Impact of User Interaction in Open Innovation Platforms on Implicit Communities: Postprint

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Date: 2023-04-01T00:00:00+00:00

Abstract

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Full Text

Research on the Influence of User Interaction on Implicit Communities in Open Innovation Platforms

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Abstract:
[**Purpose/Significance**] Based on interactive networks of two types—following and commenting—and their combined network, this study investigates the influence of user interaction in open innovation platforms on implicit communities. [**Method/Process**] We collected six months of user interaction data from the LEGO IDEAS platform and employed topology analysis, centrality analysis, and community analysis using Gephi software to construct three-phase network diagrams for following, commenting, and combined relationships, followed by evolutionary analysis. [**Results/Conclusions**] All three interactive networks exhibit scale-free network characteristics, with a small number of users involved in a large volume of interactions. The combined network more closely approximates the real network structure of open innovation platforms. "Comments" are more important for the formation of implicit communities and innovation participation. Over time, the number of nodes and connections in implicit communities shows an increasing trend, with new nodes preferring to connect to central nodes with higher connectivity, and information transmission efficiency continuously improving. In the implicit community of the combined network, subgroups based on "comment" relationships update and iterate relatively quickly over time, while subgroups based on "following" relationships remain relatively stable and persistent.

Keywords: open innovation platform; user interaction; implicit communities; community evolution; social network analysis
Classification Number: G252.0
DOI: 10.13266/j.issn.0252-3116.2022.05.011

The rise of social media has facilitated user participation in corporate innovation. An increasing number of enterprises have built open innovation platforms (OIPs) to explore external forces for product development and design. Many community structures (explicit and implicit communities [1-2]) exist in user-participating innovation platforms, influencing participant activity and the vitality of the entire platform. Explicit communities are typically formed based on "relationship structures" (such as forums, sections, or friend relationships) [3], where users participate in platform activities by joining groups. Conversely, implicit communities are not explicitly defined as groups but are organically formed through the "interaction structure" among innovative users [3]. For example, users can comment on ideas; users follow other users and track updates to their ideas. These activities construct interaction relationships among OIP users and form complex interaction networks. Implicit communities in interaction networks reflect the hidden real relationships in OIPs, exerting more concealed yet stronger influence on the platform [2-3]. Existing research has found that implicit communities play important roles in influence analysis, information dissemination, network marketing, and public opinion early warning [3], and can reveal more important knowledge than explicit communities [1]. In the OIP context, studying the implicit community structure of networks can not only reveal intricate internal relationships but also enable platform managers to implement incentive mechanisms or management measures in a targeted manner, promoting high-quality creative output and facilitating corporate innovation.

Current research on corporate OIPs is extensive, with scholars focusing more on lead user identification, knowledge sharing, and continuous contribution behavior, while relatively few studies address community structure and evolution. Research on community structure in complex networks mostly focuses on implicit community discovery algorithms, without clarifying the antecedents of implicit community formation—that is, the influence of different types of user interactions on implicit communities. Different types of interactions among OIP users (such as comments, follows) have different characteristics, forming differentiated virtual interaction networks. Over time, users establish, eliminate, or maintain interactions with other users, and the evolution of user interaction behaviors changes the entire network's topology, which is a dynamic process [4-5]. Behind these interaction behaviors, hidden social structures representing real relationships among users can be extracted [6].

Based on this, we collected user interaction data from the LEGO IDEAS (https://ideas.lego.com) open innovation platform. Based on different user interaction types, we constructed OIP user comment networks, following networks, and a combined network of comments and follows to analyze the influence of OIP user interaction on implicit communities. We aimed to explore the following questions: Do different types of interactive networks have different properties? Which type of interaction is more important for the formation of implicit community structures? How do implicit communities evolve? We hope to understand the influence of different types of user interactions on implicit community structures and provide references for managers to carry out targeted platform management, enhance OIP user activity, and promote effective creative output.

