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RESEARCH ARTICLE

Valuing User Contribution on Virtual Brand Community

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Abstract: Companies are increasingly taking advantage of contributions of users' behavior on communities. Their contributions are then transformed into references as well as guidelines of user management. This paper categorizes the user contribution value into user-contributed content value evaluated by a weighted-knowledge super-network approach and a user interaction value evaluated by weighted social network analysis. The paper uses a data set that originated from the Xiaomi Forum and finds that users in the virtual brand community fall into four categories: valuable users, knowledgeable users, social users and regular users. Finally, this paper draws conclusions on how companies can increase user value through user classification management and user incentive measures.

Keywords: Social network, User contribution value, Virtual brand community, Weighted knowledge super-network.

1. INTRODUCTION

The rapidly developing global service economy is witnessing the transformation from a traditional seller's market to a contemporary buyer's market. In this phase, users increasingly require product innovation on structure, function, form, technology, *etc*. from the perspective of their personal demands. Empirical research conducted by Dahl suggests that customers prefer user-driven products to designer-driven ones in that user-driven products have enhanced social identification [1]. Customers' active participation in innovation of enterprises manifests mainly in two ways. The first was is *via* putting forward suggestions for improvement directly: users propose improvements for new functions of products according to their own user experiences or demands. Franke *et al*. (2003) found 23% of new product ideas from users based on their needs and desires can realize business value [2]. On the other hand, users, who are the link of information exchanges of product, can facilitate a greater influence of brand and product. Therefore, it is of vital significance to develop new platforms for user requirement expression, product identification, and experience sharing, *etc*.

In his study, Nambisan (2003) argued that on-line virtual communities can be used to reinforce consumers' brand recognition, spark consumers' interest in brands or products, get feedback from consumers, and ultimately flexibly apply online-offline marketing channels [3]. Such large international companies as Kaspersky, Apple, Meizu, and Li-Ning have constructed their own virtual brand communities to fully maximize the stimulation of users' enthusiasm and creativity. Along with the rapid development of the Internet, there is a trend of increasing virtual community netizens. While a user's participation increases knowledge stock and an active atmosphere, it also brings difficulty to community management operations. Therefore, how to manage and motivate users while maintaining user loyalty have become a hot spot and focus for academics and enterprises.

Existing research, however, focuses mainly on the three following perspectives. First, factors affecting brand loyalty of community members and motivation mechanism of improving user brand recognition [4 - 6]. Second, factors affecting improving virtual brand community participation of members and how to improve interactions of community

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members [7 - 9]. Third, virtual communities' user characteristics, association recognition research [10, 11], *etc*. Little research involves user contribution value, and most of the works focus on the qualitative perspective. This paper aims to fill this theoretical research gap.

Therefore, in order to categorize and study users in communities, especially those with notable knowledge and influence, this paper has conducted relatively comprehensive study on activities of users in communities. As discussed above, activities of user participation in communities are sharing (sharing knowledge by posting messages) and interactions (scanning or replying messages to boost spread of knowledge in communities). These two actions, which are main contributions of users to communities, are main sources of our decisions of user positions and portrait. Moreover, measuring user contribution values also uses these two actions.

After surveying the new literature of this field, this paper initially categorizes user contribution value into two categories: user-contributed content value and user interaction value. First and foremost, it uses a weighted knowledge super-network approach and a social network analysis method to value the user contribution. In addition, based on finding, several methods of classification and management for users in the virtual brand community are put forward. Not only does this research enrich the theories about user contribution value, but it also provides a way of user classification management in practice.

2. CORRELATIVE STUDY

This chapter primarily discusses the overseas and domestic research results from three aspects: social networks, knowledge super-networks, and the conceptual definition of virtual brand communities and user contribution value in virtual brand communities.

2.1. Social Networks

A social network is a kind of relationship system formed by the interaction of individuals in society. Social network analysis mainly analyzes the relationships in networks and explores the network structure and attributive characteristics including individual attributes and integrated attributes. Many scholars have conducted a great deal of work about structural attributes of social networks. Christian used degree centrality and the theory of structural holes to construct a knowledge network of software developer teams and found a potential bottle-neck in communication, network mediators and coordinator through this network [12]. Agnieszka *et al*. solved the existing problem of flows of formal and informal information through the process of complaint settlement, and proved that NQA engineers play an important role in technology advisory or even information dissemination [13]. Martinez *et al*. used social network analysis to describe the organization chart within a site and emphasized the impact of the inherent structure of the Web on the effectiveness of search results, which provides guidance for the web's creation and maintenance [14].

This article uses social network analysis to study the individual properties of the network and attempts to quantify and analyze the importance and significance of individuals by degree centrality, closeness centrality and betweenness centrality.

2.2. Knowledge Super-network

The proposal of the small-world network model [15] and the scale-free network model [16] offers us new insights into generative mechanism, propagation mechanism and robustness of networks, and set off an upsurge of studying complex networks. Researchers from different fields, including physics, economics, sociology and ecology, conducted in-depth studies of complex networks, in such fields as the social network [17 - 19], the knowledge network [20 - 22], the technical network [23 - 26], and the biological network [27 - 33], *etc*. In the study of large scale networks, however, there is no engineering solution to clarify the relationship among different networks in the face of a system intertwined by logistics networks, information networks and capital networks. Therefore, some scholars began using the concept of super-networks to study the complex networks consisting of large number and kind of nodes.

Nevertheless, presenting no internationally-recognized definition of the super-network exists. There are several views in the academic sphere: 1) a network that can be captured in a hypergraph is a super-network [34, 35]; 2) a node indicates the network and an edge (or arc) indicates combined actions and preferences in a given set, and a super-network is the only way to represent all the combined actions and preferences governed by special rules [36]. At present, related studies domestically and overseas mainly focus on changeable inequality, hypergraphs, and systematic science.

Based on systematic science, the study of super-networks has achieved strategic progresses in knowledge as well as in the organizational management field. Knowledge networks have been developed to provide settings for a cycle of knowledge, including knowledge production, knowledge distribution and knowledge recreation [37]. Seufert *et al.* stated that the knowledge network is a dynamic framework formed by a behavior subject and the interrelation of the behavior subject and the resources and system used by the subject in the relationship [38]. Subsequent scholars divided the knowledge network into three types on this basis: networks among different knowledge, members, or material carriers. Through linking the super-network and knowledge network, the scholar proposed the weighted knowledge network (WKN) and weighted knowledge super-network (WKSN) [39 - 41]. This paper uses the off-line knowledge super-network method to study the online virtual brand community on the research basis of collaboration super-network.

2.3. Conceptual Definition of the Virtual Brand Community

2.3.1. Virtual Community

Many scholars have produced a number of definitions of the virtual community. Rheingold was first defined the virtual community in 1993. He thought that the virtual community was fixed personal relationships formed by long-term active participation of community users in community discussion [42]. Since then, many other scholars have conducted corresponding studies and proposed various definitions. Through study of the representative concept [43 - 48], we found that common interests or objectives, internet media and virtual social attachments, or even love are the three forming essential factors of a virtual community.

