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ABSTRACT

Based on the perspectives of information resource management and social capital measurement, this paper studies how influential users acquire, accumulate, and use their social capital in social networks to explore the general rules, which enterprises use influential users' relative competitiveness in their topic areas of expertise to advertise precisely. The paper describes the social capital differences among influential users by introducing and calculating users' relative social capital. Results show that user's social capital values in different fields are dissimilar, and the scope and intensity of social capital among different users are relative. The proposed method is proved to be effective and reasonable.

*Keywords:*online user influence, influence social capital, relative social capital measure, entropy weight measure model.

1 INTRODUCTION

Online celebrities with increased popularity have become prime businessbrokers of enterprises indeveloping social network marketing. Onlinecelebrityis a type of online users who have information influence, and they are important marketing resources for enterprises in promoting their brands or products[13]. The relationship formed by online users interacting and following one another is a type of social network. In this network, users release, spread, and interact valuable information to exert information influence on other users, thereby acquiring, accumulating, and utilizing their social capital and manifesting their network influence[7][31].User's influence is characterized by the user's personal attributes and social attributes, andonline celebrity's commercial value is the important embodiment of his or her online influence social capital value.So what type of users is suited to an enterprise for advertising? Which user can maximize the advertising effects? To solve the above problems, we need study online influential users' social capital and its relativity.Therefore, researching the measure method of online users' relative social capital is a major concern in optimizing online advertising management ROI (Return on Investment) decision andin maximizing social marketing effects.

In the exiting research literatures, scholars studied online users' influence and the method to identify influential users mainly from the following four aspects.(1) From the perspective of physics, scholars explored and described the network topology, link levels, and social relationship among online users, then obtained users' online influence using the social network analysis method[1][5].(2) From the perspective of information communication, scholars studied users' behavior in selecting information and the concern relationship among users, then obtained users' online influence throughthe PageRank algorithm[14][27].(3) From the perspective of communication, scholars analyzed the propagation characteristics and coverage of users' influence, then developed the propagation probability model of online influence to obtain users' online influence[2][30]. (4) From the perspective of information management, scholars researched users' personal features and social attributes according to users' behavior in releasing and choosing information, then built the multi-dimensional information entropy measure model of users' online influence to accumulate users' influence[15].

In summary, althoughthe methods to identify influential users from different perspectives have been explored, how online users acquire, accumulate, and use their social capital in social networks has not been comprehensively studied from the perspective of social capital measurement. The rapid rise of Internet celebrity economy urges people to study the general rule on how enterprises utilize influential users to advertise, that is, the business logic of influential users helping enterprises conduct precise advertisements in social networks. Using influential users to advertise for enterprises is actually not a new topic.Enterprises generally select a spokesperson based on the influence ranking of users provided by network platforms.However, none effective control method is available to determine whether the advertising performance is optimal. In order to help enterprises identify the suitable influential users to advertise, and fully exert users' relative competitiveness in their topic areas of expertise, we need explore how users obtain, accumulate, and use their social capital, and study the measure method of online influential users' relative social capital.

In this paper, we comprehensively investigate how influential users acquire, accumulate, and use their social capital based on information resource managementand social capital measurement theories, to explore the general rules that enterprises use influential users to push online social advertisements in social networks. The social capital differences among users can be manifested by users' online influence differences, that is, users'relative social capital. On the basis of the feature performance of social capital in users' personality and sociality, we build the measure index system and multi-dimensional information entropy measure model of online influential users to calculate users' relative social capital. The proposed entropy weight measure model can provide marketing management decision support and practical methods for enterprises in selecting suitable influential users to conduct precise advertisements and maximize advertising effects.

2 MEASURE INDEX SYSTEM OF ONLINE INFLUENTIAL USERS' RELATIVE SOCIAL CAPITAL

2.1 Social Capital and Its Relativity

On social network platforms, the "self-interest" and "altruistic" purposes and the need for social interaction and self-realization, guide users tobuild their social network by publishing, spreading,and interacting biased information with otherusers to acquire and accumulate online influence. Lin (2011)believed that social capital is resources in social networks, mainly including power, authority, and wealth[19].Granovetter(1973) thought that social capital in social networks is flowing, and can be divided into "information" and "influence"[11].Online users' social capital refers mainly to their online influence.Userattracts others' attention with his or her personality and sociality to exert his or her information influence, and accumulate social capital by selectively publishing, spreading, and interacting with topic informationin his or her focus areas[16].Given the differences in online users' education background, domain authority, and social relations, the scope and effect of their influence are also dissimilar[3][18], which shows the characteristics of online users' relative social capital.