2 Literature Review

2.1 Research on User Interaction Behavior in Online Communities

Existing research on user interaction behavior in online communities mostly classifies interaction types from the perspective of participant identity and generally focuses on a single interaction behavior of commenting or following. Research mainly includes: Studies on interaction behaviors based on comments, replies, or Q&A between different interaction subjects. Qiu Junping et al. explored the interaction network formed between bloggers and commenters based on comments and replies on Weibo [7]; Cai Zhibin et al. examined user participation characteristics in Q&A communities based on Q&A between askers and answerers [8]; K. W. Chan et al. found that the quantity and frequency of comments between users and between users and firms significantly influence users' subsequent idea submissions [9]; Liu Qian et al. studied the impact of online interaction on user idea quality based on comments among users, peers, and corporate experts [10]; N. Wang et al. found that comments and replies between idea submitters and supporters in crowdfunding platforms positively and significantly affect crowdfunding success [11]. Studies on user interaction behaviors based on following between different interaction subjects. Zan Tiancheng et al. found that networks formed among Weibo leaders based on following have a positive impact on message dissemination [12]; Jiang Yuting et al. classified user social interaction behaviors in online communities according to different interaction subjects and directions, studying the contribution of active interactions such as following and favoriting between users and between users and platforms to knowledge payment user prediction, finding that user-to-user interaction has a greater impact than user-to-platform interaction, and the greater the degree of social interaction, the greater its contribution to predicting knowledge payment behavior [13]; Zhuang Qian et al. studied the impact of following interactions between online community users on social tagging, finding significant differences in social tagging behaviors among users with different interaction characteristics [14].

User interaction behaviors in online communities are also divided into different types. Marketing research classifies consumer interactions on social platforms into two categories: opinion-based interactions (such as online word-of-mouth, user comments) and action-based interactions (such as software downloads, product purchases) [15-18]. The above studies on user interaction mostly focus on a single type of interaction, either opinion-based (online comments, replies, Q&A) or action-based (following), with few studies simultaneously considering and distinguishing between these two types of interactions. We introduce this classification of interaction types from consumer behavior research, dividing OIP user interaction behaviors into two categories: user-to-user comment interactions (opinion-based) and user-to-user following interactions (action-based), to analyze the influence of different interaction types on implicit communities.

2.2 Research on Community Structure

Currently, community structure research mainly proceeds in two directions: Community discovery research, which aims to determine what methods/algorithms can reveal implicit community structures in networks. This research direction is more common in computer science, focusing on the optimization and innovation of community discovery algorithms. Zhang Haitao et al. reviewed various community discovery methods [19]. Such studies generally assume that community changes are gradual and that there exists a core stable community structure in network changes [3]. Community structure evolution, which examines changes in interaction network structures across different time periods from a "dynamic" perspective based on the dynamic evolution of real relationship data [20]. This research aims to reveal the underlying mechanisms of implicit community evolution. Wu Jiang explored the influence of user individual attributes and network structural attributes on the dynamic evolution of user friendship networks [21]; Ba Zhichao et al. analyzed the topological structure characteristics, user characteristic distributions, information interaction types, and evolutionary patterns of information exchange networks in WeChat groups with different target needs [22]; R. Karan et al. described the temporal evolution from initial community structure to current network topology from the perspective of interaction intensity and frequency among members and the degree of overlap between different communities [23]. However, existing community structure evolution research ignores the user interaction perspective and has not considered the influence of different types of interactions on implicit community structures.

Based on the above analysis, we collected user interaction data from the LEGO IDEAS open innovation platform, constructed different types of interactive networks and their combined network, and explored the influence of OIP user interaction on the formation and evolution of implicit communities, hoping to enrich the research perspective on community structure evolution in online social networks.

3 Research Design

3.1 Research Framework

We identified two types of OIP user interaction relationships: commenting and following. Since user interaction is not limited to one type, it is necessary to study the combined network of commenting and following. Therefore, we constructed three interactive networks based on user interaction relationships: following network (follow network), commenting network (comment network), and a combined network of following and commenting (combined network). Social network analysis (SNA) can be used to reveal relationship and interaction patterns and discover implicit community structures in OIPs. We utilized three main analysis types in SNA: topology analysis, centrality analysis, and community analysis [20], with a two-month time window to study the influence of OIP user interaction networks on implicit communities from three levels: overall, individual, and small group. The research framework is shown in Figure 1 [Figure 1: see original paper].

3.1.1 Topology Analysis Topology analysis can be used to discover network structural characteristics. We constructed commenting networks, following networks, and combined networks, and calculated clustering coefficients, average path lengths, and cumulative degree distributions for each of the three interactive networks. This aims to analyze the characteristics of OIP interaction networks from an overall perspective and understand whether different types of interactive networks have different properties.