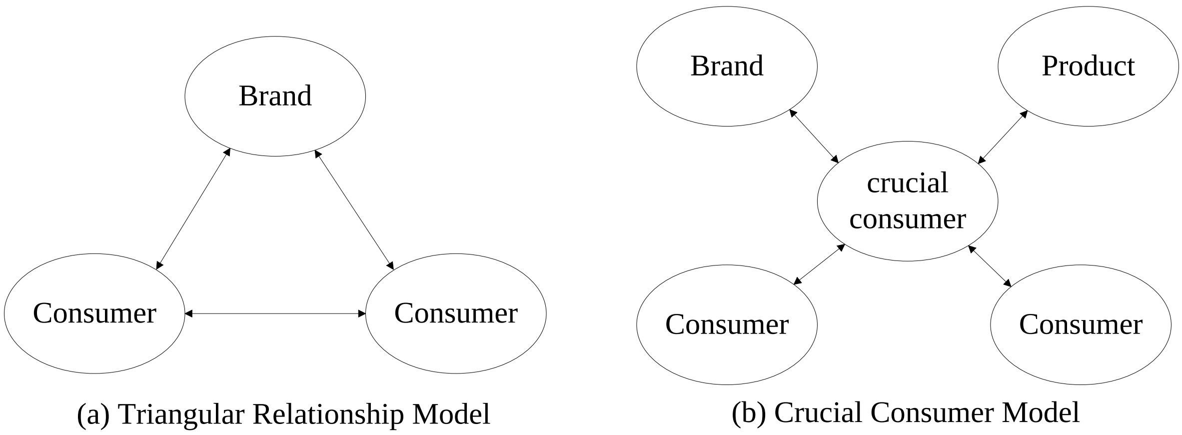

Fig. (1). Brand community model.

2.3.2. Brand Community

Muniz and O'Guinn have for the first time set comprehensive definitions on brand community: it is a specific, non-geopolitical community based on the complete social relationship between the consumers of the brand, and they put forward a triangular relationship model [49]. While McAlexander, Schouten and Koening think that the formation of the brand community was driven by consumers' common interests in same brand and given out a crucial consumer model [50]. Two representative brand community models are shown in Fig. (**1**).

2.3.3. Virtual Brand Community

Virtual brand community is a combination of the virtual community and brand community and has the following characteristics: 1) it is internet-based and not restricted by time and space; 2) it is professional; 3) it is purposefully established: enterprises desire to promote products or maintain their image, consumers desire to share product knowledge or user experiences, or third-parties desire to help consumers gain product information.

Many scholars have also conducted research about the virtual brand community. Kozinets holds that virtual brand community is a community where its members exchange their knowledge or experiences about brand/product on microblogs, BBS or forums [51]. From the macro-point of view, Liyin Jin defined an online community as one in which members communicate with each other taking the core of brand is virtual brand community [52]. In this paper, we selected Xiaomi Forum, a community set for expanding famous degree, understanding customers' needs and recognizing the innovation opportunities by Xiaomi Tech, as the object of our study.

2.4. User Contribution Value in Virtual Brand Community

The American marketing circle raised that user value is an enterprise's important competitive resource and a source of advantage in the future [53]. The effective management of user value should really be the basis of allocating resources effectively, and implementing personalized service for company [54]. The value contribution of each business user is premised by his/her ability to pay in the actual dealing process. Nonetheless, communities of users are different from traditional users; they are both buyers and information owners sharing related experiences in the community to form a new product feedback schema. Consequently, the measures of value of users based on purchasing power no longer apply.

The main motive of communities of users is to gather information, transfer knowledge, and social contacts, and acquire social recognition. Different incentives lead to different behaviors: post message, reply posts or browse the community information. These multiple behaviors form different kinds of participation types, which represent the contribution magnitude of each user in the community. Some representative accomplishments [55 - 66] of user participation types in the virtual brand community at home and abroad are presented in Table **1**.

Table 1. User participation types in the virtual brand community.

Documentary Source	User Participation Type
Armstrong (1997)	visitor/ lurker/contributor/buyer
Adler (1999)	passive person/active person /inductor/manager
Mao Bo (2006)	leader/ responder /visitor/ sharer/ learner
Gong Hui (2007)	elite/efficiency man/active person/ loner
Qiu Junping (2008)	elite/efficiency man/active person
Chen Haiqiang (2009)	key user/ edge user
Kristine (2009)	core member/ talker/ collector/ devotee/ functionalist/opportunist
Xue Ke (2010)	opinion leader/ focuser/ proliferator/ debater/ participant/ edge user
Toral (2010)	peripheral user/ full member/ community center
Xu Xiaolong (2010)	leader/responder/socializer/consultant/ spectator
He Li (2011)	key user/ domestic consumer
Zhao Wenbing (2011)	collector/internet denizen/professional user/type ME
Liu Wei (2012)	valued member/visitor/ sunk member
Song Enmei (2012)	Authoritative user/popular user
Gu Bin (2014)	consultant/key user/ edge user/ collector

For enterprises, users' requirements, product improvements and innovations posted by users constitutes user-contributed content value. The virtual brand community is a special kind of SNS network; not only do users gather information from the community, they also acquire social recognition by exchange experiences. Online interaction of users propagates indirect word of mouth exchanges, which constitute user interaction value. Based on the above-mentioned analysis, this paper tries to analyze the user value contribution based on two dimensions: user-contributed content value and user interaction value.

3. THE MODEL

Based on the above correlative researches, we find that the social network this paper emphasizes is one of the subsets in the knowledge super-network. Therefore, we first research the super-network and use it as a break through to evaluate user contribution.

3.1. Conceptual Model of the Knowledge Super-network in the Virtual Brand Community

In the virtual brand community, users' posts and replies constitute knowledge networks and social interaction relationships. There are two carriers preserving knowledge: community members (life carriers) and community sections or posts (material carriers). Life carriers convert tacit knowledge into explicit knowledge by posting as well as forming their social world by replying on the forum. Material carriers are the posts in different sections, including courses of study, information, chat. Posts, which are material carriers of knowledge, are different from off-line material carrier such as books carrying knowledge. All kinds of posts are classified into different sections according to each one's content of knowledge. Therefore, a super-network model is composed of a knowledge network, a user network, a post network, and a mapping relationship of different networks [67]. The model shown in Fig. (**2**).

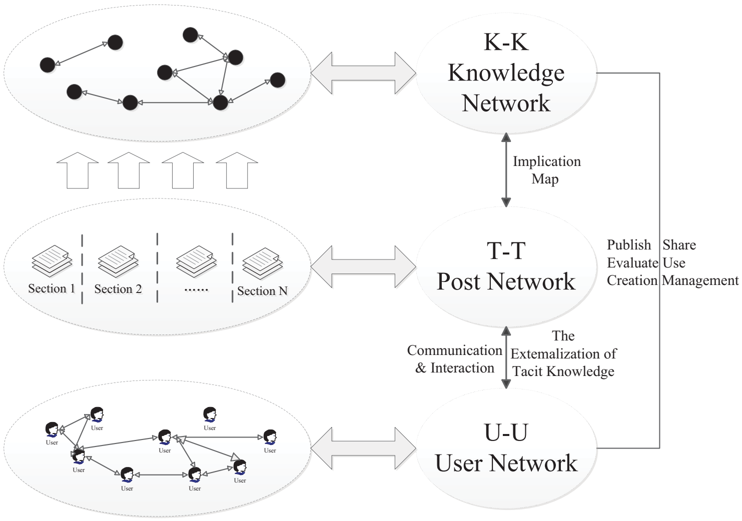

Fig. (2). Conceptual model of knowledge super-network in the virtual brand community.

