user network

No. of Nodes	No. of Edges	Weighted Degree	Average Degree	Average Distance	Diameter	Clustering Coefficient	Density
3150	3760	8981	2.3873	2.4936	9	0.0019	0.0004

shortens the average distance between people from six in the offline network (Watts, 2003) to three in the online network.

To verify the small-world network characteristics of the online user social network, we compared it with the random network. By creating a series of ER random networks with 3,150 nodes and 3,760 edges, we calculated the average clustering coefficient of these random networks (0.0003) and the average distance (22.9320). Therefore, the clustering coefficient of the user social network is significantly larger than that of the ER random network ($0.0019 > 0.0003$), while the average distance shows the opposite pattern ($2.4936 < 22.9320$). This is evidence that the online social network shows the feature of the small-world network, which is similar to the offline personnel network.

ONLINE USER INTERACTION BASED ON SOCIAL NETWORK ANALYSIS

Characteristics of Online User Interaction Based on Node Degree Analysis

In the social network, users are classified into three types based on their node degree: (1) the questioner is a user who only raises questions (i.e., posts) but does not respond to them, and the node indegree of the questioner is greater than 0, while the node outdegree is equal to 0; (2) the answerer is a user who only responds to others' questions but does not post any questions themselves, and the node indegree of the answerer is equal to 0, while the node outdegree is greater than 0; and (3), the dialogist is a user who not only raises questions but also responds to questions raised by others, and both the node indegree and node outdegree of the dialogist are greater than 0.

The average value of the network indicators for each type of user is shown in Table 2. For deeper look into the three types of users, we displayed the number of their badges rewarded by the community based on the users' active participation. The more badges a user has, the more active they are, increasing their status in the community.

Table 2 shows that the vast majority of online users in the innovation community are answerers, accounting for 75.59% of the total. It indicates that mutual assistance among users is common within the community. On average, each answerer provides more than two replies. Questioners, who actively pose questions and share their experiences in product usage, account for 19.65% of the total. On average, each questioner receives 6-7 replies. A small number of users who are active in both posing questions and answering account for 4.86% of the total. The average number of interactions for these dialogists is 13. By summarizing the characteristics of the online interactions for the three types of users and conducting a comparative analysis, the following findings were obtained.

(1) Number of online interactions: dialogists > questioners > answerers. Dialogists are more willing to interact with others, with the highest number of posts and replies (*degree_w*) and have the most interactive relations with others (*degree*). Questioners rank second in terms of the number of online interactions (*degree_w*) and the number of users connected with (*degree*). Answerers have the least number of interactions within the community.

(2) Structural hole network constraints: answerers > questioners > dialogists. In a network, a structural hole refers to a gap between nonredundant contacts through which two nonredundant actors can be "connected." According to the structural hole theory (Burt, 1992), the network constraint measures the extent to which a network is directly or indirectly concentrated in a single contact. Low-constraint networks that span structural holes provide local users better access to acquiring diverse information and resources from remote parts of the network. Therefore, dialogists, with the

Table 2. Network indicators of three types of users

Indicators	Identification	Description	Questioners	Answerers	Dialogists
			19.65% (619)	**75.59% (2,381)**	**4.86% (150)**
Node Indegree	*indegree*	The number of users who replied to the questions the focal user proposed	4.5138	0	6.3137
Node Outdegree	*outdegree*	The number of users to whom the focal user made the reply	0	1.4570	1.9020
Node degree	*degree*	The number of users who interacted with the focal users	4.5137	1.4566	8.2157
Weighted Degree	*degree_w*	The total number of interactions	6.5493	2.1184	13.3856
Network Constraint Coefficient	*structural_hole*	Network constraint coefficient of the structural hole	0.5132	0.9447	0.2912
Strength of Interactions	*strength*	The average frequency one user interacts with others	1.3563	1.4290	1.5530
Number of Badges	*badge*	Number of badges the focal user has	7.8934	6.2327	15.1438

lowest network constraint (*structural_hole*), are in the most powerful strategic position, followed by questioners and answerers in sequence.

(3) Numbers of badges: dialogists > questioners > answerers. Badges are given to the active users as a reward by the community. Therefore, the number of badges received by a user (*badge*) reflects the recognition from the firm hosting the community (Jeppesen & Frederiksen, 2006). Dialogists received the most badges, followed by questioners and answerers in sequence.

