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# **Credibility Assessment of Mobile Social Networking Users Based on Relationship and Information Interactions: Evidence From China**

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**ABSTRACT** Personalized, diversified and decentralized mobile social networking platforms provide users with an environment for accessing, sharing, distributing information and communicating emotionally. In this virtual social space, effective identification of trusted nodes can assist social networking users to make interactive strategies, and provide enterprises with scientific basis for the social interactive marketing decisions. Therefore, trust assessment plays a crucial role in establishing social connections among mobile social networking users. In this paper, based on the social relationship and information interactive data between the users of Sina Weibo, four factors, the intensity of social relations, the sphere of social influence, the information value and the control of information transmission are taken into account to build the trust assessment model. Secondly, the trust between users is quantified by node credibility and entropy weight method is employed to calculate the four factors' contribution to the node credibility respectively. Finally, the credibility of each node in Sina Weibo is calculated to identify the trusted nodes.

**INDEX TERMS** Mobile social networks, relationship interactions, information interactions, node credibility assessment, entropy weight method.

#### I. INTRODUCTION

Personalized, diversified and decentralized mobile social networks have permeated every aspect of human life [15], which can be applied to build social relationships [18] and provide users with an effective channel to share and distribute information [5]. In 2019, the number of internet users achieved 854 million in China, 96% of whom were mobile social users, and over 80% of social networking users spent more than one hour a day using mobile social applications, and half users checked the applications more than three times a day [17]. Mobile social networks promote real-time, multi-channel and personalized social interactions and cooperation among users, which can exert direct or indirect influence of one user upon others [35], because users tend to trust the information generated on the social networking platforms more than those under traditional media [8]. The recommendations of friends on the social networking platforms are the optimal choices [11], and customers are more likely to accept the

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products and services recommended by those users who have higher social influence in specific areas [23], because individual characteristics of the referrals have stronger influence on consumer purchasing intentions than information itself [13].

However, in China, only 55.4% of mobile social networking users paid via platforms in 2017, and the proportion of those who have bought products on social networks was only 44.7% [16]. The possible reasons were that the information asymmetry, the interference of mass information, combined with a variety of networking dishonest acts, such as the spread of false or fake information, malicious recommendation and phishing, made the social interactions and the decision making processes more risky in the decentralized virtual social space [22]. Hence, trust is critical to the success of online activities [2]. But how do we evaluate the credibility of other nodes on mobile social networks before we interact with them? Furthermore, how can we identify the trusted nodes from those without any direct contacts before? Answers can establish effective and efficient ways to help mobile social networking users to accurately identify the trusted nodes and information, to assist in making interactive strategies

for social networking users, and to provide enterprises with scientific basis for the social interactive marketing decisions. The concepts of trust are diversified, so are the trust assessment methods. Currently, the most popular method is to evaluate global trust of a single node in the whole network as well as local trust by friends' information. The majority of global trust assessment models measure the credibility of targeted nodes with the recommended information on the platform. In [21], untrusted nodes were found by calculating the values of node reputation and node bias in the trust network. In [41], global trust of a node was determined by the entire recommendations on the whole net which could be measured by the credibility of the recommenders. Although global trust assessment models have been proven to overcome the sparseness of interactive data, it fails to reflect the diversity and individuality of trust information. Therefore, combining global trust and local trust information to solve the problem can reconcile this contradiction. In [34], global trust of any targeted node was calculated by local trust information provided by other nodes, and global trust of those nodes who have conducted transactions with the targeted node. In [6], global trust, local trust, and nature of trust were employed to model the trust relationship where global trust was determined by a node's own integrity, ability and other qualities, while local trust depended on the closeness degree between the nodes.

