A Social Network Structure Analysis of Former Smokers in Emerging Markets Using China's Twitter

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Objectives: Social networks are widely used for proping the process of tobacco control in emerging markets, but their formation and effects are not well understood. Using the microblogging platform Sina (Sina Weibo, China's Twitter) as an example, this article conducts a multi-agent simulation analysis of the Netlogo platform to analyze the micro-level behavioral characteristics of former smokers and macro-evolutionary law in the formation of social networks in emerging markets. The results show that the tobacco control in use of social networks have two characteristics: limitations on the size of the network and the in-degree and out-degree of its nodes as well as heterogeneous attributes of the nodes. This kind of network is better at simulating a real social network than small-world and scale-free networks.

Key words: tobacco control; emerging market; nodes; social network structure
Tob Regul Sci.™ 2021;7(5-1): 2286-2297
DOI: doi.org/10.18001/TRS.7.5.1.1

Social networks are widely used for proping the process of tobacco control in emerging markets. They have penetrated all aspects of work and life, becoming an important platform for information dissemination, access, and sharing[1]. Unlike interaction through traditional methods, social networks place importance on user-generated content (UGC), with enormous influence from key nodes, and use a viral information dissemination model, which indicates that social networks have subverted the traditional mode of information dissemination and changed the position of enterprises in informational interaction among consumers. For this reason, companies are taking advantage of social networks as a new channel for brand building, marketing, and customer relationship management, which is vital in emerging markets for building a competitive advantage in the internet era.

Research on the structure of social networks begins with theoretical modelling. Classical theoretical models of social network structure include regular networks, stochastic networks, small-world networks, and scale-free networks. From different perspectives, these classical theoretical models are based on the law of social network construction, such as small world, preferential links, and other features[2]. However, the models are too simplistic, and they ignore many other factors that influence the structural evolution of real social networks, such as the properties of a node and the deletion of an existing node or edge. Therefore, empirical research to confirm the validity of theoretical models to describe real social networks is only just emerging.

Studies of social networks have increased in recent years thanks to the availability of application programming interfaces (API). The research mainly extracts local area networks (LAN) through snowball[3] or specific LAN extraction[4] and other methods. The results shows that real social networks have mixed scale-free and small-world characteristics, but current theoretical models of complex networks reveal only partial characteristics, and extracted LAN does fully capture the full characteristics of real social networks either. Therefore, to better fully understand the complexity in social networks, a new network model is needed. Bass diffusion, as one of the many models of market tools, is used to predict how innovative consumer durables are diffused in consumer markets.

In recent years, experiential models have become more popular. Researches based on experiential models started from the basic features of real social network construction has gradually made up for the shortage of classical theoretical model. From the perspective of information extraction ability, for example, the evolution model of local world is proposed in the link mode of newly added nodes[5]; from the transmission perspective of the relationship between nodes, the HK model is proposed for new links to existing nodes; in terms of internal and external competition, node/edge deletion rules are added in the dynamic process of evolution[6] and so on.

However, these studies ignore three important characteristics of evolution in social networks: (1) limitations on growth in the size of social networks; (2) limitations in the ability to focus on network nodes; and (3) differences in the node attributes of single-mode networks. Therefore, their formation and effects are not well understood, though these are important in building competitive advantage in emerging markets. So, we attempt to remedy these inadequacies in previous studies and build an experiential model that is closer to the structure of real social networks.

To analyze the evolutionary features of social networks, we propose a model of a social network with two limitations and heterogeneous node attributes. In addition, using the Sina microblogging platform (Sina Weibo) as an example, we extract relevant parameters in network evolution through an analysis of large-scale data. In addition, we regress the dynamic evolution of Sina Weibo with Netlogo software and, based on the results, offer some management recommendations for emerging markets.

The remainder of this paper is structured as follows. In the first section, we analyzed the features of social network structure; in the second section, we brought forward to heterogeneous social networks with Limitations; in the third section, we analyzed the simulation results; and the last section is our conclusions and implications.