To verify the findings, we made the hypothesis test for each indicator above (i.e., *degree_w*, *degree*, *structural_hole, badge*) to check the significance of the differences among the three types of users. First, we evaluated the normal distribution for the samples of three types of users using the Kolmogorov-Smirnov test and Shapiro-Wilk test (Öztuna et al., 2006). The results are shown in Table 3. The significance for all indicators is lower than 0.05, which means no sample follows the normal distribution. Therefore, we selected the nonparametric Kruskal-Wallis test to evaluate the hypothesis (Kruskal & Wallis, 1952). The results are shown in Table 4. The significance of all indicators (i.e., *degree_w*, *degree*, *structural_hole, badge*) in the Kruskal-Wallis test are lower than 0.05. Hence, there are significant differences between the three types of users. The comparative analysis for the three types of users, as well as the findings above, is statistically verified.

Characteristics of Online User Interaction Based on K-Core Subgroup Analysis

We explored the groups that had particularly close relationships among users. We use k-core subgroup analysis to explore the cohesive groups formed by users based on their affinity. The k-core is a typical cohesive subgroup in which the degree of each node in the k-core subgroup is not less than its core number k (Mailizar et al., 2022). By executing k-core analysis using the social network analysis tool Pajek (Nooy et al., 2012), the user social network is divided into three subgroups: 1-core group (2,493 users), 2-core group (517 users), and 3-core group (140 users). The network indicators of the three subgroups are calculated respectively as shown in Table 5.

The following findings were obtained by comparing the network indicators of the three subgroups.

(1) The number of online user interactions of the k-core group increases as the number of k goes up. According to the definition of the k-core subgroup, the higher the number of k, the higher the node degree in the k-core groups. The results show that for both the number of interactive relations between users (*degree*) and the number of interactions (*degree_w*), the 3-core group is more than

Table 3. Normality test of three types of Users

	Type of Users [a]	Kolmogorov-Smirnovb			Shapiro-Wilk		
		Statistic	df	Sig.	Statistic	df	Sig.
Degree	1	.286	619	.000	.542	619	.000
	2	.475	2381	.000	.031	2381	.000
	3	.276	150	.000	.506	150	.000
Degree_w	1	.289	619	.000	.545	619	.000
	2	.458	2381	.000	.053	2381	.000
	3	.282	150	.000	.459	150	.000
Structural_ Hole	1	.213	619	.000	.842	619	.000
	2	.521	2381	.000	.380	2381	.000
	3	.112	150	.000	.931	150	.000
Badge	1	.198	619	.000	.689	619	.000
	2	.210	2381	.000	.698	2381	.000
	3	.151	150	.000	.786	150	.000

Note. a. 1 refers to the questioner, 2 refers to the answerer, and 3 refers to the dialogist.
b. Lilliefors Significance Correction.

Table 4. The Summary of the Kruskal-Wallis test

	Degree	*Degree_w*	*Structural_Hole*	*Badge*
Chi-Square	1503.505	909.275	1506.294	292.373
df	2	2	2	2
Sig.	.000	.000	.000	.000

Note. The variables are grouped by users' type.

Table 5. The Network indicators of k-core subgroups

Indicators	Identification	1-Core Group	2-Core Group	3-Core Group
		79.14% (2493 users)	16.41% (517 users)	4.44% (140 users)
Node Indegree	*indegree*	0.3466	2.8897	10.0143
Node Outdegree	*outdegree*	0.8532	1.1780	7.3143
Node Negree	*degree*	1.1998	4.0677	17.3286
Weighted Degree	*degree_w*	1.6711	6.0793	27.4071
Closeness Centrality	*close*	0.0001	0.0013	0.0051
Betweenness Centrality	*between*	4.05E-11	2.92E-07	9.54E-06
Network Constraint Coefficient	*structural_hole*	0.9503	0.4109	0.1914
Strength of Interactions	*strength*	1.3896	1.5178	1.6488
Number of Badges	*badge*	5.7942	10.1896	16.4929

the 2-core group, and the 2-core group is more than the 1-core group. This rule also applies to both the node indegree (*indegree*) and outdegree (*outdegree*), that is, the number of interactions the user initiated and received.

(2) The network centrality of the k-core subgroup increases as the number of k increases, but the structural hole network constraint decreases as the number of k increases. Both closeness centrality (*close*) and betweenness centrality (*between*) are measures for the centrality of the network. The higher the closeness centrality and betweenness centrality, the higher the degree of the user located in the center of the network. Structural hole network constraint is an index to measure the strategic position. The lower the network constraint coefficient is, the more likely that the user possesses a better position and has advantages to accessing heterogeneous resources. Compared with the 1-core and 2-core groups, the users in the 3-core group are closer to the center of the network and in a better position.

(3) The strength of interactions of the k-core subgroup increases as the number of k increases. The strength of interactions represents the average frequency a user interacts with others. The results in Table 5 show that the interaction frequency between users increases as the user builds more interactive relations with others, that is, more interactions promote deeper interaction between users.