3.1.2 Centrality Analysis Analysis of implicit communities requires first analyzing key users who have important effects on community information dissemination. Centrality expresses the degree to which an individual in a social network is at the center of the entire network. By constructing different interactive networks, we used centrality measurement indicators: degree centrality, betweenness centrality, and closeness centrality [24] to calculate individual characteristic indicators. We analyzed user interaction behavior characteristics in different periods, depicted users' status and roles in different types of interactions and their participation effects on platform information dissemination, and analyzed the influence of individual network variables on interaction network evolution at different stages.

3.1.3 Community Analysis Community analysis aims to identify implicit communities in social networks and their dynamic evolution processes. By maximizing intra-group link density while minimizing inter-group connection density, implicit communities in networks can be discovered. We used the modularity-based Louvain community discovery algorithm to divide social network communities and identify implicit community structures in social relationship networks. First, we conducted statistical analysis on the three types of networks at each stage to obtain initial characteristic data of implicit communities. Second, we visualized implicit communities to more intuitively display the role of commenting and following relationship networks on the combined network. Finally, we conducted evolutionary analysis on the three types of networks across three stages, identifying important network relationships in the combined network through horizontal comparison of three different social networks at the same time, exploring which interaction is more important for implicit community formation, and analyzing the evolutionary characteristics of different networks by combining longitudinal changes of the same relationship network at different stages.

3.2 Data Source

LEGO IDEAS is an open innovation platform where LEGO enthusiasts can publish ideas and opinions. Enthusiasts can showcase their creative works in different themed sections and browse, support, comment on, and follow others' submitted works. As of December 2020, LEGO enthusiasts had proposed 36,531 creative ideas in the community, with excellent creative ideas being sold on shelves and gaining widespread popularity. LEGO IDEAS has mature platform components, high user participation, meets research analysis requirements, and is an ideal research object.

We wrote Python programs to crawl user interaction data in the "architecture" interest group (the group with the largest participation) on LEGO IDEAS from May 1, 2017 to October 30, 2017, including user comments on each creative project, comment times, commenters, and all user following behavior data. We cleaned the raw data by removing insubstantial or duplicate content, ultimately obtaining 3,081 sample users, and based on this, examined the interaction relationships with related users.

3.3 Data Processing and Tools

First, we constructed three different social networks based on different user interaction behaviors. Nodes represent participating users in the open innovation platform, and connections between nodes represent interaction relationships between users (such as following or commenting). If user A comments on or follows user B, there is an arc from A to B. Similarly, user B can also comment on or follow user A, creating a reciprocal relationship between users A and B represented by a bidirectional arrow, thereby forming a social network from user interaction relationships. Second, we calculated relevant network features of the three social networks (such as average path length, clustering coefficient, cumulative degree distribution, degree centrality, closeness centrality, and betweenness centrality) to complete topology analysis and centrality analysis. Then, we selected the main clusters in the commenting network, following network, and combined network for each period to analyze which type of interaction network the implicit communities in the combined network originated from. Simultaneously, we analyzed the implicit community evolution process of each interaction network across three different periods and used Gephi for network visualization.

Existing research on network evolution has no unified regulations for dividing network stages, mostly based on the actual situation of research objects. Some scholars divide online social networks by one-month intervals [25-26]. Others use two-month stages to extract online community relationship data for network evolution research [27]. Referring to previous research and combining the volume of user interaction data on LEGO IDEAS, we used a two-month time window for community evolution analysis, as this timeframe can better ensure user participation and activity in open innovation platforms.

4 Results Analysis

4.1 Interactive Network Topology Analysis

In complex network research, topology analysis can be used to discover network structural characteristics. Some widely used measurement indicators for network topology description include average path length, clustering coefficient, and degree distribution [28-29]. Previous research has proposed three models to describe network topology: random graph model [30], small-world model [31], and scale-free model [32]. Different network topologies can explain different network functions [33]. The statistical characteristics of topology analysis for different types of interactive networks are shown in Table 1 :

Table 1 Statistical Characteristics of Topology Analysis for Different Types of Interactive Networks

As shown in Table 1, in terms of node count across the three networks, half of the users are "lurkers" who never participate in any commenting. More users choose to silently follow other users or ideas, with only 9% of users participating in both types of interactions—commenting on and following other users or their ideas. The clustering coefficient shows that the comment network (0.255) has greater cohesion than the follow network (0.094), with deeper interaction levels, and the combined network (0.250) is slightly more influenced by the comment network. The follow network's clustering coefficient of 0.094 is far lower than that of the comment and combined networks, indicating that users may only follow some ideas of other users with insufficient interaction depth, or that connections between users are not random but generated based on their preferences [34], with user preferences being relatively dispersed (the follow network has a maximum in-degree of 40 and maximum out-degree of 310), resulting in less obvious clustering effects. The average path lengths of all three networks are less than 10, with any two users in the community requiring an average of fewer than 4 users to establish contact, which is smaller than the "six degrees of separation," indicating that users are willing to communicate with each other [35], innovation diffusion is rapid, and user interactions are effectively supported.