Analysis of mobile social networks is to map social activities of the physical world to the virtual networking space by means of informatization, so acquiring and analyzing mobile social interactions through information technology is an effective method to solve trust issues. However, the existing trust assessment models and algorithms under the mega data environment could not fully consider the connotation of social interactions, so network features and influence factors of trust should be studied further. Most researches merely regarded information interactions and diffusions as mobile social interactions or constructed the trust models based on the relationship interactions merely. In fact, interactions in mobile social networks include not only the information interactions, but also the relationship interactions reflecting attitudes, emotions and perspectives toward the information publishers. Moreover, few literatures explored the influence factors to establish the trust evaluation model by extracting the real social activities and providing the concrete implementation algorithms. Thus, the existing methods of mobile social trust assessment should be further optimized to predict the user behavior accurately. In order to solve the above problems, this paper comprehensively takes information interactions, relationship interactions and network features into account to assess node credibility of mobile social networking users based on global trust and local trust information. The marginal contributions are as follows: firstly, trust assessment model is constructed by analyzing all possible influence factors of mobile social trust based on relationship interactions and information interactions in Sina Weibo. Among them, relationship interactions include the intensity of social relationship interactions and the sphere of social influence, while information interactions contain two factors, the information value and the control of information transmission. Secondly, mobile social trust is quantified by node credibility to establish trust assessment model and the concrete implementation algorithms are provided. Finally, entropy weight method is employed to calculate the contribution of each factor to node credibility, and then the credibility of each node can be calculated to identify the trusted nodes.

#### **II. BACKGROUND AND HISTORY**

Trust assessment aims to assess the credibility of the entity based on the trust definition and its influence factors [36]. The most popular assessment method is to evaluate global trust and local trust of nodes. However, the trust numeralization and precision issues have not been solved completely, so various excellent models and algorithms have been proposed successively.

In traditional social networking recommendation systems, global trust information has been widely used [9]. Most of traditional credibility assessment methods depended on the past interactive information or resource-sharing behaviors, which were widely used in large-scale e-commerce communities, for example, both eBay reputation model and Amazon reputation model for auctions use the assessment system that simply adds up the number of reviews. However, information about reviews and historical transaction has timeliness, and a single influence factor will not be enough to evaluate the node credibility in the mobile social networks. Thus, the credibility assessment model of this type is hard to be applied to the large-scale distributed network environment. In [33], a reputation model consisting of global trust value and request trust value based on historical transaction data was proposed. Yet, this model never considered the node location of calculating and storing trust information, so it was merely suitable for unstructured P2P networks. In [37], trust management model was developed on basis of the reputation value of the resources and that of the nodes. This model introduced the trust features in real life, and divided the transaction reputation into two categories, resource reputation value and node reputation value. However, this model only had two influence factors, the previous transaction histories and transaction comments, so it was not capable of fully mapping the trust relationships in social networks. Although global trust models overcome the sparseness of interactive data, local trust indexes are more accurate in consideration of individual users' perspectives [3]. This is because local trust indexes can effectively reflect the diversified and individually differentiated trust information. In [24], a method was put forward to assess the intensity of trust relationship by extending the collaborative filtering matrix factor, based on the trust information and product ratings on the online review websites. Essentially, this method assessed the trust between social networking users by maximizing the local influence. In [15], an algorithm was developed to initialize the ego-i graph, which graded social relationships by calculating

the group-based credibility with three factors, the level of contacts, interactive evolutions and user attributes. However, calculating local trust value through a multi-index system is more time-consuming and more dependent on past direct communicative data, therefore, the trust relationship between nodes can be better assessed by a combination of global trust and local trust indexes [25]. In [19], a group-based trust assessment model SEGTM was presented with local transaction records and recommended trust information. This model believed that the recommended trust could be utilized to partition and assess the trust relationship within or across the group, in addition to local credibility formed by service trust and feedback trust. In [26], a general method was raised to recommend similar users, resources and social networks to node users, taking explicit and implicit relationships as well as global and local trust information into account. In short, effectiveness and accuracy of trust assessment models can be improved by using global and local trust information.

With the further development of mobile social networks, trust assessment methods are expanded through collecting and mining large-scale data, highly suited to the complex networks with thousands of rapid-changing network members and short-running interconnections [31]. In [38], data mining method was employed to assess social networking trust with the records of the previous interactions between message publishers and receivers. In this model, social networking trust was defined as the possibility of information being believed and shared by the message receivers. However, in mobile social networks, it is necessary to consider both relationship interactions and information interactions when identifying social trust relationship between the nodes. In [29], the sociological and psychological principles of trust generation were utilized to propose a credibility assessment method on account of the familiarity and similarity in interpersonal relations between social networking users, and the similarity was classified into internal similarity and external similarity in the model.