Individual online user's social capital can be characterized by user's personality and sociality. Users' personality data include mainlytheir status, authority, knowledge, and experience; the sociality data include the trust relationship and information interaction among users[4][24][25][28]. In this paper, the argument basis of relative social capital is the performance differences in users' personal attributes and social attributes. Thus, we consider online users' personality and sociality data as the measure indexes of users' social resources, relationship strength, and capacity to calculate users' relative social capital.Here we qualitatively describe online influential users' relative social capital taking public big V and professional big V as examples, shown in Figure 2.1.1.

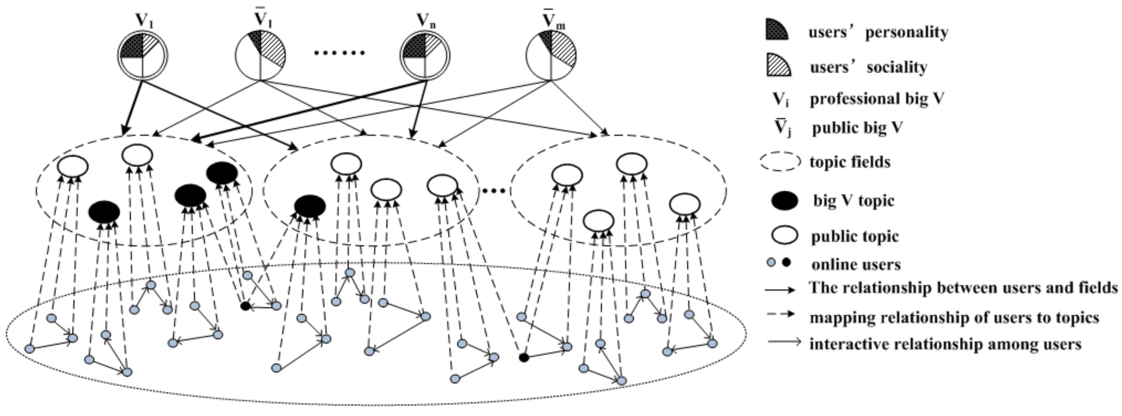

Figure 2.1.1 Structure diagram of online influential users' social resources, relationships, and capacity

Figure 2.1.1 describes the interrelationship between online users' social capacity and their discourse influence. In the figure, V represents online user, and the accumulation of shadow block in V circles represents the total social capital owned byuser, decided byuser's personality and sociality. Owing to the differences in users' cultural background, knowledge construction, experience, and social interaction ability, they also have different information influence effect on other users when discussing on one or more professional topics.As is shown in Figure 2.1.1, while the fields public big Vs' topics involved are broader than those of professional big Vs, the focusing degree of their topic content is not well.Unlike public big Vs, professional big Vs have the ability to provide professional content in their areas of expertise. In these fields, their information effect is better than that of public big Vs. For example, in the field of liquor, senior wine tasters are professional big Vs, and the tendentious product recommendation information they publish can easily gain online fans' recognition, acceptance, and purchase. Accordingly, they own higher influence strength than public big Vs in the area of liquor.

In summary, online influential user's relative social capital refers to the comparative advantage that user can better exert his or her professional influence than other users, during the process of acquiring, accumulating, and using his or her social resources, relationships, and capacity with his or her personality and interaction ability. The relativity is mainly reflected in the following aspects: (1) the total social capital values among different individual users are relative; (2) user's social capital values in different fields are different; (3) even if two users have equal amounts of social capital, the scope and effectiveness of their online influence are still relative.

2.2 Measure Indexes of Relative Social Capital

On social network platforms, users obtain the discourse power and influence through their personality, industry reputation, and ability to supply professional content and online social activities. Based on the criteria, users spread their values, lifestyle, and consumer preferences to other users to exert their information influence and achieve the purpose of continuously gaining business interests. Therefore, the personality measure indicators (such as personal experiences, knowledge background, and field authority) and the sociality measure indicators (such as trust relationships, participations, and interactions) must be defined and revealed to investigate online users' relative social capital.