(4) The number of badges the user in the k-core subgroup has, increases with the number of k. The number of badges represents the firm and community's recognition of the users. The 3-core group has the highest community recognition, followed by the 2-core group and the 1-core group in sequence.

To verify the findings above, we made the hypothesis test for each indicator to check the significance of the differences among the three subgroups. Since each indicator of the three subgroups does not follow the normal distribution (as shown in Table 6), we used the Kruskal-Wallis test with the results displayed in Table 7. The significance of each indicator in Table 7 is near to 0, which confirms the significant differences among the three subgroups.

EXTENSION STUDY: ONLINE USER INTERACTION AND COMMUNITY RECOGNITION

Hypotheses

Upon analyzing the characteristics of users' online interactions through social network analysis, we discovered that these interactions are intricately linked to the number of badges a user has earned, which serves as a recognition mechanism in the community. Recognition is sought to fulfill users' need to signal expertise and gain social status or reputation in online communities. Expectation of recognition explains why innovative users are drawn to the community and is found to be a key predictor of user contributions in online communities (Bhattacharyya et al., 2020).

We examined the characteristics of online interaction from two dimensions—the ego-centered dimension and the group dimension—and investigated their relationships with community recognition. In the ego-centered network, the number and strength of online interactions are crucial characteristics. Both Table 2 and 5 demonstrate that the number of badges follows the same trend as the number and strength of online interactions. Badges are designed to reward the active members. Therefore, the more members a user interacts with, and the higher the frequency of interactions, the more badges the user requires from the community. Thus, we propose the following hypotheses:

H1: The number of a user's online interactions positively influences the user's community recognition.
H2: The strength of a user's online interactions positively influences the user's community recognition.

We considered the group effects of the interactions, taking into account the users' role as questioners, answerers, or dialogists, as well as their membership in the k-core subgroups. Social contagion theory suggests that individuals are likely to adopt the behavior or attitudes of others in their social groups. Rishika and Ramaprasad (2019) confirmed the presence of social contagion

Table 6. Normality test of k-core subgroups

	K-Core Subgroup	Kolmogorov-Smirnovb			Shapiro-Wilk		
		Statistic	df	Statistic	df	Statistic	df
Degree	1	.508	2493	.000	.237	2493	.000
	2	.298	517	.000	.574	517	.000
	3	.323	140	.000	.433	140	.000
Degree_w	1	.348	2493	.000	.420	2493	.000
	2	.254	517	.000	.644	517	.000
	3	.300	140	.000	.470	140	.000
Structural_Hole	1	.533	2493	.000	.313	2493	.000
	2	.203	517	.000	.956	517	.000
	3	.126	140	.000	.934	140	.000
Badge	1	.194	2493	.000	.725	2493	.000
	2	.170	517	.000	.718	517	.000
	3	.163	140	.000	.856	140	.000
Strength	1	.397	2493	.000	.452	2493	.000
	2	.236	517	.000	.700	517	.000
	3	.143	140	.000	.837	140	.000
Indegree	1	.471	2493	.000	.351	2493	.000
	2	.255	517	.000	.674	517	.000
	3	.236	140	.000	.684	140	.000
Outdegree	1	.507	2493	.000	.444	2493	.000
	2	.251	517	.000	.782	517	.000
	3	.439	140	.000	.222	140	.000
Close	1	.472	2493	.000	.351	2493	.000
	2	.295	517	.000	.558	517	.000
	3	.212	140	.000	.777	140	.000
Between	1	.508	2493	.000	.005	2493	.000
	2	.434	517	.000	.155	517	.000
	3	.378	140	.000	.343	140	.000

Note. a. 1 refers to the 1-core subgroup, 2 refers to the 2-core subgroup, and 3 refers to the 3-core subgroup.
b. Lilliefors Significance Correction.

Table 7. Kruskal-Wallis test of k-core subgroups

	Degree	*Degree_w*	*Structural_Hole*	*Badge*	*Strength*	*Indegree*	*Outdegree*	*Close*	*Between*
Chi-Square	2221.893	1416.250	2159.539	418.279	251.384	751.461	93.851	765.380	767.912
df	2	2	2	2	2	2	2	2	2
Sig.	.000	.000	.000	.000	.000	.000	.000	.000	.000

Note. The variables are grouped by the k-core subgroup.

effects in the online music community, where the favoring behavior of a focal user is influenced by their connected peers. By combing the findings from Tables 2 and 5, we gained evidence that users embedded in the same group tend to exhibit similar behavior, as well as the number of badges they receive. Thus, we propose the following hypotheses:

H3: User type (i.e., questioners, answerers, and dialogists) influences the user's community recognition. Dialogists have a higher community recognition compared with questioners, and questioners have a higher community recognition compared with answerers.
H4: Membership in a k-core subgroup influences the user's community recognition. The community recognition of a user increases with the number of k-cores they belong to.