When assessing the social networking trust relationship, the frequency of information interactions, friends' comments and context information including the attributes, preferences and networks of social networking users, are usually introduced to establish the model. In [39], a trust assessment model of mobile social networks was developed by collecting the interactive data of Sina Weibo. In the model, the social interactive data collected was relatively comprehensive, and the contribution of each interaction to social trust was also taken into account. Nevertheless, neither the method of weight calculation nor the implementation of algorithm was described specifically in the model.

Based on these literatures, a variety of valuable research results have been obtained in the existing studies, which provided instructive ideas for trust assessment, but some deficiencies still existed. First of all, traditional trust assessment models with information of past social interactions or resource sharing activities were based on the basic statistical models, so the accuracy was bound to be questioned due to the poor utilization of trust information. Meanwhile, local trust models reflecting the diversified and individually differentiated trust information were time consuming, so models utilizing a combination of global trust and local trust information could effectively reconcile the above contradictions. However, the majority of existing models did not cover the influence factors comprehensively. Secondly, most trust assessment models and algorithms under the mega data environment failed to fully consider the connotation of social interactions and social network features. Therefore, based on the concepts of global trust with local trust, this paper first proposes a new trust assessment model of mobile social networks in consideration of relationship interactions and information interactions respectively. This model introduces the influence factors of social networking trust comprehensively to calculate the node credibility by mining and analyzing the large-scale data of social interactions and network attributes of Sina Weibo. Then, entropy weight method is employed to obtain the contribution of each factor to the social networking trust objectively and reasonably, and finally the credibility of each node is calculated and ranked to identify the trust relationship.

### III. RECENT FINDINGS

### A. RESEARCH METHODOLOGY



FIGURE 1. Schematic diagram of social network.

A mobile social networking platform aims to share interests, hobbies, status and activities through smart phones, tablets and other mobile terminal devices. Figure 1 shows a simple social network consisting of 8 nodes and 11 edges, and the edge values represent the weights of edges. For example, node 5 is directly connected to node 2, 3, 4, 6, 7 and 8, so node 5 has 6 neighboring nodes, that is, its degree value is 6. According to the definition of adjacency matrix, the weight matrix of the network can be obtained through the adjacency matrix representing the network adjacency relationship, shown as below.

	0	2	0	0	0	0	0	0
	2	0	2	0	2	0	0	0
	0	2	0	0	3	0	0	0
W =	0	0	0	0	3	0	0	0
	0	2	3	3	0	5	5	2
	0	0	0	0	5	0	3	3
	0	0	0	0	5	3	0	2
	0	0	0	0	2	3	2	0

Trust between mobile social networking users can be quantified and assessed by node credibility, that is, the higher the credibility, the easier the user is to be trusted by other users, the more acceptable his or her recommendations are. Based on textual interpretation of the literature, trust can be calculated and assessed by trust model, that is, a quantitative evaluation system is established to measure the trust degree of nodes with trust value. Therefore, on the basis of the features of social interactions and network structure extracted from real mobile social activities, this paper finds that trust model can be built to calculate the node credibility on the basis of four influence factors, the intensity of social relations, the sphere of social influence, the information value and the control of information transmission.

# 1) THE INTENSITY OF SOCIAL RELATIONS

In social networks, trust between users can be measured by the intensity of the link relationships [14]. The intensity of social relations is a set of social interactions among social networking users, such as "forward", "comment" and "like". Here, users are regarded as nodes in the network, and the edges between nodes show the interactions between users. The intensity of social relations reflects the importance of the nodes that a node attaches to. "Forward" indicates that a node agrees with the idea of anther node and is willing to actively disseminate the information; "Comment" is to express a node's own thoughts, and "like" only represents the interest of a node. In order to facilitate the calculation, this paper sets weights of the edges corresponding to "forward", "comment" and "like" as 5, 3 and 2 based on the participation levels of the nodes. The more frequent the social interactions of a node with other nodes, the higher the value of the intensity of social relations, and the greater its influence and credibility. In mobile social networks, The intensity of social relations represented by the weight of the edge between two nodes can be assessed by the weighted degree method [30], that is, for any node, its intensity of social relations can be defined as the sum of the weights of the edges between a node and all its associated nodes.

$$R(i) = \sum_{j \in \partial(i)} w_{ij} \tag{1}$$

According to formula  $(1), \partial(i)$  is a set of nodes directly associated with node *i*.  $w_{ij}$  is the weight of the edge between node *i* and node *j*. In figure 1, the intensity of social relations of node 5 is R(5) = 2 + 3 + 3 + 5 + 5 + 2 = 20. Similarly, the intensity of social relations of all nodes can be calculated as shown in Table 1.