EMPIRICAL ANALYSIS OF THE FEATURES OF SOCIAL NETWORK STRUCTURE

Social networks are a type of Social Networking Services. They are online communities constructed with different kinds of user nodes. The construction of social network nodes includes not only users (i.e., people) but also various institutional users (i.e., firms)[7]. Various egocentric networks are constructed by different types of users with different motivations. Macro-level complex behaviors thus appear in interactions between micro-level individuals, and the self-organization behavior of the overall network in turn affects these individuals, resulting in an ever-changing social network structure[8]. Previous studies have indicated that social networks have small-world, scale-free, and other characteristics. On this basis, we further analyze the macro-level evolution and micro-level behavioral characteristics of social networks and conduct an empirical analysis using Sina Weibo as an example.

Limited Size of Networks

Nodes of social networks map the individual users, institutional users, and other entities in the virtual world of the internet. The limitation on the number of individual users, institutional users, and other entities mean that, even with multiple network identities, the size of online social networks is bound to be limited.

Currently, the evolutionary model of most networks expands by the number of nodes per constant unit of time. Over time, the network will tend to be unlimited in size[9]. Obviously, this kind of evolutionary model is not consistent with the actual evolutionary rules of social networks.

The evolution of social networks is similar to the dissemination of technological innovation and sales of traditional durable goods. The increment in network size is not constant; rather, it is closely related to two factors: first, external influence—that is, encouraging potential users to join social networks using all kinds of media to promote social networking characteristics; second, internal influence—that is, urging potential users to join social networks by building on existing users. Frank M. Bass developed the Bass diffusion model, which is often used as a tool of market analysis to predict new products and new technology needs. The Bass diffusion model is one of many market tools, and its main function is to describe and predict market purchases of newly developed consumer durables. The model attributes the diffusion rate of new products to two major factors: first, the innovation factor, or the external influence factor, which is mainly transmitted through the mass media; second, the imitation factor or internal influence factor, which refers to the effect between people. That is why the Bass model is suitable for describing the limited size of the network.

Considering the internal consistency between the increase in the size of a social network and the influencing factors of technological innovation dissemination, the Bass model's growth equation can be used to describe the evolution of social network size, as follows:

$$\Delta M(t+1) = a\left(\overline{M} - M(t)\right) + bM(t)\left(\overline{M} - M(t)\right) \quad (1)$$

where $\Delta M(t+1)$ is the increase in the number of social network users at time $t+1$; $M(t)$ is the number of existing social network users at time t; a is the innovation factor, which is related to external factors; b is simulation factors related to internal factors; and $\overline{M}$ is the maximum number of social network users. Equation (1) can be revised as

$$\begin{aligned} M(t+1) &= -bM^2(t) + \left(1 - a + b\overline{M}\right)M(t) + a\overline{M} \\ &= \alpha M^2(t) + \beta M(t) + \gamma \end{aligned} \quad (2)$$

where $\alpha = -b$; $\beta = \left(1 - a + b\overline{M}\right)$;and $\gamma = a\overline{M}$.

To confirm the validity of the Bass model, we simulate the increased scale of users of Sina Weibo, based on data in its annual and semiannual reports, in which the innovation coefficient; simulation coefficient; largest user scale=700.78 million. The simulation results show that the Bass model can simulate the growth of users in Sina Weibo effectively, as shown in Table 1.

Table 1
Characteristics of the Study Group Including Those Who Did and Did Not Use Self-medication

	Coefficients	Standard error	t Stat	P-value	Lower 95%	Upper 95%	Lower limit 95.0%	Upper limit 95.0%
α	16.0683	0.8682	18.5073	9.99E-68	14.3649	17.7716	14.3649	17.7716
β	1.0027	9.14E-05	10964.98	0	1.0025	1.0029	1.0025	1.0029
γ	0.9999	1.83E-09	-23.0483	3.83E-98	-4.6E-08	-3.9E-08	-4.6E-08	-3.9E-08

In-Degree and Out-Degree Limitation of the Nodes

The out-degree of network nodes represents the number of its interest users; and the in-degree represents the number of users who choose it as the interest object. According to the limitations on the social network size $\lim_{t\to\infty} M(t) = \overline{M}$, the existence of a theoretical upper limit in the number of out-degree and in-degree network nodes is known, namely $\overline{M}$ -1, and the actual number of out-degree and in-degree nodes is much lower than the theoretical upper limit.