3.2. Factor Analysis of the Model

3.2.1. Network Type

This paper studies the user value contribution in a community but does not involve storage and distribution of knowledge in material carriers. As a result, we only focus on two types of knowledge networks in this work:

(1) Knowledge network: Connections among all the knowledge. The model is G_k (K, E_{k-k}). Thereinto, K = {k_1, k_2,...k_n} denotes point sets of knowledge in the virtual brand community and $E = \{(k_i, k_j)|\theta(k_i, k_j) = 1\}$ denotes edge sets. Boolean variable θ (k_i, k_j) = 1 is introduced to represent the co-occurrence of knowledge i and knowledge j in a post.

(2) Member network: Connections among all the community members. The model is $G_p = (P, E_{p-p})$. There into, P = {p_1, p_2,..p_n} denotes members in virtual brand community and $E = \{(p_i, p_j)|\theta(k_i, k_j) = 1\}$ denotes edge sets. Boolean variable θ (k_i, k_j) = 1 is introduced to represent the interactive relationship between member i and member j in a post.

3.2.2. The Relationship Between the Knowledge Network and the Member Network

The relationship between the knowledge network and the member network can be represented as $E_{p-k} = \{(p_i, k_j)|\emptyset(p_i, k_j) = 1\}$. $\emptyset(p_i, k_j) = 1$ is introduced to represent that knowledge k_j is mastered by member p_i. There are two mapping relationships which could reflect the distribution of knowledge resources in a life carrier or the situation of grasping knowledge of members. The corresponding mapping relationships is as simple as follows:

1. Mapping from knowledge to member: $P_k^j = \{p_i|\emptyset(k_j, p_i) = 1, k_j \in K, p_i \in P\}$ denotes a set of members who has mastered knowledge k_j
2. Mapping from member to knowledge: $K_p^i = \{k_j|\emptyset(p_i, k_j) = 1, k_j \in K, p_i \in P\}$ denotes a set of personal knowledge of member p_i.

3.2.3. The Weight of Relationships in the Knowledge Network Model

Although the knowledge network, the member network and their relationships may help us to define the distribution of knowledge resources in a life carrier as well as find and locate the specific knowledge, they cannot measure the value of knowledge or of a user. However, a weighting process based upon frequency to various relationships is an absolutely fantastic solution to this quantification problem.

1. Connections of the knowledge network $(\mathrm{E_{k-k}})$: $\mathrm{W(E_{k-k}) = \{\, w(k_i, k_j) | \varepsilon(k_i, k_j) = 1\}}$ are introduced to represent the weight set of $E_{k\text{-}k}$, which marks the compactness degree of co-occurrence relationship of knowledge.
2. Connections of member networks (E_{p-p}): $\mathrm{W(E_{p-p}) = \{w(p_i, p_j) | \varepsilon(p_i, p_j) = 1\}}$ are introduced to represent the weight set of $E_{p\text{-}p}$, which marks the compactness degree of user interactive relationships.
3. Connections between knowledge and a member (E_{p-k}): $\mathrm{Q(E_{p-k}) = \{q(p_i, k_j) | \emptyset(p_i, k_j) = 1\}}$ are introduced to represent the weight set of ($E_{p\text{-}k}$) which marks the mastery degree of knowledge k_j by user p_i.
4. Knowledge stocks: Q(k) = {q(k_j)} are introduced to represent the weight set of knowledge storage q(k_j) denotes storage of knowledge k_j of all users.

3.3. WKSN-based User-Contributed Content Value Model and its Construction Method

3.3.1. Model

According to user-contributed content value in the virtual brand community, we can find and locate key users who grasp important or scarce knowledge, then scoop out the deeper customer need and encourage users to participate in product design, development and improvement to finally realize innovation. This means that our objective is finding important information and users who have mastered this information. This objective could be achieved through a WKSN-based user-contributed content value model, which takes users and knowledge as nodes and user interaction and co-occurrence of knowledge as the relationship between nodes, as shown here:

$$\mathrm{CVM}_{WKSN} = \left(\mathrm{K}, \mathrm{P}, E_{k-k}, E_{p-p}, E_{p-k}, \mathrm{Q}(k_j), W(E_{k-k}), Q(E_{p-k})\right)$$

3.3.2. Construction Method

The construction method is shown below:

1. Obtain point sets of users and knowledge
   This paper applies data mining technology in data collection to obtain user information and knowledge content. All users constitute the point set of users. Point sets of knowledge are obtained by text mining whose core technologies are preprocessing, segmentation and extracting feature words [68], and combined with ontology and domain knowledge dictionary, *etc*.
2. Determine the relationship set
   User relationship set ($E_{k\text{-}k}$): the interactive relationship (post or reply) between members in a post is the edge of the user network.
   Knowledge relationship set ($E_{p\text{-}p}$): the co-occurrence relationship between knowledges in a post is the edge of the knowledge network. Set of relationship between knowledge and user ($E_{p\text{-}k}$): the connection between knowledge extracted from posts and users publishing this post is the edge of the network.
3. Calculate the weight set of knowledge stock of all users
   We apply the frequency of knowledge in all users' knowledge set as Knowledge stocks and constitutes the weight sets of knowledge stock of all users.
4. Calculate weight set: $W(E_{k\text{-}k})$, $Q(E_{p\text{-}k})$
   $W(E_{k\text{-}k})$ represents the concurrent times of knowledge in different posts. The more times, the bigger knowledge relevance and higher the weight. $Q(E_{p\text{-}k})$ is measured by the absolute value of frequency of knowledge in all posts by each user.
5. Build the model

Based on the above computation and combined with research findings, we can construct the WKSN-based user-contributed content value model.

3.4. WSNA-based User Interaction Value Model and its Construction Method

3.4.1. Model

People who registered an account are members in the virtual brand community, and those members' interactions (post or reply) form weakly tied social networks. Some prominent users are likely to hold the positions of structural hole and foster and support the free flow of useful information. However, potential negative effects generated by them should not be underestimated. For the perspective of enterprises, managers need to grasp user relationship information to find users in the positions of the structural hole and lead them to spread beneficial information. Moreover, this objective could be achieved through a Weighted Social Network Analysis-based user interaction value model, which takes users as nodes and user interactions in same post as the relationship between nodes, as shown here:

$$IVM_{WSNA} = (P, E_{p-p}, W(\mathrm{E_{p-p}}))$$

3.4.2. Construction Method

The construction method is shown below:

1. Get point set of users
   All users constitute the point set of users.
2. Determine the user relationship set: $E_{p\text{-}p}$
   Interactive relationship (post or reply) between members in a post is the edge of network.
3. Calculate weight set: $W\,(\mathrm{E_{p\text{-}p}})$
4. Build the model
   Based on the above computation and Combined with research findings, we can construct WSNA-based user interaction value model.

4. DATA AND RESULTS

4.1. Data Processing

The research object of this paper was the most influence and representative community in China, Xiaomi Forum-in China, which owned by Xiaomi Tech. Until December 22, 2014, about 224,968,490 posts had been published in 30 different sections and 31,122,980 people had registered in the Xiaomi Forum.