 TABLE 1. Comparison of degree value and intensity of social relations.

Node	1	2	3	4	5	6	7	8
Degree value	1	3	2	1	6	3	3	3
R	2	6	5	3	20	11	10	7

Table 1 shows that nodes 6, 7 and 8 have the same degree value, so their importance cannot be distinguished only based on the number of neighboring nodes. Therefore, the intensity of social relations between nodes in this paper is introduced to differentiate the nodes.

# 2) THE SPHERE OF SOCIAL INFLUENCE

The local influence assessment method [40] can be used to quantify the sphere of social influence of a node in the social network analysis. The larger the sphere of social influence of a node is, the greater its influence and credibility are. Meanwhile, if a node's sphere of social influence is large and its friends are also relatively more influential, the node can influence more people. The sphere of social influence of a node can be quantified by the number of its friends which can be reflected as the degree value in the network. Calculating the sum of degree values of multilevel neighboring nodes is the way to assess the local influence of a node, that is, the sphere of social influence. For any node, its sphere of social influence can be denoted as follows:

$$Q(j) = \sum_{w \in \Gamma(j)} D(w)$$
(2)

$$SL(i) = \sum_{j \in \Gamma(i)} Q(j)$$
(3)

In formulas (2) and (3), D(w) is the degree value of the node w, while  $\Gamma(i)$  and  $\Gamma(j)$  represent the neighboring nodes set of node *i* and that of node *j* respectively. Taking figure 2 as an example, the sphere of social influence of the node 8 is SL(8) = Q(7) + Q(9) + Q(10). According to the formulas (2) and (3), Q(7) = D(6) + D(8) + D(10) = 13, Q(9) = D(8) = 3, Q(10) = D(7) + D(8) + D(11) + D(12) + D(13) + D(14) = 18,thus, SL(8) = 13 + 3 + 18 = 34. Similarly, the sphere of social influence of node 4 is SL(4) = 3 + 3 + 5 = 11. Thus, SL(8) > SL(4). The calculation result is consistent with what is shown in figure 2. Although node 8 and node 4 have the same number of neighboring nodes, the nodes connected by node 8 are more important than those connected by node 4, which means node 8 is more significant than node 4 in the network. Therefore, node credibility can be measured by the sphere of social influence.



FIGURE 2. A simple schematic network.

# 3) THE INFORMATION VALUE

The information value is also one of the factors that affect node credibility. The higher the value of information a node releases, the easier it is to affect the behaviors of other nodes, and the more likely the information is to be transmitted, that is, the wider the spreading scope of the node in the network is. SIR model [27] is very effective and efficient in evaluating the spreading scope of a node in the network so as to assess the information value published by that node.

In mobile social network researches, nodes are usually regarded as the sources of virus infection to infect other nodes, and the infection range of a node is considered as the influence factor of node importance. The SIR model divides the nodes in the network into three categories: to be infected, infected and cured [1], [4].  $\sigma(S_i)$ , the number of cured nodes in the network, symbolizes the importance of node  $S_i$ , which is usually computed by the average of multiple simulations. In figure 3, at the time of t, node 10 is the infected node which may infect its neighboring nodes with a certain probability, and node 14 is the cured node, while the remaining nodes are those to be infected. At the time of t+1, node 10 becomes the cured node, and no longer infects other nodes or is infected by others. Node 7 and node 13 are the newly infected nodes who continue to infect their neighboring "to be infected" nodes. This process is repeated until no single infected node exists in the network and the iteration ends. Then, the number of cured nodes in the network denotes the influence of node 10, that is, the value of information published or forwarded by node 10.



FIGURE 3. The schematic diagram of SIR communication.