Michael H. Goldhaber, who first proposed the attention economy, has pointed out that the web-based "new economy" is in essence the "attention economy." In this economic form, the most important resource is neither financial capital in the traditional sense nor information but attention[10]. Although the social radius of social networks is expected to expand, as is social capital, because attention is limited, the selected object of interest (out-degree) is necessarily limited. Moreover, different users have different numbers of out-degree nodes. For example, on Sina Weibo, the average value of out-degree nodes among 200,000 randomly selected users is 113. The out-degree distribution is shown in Figure 1.

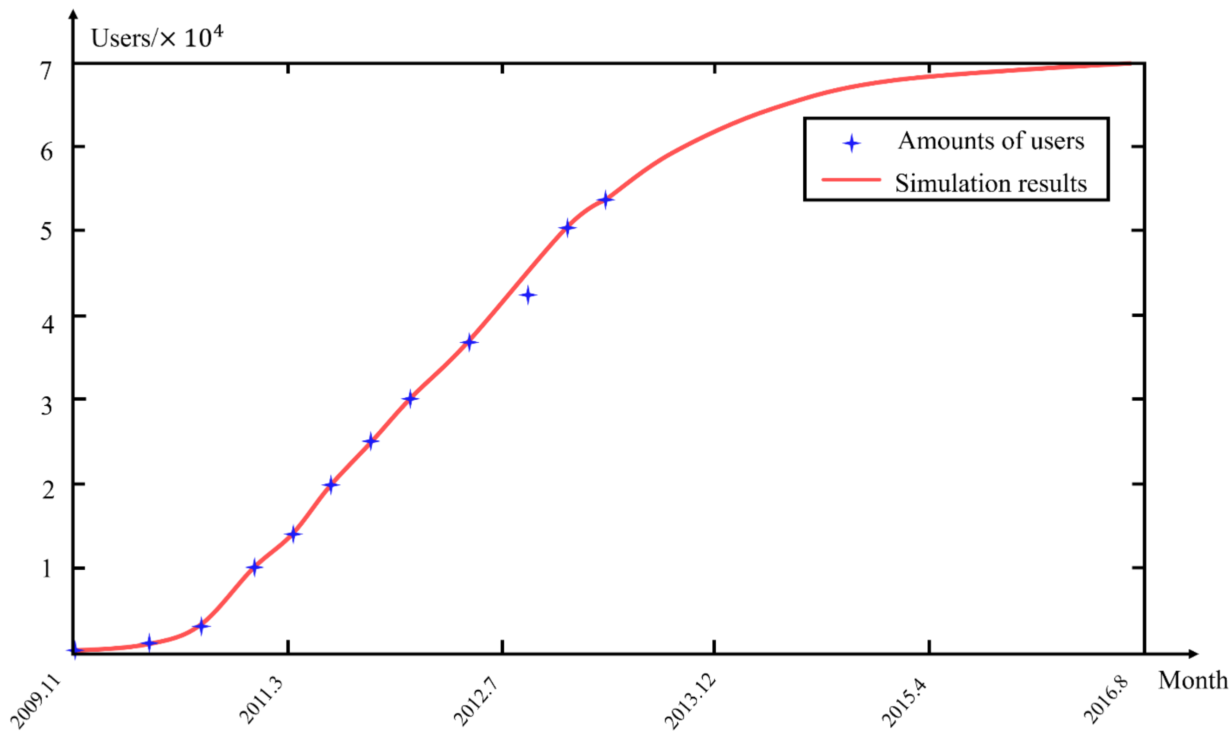

Figure 1. Out-degree distribution of Sina Weibo users

The sum of out-degree nodes in social networks equals its sum of in-degree nodes, namely $\sum_{i=1}^{M} n_{out}(i) = \sum_{i=1}^{M} n_{in}(i)$. Although social networks have a preferential link characteristic—that is, a small number of nodes have many links—the limitations on out-degree nodes inevitably limit the number of in-degree nodes. In addition, different users have different numbers of in-degree nodes. For example, on Sina Weibo, the maximum value of in-degree nodes among 200,000 randomly selected users is 8,286,157. The in-degree distribution is shown in Figure 2.

Heterogeneity of Nodes

Depending on the differences in sets that make up the network entity, complex networks can be divided into single-mode networks, dual-mode networks, and tri-mode or higher-mode networks according to the node type. Social networks are generally regarded as single-mode networks comprising single actors. However, their constituent nodes have different properties, including heterogeneity in the number of users and of out-degree and in-degree nodes and becoming mutual followers.