We collected 5641 posts published from October 19, 2013 to August 25, 2014 in the Play&Tutorial category of Redmi by LocoySpider. There are 866 posts available to study after empty, repetitive or non-returned posts and posts with views below 400 are removed. Knowledge is able to be reflected by keywords in posts, so we extracted keywords from posts by the NLPIR Chinese auto-segmentation system and obtained 925 keywords with a total word frequency of 22344. In valid posts, the number of people that participated in an interaction (post or reply) is 9230, of which 628 have published a post. Afterwards, we clarified the co-occurrence relationship among keywords-*i.e.*, knowledge, interaction relationships among users and mapping relationship between keywords and users.

4.2. Evaluation of User-Contributed Content Value Based on WKSN

Pajek is a basic tool for network study in this paper. It can process the extremely complicated network through rapid analysis and simulation, and provide a visual interface to help users to understand the data characteristics more directly and accurately.

4.2.1. User-Contributed Content Value Model

First and foremost, we analyze the weighted knowledge network, which takes knowledge as nodes and co-occurrence of knowledge as edges to find core knowledge. As shown in Fig. (**3**).

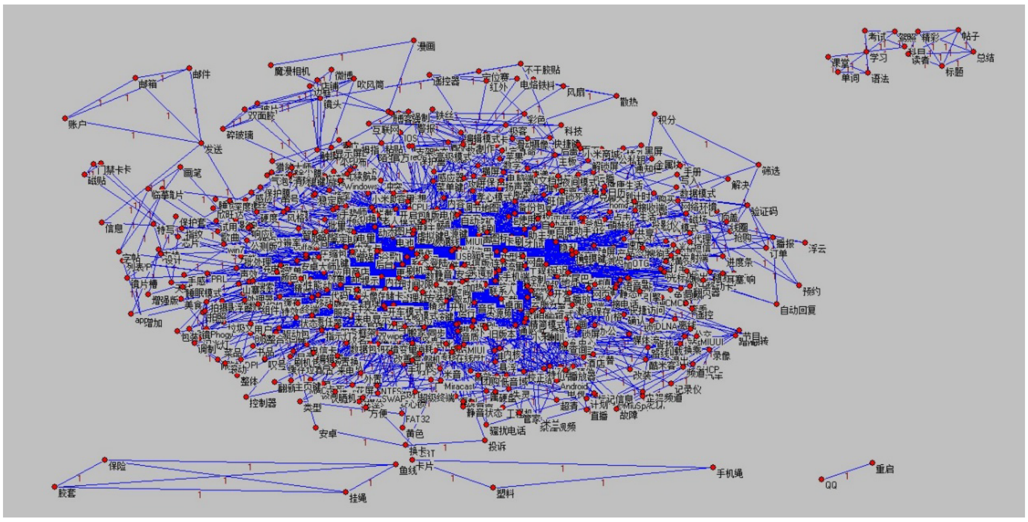

Fig. (3). Weighted knowledge network in virtual brand community.

Degree Centrality				Closeness Centrality				Betweenness Centrality			
Rank	Vertex	Cluster	Id	Rank	Vertex	Cluster	Id	Rank	Vertex	Cluster	Id
1	7	133	root	1	7	0.3557	root	1	7	0.0829	root
2	3	107	软件(software)	2	3	0.3461	软件(software)	2	3	0.0621	软件(software)
3	6	93	系统(system)	3	12	0.3321	设置(setting)	3	12	0.0494	设置(setting)
4	12	85	设置(setting)	4	6	0.3230	系统(system)	4	52	0.0457	屏幕(screen)
5	26	72	功能(function)	5	26	0.3228	功能(function)	5	26	0.0339	功能(function)
6	52	64	屏幕(screen)	6	60	0.3146	模式(mode)	6	6	0.0337	系统(system)
7	102	62	WiFi	7	52	0.3127	屏幕(screen)	7	102	0.0305	WiFi
8	14	60	内存(memory)	8	19	0.3100	应用(application)	8	70	0.0239	电池(battery)
9	19	60	应用(application)	9	102	0.3073	WiFi	9	19	0.0234	应用(application)
10	82	49	修改(modification)	10	15	0.3066	程序(procedure)	10	35	0.0222	移动(moble)
11	34	49	recover	11	162	0.3024	数据(data)	11	106	0.0162	文件(document)
12	106	48	文件(document)	12	55	0.3022	流量(flow)	12	82	0.0158	修改(modification)
13	60	47	模式(mode)	13	14	0.3018	内存(memory)	13	14	0.0148	内存(memory)
14	146	47	存储(storage)	14	33	0.3002	连接(connection)	14	33	0.0126	连接(connection)
15	35	46	移动(mobile)	15	82	0.3001	修改(modification)	15	60	0.0124	模式(mode)
16	72	44	驱动(dirver)	16	146	0.3001	存储(storage)	16	162	0.0123	数据(data)
17	70	44	电池(battery)	17	35	0.2999	移动(mobile)	17	61	0.0119	声音(voice)
18	33	44	连接(connection)	18	34	0.2989	recover	18	96	0.0113	效果(effect)
19	1	42	安装(install)	19	70	0.2985	电池(battery)	19	72	0,0111	驱动(dirver)
20	178	41	刷机(rom)	20	13	0.2975	SD 卡(SD card)	20	242	0,0110	输入(input)
				Sum: (all value)		149.0804		Sum: (all values)		1.0771	

Fig (4). Centrality analysis of weighted keyword network.

Rank	Vertex	Value	Id
1	369	848.0000	root
2	366	484.0000	软件(software)
3	370	436.0000	设置(setting)
4	368	325.0000	系统(system)
5	380	276.0000	WiFi
6	376	261.0000	屏幕(screen)
7	375	249.0000	recovery
8	373	233.0000	应用(application)
9	377	212.0000	模式(mode)
10	374	205.0000	功能(function)
11	381	194.0000	文件(document)
12	371	194.0000	内存(memory)
13	384	184.0000	音量(volume)
14	383	161.0000	刷机(rom)
15	378	157.0000	驱动(dirver)
16	379	148.0000	修改(modification)
17	365	147.0000	安装(install)
18	382	145.0000	存储(storage)
19	367	126.0000	更新(update)
20	372	109.0000	程序(procedure)
Sum(all values):		5094.0000	

Fig. (5). Core keyword frequency statistic.

It is clearly observed that most instances of knowledge are connected together, while a small percentage of keywords, such as words and licenses, are independent of integrity. We can find in a preliminary estimate the core knowledge or focus area of users. Furthermore, we adopt a centrality index [69, 70] to measure the "power" of keywords in the network in order to analyze the current status and characteristics of users' knowledge deeply. Operation results are shown in Fig. (**4**).

Based on the Pareto Principle, this paper sort keywords according to three centrality indices and counts the word frequency of top-ranking keywords. Finally, determining top 20 keywords to a total word frequency of 5094 as core knowledge. The results are shown in Fig. (**5**).