# 4) THE CONTROL OF INFORMATION TRANSMISSION

The control of information transmission refers to the probability that the information passes through a node in the process of transmission. During the process, the more information passes through a node, the more control the node has over the information transmission, and the greater the influence as well as the credibility the node has. Betweenness [10] is a nodal importance assessment method based on the shortest path [12], which is an important quantitative tool to evaluate the control of information transmission. The method considers that the more shortest paths pass through a node in the network, the algorithm to assess its credibility by using the betweenness is as follows:

$$B(i) = \sum_{i \neq s, i \neq t, s \neq t,} \frac{g_{st}^l}{g_{st}}$$
(4)

In formula (4),  $g_{st}$  is the number of shortest paths from node s to node t, and  $g_{st}^i$  is the number of paths through node i in all shortest paths from node s to node t. Betweenness reflects the control ability of a node on the information transmission in social networks. If all the shortest paths of a network pass through a node, the node will be proved to play a vital role in the information transmission, and vice versa.

According to the definition of betweenness, the shortest path starting or ending at a node itself is not included in the molecule, so betweenness of the nodes with degree value of 1 is 0, which makes it impossible to calculate in some particular situations. Therefore, this paper makes some improvements to avoid this type of situation, and the improved algorithm is shown in formula (5).

$$B(i) = \sum_{i \neq s, i \neq t, s \neq t,} \frac{g_{st}^{i} + 1}{g_{st} + n}$$
(5)

Betweenness is effective in identifying the intermediate nodes during the information transmission. In figure 4, the betweenness of node 6 is the largest, which means that its control of information transmission is the strongest, followed by node 5 and node 7. After calculation, the betweenness value of each node is shown in table 2, which is consistent with what is shown in figure 4.



FIGURE 4. Schematic diagram of the control of information transmission.

 TABLE 2. The betweenness value of nodes.

No de	1	2	3	4	5	6	7	8	9	10
В	0.00	0.00	0.00	0.00	0.22	0.50	0.22	0.00	0.00	0.00
	64	64	64	64	29	32	29	64	64	64

# 5) THE CREDIBILITY OF SOCIAL NETWORKING USERS

The paper supposes that  $w_1, w_2, w_3$  and  $w_4$  are the contributions of four factors to the credibility of mobile social networking users, namely, the intensity of social relations, the sphere of social influence, the information value and the control of information transmission. For any node *i*, its credibility can be calculated by formula (6), and  $w_1, w_2, w_3$  and  $w_4$  can be calculated by entropy weight method.

Credibility(i) = 
$$w_1 * R(i) + w_2 * SL(i) + w_3 * SIR(i) + w_4 * B(i)$$
 (6)

Entropy weight method, an effective method to rank various influence factors objectively, can be employed to calculate the weight of the influence factors by using information entropy [7], [20]. For example, in the network with *n* nodes, if the credibility is assessed by *m* kinds of influence factors, the assessment matrix of  $m \times n$  can be obtained as below.

$$R = \begin{bmatrix} r_{11}, & r_{12}, & \cdots, & r_{1n} \\ r_{21}, & r_{22}, & \cdots, & r_{2n} \\ \vdots, & \vdots, & \ddots, & \vdots \\ r_{m1}, & r_{m2}, & \cdots, & r_{mn} \end{bmatrix}$$

In the assessment matrix,  $r_{ij}$  represents the credibility of node *j* according to the factor index *i*. Each row in the matrix is normalized, and then the information entropy  $H_i$  of the influence factor *i* is calculated as shown in formula (7) and (8).

$$H_{i} = -\frac{1}{\ln n} \sum_{j=1}^{n} p_{ij} \ln p_{ij}$$
(7)

$$p_{ij} = \frac{r_{ij}}{\sum\limits_{k=1}^{n} r_{ik}} = r_{ij}$$
(8)

The smaller the information entropy coefficient of an influence factor, the greater its weight should be given, because small information entropy coefficient indicates that the algorithm can provide more information for credibility assessment, which plays a greater role in comprehensive assessment, and vice versa. Therefore, the weight of the influence factor i can be calculated by formula (9).

$$w_i = \frac{1 - H_i}{\sum_{j=1}^{m} (1 - H_j)}$$
(9)

#### B. DATA FETCHING AND DATA ANALYSIS

# 1) DATA FETCHING

Mobile social networks record various behavioral data of the users, which can completely describe or reflect the activities of the mobile social networking users. Compared with We Chat, a friends' network dominated by strong social relations, the microblog network covering both strong and weak relations is more applicable. In the preparation phase, the open interface of Sina Weibo is accessed to obtain real mobile social networking data, and the privacy of mobile social networking users is guaranteed in the process of background calculations. The data fields fetched are shown in table 3, which basically summarize all possible social activities between two nodes in Sina Weibo.