Empirical Model

We used the regression method to examine the effect of user interaction on community recognition, and the following model has been established:

$$Y = \beta_0 + \beta_1 num + \beta_2 strength + \beta_3 type + \beta_4 kcore + \beta_5 C + \varepsilon \tag{1}$$

In equation 1, the dependent variable *Y* is community recognition, which is measured by the number of badges obtained by users. The main independent variables include the number (*num*) and strength (*strength*) of the user's online interaction, the user type (*type*), and the k-core subgroup (*kcore*) to which the user belongs. Among them, the number of online interactions can be measured by several indicators: *degree*, *degree_w*, *indegree*, and *outdegree*. C is the control variable, including the length of time the user was registered in the community (*user_age*) and the number of likes the user received (*kudos*).

The correlations among all variables are shown in Table 8. The variance inflation factor VIF of the regression is shown in Table 9. Both the mean VIF and the VIF for the single independent variable are less than 5, indicating that there is no obvious multicollinearity, and it is suitable for regression (Chen et al., 2012).

RESULTS

The results of ordinary least squares (OLS) estimation are shown in Table 10. Columns (1) and (2), respectively, select the network indicators of *degree* and *degree_w* to measure the number of online interactions. The results show that the coefficients of *degree* and *degree_w* are significantly positive, indicating that the more online interactions, the higher the community recognition. H1 is supported. Furthermore, according to the direction of online interactions, column (3) divides online interactions into the interactions from others (*indegree*) and the interactions replied to others (*outdegree*) and examines their effects separately. Among them, the main role is the user's reply to other users (*outdegree*), which has a significant positive effect on community recognition, while the coefficient of *indegree* is not significant. Combining the results of (1), (2), and (3), the coefficient of *strength* is significantly positive, indicating that the more frequent interactions with a single user, the more likely the user gains high community recognition. H2 is supported.

From the group perspective, when the number and strength of user interactions are controlled in the regression, both the user type and k-core membership still have significant effect on community recognition. For different types of users, the community recognition of answerers is lower than questioners, and that of dialogists is higher than that of questioners. H3 is supported. For different k-core subgroups, the 2-core group and 3-core group have higher community recognition than the 1-core group, and the regression coefficient of *kcore_3* is much larger than that of *kcore_2*, indicating

Table 8. Correlation between online user interactions and community recognition

	1	2	3	4	5	6	7	8
1 Badge	1.000							
2 Degree	0.2817*	1.000						
	(0.000)							
3 Degree_w	0.2991*	0.9762*	1.000					
	(0.000)	(0.000)						
4 Indegree	0.2114*	0.5230*	0.5607*	1.000				
	(0.000)	(0.000)	(0.000)					
5 Outdegree	0.1953*	0.8385*	0.7865*	-0.026	1.000			
	(0.000)	(0.000)	(0.000)	(0.146)				
6 Strength	0.1132*	0.021	0.1307*	0.024	0.009	1.000		
	(0.000)	(0.238)	(0.000)	(0.184)	(0.594)			
7 Type	0.0654*	-0.0370*	-0.020	-0.2062*	0.0885*	0.0489*		
	(0.000)	(0.038)	(0.257)	(0.000)	(0.000)	(0.006)		
8 Kcore	0.3663*	0.4003*	0.4167*	0.4864*	0.1585*	0.0758*	0.0469*	1.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.009)	

Note. The p-value is in the bracket.
The * denotes statistical significance at the 5% levels.

Table 9. Variance inflation factor (VIF)

Variables	VIF_1	VIF_2	VIF_3
Degree	1.28		
Degree_w		1.32	
Indegree			1.63
Outdegree			1.10
Strength	1.01	1.03	1.01
Type_1	1.34	1.34	1.59
Type_2	1.42	1.41	1.42
Kcore_1	1.27	1.26	1.27
Kcore_2	1.55	1.57	1.66
User_Age	1.07	1.07	1.07
Kudos	1.04	1.04	1.04
Mean VIF	1.25	1.26	1.31

that the 3-core group has the highest community recognition. H4 is supported. The control variables of *user_age* and the number of likes (*kudos*) also significantly affect community recognition. Older users and users who are favored by other users are more likely to gain high community recognition.

