Social Network Structure and Influencing Factors of Virtual Knowledge Communities: A Case Study of Zhihu Postprint

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Abstract

[Purpose/Significance] This study investigates the structural characteristics and influencing factors of social networks in virtual knowledge communities. By comprehensively describing the interpersonal network structure within such communities, it reveals the socialization processes that influence network formation.

[Method/Process] Taking the "vaccine" topic on Zhihu.com as a sample, an interpersonal network is constructed based on user follow relationships. Exponential Random Graph Models (ERGM) are employed to examine the main configurations of social networks and the mechanisms of network formation from two aspects: pure structural effects and actor-relationship effects.

[Results/Conclusion] The findings reveal that the network exhibits self-organization, wherein convergences, expansiveness, transitive closure, and general transitivity are positively significant, while the 2-path effect is negatively significant. At the user level, the degree of knowledge contribution demonstrates significant heterophily, and both user prestige and knowledge contribution exhibit significant receiver effects.

Full Text

Preamble

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Social Network Structure and Influencing Factors of Virtual Knowledge Communities: A Case Study of Zhihu.com

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Abstract

[**Purpose/Significance**] This study investigates the structural characteristics and influencing factors of social networks in virtual knowledge communities, revealing the socialization processes that shape network formation through a comprehensive description of interpersonal relationship networks. [**Method/Process**] Using the "vaccine" topic on Zhihu.com as a sample, we constructed an interpersonal relationship network based on user follow relationships and employed Exponential Random Graph Models (ERGM) to examine the primary network configurations and formation mechanisms from two perspectives: pure structural effects and actor-relation effects. [**Results/Conclusions**] The findings indicate significant network self-organization, with positive significant effects for convergence, expansion, transitive closure, and generalized transitivity, while the 2-path effect is negatively significant. At the user level, knowledge contribution exhibits significant divergence, and both user reputation and knowledge contribution demonstrate significant receiver effects.

Keywords: virtual knowledge community; network structure; exponential random graph; ERGM
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1 Research Background

The exponential growth and fragmented distribution of information have increased the difficulty of accessing practical information, further intensifying the demand for precise, targeted information. To facilitate direct information exchange among internet users, a new type of virtual community centered on knowledge has emerged. Virtual Knowledge Community (VKC), a knowledge-oriented form of virtual community, typically adopts the concept proposed by Chen Yu in China: under the support of modern information technology, a new type of scientific community that combines real carriers and virtual connections, with unprecedented flexibility and creativity, aiming at knowledge creation and dissemination [1]. With the rise of instant messaging and social networking services, the form and extension of virtual knowledge communities have undergone significant changes, gradually evolving toward a socialized model with more participants and increasingly stable relationships [2]. This model constructs knowledge communities based on user interests or knowledge themes [3], where each individual serves as both a creator and consumer of knowledge, and the relationship network among individuals undertakes the dissemination and sharing of information resources. The increasingly close user network further stimulates knowledge interaction within the community, presenting characteristics such as socialization, user elitism, topic specialization, and knowledge originality [2].

In recent years, virtual knowledge communities represented by Zhihu.com have gained widespread recognition and participation. Both everyday professional knowledge and sudden public events can generate extensive discussions. Due to the community's knowledge attributes and the relatively transparent and rich knowledge backgrounds of core members, virtual knowledge communities possess natural authority. Under the community's voting-based selection mechanism, core viewpoints not only reflect mainstream community opinion but also exert tremendous influence on the entire internet public opinion landscape [4]. Therefore, understanding the social network structure and influencing factors of virtual knowledge communities is a crucial prerequisite for clarifying community information flow patterns, promoting knowledge dissemination, and achieving effective guidance of online public opinion.