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them	the	Sina	"forw	user	the	micro	"like"	ID
e	numb	Weib	ard"	ID	numb	blog	ID	regist
	er of	o ID	ID		er of	conte		ry
	"forw				"like"	nt		time
	ard"							
numb	numb	mess	numb		"	authe		
numo	er of	age	er of	locati	com	nticat	com	pictur
fans	friend	sourc	com	on	" ID	ion	ments	e ID
	s	e	ments			status		



FIGURE 5. Cloud chart of Sina Weibo figure.

#### 2) CLOUD CHART OF SINA WEIBO

In mobile social networks, nodes in the same community are closely related, while connections among the nodes in different communities are sparse [28], [32]. Therefore, mobile social networking data under topic "Beauty and Makeups", is used as an entry point to build the cloud chart of Sina Weibo. The chart, including 739 nodes and 1,422 edges, shows the interactions among 739 Sina Weibo users. The final cloud chart is shown in figure 5, where nodes with the same color are closely connected and those with different colors are sparsely connected. Thus, the cloud chart reflects the clustering characteristics of mobile social networks. Figure 6, the degree distribution diagram of Sina Weibo shows that the majority of nodes in the network have very small degree values, while a few nodes have very high degree values, that is, the vast majority of users draw very little public attentions, while the relatively small number of users have a large group of fans. We can also find that a node with a very high degree value is often located in the center of the nodes of the same class.



FIGURE 6. Degree distribution diagram of Sina Weibo.

# C. RESULTS AND DISCUSSION

1) THE VALUE OF EACH INFLUENCE FACTOR

Firstly, value of the intensity of social relations can be calculated according to formula (1). Figure 7 shows the distribution



FIGURE 7. Distribution diagram of social relations intensity.

of the intensity of social relations in Sina Weibo, where only a few nodes have high social relationship intensity in conformity to the characteristics of power-law distribution. Secondly, the sphere of social influence can be calculated by formula (2) and formula (3), and the calculation results show that most nodes have similar social influence sphere, and only a few nodes are with great or small influence sphere. The nodes are normally distributed, shown in figure 8. Thirdly, the SIR model is applicable to calculate the value of information that a node publishes. In this experiment, the parameters of SIR model are set as follows: infection probability  $\beta = 0.1$ , cure probability  $\mu = 0.005$ , and the influence of each node is determined by the average value of 1000 simulations. The distribution of information value published by nodes in Sina Weibo can be obtained through SIR simulation experiments, as shown in figure 9. Last but not the least, the control of information transmission is assessed by utilizing the betweenness, which is described in formula (5). The distribution diagram of the control of information transmission shows that most nodes have similar control over information, and only a few nodes have great or little control over that in Sina Weibo. The distribution diagram is shown in figure 10. In the following four diagrams, the abscissae are the nodes, while the ordinates are the influence factors. For the convenience of observation, the ordinates are processed by log.

# 2) WEIGHTS OF INFLUENCE FACTORS

By calculating the weight of each factor, its influence on node credibility can be assessed. Entropy weight method is more objective and accurate than other subjective assignment methods. Firstly, the standardized matrix R is constructed based on the calculated result of four influence factors, and the matrix rows represent the importance value of each node after the standardized processing of node influence:

$$R = \begin{bmatrix} r_{11}, & r_{12}, & r_{13}, & \cdots, & r_{1n} \\ r_{21}, & r_{22}, & r_{23}, & \cdots, & r_{2n} \\ r_{31}, & r_{32}, & r_{33}, & \cdots, & r_{3n} \\ r_{41}, & r_{42}, & r_{43}, & \cdots, & r_{4n} \end{bmatrix}$$



FIGURE 8. Distribution diagram of social influence sphere.