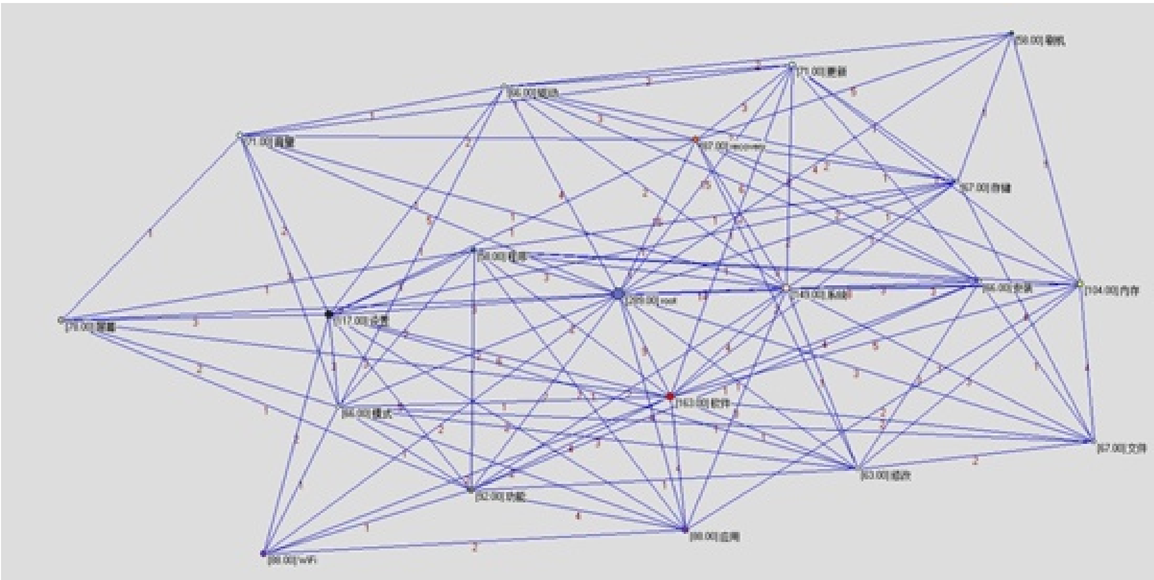

Fig. (6). Weighted core keyword network.

Besides, draw weighted top-keywords network which takes top 20 keywords as nodes, co-occurrence of knowledge as edges and co-occurrence frequency as edge weight. As shown in Fig. (**6**), we can see the compactness degree of relationship among keywords.

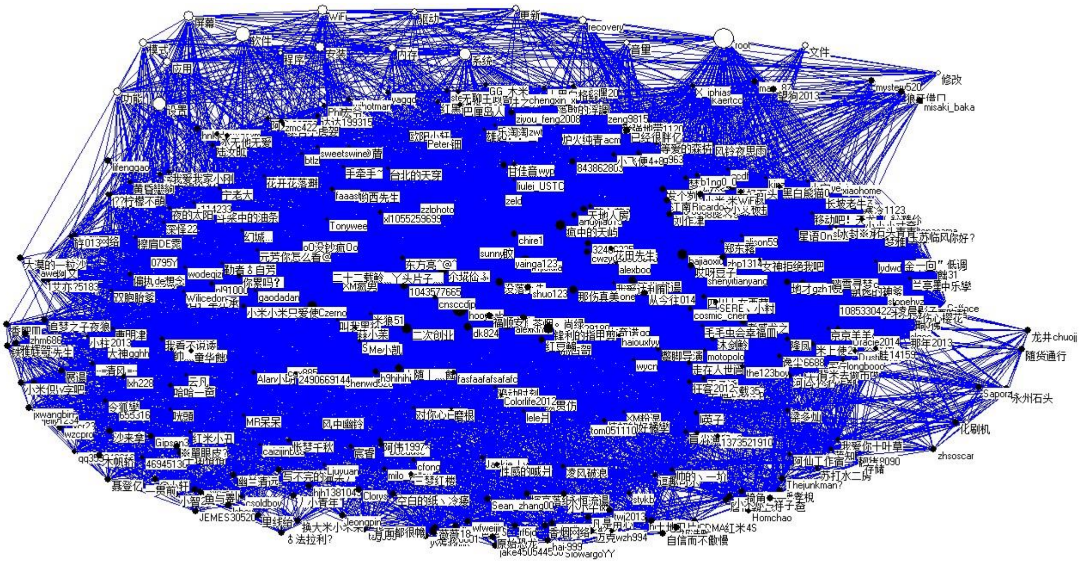

Fig. (7). WKSN-based user-contributed content value model.

Last but not least, based on above-mentioned analysis and construction method of the user-contributed content value model, we can draw a weighted knowledge super-network which is mainly composed of the top 20 keywords network and corresponding user network. Specifically, empty circles represent keywords, filled circles represent users, edges represent interaction relationships, co-occurrence relationships, or mapping relationships, as shown in Fig. (**7**).

Rank	Vertex	Value	Id
1	33	868.0000	hooyeah
2	29	409.0000	二次创业(ErCiChuangYe)
3	78	339.0000	caizijinbao
4	112	310.0000	哟西先生(YouXiXianSheng)
5	11	289.0000	dk824
6	15	281.0000	XM 疯男(XM FengNan)
7	14	263.0000	佘埖伭ふ(XiaoHuaXian)
8	32	262.0000	小米小米只爱使(XiaoMiXiaoMiZhiAiShi)
9	16	251.0000	alexkinds
10	56	243.0000	叫我黑猪(JiaoWoHeiZhu)
624	550	1.0000	qq597533129
625	613	1.0000	bobdcy
626	529	1.0000	芙蓉(FuRong)
627	628	1.0000	米粉丽人(MiFenLiRen)
628	534	1.0000	断了的线 520(DuanLeDeXian 520)
Sum(all values)		5094.0000	

Fig (8). Evaluation results of user-contributed content value.

4.2.2. Evaluation of User-contributed Content Value

As you can see from Fig. (**7**), the model is able to reflect the distribution and stock of each instance of knowledge in the community, and it also can reflect the knowledge mastery condition of each user.

This paper applies the numerical magnitude of core knowledge storage to evaluate the user-contributed content value. A higher value number corresponds with a greater contribution of the user. As a consequence, the operational result of user-contributed content value by Pajek is shown in Fig. (**8**).

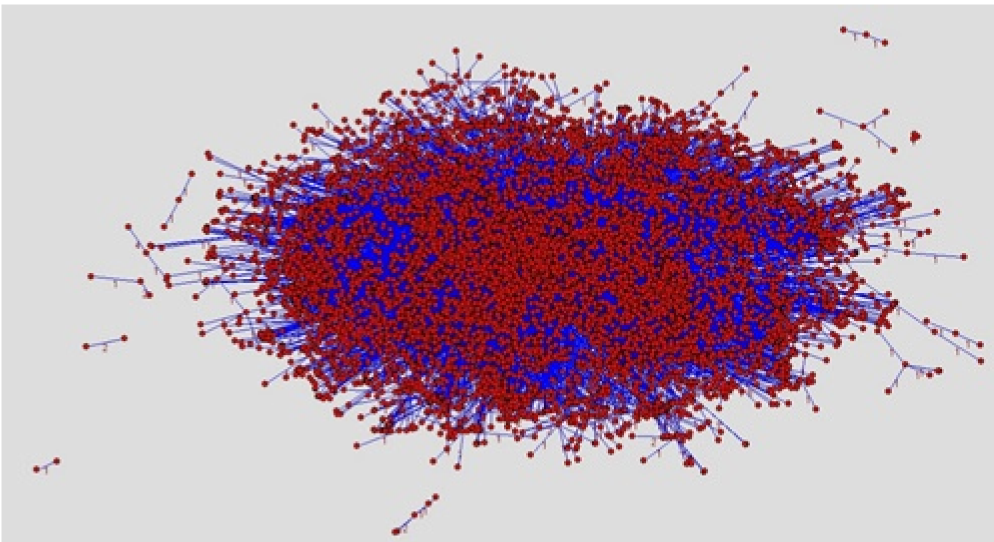

Fig. (9). Weighted user network of WSNA-based user interaction value model.