(1) Measure indexes of personality

In social networks, user's personality is mainly reflected by user's individualand ability characteristics[23]. Falcone et al. (2011) found that "trust" is an important basis for users to obtain and accumulate social capital[9]. Feng (2010) found that information published by certified high-gradeusers can be easily trusted by consumers in online communities[10]. Zhu et al. (2015) found that talented users usually own highpopularity and attract other users to establish a connection with them in social networks[33].Online user's personal ability mainly refers to user's ability to provide professional content, which can be measured by the quantity and quality of texts published, and the number of user's followers[20][29]. Accordingly, we select user's level, status of identity authentication, number of followers, number of texts published, and number of high-quality texts, as measure indexes of users' personality to describe the features of users' relative social capital reflected by personality data.

(2) Measure indexes of sociality

In social networks, if user A focuses on user B, and acquires information or other online resources from B by interacting with B, then such process can provide B with the right to A[8]. The social network platform is an open information interactive system, which allows users to publish information to attract other users' attention. If user's information text is clicked, replied, or spread by others, the text is considered to have an influence on others; the more attention and more frequent interaction, the more significant its influence is. Yamaguchi et al. (2010) found that a user followed by many discourse authorities may also be an authority on the Internet[32]. Thus, we select average text clicks, average text replies, and number ofhigh-level users' replyas measure indexes of users' sociality to describe the features of users' relative social capital reflected by sociality data. The measure index system of online influential users' relativesocial capital is shown in Table 2.2.1.

Table 2.2.1 Measure index system of online influential users' relative social capital

First-grade indexes	Second-grade indexes	Index description	References
Personality	User's level	User's level on the network platform.	[9] [10]
	User'sidentity authentication	If the user's identity is authenticated, then the value is 1; otherwise, the value is 0.	
	Number of followers	The total number of user's followers.	[17] [20] [29] [33]
	Number of texts published	The number of texts published in the statistical period.	
	Number of high-quality texts	The quality of single text is judged comprehensively by its keywords, word count, picture number, and hyperlink number.	
Sociality	Average text clicks	The ratio of total text clicks to text number in the statistical period.	[8]
	Average text replies	The ratio of total text replies to text number in the statistical period.	
	Number of high-level users' reply	The number of high-level users' reply in the statistical period.	[32]

3 MEASUREMODEL OFONLINE INFLUENTIAL USERS' RELATIVE SOCIAL CAPITAL

Information entropy is proposed by Shannon and is used mainly to measure the value of uncertaininformation and its influence[26].Zhang et al. (2012) measured the quality of listed companies' internal control information using the entropy method[34].Ding et al.(2012) applied measure indexes, such as fuzzy absolute entropy, relative entropy, and interactive entropy, to measure the value of fuzzy information[6]. He et al. (2014) used the entropy weight model to build a three-dimensional measure index system composed of quality entropy, timeliness entropy, and interaction entropy to measure the information influence of group complaints on the Internet[15]. Using information entropy to measure the value of uncertain information is reasonable and feasible.

On social network platforms, users obtain and accumulate their social capital resources and relationships by releasing and spreading valuable information to enhance their online influence further. User's online influence is represented by user's personality and sociality information, thereby having the information value.The user's topics cover relatively wide areas, and the social capital values owned by the user in different fields are also different. We suppose that the field of users' topics focus is known on one network platform; the social capital values in different specialties of the field can be calculated by the relevance between texts supplied by the user and the specialty, combined with user's total social capital.

3.1 Definition of Measure Indexes of Relative Social Capital

DefinitionOn the social network platform,we suppose the field of users' topics focusas F , $F=\{f_1, f_2, \cdots f_k, \cdots, f_m\}(k=1,2,\cdots,m)$; and f_k indicates the kth specialty of the field. For any user U_i ,we recordthe vector composed of relevancebetween U_i and various specialties as R_i , $R_i=\{r_{i1}, r_{i2}, \cdots, r_{ik}, \cdots, r_{im}\}(k=1,2,\cdots,m)$; and r_{ik} indicates the relevance between U_i and the kth specialty. The property items of U_i are composed of user's personality data, sociality data and the relevance between U_i and various specialties, recorded as $U_i=\{x_{i1}, x_{i2}, x_{i3}, x_{i4}, x_{i5}, y_{i1}, y_{i2}, y_{i3}, R_i\}$. $x_{i1}, x_{i2}, x_{i3}, x_{i4}, x_{i5}$ represent user's level, user's status of identity authentication, number of followers, number of texts published, and number of high-quality texts of U_i. These data are used to access the value of user's personality information. y_{i1}, y_{i2}, y_{i3} represent average text clicks, average text replies, and number of high-level users' reply. These data are used to access the value of user's sociality information.