The cumulative degree distributions of the networks are shown in Figures 2 [Figure 2: see original paper], 3 [Figure 3: see original paper], and 4 [Figure 4: see original paper]. The degree distributions of all three networks follow a power-law distribution, allowing us to conclude that the three interactive networks all have scale-free characteristics with high goodness-of-fit (follow network: R^2=0.96; comment network: R^2=0.98; combined network: R^2=0.98). This indicates that a small number of users are involved in a large number of interactions, serving as the "hubs" of the network. As the network scale continues to expand, new nodes tend to connect with hub nodes that have higher connectivity. The comment network's fitting coefficient is slightly higher than that of the follow network, meaning that compared to following users or their idea updates, platform users engage more in commenting interactions or have intense discussions about certain ideas (the comment network has a maximum in-degree of 200).

4.2 Centrality Analysis

We divided the research data into three phases with a two-month time window, calculated centrality indicators for each network: degree centrality, betweenness centrality, and closeness centrality [24], and identified key user nodes based on centrality analysis to examine how individual network variables influence interaction network evolution at different stages.

4.2.1 Degree Centrality Analysis Degree centrality refers to the total number of direct connections between a node and other nodes. A higher degree means a node is more important. In various social relationship networks, users with high degree centrality values are usually the most active and influential. We calculated the degree centrality of all individuals in the three types of interactive networks and displayed the top 10 users with highest degree centrality across three stages (see Table 2) for more intuitive comparison of key user characteristics across different networks.

Table 2 Top 10 Users with Highest Degree Centrality at Different Stages

In Table 2, in the three types of interactive networks during May-June, only two users (#14, #101) appeared simultaneously in the top 10 of all three network types. In other words, users with the most follow relationships do not necessarily have the most comment relationships. In the merged network, 7 of the top 10 users appeared in the comment network, while 5 appeared in the follow network's top 10. During July-August, similarly only two users (#32, #33) appeared simultaneously in the top 10 across all three network types, with both follow and comment networks having 6 users appearing in the combined network's top 10, showing equal influence. During September-October, four users (#33, #41, #51, #139) appeared simultaneously in the top 10 across all three network types. The follow network had 4 users appearing in the combined network's top 10, while the comment network had 10 users appearing in the combined network's top 10. The data shows that from May to October, comment relationships dominate user interactions, but the influence of follow relationships gradually becomes prominent, and several users in the follow network consistently rank high (#98, #101, #33), indicating that follow relationships can form more enduring and stable relationship structures.

4.2.2 Betweenness Centrality Analysis Betweenness centrality measures a node's control ability over information transmission and community resources between other nodes. If a node lies on many shortest paths between other node pairs, it has high betweenness centrality [20]. Users with high betweenness centrality are typically seen as bridges between different communities. Table 3 shows the top 10 users by betweenness centrality for each interactive network across three stages. The results show that during May-June, the combined network's top 10 betweenness centrality users were evenly split between follow and comment networks (6 each). Two users appeared in both the comment and follow networks' top 10 lists, and #14 also appeared in the May-June degree centrality top 10 list, indicating that this user not only actively participates in both commenting and following interactions but also controls and coordinates interactions with other users and the network.

During July-August, 6 of the top 10 in the combined network came from the comment network and 4 from the follow network. During September-October, the comment network provided more high betweenness centrality users (8 overlaps) in the combined network, while the follow network had only 3 overlaps. Across the three phases, the proportion of high betweenness centrality users from the comment network in the combined network slightly increased. Compared to follow relationships, users actively participating in creative discussions have more control over information transmission and community resources. Users #14, #19, #63, #98, and #101 rank high in both betweenness centrality and degree centrality, indicating they are active platform users with strong influence in innovation participation and diffusion processes.