Heterogeneity in the Number of Users articipants

For example, the users of Sina Weibo can be divided into five types: non-authenticated users, authenticated individual users, authenticated institutional users, female bloggers, and expert bloggers. Using an open-source API available on the Sina Weibo platform and a data interface application we developed, with a snowball crawling algorithm and breadth-first search (BFS), we identified more than 70 million users on Sina Weibo during the period July to October 2012. As shown in Table 2, the proportion of various types of Sina Weibo users varies widely.

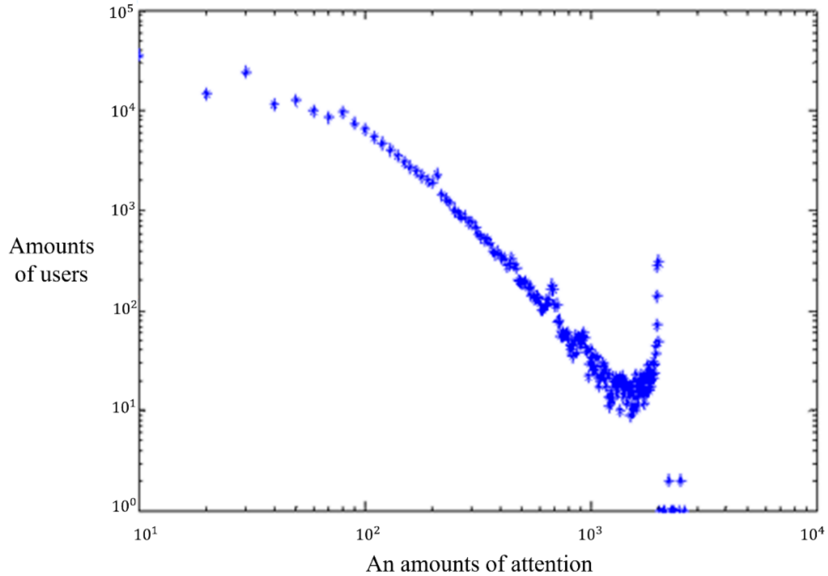

Figure 2. In-degree distribution of Sina Weibo users

Table 2
Analysis of the selected users on Sina Weibo

	Non-authenticated	Individuals	Institutions	Female bloggers	Expert bloggers	Total
No. (10,000 people)	6,809.3	36.4	18.1	18.1	369.4	7,251.3
Proportion	93.90%	0.50%	0.25%	0.25%	5.09%	100.00%

Heterogeneity of Out-Degree Nodes

Research on behavioral economics shows that specific information is associated with specific people. The selection of the right person as a source of information and advice is common in human information behavior[11]. Social networks have created a new kind of information acquisition mode: users access informational content in the form of "interests." Different types of users have different types of information needs, therefore, when choosing the objects of interest, users may be concerned only with their own information needs. That is, user types in social network nodes here have a choice preference: heterogeneity in out-degree nodes. We randomly selected 50,000 users of Sina Weibo, who are divided into five types of users. Our statistical analysis indicates large differences between the distribution of user interests in each type of node (see Table 3) and the choice preference probability of each type (see Table 4).

Heterogeneity of In-Degree Nodes

The authoritative effect shows that people with high status and prestige are more likely to receive attention. In social networks, after the authoritative effects play a role, their advantage rapidly expands to form the choice preference of authority under the stimulation of Matthew: the heterogeneity of in-degree nodes. For example, the authentication function and user classification of Sina Weibo reduce barriers in user identification authority. Therefore, certified users tend to attract more attention than non-authenticated users.

Heterogeneity in Becoming Mutual Followers

Becoming mutual followers refers to the mutual interests between users in social networks. The rights setup in becoming mutual followers is not entirely the same in different types of social networks. In Renren and WeChat, for example, it is based on two-way authentication, and becoming mutual followers is a necessary condition for building relationships, so there is no heterogeneity in becoming mutual followers; however, a one-way following mechanism is adopted in Sina Weibo, so users have the right to establish a relationship as mutual followers. Hence, different types of users present different tendencies in becoming mutual followers[12]. Table 5 shows the preference for becoming mutual followers among different types of users.