3.2 Determination of Index Weight

Different users' personalityand sociality data are dissimilar. A weight must be provided to every index item when calculating online influential users' social capital. Different weights may lead to different calculation results; thus, the weighting method must be properly selected. Weighting method that combines subjective and objective factors is a common method to optimize index weight. Entropy weight method is a widely used objective weighting method[21][35].The method calculates the entropy value of each index to reflect the information amount it provided. Notably, the index with small entropy value has high importance. In this paper, we consider the objective and subjective evaluation factors, using the experts' grading method to determine the weight of first-grade indexes first, and then adopting the entropy weight method to calculate the weight of second-grade indexes.

On the social network platform, n users are selected. The process of calculating second-grade indexes weight is described below.

(1) Build the initial matrix.

$$D=\begin{bmatrix} x_{11} & \cdots & x_{15} & y_{11} & \cdots & y_{13} \\ x_{21} & \cdots & x_{25} & y_{21} & \cdots & y_{23} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ x_{i1} & \cdots & x_{i5} & y_{i1} & \cdots & y_{i3} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ x_{n1} & \cdots & x_{n5} & y_{n1} & \cdots & y_{n3} \end{bmatrix}$$

(2) Process data dimensionless.

The data must be normalized to eliminate the adverse effects caused by the non-uniform dimension. All indexes are positive indexes, and the larger their values, the better. The normalization method is given as follows:

$$x_{ia}^{'}=\frac{x_{ia}-\min_a(x_{ia})}{\max_a(x_{ia})-\min_a(x_{ia})}(i=1,2,\cdots,n;a=1,2,\cdots,5) \tag{1}$$

$$y_{ib}^{'}=\frac{y_{ib}-\min_b(y_{ib})}{\max_b(y_{ib})-\min_b(y_{ib})}(i=1,2,\cdots,n;b=1,2,3) \tag{2}$$

The matrix after normalizing can be expressed by

$$D'=\begin{bmatrix} x_{11}^{'} & \cdots & x_{15}^{'} & y_{11}^{'} & \cdots & y_{13}^{'} \\ x_{21}^{'} & \cdots & x_{25}^{'} & y_{21}^{'} & \cdots & y_{23}^{'} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ x_{i1}^{'} & \cdots & x_{i5}^{'} & y_{i1}^{'} & \cdots & y_{i3}^{'} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ x_{n1}^{'} & \cdots & x_{n5}^{'} & y_{n1}^{'} & \cdots & y_{n3}^{'} \end{bmatrix}$$

(3) Calculate the proportion of indexes $p_{ia}(x)$, $p_{ib}(y)$.

$$p_{ia}(x)=\frac{x_{ia}^{'}}{\sum_{i=1}^{n}x_{ia}^{'}}(i=1,2,\cdots,n;a=1,2,\cdots,5) \tag{3}$$

$$p_{ib}(y)=\frac{y_{ib}^{'}}{\sum_{i=1}^{n}y_{ib}^{'}}(i=1,2,\cdots,n;b=1,2,3) \tag{4}$$

(4) Calculate the entropy value of each index e_a, e_b.

$$e_a=-k\sum_{i=1}^{n}p_{ia}(x)\ln p_{ia}(x)(i=1,2,\cdots,n;a=1,2,\cdots,5) \tag{5}$$

In this formula, $k=\frac{1}{\ln n}$, and when $p_{il}=0$, $p_{il}\ln p_{il}=0$. The entropy value of e_b can be calculated in a similar way.

(5) Calculate the weight of each index.

$$\omega_a=\frac{1-e_a}{\sum_{a=1}^{5}(1-e_a)},\omega_b=\frac{1-e_b}{\sum_{b=1}^{3}(1-e_b)} \tag{6}$$

In this formula, $\sum_{a=1}^{5}\omega_a=1$, $\sum_{b=1}^{3}\omega_b=1$.

3.3 Relevance Between Online Influential User and Each Specialty

The relevance between one user and one specialty depends on the closeness between text content supplied by the user and specialty content. The value can be obtained by calculating the cosine similarity between user's text content vector and specialty content vector built through the TF-IDF method[12]. TF-IDF formula is expressed as follows:

$$TF-IDF(t,d)=\frac{tf(t,d)\times\log(N/n_t+0.01)}{\sqrt{\sum_{i=1}^{m}[tf(t,d)\times\log(N/n_t+0.01)]^2}} \tag{7}$$

$TF-IDF(t,d)$ is the weight of word item t in text d; $tf(t,d)$ is the frequency of word item t in text d; N is the number of texts; n_t is the number of texts, which contain word item t; m is the number of word items in text d; the denominator is the normalized factor of weights of word items.