According to the operational results, hooyeah is the largest contributor to community knowledge and far exceeds other users. ErCiChuangYe ranked 2nd with 409 points. Although MiFenLiRen as well as other users have taken part in community interactions, their contribution value is low.

4.3. Evaluation of User Interaction Value Based on WSNA

4.3.1. User Interaction Value Model

We can draw the weighted user network, which takes 9230 users as nodes, interaction relationships as edges and number of interactions in posts as weight of edges by Pajek. The results are shown in Fig. (**9**).

Cluster	Frep	Frep%	CumFrep	CumFrep%	Representation
1	7319	79.2958	7319	79.2958	疯狂火吻(FengKuangHuoWen)
2	819	8.8732	8138	88.1690	cjw-elsa
3	275	2.9794	8413	91.1484	南方的雪(NanFangDeXue)
4	135	1.4626	8548	92.6111	燃烧的努势(RanShaoDeNuShi)
5	90	0.9751	8636	93.5861	hyou 大摩昭(hyouDaMoZhao)
113	1	0.0108	9217	99.8592	疯中的天屿(FengZhongDeTianYu)
115	2	0.0217	9219	99.8808	Alan 小明(AlanXiaoMing)
118	1	0.0108	9220	99.8917	XM 疯男(XM FengNan)
150	1	0.0108	9221	99.9025	小米小米只爱天使(XiaoMiXiaoMiZhiAiShi)
157	1	0.0108	9222	99.9133	caizijinbao
160	1	0.0108	9223	99.9242	叫我黑猪(JiaoWoHeiZhu)
167	1	0.0108	9224	99.9350	。0 没钞疯 0。(。0MeiChaoFeng0。)
183	1	0.0108	9225	99.9458	dk824
194	1	0.0108	9226	99.9567	Czerno
198	1	0.0108	9227	99.9675	二次创业(ErCiChuangYe)
199	1	0.0108	9228	99.9783	1043577665
200	1	0.0108	9229	99.9892	alexkinds
496	1	0.0108	9230	100.0000	hoyeah
Sum	9230	100.0000			

Rank	Vertex	Cluster	Id
1	729	496	hooyeah
2	389	200	alexkinds
3	91	199	1043577665
4	370	198	二次创业(ErCiChuangYe)
5	25	194	Czerno
6	67	183	dk824
7	141	167	。0 没钞疯 0。(。0MeiChaoFeng0。)
8	1220	160	叫我黑猪(JiaoWoHeiZhu)
9	1703	157	caizijinbao
10	385	150	小米小米只爱天使(XiaoMiXiaoMiZhiAiShi)
11	365	118	XM 疯男(XMFengNan)
12	45	115	Alan 小明(AlanXiaoMing)
13	715	115	Tonywee
14	137	113	疯中的天屿(FengZhongDeTianYu)
15	351	107	余垅佡ふ(XiaoHuaXian)
16	246	105	浮生如茶-游(FuShengRuCha-You)
17	391	101	Zzlphoto
18	381	99	你累吗？(NiLeiMa?)
19	656	97	甘州骠骑(GanZhouPiaoJi)
20	1136	95	勤者♁自劳(QinZheZiLao)

Fig. (10). Calculational results of degree centrality.

4.3.2. Measurement Index and its Calculation

User interaction network is based on weak ties in the virtual brand community. Moreover, the research objective here is to find influential and prestigious user in community. Therefore, we can use social network analysis technology to evaluate user interaction value.

A centrality index [71] of social network analysis technology is a useful tool for researcher to find core members in a group. It mainly contains three indices: degree centrality, closeness centrality, betweenness centrality.

Cluster	Frep	Frep%	CumFrep	CumFrep%	Representation
1	7401	80.1755	7401	80.1755	疯狂火吻(FengKuangHuoWen)
2	1299	14.0721	8700	94.2476	Sweetswine
3	242	2.6216	8942	96.8692	8.88889E+05
4	144	1.5600	9086	98.4292	yuzf0001
5	47	0.5092	9133	98.9384	春天的雨妫(ChunTianDeYuZhou)
42	1	0.0108	9223	99.9133	二次创业(ErCiChuangYe)
43	1	0.0108	9224	99.9242	Czerno
45	2	0.0217	9226	99.9458	alexkinds
47	1	0.0108	9227	99.9567	1043577665
54	1	0.0108	9228	99.9675	。0 没钞疯 0。(。0MeiChaoFeng0。)
67	1	0.0108	9230	99.9892	gd5320
100	1	0.0108	9231	100.0000	hooyeah
Sum	9230	100.0000			

Rank	Vertex	Value	Id
1	729	0.1574	hooyeah
2	132	0.1061	gd5320
3	141	0.0894	。0 没钞疯 0。(。0MeiChaoFeng0。)
4	1220	0.0718	叫我黑猪(JiaoWoHeiZhu)
5	91	0.0690	1043577665
6	389	0.0674	Alexkinds
7	25	0.0635	Czerno
8	65	0.0624	?
9	370	0.0621	二次创业(ErCiChuangYe)
10	67	0.0588	dk824
11	365	0.0541	XM 疯男(XM FengNan)
12	137	0.0472	疯中的天屿(FengZhongDeTianYu)
13	385	0.0430	小米小米只爱天使(XiaoMiXiaoMiZhiAiShi)
14	24	0.0406	煙鬼(YanGui)
15	381	0.0384	你累吗？(NiLeiMa?)
16	45	0.0380	Alan 小明(Alan XiaoMing)
17	416	0.0376	红豆鳊(HongDouBian)
18	715	0.0370	Tonywee
19	351	0.0359	余垅佡ふ(XiaoHuaXian)
20	1703	0.0331	caizijinbao

Fig. (11). Calculational results of betweenness centrality.

1. Degree Centrality

Degree centrality measures the number of nodes connected to a member. The larger the number is, the more active the member is. The active members have more influence than other less active members. From the operation results Fig. (**10**), there are great differences among nodes, with hooyeah having the largest degree centrality, which means his position is of vital significance.

Cluster	Frep	Frep%	CumFrep	CumFrep%	Representation
1	22	0.2383	22	0.2383	罗永灿(LuoYongCan)
2	118	1.2783	140	1.5166	Sybff
35	1	0.0108	141	1.5275	lucha8025
36	11	0.1192	152	1.6466	渐渐 205(JianJian 205)
39	5	0.0542	157	1.7008	冰封爱恋待红飘(BinFengAiLianDaiHongFan)
40	6	0.0650	163	1.7658	沐剑鲐(MuJianLing)
41	19	0.2058	182	1.9716	lucksmallfish
42	12	0.1300	194	2.1016	疯狂火吻(FengKuangHuoWen)
92	4	0.0433	9212	99.7942	Alan 小明(Alan XiaoMing)
94	7	0.0758	9219	99.87	煙鬼(YanGui)
95	2	0.0217	9221	99.8917	Czerno
96	3	0.0325	9224	99.9242	疯中的天屿(FengZhongDeTianYu)
98	2	0.0217	9226	99.9458	dk824
99	1	0.0108	9227	99.9567	二次创业(ErCiChuangYe)
100	4	0.0433	9231	100.0000	。0 没钞疯 0。(。0MeiChaoFeng0。)
Sum	9230	100.0000			