2 Literature Review

Currently, virtual knowledge communities have become a core area of new media research, with numerous domestic and international scholars conducting in-depth investigations from various perspectives. Regarding the primary factors influencing the formation of virtual knowledge communities, existing research mainly approaches from the user perspective, attempting to explain overall network characteristics by examining individual knowledge behaviors. Researchers such as Chen Xiaoyu have conceptualized these user behaviors into three patterns: knowledge seeking, knowledge contribution, and knowledge adoption [5], with knowledge contribution widely recognized as critical for community structure and knowledge sharing [6]. Representative studies are summarized in .

As shown in the table, research by scholars like S. Zhang and W. Rutten primarily employs quantitative methods such as regression analysis and structural equation modeling, using data obtained through questionnaires or web statistics, yielding strongly explanatory conclusions. However, such studies can only identify the main factors influencing user knowledge contribution behavior and cannot effectively explain how these behaviors generate specific network structures. With the widespread application of social network analysis across social science disciplines, some scholars have begun empirical research on virtual knowledge communities from a social network perspective. For instance, Liu Pei [20] randomly selected topics from Zhihu.com, treating comments, replies, and responses under topics as connections between nodes to map interpersonal relationship networks and describe network characteristics. Nevertheless, these studies remain at the stage of revealing descriptive network features centered on centrality and cluster analysis, rarely addressing micro-structural features and member attribute characteristics. Consequently, they can only describe the real-time state of networks but struggle to reveal network structures and their underlying social processes. Therefore, achieving a comprehensive understanding of virtual knowledge community networks requires analyzing both network structures and their formation processes while considering how individual attribute features influence network configurations. The Exponential Random Graph Model (ERGM) employed in this study provides effective methodological support for this purpose.

3 Research Design

3.1 Sample and Data

The empirical subject of this study is Zhihu.com, a representative social Q&A website in China that launched in December 2010. As China's first interpersonal network-based Q&A platform, Zhihu.com emulated Quora's successful model while integrating follow mechanisms from Facebook and Twitter, collaborative editing from Wikipedia, and user voting from Digg, innovatively reorganizing these dispersed Web 2.0 functionalities and pioneering socialized Q&A in China. In product design, Zhihu.com inherits Quora's characteristics while implementing localized innovations that emphasize real-identity-based interpersonal relationships. By January 2017, Zhihu.com had over 65 million registered users, generating more than 250,000 topics and over 15 million questions [21], making it the most typical social Q&A community in China.

Zhihu.com provides both Q&A services similar to "Baidu Knows" and follow mechanisms adopted by social platforms like Weibo, offering users three dimensions for content discovery and dissemination: user following, question following, and topic following. At the user level, each user can monitor the activities of followed users on their personal homepage, including new content publication or evaluations of other content, and can also invite followed users to answer when initiating new discussions. The follow mechanism makes social relationships among network individuals more direct and stable; therefore, this study uses it as the basis for constructing social networks.

Currently, social network research primarily employs "snowball sampling" for data collection, which involves randomly selecting initial members and asking them to recommend connected members, thereby accumulating sample size [22]. While convenient, this method requires clearly defined network boundaries. As a virtual knowledge community, Zhihu.com lacks traditional geographical or organizational boundaries; instead, all officially published content is categorized under specific topics. This study uses particular topics as boundaries, collecting all following users under a topic and their mutual follow relationships to construct social networks. In principle, selected topics should have appropriate user scale, reasonable hierarchical topic settings, and certain professionalism and knowledge attributes. Considering these criteria, this study selected the "vaccine" topic—a concept the public can understand and care about, yet requiring professional knowledge for in-depth discussion. Additionally, this established topic possesses a sizable, diverse user group maintaining high-frequency Q&A and discussion activities, thus representing general characteristics of the Zhihu community.

3.2 Model Construction

3.2.1 Basic Principles of Exponential Random Graph Models Complex and dynamic network research represents a key challenge in contemporary social network analysis, as descriptive social network analysis cannot adequately reflect structural features and influencing factors. This study employs Exponential Random Graph Models (ERGMs), a relatively advanced social network analysis method that explains how and why connections form in networks [23]. Unlike traditional statistical models, ERGMs analyze the probability of special structures affecting network formation, positing that any observable network is one possible configuration among all possible node arrangements. If the observed network exhibits specific structural features significantly different from random networks, these features and their social processes influence network formation [24]. In ERGMs, the dependent variable is the probability of a connection between two nodes, while independent variables are a series of network structure statistics. Through modeling, the model identifies special structures affecting network emergence probability and ultimately determines important local relationships.