On the social platform, the specialties are collections of users' texts. We assumethat T is the set of the word items of all specialties in one field, $T=\{t_1,t_2,\cdots,t_n\}$. Then, the text sets of any specialty f_k and any user U_i can be represented by an n-dimensional vector containing these word items, recorded as $Sf_k=(S_{f1},S_{f2},\cdots,S_{fp},\cdots,S_{fn})$, $SU_i=(S_{u1},S_{u2},\cdots,S_{up},\cdots,S_{un})$. S_{fp}, S_{up} indicate the average weight of word item t_p in texts of specialty f_k andtexts ofuser U_i, respectively.

(1) Calculate S_{fp}, S_{up}.

We assume the number of texts in specialty f_k is Nf_k, then S_{fp} is calculated from the following formula:

$$S_{fp}=\frac{\sum_{j=1}^{Nf_k}[TF-IDF(t_p,d_j)]}{Nf_k} \tag{8}$$

d_j is the text in specialty f_k; $TF-IDF(t_p,d_j)$ is the weight of word item t_p in text d_j, which can be obtained from Formula(7).

Assuming that the number of texts U_i supplied is NU_i, then S_{up} is calculated from the formula as follows:

$$S_{up}=\frac{\sum_{l=1}^{NU_i}[TF-IDF(t_p,d_l)]}{NU_i} \tag{9}$$

d_l is the text published by U_i; $TF-IDF(t_p,d_l)$ is the weight of word item t_p in text d_l, which can be obtained from Formula(7).

(2) Calculate the relevance between user U_i and specialty f_k.

The relevance r_{ik} between user U_i and specialty f_k can be obtained by calculating the cosine similarity between user text content vector and specialty content vector. The formula is expressed as follows:

$$r_{ik}=\frac{\sum_{p=1}^{n}S_{fp}S_{up}}{\sqrt{\sum_{p=1}^{n}S_{fp}^2}\sqrt{\sum_{p=1}^{n}S_{up}^2}} \tag{10}$$

3.4 Measure Model of Online Influential Users' Relative Social Capital

On the social network platform, we suppose the measure index set of the social capital of any user U_i is recorded as $U_i=\{x_{i1}, x_{i2}, \cdots, x_{i5}, y_{i1}, y_{i2}, y_{i3}\}$. The personality value of U_i is $IP(U_i)$, and the sociality value of U_i is $IS(U_i)$. Their calculation formulas are as follows:

$$IP(U_i) = \alpha \sum_{a=1}^{5} \omega_a x_{ia} \tag{11}$$

$$IS(U_i) = \beta \sum_{b=1}^{3} \omega_b y_{ib} \tag{12}$$

Thus, the total social capital formula of U_i is as follows: $C(U_i) = IP(U_i) + IS(U_i)$ (13)

α and β indicate weight of first-grade indexes and weight of second-grade indexes, respectively.

Given the difference in users' knowledge background, domain authority, and social relationships, different users' online influence is also dissimilar. The effect values of user's online influence in different specialties are also different, thereby indicating the difference in the relative social capital.

We assume the field of users' topics focus as F, and F includes m specialties. The vector composed ofthe relevancebetween U_i and various specialties is R_i, $R_i = \{r_{i1}, r_{i2}, \ldots, r_{ik}, \ldots, r_{im}\}$ $(k=1,2,\ldots,m)$; and r_{ik} indicates the relevance between U_i and the kth specialty. The relative social capital $RC_{U(i)}$ of U_i in each specialty can be calculated as follows:

$$RC_{U(i)} = C(U_i) \times R_i^T \tag{14}$$

The social capital of U_i in specialty f_k can be calculated as follows:

$$RC_{U(ik)} = C(U_i) \cdot r_{ik} \tag{15}$$

$C(U_i)$ is the total social capital of user U_i.

4 EMPIRICAL STUDY AND RESULT DISCUSSION

4.1 Data Collection and Processing

To describe and calculate users' relative social capital quantitatively, we choose the "car home forum website" as the experimental platform; and collect data by observing active users in product forums of "Jeep" brand community. We assume that "Jeep" brand community is the field of users' topic focus, and the product forums are specialties in the field. In experiment, we consider "day" as the observation unit. The data collection period is six months, from Sept.1, 2015 to Feb.29, 2016.