Rank	Vertex	Value	Id
1	1220	0.3211	叫我黑猪(JiaoWoHeiZhu)
2	729	0.3208	hooyeah
3	141	0.3182	。0 没钞疯 0。(。0MeiChaoFeng0。)
4	365	0.3133	XM 疯男(XM FengNan)
5	67	0.3130	dk824
6	370	0.3087	二次创业(ErCiChuangYe)
7	137	0.3078	疯中的天屿(FengZhongDeTianYu)
8	91	0.3072	1043577665
9	381	0.3071	你累吗？(NiLeiMa?)
10	389	0.3061	alexkinds
11	631	0.3010	芙蓉(FuRong)
12	25	0.3005	Czerno
13	863	0.3002	哟西先生(YouXiXianSheng)
14	24	0.2999	煙鬼(YanGui)
15	416	0.2956	红豆鳊(HongDouBian)
16	715	0.2947	Tonywee
17	351	0.2947	佘堀佡ふ(XiaoHuaXian)
18	1173	0.2936	薇薇 18(WeiWei18)
19	385	0.2935	小米小米只爱使(XiaoMiXiaoMiZhiAiShi)
20	1136	0.2926	勤者≦自劳(QinZheZiLao)

Fig. (12). Calculational results of closeness centrality.

2. Closeness Centrality

Closeness centrality quantifies the number of times a user acts as a bridge as the shortest path between two other users. It was introduced to describe the control of users on community of others. The higher probability the position is, the greater the betweenness is. From the operational result Fig. (**11**), Hooyeah plays a much more important intermediating role in the community than others, and others' interactions appear dependent on him.

3. Betweenness Centrality

Betweenness centrality is defined as the reciprocal of the farness of a node, which is the sum of its distances from all other nodes. The more central a node is, the lower its total distance from all other nodes is. A central user has a greater ability to disseminate information. From the operational results Fig. (**12**), user JiaoWoHeiZhu as well as other users positioned themselves at central positions and have a much more significant effect than others.

4.3.3. Evaluation of User Interaction Value

User interaction value denotes the users' 'power' in the social network, characterized by the influence, control force and dissemination capacity. We think users contribute to the online word of mouth exchanges when and only when his/her three indices are high. According to generated result of user centricity, we sorted the users in the community and the results are shown in Table **2**.

From Table **2**, we find that hooyeah, Jiao WoHei Zhu and ErCi Chuang Ye and other users occupy an important role in the social network's structure because their degree centrality, closeness centrality and betweenness centrality are at the top of the corresponding list.

Table 2. Centricity sequence in WSNA-based user interaction value model.

User name	Degree Centrality	User name	Betweenness Centrality	User name	Closeness Centrality
Hooyeah	0.0728	hooyeah	0.1574	叫我黑猪(JiaoWoHeiZhu)	0.3211
Alekinds	0.0393	gd5320	0.1061	hooyeah	0.3208
二次创业(ErCiChuangYe)	0.0326	oO 没钞疯 Oo(oOMeiChaoFengOo)	0.0894	oO 没钞疯 Oo(oOMeiChaoFengOo)	0.3182
1043577665	0.0289	叫我黑猪(JiaoWoHeiZhu)	0.0718	XM 疯男(XM FengNan)	0.3133
Czerno	0.0278	1043577665	0.0690	dk824	0.3130
oO 没钞疯 Oo(oOMeiChaoFengOo)	0.0263	alekinds	0.0674	二次创业(ErCiChuangYe)	0.3087
dk824	0.0262	Czerno	0.0635	疯中的天屿(FengZhongDeTianYu)	0.3078
XM 疯男(XM FengNan)	0.0261	二次创业(ErCiChuangYe)	0.0621	1043577665	0.3072
叫我黑猪(JiaoWoHeiZhu)	0.0228	dk824	0.0588	你累吗？(NiLeiMa?)	0.3071
小米小米只爱使 (XiaoMiXiaoMiZhiAiShi)	0.0223	XM 疯男(XM FengNan)	0.0541	alekinds	0.3061
...	...	...	…	…	…
米果酿(MiGuoLiang)	0.0001	米粉丽人(MiFenLiRen)	0.0000	岩琪(YanQi)	0.0002
lmy8026	0.0001	Sweetswine	0.0000	疯狂火吻(FengKuangHuoWen)	0.0002
我是奶粑(WoShiNaiBa)	0.0001	疯狂火吻(FengKuangHuoWen)	0.0000	罗永灿(LuoYongCan)	0.0002

5. USER CLASSIFICATION MANAGEMENT

5.1. User Classification

5.1.1. Classification Indicators

Based on the above analysis of user value contribution in the virtual brand community, users can be sorted by user-contributed content value and user interaction value and the corresponding evaluation indices as follows:

(1) Evaluation index of user-contributed content value.

In this paper, user-contributed contents are simplified and measured by keywords of posts and user-contributed content value was evaluated by core knowledge storage of users.

(2) Evaluation index of user interaction value.

This paper chooses degree centrality, closeness centrality and betweenness centrality as the evaluation index of user interaction value.

5.1.2. Classification Results

In this paper, users are grouped through correlation cluster analysis based on two evaluation indices of user-contribute value, and are classified into four relatively independent categories. The method we adopt is k-Means proposed by McQueen in 1967. This method clusters items into k clusters based on the distance the items are from the centroid of the previous iteration. Specifically, each user is uniquely identified with a username and four variables (user-contributed content value, degree centrality, closeness centrality and betweenness centrality) are used in user classification by using the Q-type cluster. The results of the clustering analysis are shown in Tables **3-6**:

Table 3. Initial clustering center.

	Cluster			
	1	2	3	4
Degree Centrality	.0728	.0326	.0229	.0001
Closeness Centrality	.3211	.3153	.3214	.0002
Betweenness Centrality	.1626	.0582	.0636	.0000

(Table 3) contd.....

	Cluster			
	1	2	3	4
User-Contributed Content Value	806.00	409.00	243.00	.0000

Table 4. Final clustering center.

	Cluster			
	1	2	3	4
Degree Centrality	.0728	.0238	.0050	.0003
Closeness Centrality	.3211	.3068	.2324	.1989
Betweenness Centrality	.1626	.0551	.0069	.0002
User-Contributed Content Value	806.00	269.69	62.29	.71

Table 5. The distance between the final clustering center.

Cluster	1	2	3	4
1		536.308	743.711	805.291
2	536.308		207.403	268.983
3	743.711	207.403		61.580
4	805.291	268.983	61.580	

Table 6. The final case number in each cluster.

Cluster	1	1.000
	2	13.000
	3	114.000
	4	9102.000
Valid		9230.000
Default		.000

With the results of clustering, users in the community can be divided into four categories (Table **7**):

Table 7. User segmentation.

Categories	Members
1	hooyeah
2	Czerno, Alan XiaoMing, dk824, 1043577665, oOMeiChaoFengOo, XiaoHuaXian, XM FengNan, ErCiChuangYe, XiaoMiXiaoMiZhiAiShi, alexkind, YouXiXianSheng, JiaoWoHeiZhu, caizijinbao
3	YanGuang, HuangKaiHuaLuoPan, MR DaiDai, Sawalice, _ChaYan ShangLv, FengZhongDeTianYu, lwjieiuia, hnkjdxswgcxm, YuYuChong, yuzf0001, ZhuoDaYuan *et al.*
4	FengKuangHuoWen, sweetswine, XDH KaiFen, WoXingCong I, RenTiJiRou, cwj-elsa, PoJinYi, WoSiFengSiChou, 8.88889E+13, WeiXiaoMiJiaYou!, neB520, richardqiang, MengShanFengJing *et al.*

From the ANOVA Table **8**, it can be seen that the four variables have significant positive correlation with user classification. This illustrates the rationality of the evaluation index and the feasibility of the Q-type cluster.