The ERGM inherits fundamental social network theories and assumptions, most importantly the notion that network relationships are interdependent—i.e., network self-organization exists [23]. In empirical analysis of specific networks, the model treats each individual as an actor in specific social relationships rather than unrelated analytical units. When one relationship emerges, the presence of another relationship is necessarily influenced. Therefore, ERGMs aim not to examine the probability of a single relationship but the conditional probability of a relationship given other relationships in the network. Additionally, ERGMs posit that social networks emerge locally, enabling randomized network generation through controlling local connection conditions without specifying global features, thus testing whether multiple local processes can produce global network characteristics [25].

In summary, the ERGM is a relationship-based, comprehensive empirical model that considers various factors in network generation processes. It can infer whether local configurations in observed networks differ from random networks and quantitatively assess differential impacts of various network generation processes on network structure. For online knowledge communities with ambiguous boundaries, large scale, complex relationship structures, and prominent member characteristics, ERGM is undoubtedly an effective tool. In recent years, this model has yielded fruitful results in studies of migrant worker networks [26] and international trade networks [27]. Applying it to virtual knowledge community research can reveal network structures and their underlying socialization processes while enriching and supplementing the ERGM framework.

3.2.2 Conceptual Model and Parameter Setting As shown in [Figure 1: see original paper], this study examines virtual knowledge community social relationship formation from two perspectives: network self-organization processes and actor attribute-based processes. Each process results from the combined effect of several social effects (e.g., reciprocity, expansiveness). In ERGMs, these social effects are reflected through local network structures called "configurations," which are refinements of the overall network. The quantity of each configuration, as an independent variable, affects the emergence probability of specific networks.

Network self-organization is an internal social network process where the existence of some relationships facilitates the formation of others. As it does not involve individual actor attributes or other exogenous factors, it represents an endogenous "pure structural" effect. Selected network structure parameters include arcs, reciprocity, cycles, and connectivity, with specific configuration forms and meanings detailed in .

Beyond pure structural effects, individual attributes' influence on network structure must be considered. In social network theory, this is termed "actor-relation effects." At the individual level, each actor participates in social networks with specific attribute features that influence participation behaviors and consequently affect local network structure formation and change. Synthesizing domestic and international research on virtual community user behaviors, this study selected three attributes as actor-relation variables: social connections, reputation, and knowledge contribution. From a knowledge acquisition perspective, due to Zhihu's push mechanism for followed users' activities, the number of users a particular user follows reflects accessible information quantity; thus, this study uses total follow count to measure social connections. Conversely, the degree to which a user is followed by others reflects community reputation. Finally, knowledge contribution level can be assessed through the number of upvotes received from other users. After identifying these three attribute factors, the model tests whether users with different attributes exhibit significant sender effects, receiver effects, or homophily/heterophily effects.

3.2.3 Establishment of Exponential Random Graph Models In summary, ERGM is an exponential model using network structure statistics as independent variables and network probability as the dependent variable. For a network with N nodes, the node set is V = {1, …, n}, where i V indicates node i belongs to set V. Set J represents all possible relationships among nodes in V, i.e., J = {i, j}, i, j V, and i $\neq$ j. For any observable network G = (V, E), all relationship sets E in the network can be regarded as subsets of J. Accordingly, through random variable y_{ij} representing element (i, j) in set J: if (i, j) E, then y_{ij} = 1, otherwise 0. These relationship variables can be arranged in a random adjacency matrix Y = [y_{ij}], with all random adjacency matrices constituting the possible set of network adjacency matrices. Thus, using P_r(Y = y|) to represent the probability of network y appearing in feasible set Y under condition constitutes the general mathematical expression of exponential random graphs:

$$P_r(Y = y|\theta) = \frac{\exp[\sum_H \theta_H Z_H(y)]}{k(\theta)} \quad \text{(Formula 1)}$$

where k( ) is a normalization constant ensuring the model has an appropriate probability distribution (i.e., the sum of probability functions across all graphs equals 1). H represents all possible factors affecting network formation, and Z_H(y) represents a series of statistics that may influence network formation. Specifically, based on existing research, H generally includes pure structure statistics reflecting network self-organization, actor-relation effect statistics reflecting node attributes, and exogenous structure variables reflecting other external network influences, denoted by , β, and γ respectively. Accordingly, Formula 1 can be further specified as:

$$P_r(Y = y|\theta) = \frac{\exp[\theta^T Z_\theta(y) + \beta^T Z_\beta(y, x) + \gamma^T Z_\gamma(y, g)]}{k(\theta)} \quad \text{(Formula 2)}$$

For Z_ (y), Z_β(y, x), and Z_γ(y, g), if a statistic's parameter estimate passes significance testing, it indicates that network structure importantly influences overall network formation. A positive parameter estimate suggests that, controlling for other conditions, the probability of that structure appearing is much higher than expected, and vice versa.

3.3 Model Fitting Process

This study used a web crawler to collect raw data and employed social network analysis tool UCINET and visualization software NetDraw to present Zhihu's social network. ERGM is a generative model aiming to reveal factors significantly affecting network formation and development. Therefore, after determining network statistics, the process involves simulation, estimation, and heuristic goodness-of-fit (GOF) to make model simulation results increasingly approximate the original network's structural features.

Parameter estimation presents the greatest challenge. Domestic and international ERGM research primarily focuses on real communities, lacking sufficient empirical references for virtual community studies. Without prior knowledge of community network structures, determining which parameters to include in the model is difficult. This study addresses this by starting with a Bernoulli model (P1 model, including only arc variables and attribute variables) and continuously adding new parameters by testing GOF statistics until obtaining applicable results. The research process is illustrated in [Figure 2: see original paper].

4 Empirical Analysis

4.1 Network Selection and Presentation

Through web crawler software, we obtained 1,765 followers of Zhihu.com's "vaccine" topic as the total sample (data collection date: April 1, 2016) and retrieved each user's follow list, yielding 337,366 follow relationships. After removing users outside the total sample, we initially obtained a social network among 1,765 users, represented by an adjacency matrix.

Preliminary descriptive analysis revealed this as a sparse network with density of only 0.0014. The difference between maximum and minimum node degrees reached 320, with a standard deviation of 15.026, indicating the network primarily revolves around a small number of core nodes with infrequent connections among most nodes. Further investigation showed that isolated or low-degree nodes constitute a large proportion, with the vast majority of users having very sparse recent community activities—typically considered "zombie users" resulting from the topic's lack of exit mechanisms. To accurately reflect the community's social network structure, we simplified the sparse overall network into a core network composed of active users. Following the simplification method provided by Li Lin [28], we continuously removed nodes with degree 1 on the largest connected subgraph, then nodes with degree 2, sequentially increasing the minimum node degree to a critical value (calculated as: P_c = 1 - 1/(k^2)(k-1), where P_c is the critical percentage of removed nodes and k is average node degree), ultimately retaining 81 nodes with in-degree reaching 20 to form the core user network for the "vaccine" topic, as shown in [Figure 3: see original paper].

4.2 ERGM Estimation Results and Analysis

4.2.1 Parameter Estimation Results Substituting the observed network into Formula 1 for parameter estimation yielded the results shown in . All parameters adequately met convergence requirements (t-statistics < 0.1). Parameters with absolute values exceeding twice their standard errors were considered significant, marked with *.

4.2.2 Analysis of Pure Structural Effects **Arc:** The model yielded a negative arc effect, interpretable as the baseline tendency for relationship formation.