(1) Datacollection.In the experiment, we use web crawler tool GooSeeKer(www.gooseeker.com) to grab the data of product forums and user and save these data as XLSM file.Product forum's data include forum's name, user's name, time of publication, number of forum essence posts, and text content of essence posts. User's data include user's name, user's level, user's status of identity authentication, number of fans, number of posts, text content of posts, time of publication, number of comments, number of clicks, level of people commenting, number of essence posts, and text content of essence posts.

(2)Data processing

1)Product forum data.

①The number of forum essence posts is the total amount of essence posts published in the statistical period.

②Keywords of product forum. We apply ICTCLAS(Institute of Computing Technology, Chinese Lexical Analysis System)[22] to segment the text content of essence posts on each product forum, and then mark and count keywords of each product forum.

2) User data.

We suppose essence post numberis more than 1 for the initial threshold, and delete users whose essence post number is 0.

① The status of user's identity authentication refers to whether the user is certificated as a car owner; the value is 1 if certificated, and the value is 0 if otherwise.

② The number of user's followers refers to his or her number of fans.

③ The number of user'stexts published refers to the number of posts user published in the statistical period.

④ The number of user's high-quality textsrefers to the number of essence posts user published in the statistical period. The quality of single text can be comprehensively calculated by its keywords, word count, picture number, and hyperlink number. In "Jeep" brand community, high-quality text is generally classified as essence post.
⑤ Average text clicks are the ratio of total clicks of user's posts to his or her number of posts in the statistical period.
⑥ Average text replies are the ratio of total replies of user's posts to his or her number of posts in the statistical period.
⑦ Number of high-level users' reply is the total number of high-level users' replies of user's posts published in the statistical period.
⑧ Keywords of user's text content can also be obtained using a similar approach of obtainingkeywords of product forum.

The processed data only keep the entire number, and these data are stored in the product forum information table and the user information table. The selected partial user data are shown in Table 4.1.1.

Table 4.1.1 List of partial user data in the statistical period

User	Personality					Sociality		
User (U_i)	User's level	User's identity authentication	Number of followers	Number of texts published	Number of high-quality texts	Average text clicks	Average text replies	Number of high-level users' reply
U_1	16	1	812	23	14	30805	84	246
U_2	23	1	1164	18	13	5468	37	178
U_3	20	1	390	19	13	5642	36	148
U_4	7	0	78	15	6	3027	31	51
U_5	15	1	63	16	6	21085	45	35
U_6	15	0	466	25	20	13265	52	84
U_7	10	1	224	7	4	2423	32	23
U_8	7	1	126	16	2	16020	60	58
U_9	8	0	42	15	14	12133	47	53
U_{10}	10	1	16	8	1	43068	155	100

4.2 Data Calculation

(1) Determine the weight of each index

We invite 10 experts from MBA to determine the weights of first-grade indexes, and then normalize the above index data to calculate the weights of second-grade indexes. The results are shown in Table 4.2.1.

Table 4.1.2 Weights of first-grade and second-grade indexes

First-grade indexes	Weight	Second-grade indexes	Weight	Comprehensive weight
Personality	0.55	User's level	0.229	0.126
		User's identity authentication	0.184	0.101
		Number of followers	0.307	0.169
		Number of texts published	0.119	0.065
		Number of high-quality texts	0.162	0.089
Sociality	0.45	Average text clicks	0.229	0.135
		Average text replies	0.442	0.199
		Number of high-level users' reply	0.259	0.117
Total	1	—	—	1

(2) Calculate user's social capital

We first normalize the data in Table 4.1.1, and then combined with the weight data in Table 4.2.1, we calculate each user's social capital according to Formulas (11)–(13). The result is shown in Table 4.2.2.

Table 4.2.2 Social capital value of online users

Online userU_i	Personality value$IP(U_i)$	Sociality value$IS(U_i)$	Social capital value$C(U_i)$
U_1	0.408	0.290	0.698
U_2	0.492	0.100	0.592
U_3	0.360	0.084	0.444
U_4	0.061	0.017	0.078
U_5	0.227	0.089	0.316
U_6	0.283	0.099	0.383
U_7	0.169	0.001	0.171
U_8	0.154	0.107	0.261
U_9	0.102	0.072	0.173
U_{10}	0.128	0.359	0.488

On the basis of the data in Table 4.2.2, we acquire the distribution curves of personality value, sociality value, and social capital value of each user, as shown in Figure 4.2.1.