Our study shows that users with different characteristics have different micro-level motives for joining social networks. Therefore, a social network is formed with limitations on the size of the network and on the number of in-degree and out-degree nodes, as well as nodes with heterogeneous attributes. The existing research on single-mode homogeneous networks cannot accurately distinguish relationships between users with different characteristics[13]. Therefore, it is necessary to account for the heterogeneity in social networks, explore the impact of different user preferences on the evolution of social networks, and build the evolutionary rules for actual social networks on this basis.

Table 3
Interest probability of five kinds of Sina Weibo users

Interest probability	Non-authenticated	Individuals	Institutions	Female bloggers	Expert bloggers
Non-authenticated	31.58%	27.28%	9.19%	19.46%	12.49%
Individuals	35.57%	22.25%	9.29%	22.36%	10.53%
Institutions	32.57%	14.94%	14.23%	22.86%	15.40%
Female bloggers	34.14%	14.23%	6.20%	25.44%	19.99%
Expert bloggers	35.40%	13.65%	8.20%	24.27%	18.48%

Table 4
Choice preference probability of five kinds of Sina Weibo users

Interest probability	Non-authenticated	Individuals	Institutions	Female bloggers	Expert bloggers
Non-authenticated	21.08%	16.83%	29.31%	21.02%	11.76%
Individuals	18.19%	15.01%	31.28%	12.33%	23.19%
Institutions	22.53%	12.77%	24.76%	11.86%	28.08%
Female bloggers	27.85%	22.13%	26.12%	15.11%	8.79%
Expert bloggers	25.13%	21.89%	25.15%	17.22%	10.61%

Table 5
Preference for becoming mutual followers among five kinds of Sina Weibo users

	Probability of becoming mutual followers	**Proportion of each type of user**				
		Non-authenticated	Individuals	Institutions	Female bloggers	Expert bloggers
Non-authenticated	38.10	17.80	0.90	0.40	11.90	7.10
Individuals	54.40	19.40	11.60	2.10	12.50	8.80
Institutions	46.80	15.30	5.20	8.10	12.10	6.10
Female bloggers	57.00	19.30	1.80	0.50	18.50	16.90
Expert bloggers	53.90	20.60	1.20	0.50	16.30	15.30

MODEL OF HETEROGENEOUS SOCIAL NETWORKS WITH LIMITATIONS

On the basis of the existing empirical model of social networks, we add the characteristics of having two limitations and heterogeneous node attributes to an evolutionary mechanism in social networks. Hence, we outline four basic rules of social network evolution.

Rule 1: The number of new users per time period is related to the existing network size and the scale of potential users, as shown in equation (1); the type of new nodes is determined by probability.

Rule 2: The number of new out-degree nodes is limited. Their link is in line with the local preferential link[5], as well as the choice preference of user types, namely, the heterogeneity of out-degree nodes.

Rule 3: Existing nodes can add new edges. New links can be produced in three ways: (1) random links with other nodes on the basis of probability[14]; (2) links with the interest nodes based on triangle recommendation mechanism; and (3) the links with existing followers based on the rules for becoming mutual followers.

Rule 4: Existing nodes are allowed to exit the network or disconnect old links[6].

Initial Network Settings

An initial social network is made up of M_0 nodes with k class(es) of different characteristics. A fully coupled network of N_0 edges is formed, as shown in equation (3).

$$\begin{cases} M_0 = \sum_{i=1}^{k} M_{0i} \\ N_0 = M_0(M_0 - 1) \end{cases} \tag{3}$$

Network Evolution

At each point in time, the following steps are executed repeatedly until the total number of network nodes reaches $\overline{M}$.

New Nodes

At time t, the number of new nodes $\Delta M(t)$ is shown as equation (1). Based on the probability $p_{ch\_i}(i = 1,2,\cdots,k)$, new nodes select their characteristics and satisfy equation (4).

$$\sum_{i=1}^{k} p_{ch\_i} = 1 \tag{4}$$

First, we determine the number of links of new nodes. Based on the out-degree distribution of the subordinate type of social network, a new node new_j determines the out-degree $n_{link\_out\_i\_new\_j}$ depending on $p_{link\_out\_i}(i = 1,2,\cdots,k)$.