Reciprocity: Unlike most real-community social networks, the reciprocity estimate for the sample network is not significant, indicating infrequent bidirectional reciprocal relationships—consistent with observations. Compared to general friendship relationships, following other users on Zhihu is a unilateral choice by the follower without requiring confirmation. Observed reciprocity in the network typically reflects deep-level connections, such as real interpersonal relationships or close information exchange. However, in broader social networks purely for knowledge exchange, followed users lack obvious motivation for reciprocal following. Furthermore, for social media platforms using follow mechanisms (like Zhihu, Weibo, and public accounts), information recipients naturally include all internet users. Without blocking mechanisms, information publishers cannot control dissemination scale. This differs significantly from social platforms centered on online friendships (e.g., WeChat, QQ) where friendships require mutual confirmation, necessitating differentiated public opinion management strategies.

2-path: This parameter shows a negative significant effect, indicating that, given other effects, the observed network contains significantly fewer 2-path configurations than expected. In other words, connections among users in the sample network are less constrained and controlled by intermediaries. In internet environments with low knowledge dissemination costs and diverse acquisition channels, the role of "information transmitters" in networks is diminished. This conclusion aligns with centrality analysis results, where a small number of star nodes simultaneously possess high degree centrality and betweenness centrality, acting as both opinion leaders and information bridges. While media plays a crucial role in shaping public opinion in real-world information dissemination networks, information publishers have more direct influence on recipients in online society, gradually diluting traditional media's role. Therefore, in major public opinion events, identifying and guiding key information sources in virtual knowledge communities must occur early, leaving extremely short reaction time for relevant management departments and demanding higher public opinion handling capabilities.

Convergence and Expansion: These effects represent centralization tendencies of in-degree and out-degree distributions, respectively, with both estimates being positively significant. The convergence effect indicates significant core nodes in the sample network—star users receiving frequent follows while rarely following others. Similarly, the expansion effect reflects central tendency of network expansion, with some information seekers or receivers being highly active in the social network. For public opinion management, convergence and expansion effects prominently reflect the role of "opinion leaders," particularly a small number of active professional users who significantly influence public opinion direction on specialized topics. Currently, official media credibility faces varying degrees of questioning in traditional public opinion fields [29], and the stigmatization of "experts" is an undeniable objective phenomenon [30]. Unlike traditionally defined public intellectuals, virtual knowledge communities contain numerous ordinary users with professional backgrounds who accumulate discourse power through continuous knowledge contribution and gradually become community opinion leaders. The virtual internet environment provides the public with direct access to knowledge from these core users, further amplifying core users' influence on community opinion. The community's push mechanism also enables core users to serve as information dissemination bridges. For knowledge content posted by ordinary users, attention (view count) and recognition (upvote count) depend more on whether core users notice and approve the content rather than the content's intrinsic quality.

Transitivity and Closure: Generalized transitivity is significant, indicating more transitivity observed in the network. The significantly positive effect of transitive closure shows a notable trend toward hierarchical path closure in the sample network. These parameters indicate the network tends to operate through small-group structures. In friendship relationships, transitive closure can be expressed as actor i tending to choose actor j as a friend if j is a friend of i's friend h. In virtual knowledge communities, this effect suggests user following behavior is influenced by already-followed users—an implicit "recommendation" mechanism. On the Zhihu platform, information pushed to user i primarily comes from followed user h's activities, including both original content published by h and h's evaluative information behaviors toward others. Therefore, when user i receives information pushed by h, it 实质上 completes a recommendation from j to i, facilitating i's following behavior toward j. In public opinion management, this effect further corroborates the analysis in the 2-path parameter section: as media functions weaken, focus should be placed on improving attention to and timeliness of information source identification.