FIGURE 9. Distribution diagram of information value.



FIGURE 10. Distribution diagram of the control of information transmission.

Secondly, the information entropy of each influence factor is calculated according to formula (10), with which the weight of each factor can be obtained, as shown in formula (11).

$$H_i = -\frac{1}{\ln n} \sum_{j=1}^n r_{ij} \ln r_{ij}, \quad i = 1, 2, 3, 4$$
(10)

$$w_i = \frac{1 - H_i}{4 - \sum_{i=1}^2 H_i}, \quad i = 1, 2, 3, 4$$
 (11)

TABLE 4. The weight of each influencing factor to node credibility.

Influencing Factor	The Weight to Node Credibility
R	0.2398
SL	0.3172
SIR	0.0485
В	0.3946

Then, after calculation by entropy weight method, the contribution of each influence factor to node credibility in Sina Weibo is shown in table 4.

The weights can be plugged into formula (6) to calculate the credibility of each node, and the distribution of node credibility in Sina Weibo is shown in figure 11.



FIGURE 11. Distribution diagram of node credibility.

#### 3) CALCULATION RESULTS OF NODE CREDIBILITY

The top 10 nodes of the intensity of social relations (SR), the sphere of social influence (SI), the information value (SIR), the control of information transmission (B), and the node credibility (NC) are shown in table 5 respectively.

TABLE 5. The top 10 nodes of each influencing factor and the credibility.

Ranking	1	2	3	4	5	6	7	8	9	10
SR	204	79	667	635	148	712	546	448	95	655
SI	204	79	667	635	148	712	95	448	546	655
SIR	204	79	667	635	148	712	233	362	234	95
В	79	667	204	712	635	95	546	148	727	655
NC	79	204	667	635	148	712	95	546	655	448

#### 4) DISCUSSION

The results unfold some findings. First of all, if social trust model only relies on a single influence factor, there will be a large deviation. So in consideration of accuracy, it is reasonable to find the influence factors from the aspects of relationship interactions and information interactions. Secondly, based on the real mobile social networking activities,

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this paper gives weight to each factor through objective calculation by the method of entropy weight coefficient instead of subjective judgment. Among the four influence factors, the control of information transmission is proven to contribute the most to node credibility, followed by the sphere of social influence, the intensity of social relations and the information value. Thirdly, it can be seen from the distribution diagrams that only a few nodes have high relationship intensity with other users, and both the nodes with strong or weak influence sphere and those with great or little control over information are less. In addition, there is a huge amount of information in Sina Weibo, but the majority is worthless. Therefore, it is of great significance to assess the credibility on the nodes and the information they publish. Fourth, there are few nodes with higher credibility, among which nodes 204, 79, 667, 635, 148 and 712 are ranked the same in factors SR, SI and SIR, but differently in factor B. Because the sum of the weights of factors SR, SI and SIR is greater than the weight of factor B, the ranking of node credibility is similar to that of SR, SI and SIR. Meanwhile, the credibility ranking of the remaining nodes depends more on the factor B with a larger weight, as the nodes are ranked differently in each factor.

# **IV. CONCLUSION**

This paper proposes a trust assessment model and the related ranking method under mobile social networks based on the relationship interactions and information interactions among the nodes. The model introduces four influencing factors, the intensity of social relations, the sphere of social influence, the information value and the control of information transmission. Then the weight of each factor to node credibility is calculated by the method of entropy weight coefficient objectively. Finally, the node credibility is calculated to quantify the social trust in mobile social networking environment so as to identify the trusted nodes. Mobile social networks are not only the interactive tools for tightly connected users, but also networks with lots of potential friends. Trust assessment model can be used to assess the credibility of nodes without direct contact in order to analyze and predict user behaviors under mobile social networks, to establish social networks and availably enhance the networking influence of individuals, to effectively control and guide the communication of public opinions for the governments, and to provide a scientific basis for corporate marketing strategies and decision-making process. Simultaneously, the research conclusions can be applied to the business recommendation system based on node credibility, which also lay a foundation for further research on consumers' online purchasing decisions.

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