Table 8. ANOVA table.

	Cluster		Error		F	Sig.
	Mean Square	df	Mean Square	df		
Degree Centrality	.005	3	.000	9227	6126.041	.000
Closeness Centrality	.097	3	.001	9227	67.525	.000
Betweenness Centrality	.023	3	.000	9227	4930.418	.000
User-Contributed Content Value	669160.313	3	27.926	9227	23961.549	.000

5.1.3. Results Analysis

User-contributed content value and user interaction value can be used to construct the user classification matrix which is shown as Fig. (**13**).

Valuable users: while the proportion of these users is lowest, they add the most benefit to the virtual brand community. They are willing to contribute their own knowledge and actively participate in community interaction. Therefore, valuable users deserve serious attention from enterprises.

Knowledgeable users: these users have and love to share rich user experience and unique insight of products. Nevertheless, they have weaker connections with others in the community. Albeit the number of these users is relatively small, they are professional. As a consequence, knowledgeable users are important messengers of users' needs for community managers.

Social users: these users take an active part in community interaction with great influence, in spite of the fact that their knowledge contribution is relatively low. As a result, social users play an important role in marketing and information propagation.

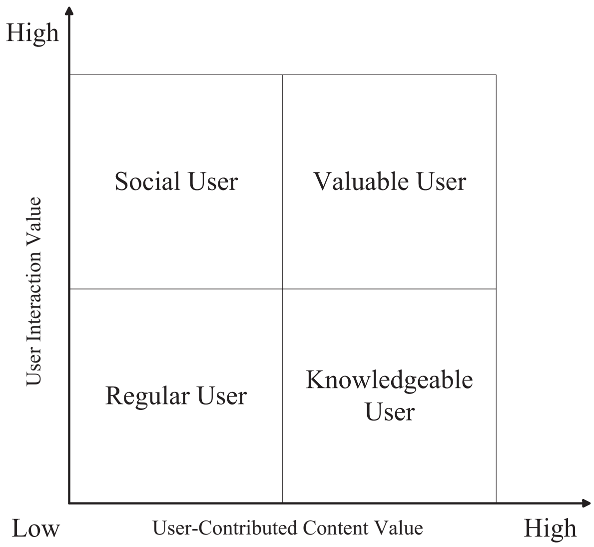

Fig. (13). User classification matrix in the virtual brand community.

Regular users: most of the users in the virtual brand community are regular users. They rarely interact with others and share experiences but depend on the community to a certain degree for useful information. Enterprises should take actions to tie-in users because they are on the edges of the community.

5.2. Management Policy Based on User Classification Results

5.2.1. Valuable User

The objective of valuable user management is maintaining a stable relationship between enterprise and users. Enterprises can formulate management strategies from two perspectives: on one hand, giving a material and spiritual reward. Materially, utilizing community manager even enterprise staff when he/she makes a specific contribution or give him/her a special purchase funnel with a certain discount. Mentally, making user's contribution clearly by user rank. On the other hand, developing a one-on-one or even management strategy to find core knowledge and creative point shared by valuable users so that enterprise can better satisfy the demands of consumers and improve the product competition in the markets.

5.2.2. Knowledgeable User

The objective of knowledge user management is encouraging users to further share their tacit knowledge and propose innovation spots for innovation. We can find that knowledgeable users are mainly concentrated in general groups which is more professional in the community. All members hoping to enter the group must pass the audit of community manager. As a consequence, in order to un-upgraded users, community manager should evaluate user contributions regularly and update users' groups timely without application and audit to give them the approval of the society and enhance their enthusiasm. To upgraded users, community managers should assure the safety of users' personal information and improve material incentives.

5.2.3. Social User

The objective of social user management is giving full play to their prestige and power in interaction networks. Community managers can formulate management strategies from three directions. To begin with, allowing social users to organize promotion activities online or offline to improve their influence and self-gratification. In addition, giving them certain financial incentives including price concessions and strengthening their participation consciousness according to their activity significantly in the community. Finally, guiding these users to study product knowledge and functions in corresponding sections of their own initiative. Keeping social users' sustaining influence through interacting with others with the view of specialization.

5.2.4. Regular User

Regular users are the principal composition of the virtual brand community. They expect professional knowledge in the community, privilege of purchase and so on and so forth. The objective of regular user management is preventing user loss and facilitating translating user to valuable users, knowledgeable users or social users. The community should create a fair, friendly, advanced and reliable atmosphere to improve the community identity of users. In addition, optimizing community capabilities and adding something of interest to increase users' desire of participation.

CONCLUSION AND DISCUSSION

This paper analyzes the user contribution value and comes to four conclusions. Based on former academic studies on virtual communities, virtual brand communities, weighted knowledge super-network, and user contribution value, it proposes that there is user contribution value from the virtual brand community and comprehensively evaluates it from two perspectives.

1. Divide the user contribution value into user-contributed content value and user interaction value. In virtual brand communities, by publishing posts, users show their recessive knowledge, share experience related to brands, propose demands for products, which contribute content values for enterprises. Users' interaction also happen by replying and scanning activities in virtual brand communities indirectly help enterprises to conduct brand marketing and spread public praise, which gives value to user interaction relationships.
2. Use the weighted knowledge super-network approach and social network analysis method to first value the user contribution. Through weighted knowledge super-network, according to focuses and grasp pf core keywords of virtual brand community user, we can calculate volume of core knowledge of users. User interaction relationship value uses social network analysis to calculate degree centrality, betweenness centrality, closeness centrality, then sorts, compares and contrasts these three indicators to evaluate.
3. Cluster and classify the users into valuable users, knowledgeable users, social users and general users based on user contribution value. There are relatively few value users in communities, but their user contribution value and user interaction value are relatively high, which are of vital significance to community development. Knowledge users have knowledge and are willing to share, but they lack interaction. We should motivate them to participate in interactions to transfer them into value users. Social intercourse users interact with other members actively, which can help to spread public praise of enterprises. Normal users, which consists most of community users and are marginal users in communities, are easy to lose. As a consequence, we need to reinforce management and transfer them into other three categories of users.
4. Construct the user classification management tactic. Propose user differentiation, focus on management strategies to conduct optimization of user management to boost participation of community members and brand recognition.

Nevertheless, under the restriction of time and space, there are some limitations of the thesis:

1. We simply consider the frequency of words and ignore the low frequency of new knowledge in the process of recognition of core knowledge.
2. We adopt the content value and interaction relationships in user classification, but do not consider the individual characteristics. For instance, such factors as age, sex may affect the classification results.

Finally, some suggestions for future studies are proposed: Firstly, deep research of the extraction method of keywords based on technological progress and industry characteristics to improve extraction accuracy. Secondly, explore the influence of personal characteristics on user classification result in the process of cluster analysis. Finally, study effects of individual characteristics on user categorization so that we are able to include more comprehensive information and have more effective strategies of user categorizing and management.

CONFLICT OF INTEREST

The authors confirm that this article content has no conflict of interest.

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