4.2.3 Analysis of Actor-Relation Effects **Sender Effects:** Sender effects examine whether actors with certain attributes are more likely to send connections to others. Zhihu.com is a comprehensive knowledge community with over 100,000 topics, allowing users to participate in multiple topic networks according to interests or needs. The sender effect for social connections is not significant, indicating no evidence that connections accumulated from other topics make users more willing to follow others within a specific topic network. Assuming information propagates along the reverse direction of user follow networks, the above conclusion suggests that in virtual knowledge communities, focus should be placed on opinion leaders' direct audiences rather than active information recipients when identifying information receiver groups during sudden public opinion events. When public opinion emerges in a relevant topic, beyond the information source itself, the scale of the first batch of recipients receiving specific messages importantly influences public opinion dissemination scale and speed—their actions toward information determine whether it continues spreading through the community network. Therefore, before public opinion outbreaks, individuals with direct connections to potential information sources should be monitored closely.

Receiver Effects: Receiver effects examine two attributes: user reputation and knowledge contribution. The model shows both parameters are significant—users with higher reputation and those contributing high-quality knowledge more easily gain followers. Receiver effects help identify core nodes in virtual knowledge communities. Combining these conclusions with observations reveals two groups more likely to become opinion leaders, corresponding to "reputation" and "contribution" attributes: first, publicly verified celebrities within the community who, despite not necessarily having close ties to specific topics, carry over their social influence into the virtual knowledge community and play non-negligible roles in public opinion dissemination; second, active users with relevant professional backgrounds—knowledge elites from various industries with higher education levels. While these grassroots users lack inherent influence, they are the community's primary knowledge contributors.

Homophily/Divergence: The model examined divergence effects for three attributes: social connections, reputation, and contribution. Knowledge contribution levels among users show significant divergence—in the sample network, connected users typically have different numbers of upvotes. Zhihu's upvote mechanism 实质上 constitutes a voting system for content quality, providing quantitative feedback on knowledge contribution levels while measuring users' knowledge levels and contribution willingness. This effect reflects the unidirectional knowledge transfer pattern from producers to consumers at the information level. It also demonstrates that user relationship networks in virtual knowledge communities are primarily established based on knowledge dissemination, with social functions being derived features. This represents an essential difference from other virtual communities, particularly those centered on social functions.

5 Conclusion and Discussion

Using Zhihu.com's "vaccine" topic as a sample, this study examined social relationship network characteristics in virtual knowledge communities. From network self-organization and actor attributes perspectives, we statistically analyzed primary network configuration forms and examined main reasons affecting network structure formation. The 2-path effect shows significant negative effects, while convergence, expansion, transitive closure, and generalized transitivity are positively significant. From the user perspective, user reputation and knowledge contribution exhibit receiver effects, with the latter also showing significant divergence.

The study reveals that user relationships in virtual knowledge communities are multi-level and block-distributed, with two centers—knowledge producers and knowledge consumers—where core users tend to contribute knowledge while peripheral users primarily browse. Additionally, ordinary community members prefer to follow "stars" and "knowledge elites": the former are public figures in real society whose fame is partially inherited in the real-name virtual community; the latter are ordinary users with relevant professional backgrounds who accumulate discourse power through continuous knowledge contribution and gradually become community opinion leaders. The virtual internet environment provides the public with direct access to knowledge from these core users, further amplifying core users' influence on community opinion. The community's push mechanism also enables core users to serve as information dissemination bridges.

Accurately understanding virtual knowledge community network structures and their influencing factors is key to improving virtual community services, expanding knowledge dissemination, and grasping online public opinion dynamics. This study's findings have practical significance. However, in internet environments, community networks are not only complex but also diverse. This study only examined Zhihu.com's user follow network; future research using larger samples and introducing multiple networks such as discussion relationship networks and social support networks would facilitate deeper understanding of virtual knowledge community network structures. Additionally, network statistical models such as latent variable network models and stochastic block models provide alternative approaches for studying virtual knowledge community network formation processes.

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Author Contributions

Liu Yunong: Proposed research topic, collected and processed data, drafted manuscript.
Liu Minrong: Revised manuscript, finalized manuscript.

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