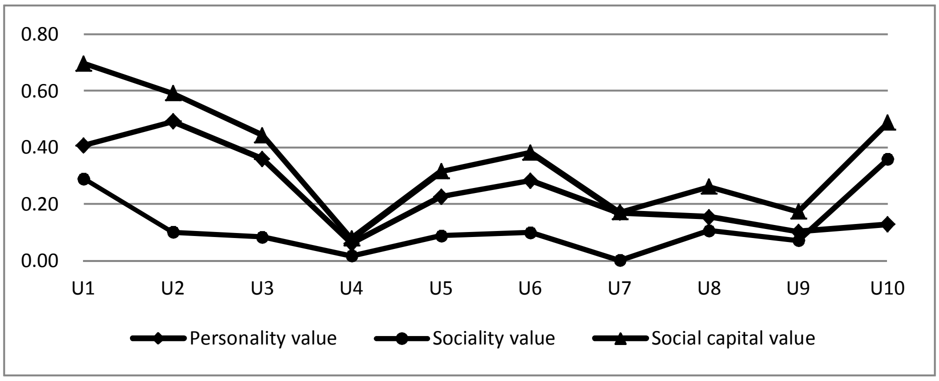

Figure 4.2.1 Distribution curves of users' social capital values, personality values, and sociality values

(3)Calculate user's relative social capital

Considering U_1, U_2, U_7, U_9, and U_{10} as examples, we first mark and count the keywords of product forum and $U_i$using a word segmentation tool, and then calculate the relevance between users and each specialty according to Formulas (8)–(10). The result is shown in Table 4.2.3.

Table 4.2.3 Relevance between users and each specialty

User U_i	Wrangler P_1	Guide P_2	Grand Cherokee P_3	Free Light P_4
U_1	0.601	0.727	0.000	0.000
U_2	0.888	0.000	0.000	0.000
U_7	0.000	0.000	0.689	0.000
U_9	0.810	0.000	0.124	0.000
U_{10}	0.143	0.081	0.900	0.078

We calculate user's relative social capital value in different specialties according to Formulas (14)–(15). The result is shown in Table 4.2.4.

Table 4.2.4 User's relative social capital value in different specialties

User U_i	Wrangler P_1	Guide P_2	Grand Cherokee P_3	Free Light P_4
U_1	0.419	0.507	0.000	0.000
U_2	0.526	0.000	0.000	0.000
U_7	0.000	0.000	0.118	0.000
U_9	0.140	0.000	0.021	0.000
U_{10}	0.070	0.040	0.439	0.038

The social capital value distribution of U_1, U_2, U_7, U_9, and U_{10}in each specialty is shown in Figures 4.2.2 and 4.2.3.