4.2.3 Closeness Centrality Analysis Closeness centrality measures the extent to which users in a network are not controlled by other users. Closeness centrality analysis can discover quick pathways for message transmission and nodes that play important roles in message dissemination. Table 4 shows the top 10 users by closeness centrality in different interactive networks for each phase. During May-June, there were 4 overlaps between follow network and combined network, and 5 overlaps between comment network and combined network. During July-August, there were similarly 4 overlaps between follow network and combined network, and 5 overlaps between comment network and combined network. During September-October, both follow and comment networks had 5 overlaps with the combined network. Across the three phases, the proportion of high closeness centrality users from the follow network in the combined network gradually became prominent. Compared to comment relationships, users in the follow network can obtain community information more easily. Nodes ranking higher can more quickly obtain information transmission from other nodes, such as #33.

4.3 Community Analysis

We used the modularity-based Louvain community discovery algorithm to analyze clustering behavior in the three networks and conducted statistical analysis. Table 5 shows the network statistics for May-June. The results show that the follow network contains 85 clusters, with the largest cluster containing 119 nodes (21.5% of total network nodes). Visualization shows 9 clusters with size greater than 10, as shown in Figure 5 [Figure 5: see original paper]. The largest cluster's core user is #98 (RobenAnne), the most-followed user, followed by user #101 (POTATOX). Several other large clusters are also dominated by active users. The comment network contains 188 clusters, with visualization showing 9 clusters larger than 10. The largest cluster (purple) contains 109 nodes, accounting for 21.8% of total network nodes.

We constructed the combined network based on these two relationship types. The combined network contains 877 users and 1,802 edges, with 104 clusters. The largest cluster has 394 users and 698 edges, accounting for 44.9% of combined network members—much larger than the largest clusters in comment and follow networks, meaning some users connect these two networks. Figure 5 shows clusters larger than 120 in the combined network, where the light blue community can be found in the follow network, while the rest mainly come from the comment network. This indicates that in May-June community formation, comment relationships are more important as they form the foundation of the combined network and represent the main community.

Table 6 shows network statistics for July-August. The follow network contains 72 clusters, with the largest cluster containing 259 nodes (32.9% of total network nodes). Visualization shows 9 clusters larger than 10, as shown in Figure 5. The largest cluster's core user is #33 (Tim10000), an exceptionally active user who follows more than 200 users. The July-August combined network has

1,336 nodes and 2,532 edges, much larger than the previous phase, indicating many new users joined the "architecture" themed community during this phase. Clusters larger than 120 are shown in Figure 5, where the blue cluster can be found in the follow network while the rest mainly come from the comment network. In this phase's community formation, due to #33's exceptional activity, comment and follow networks contributed equally to combined network implicit community formation. However, after removing #33, almost all members of this sub-community become isolated nodes—#33 alone connects to numerous users, while other users have few follow relationships among themselves. In terms of interaction depth, comment relationships still strongly influence combined network implicit community formation.

Table 7 shows network statistics for September-October. The follow network contains 107 clusters, with the largest cluster containing 471 nodes (42.8% of total network nodes). Visualization shows 6 clusters larger than 10, as shown in Figure 5. The largest cluster is still dominated by user #33 (Tim10000), whose number of followed users increased from the previous phase. The comment network contains 123 clusters, with visualization showing 13 clusters larger than 10, each main cluster significantly larger than the previous phase, indicating some creative projects stood out and attracted large numbers of user comments.

The September-October combined network has 1,527 nodes and 3,372 edges, larger than the previous phase. The main cluster is shown in Figure 5, with the largest cluster containing 733 users and 1,243 edges, accounting for 48% of combined network members—still much larger than the largest clusters in follow and comment networks. The main cluster in the combined network shows the blue portion can be found in the follow network, while the other two main portions come from comment networks. In this phase's community formation, due to #33's continued exceptional activity, the quantity of "follow" relationships exceeded "comment" relationships, but almost all edges in this portion are issued by node #33, with few interactions between other nodes and few nodes following #33. In terms of interaction depth, comment relationships are not dominant in quantity but still significantly influence innovation dissemination in combined network implicit communities. In terms of implicit community structure stability, follow relationships maintain long-lasting and stable structures, with the comment-based implicit community centered on "Tim10000" appearing in the combined network's largest implicit community for two consecutive phases.

Since the combined network is closest to the actual interaction network, we further compiled basic information statistics for the combined network across three phases to clarify network evolution characteristics (see Table 9). Over time evolution, the number of nodes and connections in the combined network shows an increasing trend, while density and average degree show little change across the three phases. This indicates that as time progresses, the network does not become increasingly dense; compared to dense fully-coupled networks, actual networks remain sparse. In terms of average path length, the network's average distance shows a decreasing trend over time. Research shows many actual networks exhibit this trend, also known as the diameter shrinkage phenomenon [36], indicating that over time, relationships among platform users continuously increase, with more users continuously participating in platform activities. This relationship intensity is not high but can improve information transmission efficiency in OIPs, expanding information diffusion scope. Increased transmission efficiency also enhances learning effectiveness among users, benefiting user creative contributions.