Then, we determine the number of new links between new nodes and all kinds of attribute nodes. The number of links $k_{new\_j\_link\_i}$ between new nodes new_j and attribute nodes i can be calculated as follows.

$$k_{new\_j\_link\_i} = n_{link\_out\_i\_new\_j} \times p_{s\_link\_i} \tag{5}$$

where r represents the type of new nodes new_j; $p_{s\_link\_i}$ is the probability that the s th class of nodes links with the i th class of nodes, which satisfies equation (6).

$$\sum_{i=1}^{k} p_{s\_link\_i} = 1 \tag{6}$$

Then we define new nodes and select the range of the objects of interest, which can be chosen by new nodes within LAN Ω at the range of the located radius r_0. In addition to the new nodes, an alternative set $\Gamma_i(i = 1,2,\cdots,k)$ is constituted by attribute users i in a LAN.

Then we determine objects of interest of the new nodes. In the alternative sets of attribute node i, new nodes refer to the link rules of a scale-free network and select their objects of interest, depending on $p_{new\_j\_i\_h}$, which satisfies equation (7):

$$p_{new\_j\_i\_h}(h \in \Gamma_i) = \frac{n_{in\_h}}{\sum_{f=1}^{n_{\Gamma_i}} n_{in\_f}} \tag{7}$$

where n_{in_h} is the in-degree of node h; n_{Γ_i} is the number of nodes in the alternative set Γ_i.

New Edges of Existing Nodes

First, we select an existing node. Based on the probability p_{old_i}, n_{old} existing node(s) is (are) chosen randomly.

In the reference to link rules in an NW small-world network, an existing node old_j is chosen randomly for the existing node n_{old_i} based on the probability $p_{old\_link\_nw}$. And a link between the existing node n_{old_i} and the existing node n_{old_j} is established.

In the reference to the TF link rules in the HK model, an existing node old_f is chosen randomly for the existing node n_{old_i} based on the probability $p_{old\_link\_hk}$. And an interest set of Φ_{old_f} is determined for the node old_f. Interest objects are selected in the interest set Φ_{old_f} according to the probability $p_{old\_i\_f\_h}$.

$$p_{old\_i\_f\_h}\left(h \in \Phi_{old\_f}\right) = \frac{n_{in\_h}}{\sum_{f=1}^{n_{\Phi_{old\_f}}} n_{in\_f}} \qquad (8)$$

where $n_{\Phi_{old\_f}}$ is the number of nodes in the interest set Φ_{old_f}.

Then, we determine the objects of becoming mutual followers. The interest set Φ_{new_j} is determined for new nodes new_j. The proportion of becoming mutual followers p_{hf_i} is ascertained according to the feature of becoming mutual followers of class i to which the new nodes belong. Depending on probability $p_{i\_hf\_h}$, nodes of becoming mutual followers are confirmed, and they satisfy equation (9).

$$p_{hf\_i} = \sum_{h=1}^{k} p_{i\_hf\_h} \qquad (9)$$

Deletion of Existing Nodes and Disconnection of Existing Edges

We then select and delete nodes. n_{delete_old} existing nodes are randomly selected depending on p_{delete_node} and deleted. Then, we select disconnected edges. n_{delete_link} existing nodes are randomly selected depending on p_{delete_link} and deleted.

ANALYSIS OF SIMULATION RESULTS

The multi-agent simulation platform Netlogo is used in the study, and the results of our empirical analysis on Sina Weibo are used as model parameters (Tables 1-5) to simulate a social network with two limitations and heterogeneous node attributes. As the simulation results show, we build a social network according to the evolutionary rules of a social network with two limitations and heterogeneous node attributes, which has the shortest path on average and a higher average clustering coefficient. In addition, its in-degree is subject to a power-law distribution with small-world and scale-free features; moreover, the network's influence and control are not the same for different types of nodes.

Analysis of Overall Network

The time length of the simulation is set at 289, and then a social network with two limitations and heterogeneous node attributes is formed with 2,025 nodes and 38,108 edges. Then, the network is compared with random network, small-world network, and scale-free networks with the same number of total nodes and closed edges, as shown in Table 6. Our simulation results show that a social network with two limitations and heterogeneous node attributes has characteristics of small-world networks, but its out-degree distribution is fixed, and the in-degree distribution follows a power law (Table 6); in addition, it is scale free. But its large clustering coefficient (Table 6) is in line with the characteristics of actual social networks[15].