Table 10. OLS regression results

Variables	(1)	(2)	(3)
Degree	0.083***		
	(0.018)		
Degree_w		0.056***	
		(0.011)	
Indegree			0.029
			(0.036)
Outdegree			0.096***
			(0.025)
Strength	0.381***	0.302***	0.383***
	(0.110)	(0.112)	(0.110)
Type_Answerers	-1.087***	-1.089***	-1.323***
	(0.209)	(0.208)	(0.234)
Type_Dialogists	1.475***	1.438***	1.438***
	(0.520)	(0.518)	(0.522)
Kcore_2	1.699***	1.706***	1.744***
	(0.279)	(0.278)	(0.284)
Kcore_3	3.997***	3.925***	4.313***
	(0.597)	(0.593)	(0.667)
User_Age	0.007***	0.007***	0.007***
	(0.000)	(0.000)	(0.000)
Kudos	0.009***	0.009***	0.009***
	(0.002)	(0.002)	(0.002)
Constant	153.136***	153.220***	153.438***
	(4.871)	(4.869)	(4.870)
Observations	3,150	3,150	3,150
R-squared	0.593	0.593	0.594

Note. The robust error is in the brackets.
The ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

CONCLUSIONS AND IMPLICATIONS

Conclusions

In this paper, we presented a study of online interactions using social network analysis in the context of Microsoft's Power BI Community. Our analysis provides a detailed depiction of user interaction behavior through the construction of a user social network, identifying distinct subgroups and their interaction characteristics. We examined the impacts of users' online interactions on community recognition from both individual and group perspectives. The following conclusions are found.

(1) Interaction characteristics vary among different types of users. Dialogists are the most active, with the highest number of posts and replies and the most interactive relations with others. Questioners follow, and answerers have the lowest rank. Dialogists also have the most favorable network position

among the three types of users, with the lowest network constraint, enabling them to obtain more diverse knowledge from others.

(2) Interaction characteristics of users in the different k-core subgroups are heterogeneous. The larger the k number of the k-core subgroup, the more user interactions and the higher the interaction frequency among users. Users in higher k-core subgroups are closer to the network center and in a more favorable network position.

(3) Users' online interaction significantly affects their community recognition from both individual and group perspectives. The more a user interacts with others online with a higher strength, the more badges they earn and the higher their community recognition. Additionally, different types of users have varying levels of recognition, with dialogists having the most badges and highest recognition, followed by questioners, and answerers having the lowest. For different k-core subgroups, the higher the k number of the k-core subgroup, the higher the community recognition. The result confirms group membership on a user's community recognition. Social contagion may provide an explanation because online users embedded in the same group tend to exhibit similar behavior and seek recognition from the community through badges.

Our study provides insights into the interaction behavior of users in online innovation communities and highlights the importance of online interactions for community recognition. Rather than characterizing the online interactions from the ego-centered perspective, the characteristics of online interactions in certain user groups should be considered.

Implications for Practice

The online innovation community should design a reasonable interaction mechanism to ensure the interactions between online users, which will facilitate knowledge sharing among the innovators and help users to generate innovative ideas. Taking the Microsoft Power BI Community as an example, its current interaction mechanism design is effective, which makes the user who interacts more get higher community recognition. It should be noted, however, that most users in the community are the answerers who reply to others' questions but do not pose their own questions and ideas in the Power BI software. The ratio of the dialogists who are active in both posting and replying is low. Therefore, the Power BI Community needs to formulate new incentive policies to motivate users to actively post questions when using the Power BI software.

If online users want to get higher recognition in the community, they need to interact with other users by posting and replying. Through posting questions and sharing experience of usage, a user can quickly build connections with others, while active replies to others' issues are more helpful for users to improve community recognition. Therefore, a new member can first establish relationships with other users by posting and then enter into the group of active users by replying. Users who want to improve community recognition should also consider strengthening in-depth communication with individuals. When a user becomes a member of the group of active users, they are more likely to access more innovation knowledge and obtain higher community recognition.

Limitations and Future Research

This study has several limitations. First, we only used one community as an example to build the online social network and characterize the user interactions, so the generalizability of our findings needs to be evaluated in different online innovation communities and various online networks. Second, the cross-sectional data used in our empirical study may have weakened the validity of the OLS estimation. Future studies can address this limitation by using panel data, which can be formed by continuously collecting online community data during a period and characterizing online interactions in different time windows. Third, our study only provides a preliminary investigation of online interaction characteristics from a group perspective. Subsequent research should consider group characteristics and their effects on user behaviors. Complex group identification algorithms can be used to identify user groups and their interaction characteristics. Additionally, the effects of groups on user innovation and the underlying mechanisms should be further investigated.

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