Table 9 Basic Information of Combined Network Across Three Phases

We attempted to explore the antecedents of implicit community formation and analyzed the influence of user interaction on implicit communities from three levels. The results show: The degree distributions of the three interactive networks follow power-law distributions, with all networks having scale-free characteristics. Different interaction relationships form new implicit communities around core users, with the combined network being closer to the real network structure of OIPs. From the composition and interaction depth of combined network relationships, comment relationships have greater influence on the formation of combined network implicit communities and innovation diffusion. From network evolution perspective, as time progresses, the number of nodes and connections in implicit communities shows an increasing trend, and information transmission efficiency improves. In the combined network's implicit community, subgroups based on comment relationships update and iterate relatively quickly, while subgroups based on follow relationships remain relatively stable and persistent.

There are significant differences in how comments and follows influence implicit communities. The three-phase implicit community structures formed based on comment relationships change considerably, with no stable subgroups existing. The possible reason is that commenting on the platform requires more operational and learning costs than following, which to some extent gives comment-based interaction networks a more important ideological and learning foundation, increasing relationship value among users. This makes the formed implicit communities better reflect real user relationship characteristics while improving user platform participation and creative output capacity. Additionally, users' follow relationships continuously accumulate, causing the follow network to grow over time, which facilitates user information acquisition and results in relatively stable implicit community structures based on follow relationships in the short term. However, if users' interests and follow focus change, the implicit community structure may be reshaped.

The main contributions of this paper are: Introducing the classification of community interaction types from consumer behavior research, dividing OIP user interaction behaviors into two categories: opinion-based interaction and action-based interaction, addressing the lack of discussion on different OIP user interaction types in existing literature. Analyzing the antecedents of implicit community formation from a user interaction perspective, enriching the research framework for implicit community discovery. Employing dynamic evolution analysis of interaction networks to present the evolution process of different interaction networks at the same stage and across different stages, revealing the formation and network structure evolution of implicit communities from a "dynamic" perspective.

We propose the following recommendations: For community managers, they should encourage users to follow ideas they are interested in, especially community newcomers or less experienced users, and incentivize them to actively participate in commenting, as this may lead to inspiration and provide quality ideas for the community. Users who comment on others' ideas should be given "badges" or point rewards to better promote inter-user learning and improve creative quality.

We conducted the research design in accordance with relevant standards, but there are still some limitations: Interest group limitation. We selected the interest group with the largest participation, which has some representativeness but lacks universality. Time length. Future research should expand the time length; while six months can observe user network evolution, longer time periods may contain different changes. Future research will expand the breadth and length of data selection, increase creative text topic mining, and propose feasible suggestions for how platforms can improve user continuous, deep interaction and enhance creative quality.

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Author Contributions: Ji Haiying: Topic selection, research design, data collection, initial draft writing Qi Guijie: Research direction and ideas, paper guidance and revision Li Na: Data analysis and processing, paper revision

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Abstract: [Purpose/Significance] Based on interactive networks of two types—following and commenting—and their combined network, this study investigates the influence of user interaction in open innovation platforms on implicit communities. [Method/Process] This study collected six months of user interaction data from the LEGO IDEAS platform, employed topology analysis, centrality analysis, and community analysis, and then used Gephi to construct three-phase network diagrams for following, commenting, and combined relationships, followed by evolutionary analysis. [Results/Conclusions] This paper demonstrates that all three interactive networks exhibit scale-free network characteristics, with a small number of users involved in a large volume of interactions. The combined network more closely approximates the real network structure of open innovation platforms. Comments are more important for the formation of implicit communities and innovation participation. Over time, the number of nodes and connections in implicit communities shows an increasing trend, with new nodes preferring to connect to central nodes with higher connectivity, and information transmission efficiency continuously improving. In the implicit community of the combined network, subgroups based on comment relationships update and iterate relatively quickly over time, while subgroups based on follow relationships remain relatively stable and persistent.

Keywords: open innovation platform; user interaction; implicit communities; community evolution; social network analysis

Note: Figure translations are in progress. See original paper for figures.