Table 6
Comparison of various networks

Network name	Network diameter	Average clustering coefficient	Average path length
Random network	13	0.009	2.973
Small-world Network	14	0.355	5.24
Scale-free network	11	0.064	2.258
Network with two limitations and heterogeneous node attributes	7	0.148	3.306
Simulation network excluding becoming mutual followers	11	0.092	4.095
Simulation network excluding idol effectand becoming mutual followers	11	0.086	4.335

The increase in clustering coefficients in social networks with two limitations and heterogeneous node attributes is correlated with two rules: first, a TF link rule and, second, rules for becoming mutual followers. In the TF rule, if a link has been established by nodes i and j at time t during the evolutionary process, then at time $t+1$, node l, a neighbor of node j, is selected to link with node i. In undirected networks, a closed triangle is formed by i, j, and l because of the TF rule, as shown in Figure 3a, to increase the network clustering coefficient. However, if a real social network is a directed graph (e.g., a microblog), nodes i, j, and l do not form a closed triangle, as shown in Figure 3b. Thus the network clustering coefficient is not significantly increased by the TF rule, as shown in Table 7. On the basis of the TF rule, the rule of becoming mutual followers is added. A closed triangle between nodes i, j, and l can be formed by building a link between nodes l and i, shown in Figure 3c. Hence, the clustering coefficient of the social network can be improved effectively, as seen in Table 7. (Table 1).

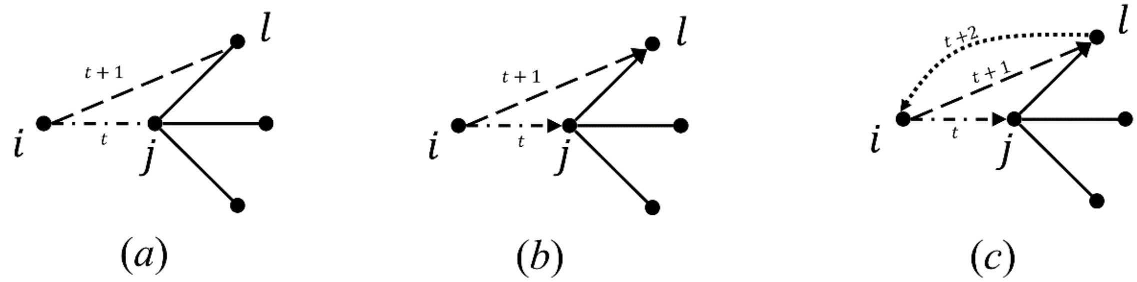

Figure 3. Boxplot of the centrality of degree for each type of node attribute

Table 7
Parameters of two in-degree logarithmic distributions on the simulation results

	Coefficients	Standard error	t Stat	P-value	Lower 95%	Upper 95%	Lower limit 95.0%	Upper limit 95.0%
Intercept	3.539	0.143	24.757	0.000	3.255	3.823	3.255	3.823
X Variable 1	-1.631	0.085	-19.226	0.000	-1.800	-1.463	-1.800	-1.463

Node Analysis

Centrality of Degree

In a social network, the in-degree of nodes can be used to express the centrality of degree. When the centrality of a node is higher, the node has more links and thus a larger impact. In the social network with two limitations and heterogeneous node attributes obtained by the simulation, the average centrality of degrees is not the same for nodes with different attributes.

Among five types of users, the average centrality value of degree for non-authenticated users and expert bloggers is relatively low. But a few users boast a higher centrality of degree with greater influence; the average centrality value of degree for authenticated individual users, authenticated institutional users, and female bloggers is higher. Among them, the centrality of degree for female bloggers is evenly distributed, which is noteworthy.

Centrality of Intermediary Agents

If a node is located at *n* shortcuts of all pairs of nodes, then the greater *n* is, the more important the position of the node in the network is. Centrality of intermediary agents can be used to characterize the nodes' degree of control over the information. In the social network with two limitations and heterogeneous node attributes obtained by the simulation, the average centrality of intermediary agents is not the same for nodes with different attributes.

Among five types of users, the average centrality value of intermediary agents for non-authenticated users and expert bloggers is relatively low. But a few users with higher centrality of intermediary agents have greater control over information dissemination; the average centrality value of intermediary agents for authenticated individual users, authenticated institutional users, and female bloggers is higher, and they have higher average ability to control information dissemination.