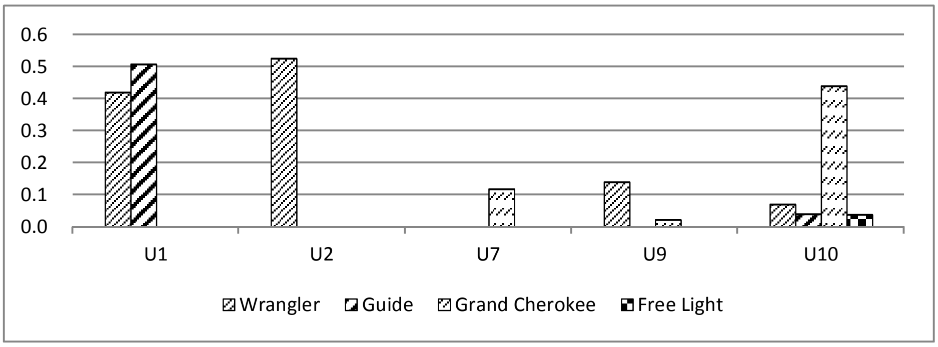

Figure 4.2.2 Social capital value distribution of users in each specialty

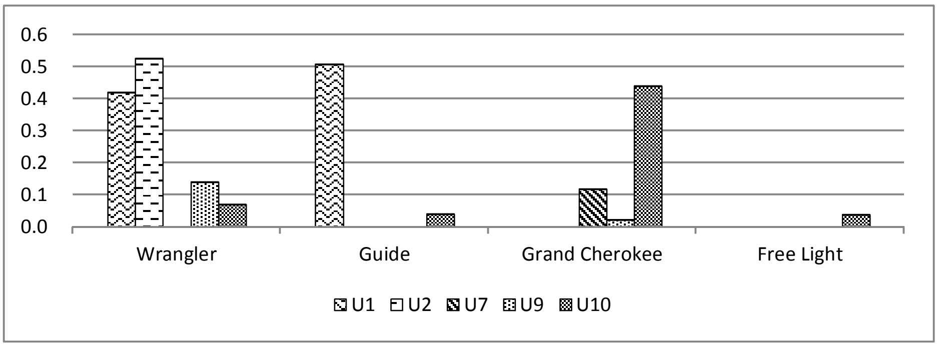

Figure 4.2.3 Relative social capital value of users in each specialty

4.3 Results, Discussion, and Analysis

As shown in Figure 4.2.1, online user's social capital is determined by user's combined personality and sociality data. The total social capital values of users owning different experiences and background are dissimilar. Even if two users have equal amounts of social capital, their personality and sociality values may also be different, such as the case of U_7 and U_9. Figure 4.2.2 and 4.2.3 show that the strengths of user's social capital values in different specialties are different, and the scope and intensity of social capital among different users are relative. As shown in Figure 4.2.2, U_{10} has online influence in all product specialties, and this user's influence strengths in various product specialties are different. U_2 and U_7 have online influence in only one product specialty, and the intensity of U_2's social capital in "Wrangler" is higher than that of others' social capital. Although the social capital amounts of U_7 and U_9 are close, the specialty scope and strength of their social capital are still relatively different.In Figure 4, the social capital values of U_1, U_2,U_9, and U_{10} in "Wrangler" in the descending order is $U_2>U_1>U_9>U_{10}$. However, their total social capital in the descending order is $U_1>U_2> U_{10}>U_9$. Thus, even if user's social capital value is high, this user's relative social capital in one specialty may be low.

In summary, the social capital of online users depends on their personality and sociality and is relative. User's social capital values in different fields are different. Furthermore, the amount, scope, and intensity of social capital among different users are relative. The results show that relative social capital can fully define the scope and strength of user's online influence.

The above conclusions have targeted decision support value for enterprises in pushing social advertisements with the aid of online influential users. Apart from the total amount of user's social capital, personality features, and sociality features are another important factors that must be considered by enterprises when choosing an online celebrity to endorse advertisements. Such consideration can help enterprises in maximizing user's relative advantage in using his or her area of expertise and further maximize the utility value of this user's social capital. Furthermore, with the aid of users' relative social capital, enterprises can establish a match mechanism between online celebrity and marketing objectives. Enterprises can also determine and cultivate online celebrities with commercial potential to improve their online advertising effects.

5 CONCLUSIONS

Researching the measure method of online influential users' relative social capital can help enterprises in determining a suitable online celebrity that matches their target advertisement to maximize the advertising effects. In this study, we comprehensively investigate how influential users acquire, accumulate, and use their social capital based on information resource management and social capital measurement theories. We also explore the general rules used by enterprises to facilitate influential users in pushing online social advertisements in social networks. The characteristics of relative social capital embodied in user's personality and sociality attributes are verified. On the basis of these characteristics, we build the measure index system and information entropy measure model of the relative social capital of online influential users to obtain a measure method of relative social capital. The proposed method can provide decision support theory and practical method for enterprises when selecting influential users to conduct precise advertisement.

The main conclusions are as follows:

(1) In social network platforms, users' social capital refers mainly to their online influence. Given the difference in users' cultural background, knowledge construction, experiences, and social interaction, the scope and strength of users' social capital are also dissimilar. The relative difference is the users' relative social capital, which is represented by users' personality and sociality data. On the basis of these data, we build a measure index system and information entropy measure model of online influential users' relative social capital and obtain a measure method of relative social capital.

(2) The empirical research shows that the model method can effectively evaluate the utility value of social capital and define the difference in the specialty scope and the strength of social capital among users. The method can help enterprises in building the matching relations between influential users and target advertisements. In this age of Internet celebrity economy, enterprises must not only consider the total amount of users' social capital but also regard the marketing objectives, observe the relative advantage of users' social capital in their fields of expertise to maximize the utility value of users' social capital, and provide decision support for advertising performance management. Compared with the approach that determines online advertising spokesperson using influential users' list, the proposed method is more scientific and reasonable.

Future research work mainly focus on the following issues: the optimization of the measure index system of users' social capital; the dynamic evaluation of online influential users' relative social capital; and the matching relations between online users and marketing objectives based on the relative social capital. Solving these problems can help enterprises cultivate and select online advertising spokespersons at a low cost and thus maximize the advertising effects.

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