Hence, whether we conduct overall network analysis or node analysis, the results of our empirical analysis showed a regular pattern that fits Bass model very well, so they are persuasive enough to support the presence of social networks with two limitations and heterogeneous node attributes in emerging markets.

CONCLUSIONS AND IMPLICATIONS

Conclusions

The mode and effect of information dissemination in a social network are determined by the social network structure, and the structure of social networks is the basis for studying social networks. On the basis of previous studies, in this paper, we explore the micro-level behavioral characteristics of various nodes in a social network and the macro-evolution law of its formation. In addition, we conduct a simulation analysis based on multi-agent empirical analysis with Sina Weibo as our sample, using the Netlogo platform. We reached two conclusions.

1. Social networks have two limitations and heterogeneous characteristics: the limited size of the network, the limited number of in-degree and out-degree nodes, and the heterogeneous characteristics of the nodes.

2. Our social network model with two limitations and heterogeneity is better at simulating a real social network. From a macro-level perspective, the overall structure of this social network has both small-world and scale-free characteristics, but it cannot be replaced only by a small-world network or a scale-free network; from a micro-level perspective, it can better reflect the influence and control of nodes in the network with different characteristics.

Theoretical Contributions and Marketing Implications

In most theoretical studies on existing social networks, the number of network nodes and variances in the number of edges are basically the same in the default period (e.g., the increase in nodes per period is fixed); network nodes have the same behavioral characteristics, and as a result the network size tends to be infinite over time and the differences in network node characteristics is neglected. In this study, to make up for this deficiency, diffusion theory and the attention economy are introduced into the research on social network structure. As shown in both the theoretical analysis and empirical study, as the projection of real society into a virtual society, social networks also enjoy two limitations and heterogeneous node attributes in addition to small-world and scale-free characteristics, and nodes with all kinds of attributes have different positions in the network.

The two limitations and heterogeneous node attributes of social networks can provide a basis for developing marketing strategies in emerging markets:

1. The evolution of overall network size is subject to an S-shaped curve. Therefore, for enterprises with a social network platform, the strategic focus of the attraction and retention of users should differ based on the stage of network evolution. For example, when a social network is at the beginning of its development, companies should pay more attention to attracting new users.

At the mature stage, companies need to decrease their churn rate. More importantly, they need to retain high-value users.

2. In-/out-degree nodes are both limited. Therefore, social network nodes, whether individuals or institutions, should choose their objects of interest and topics in a smarter way, to avoid being obsessed with too much information. For example, social networks may need to allow users to form unidirectional connections as "followers," such as a company creating a fan page on Facebook, and users sign up as "fans." This would allow companies or brands to attract thousands of fans at the same time. Users who become followers of a company or brand may want to do so without granting the firm access to their profile.

3. Nodes have heterogeneous attributes. Hence, branding and customer relations management at enterprises can be managed effectively through their understanding of their own characteristics and their impact on other nodes, which means companies should identify their influential nodes in social networks. Known methods range from node centralities, such as degree, closeness, and betweenness, to diffusion-based processes, like PageRank and LeaderRank. Recently, a new local ranking algorithm named ClusterRank has been proposed, which takes into account not only the number of neighbors and their influence but also the clustering coefficient[16].

4. The operator of a social network platform can also expand the number of key nodes (e.g., female bloggers with both high centrality of degree and intermediate agents) to strengthen the effectiveness of information dissemination on the platform.

Limitations and Directions of Future Research

Based on social network structure, this research analyzes the influence and control of different types of attribute nodes in the network. However, the strength and weakness of the social relationship are not considered. It is strongly suggested that a weighted social network two limitations and heterogeneous node attributes should be built in the future.

The example used in this study is Sina Weibo, whose users are divided into five groups: non-authenticated users, authenticated individual users, authenticated institutional users, female bloggers, and expert bloggers. Other characteristics can be used to subdivide each of these groups—for instance, institutional users can be subdivided by industry, size and so on. In future studies, the characteristics of user behavior in subdivided classes and their influence and control in the social network structure will be further explored.

Social network structure is the research basis of information dissemination. In the future, on the basis of the existing social network with two limitations and heterogeneous node attributes, the influence of nodes with different attributes on information dissemination, and reaction of information dissemination to the social network structure will be analyzed. In addition, a model of interactive effects between social network structure and information dissemination will be built.

Author Declaration

This research is not funded by any organization related to tobacco production.

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