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Transaction credit in the unstructured crowd transaction network

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Abstract

Purpose – Current models of transaction credit in the e-commerce network face many problems, such as the one-sided measurement, low accuracy and insufficient anti-aggression solutions. This paper aims to address these problems by studying the transaction credit problem in the crowd transaction network.

Design/methodology/approach – This study divides the transaction credit into two parts, direct transaction credit and recommended transaction credit, and it proposes a model based on the crowd transaction network. The direct transaction credit comprehensively includes various factors influencing the transaction credit, including transaction evaluation, transaction time, transaction status, transaction amount and transaction times. The recommendation transaction credit introduces two types of recommendation nodes and constructs the recommendation credibility for each type. This paper also proposes a "buyer + circle of friends" method to store and update the transaction credit data.

Findings – The simulation results show that this model is superior with high accuracy and anti-aggression.

Originality/value – The direct transaction credit improves the accuracy of the transaction credit data. The recommendation transaction credit strengthens the anti-aggression of the transaction credit data. In addition, the "buyer + circle of friends" method fully uses the computing of the storage ability of the internet, and it also solves the failure problem of using a single node.

Keywords Crowd intelligence, Crowd transaction network, Transaction credit model

Paper type Research paper

1. Introduction

In recent years, the e-commerce platform in China has developed dramatically and has made remarkable achievements. At the same time, however, it has also exposed some inherent

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defects, such as lack of interaction, isolated information on the platform, lack of personalization during searching and matching and lack of accuracy and inability to prevent aggression when evaluating the transaction credit.

Chai (2016) believes that e-commerce will generate a networked and intelligent industrial form in the future. The development of the internet and the Internet of Things has aided the building of connections among transaction subjects, among transaction objects and between transaction subjects and objects, showing the trend of informatization and networking. With the application of intelligent technology and big data, both the subject and object now become more intelligent. With the help of the network, all intelligent agents with their thoughts of the consciousness space can be mapped together to the information space. Through network interconnection, interaction, intelligent search, precision matching and other operations, e-commerce can develop new features such as unstructured and dynamic interconnections, moving to a new generation – the crowd transaction network, which is the trend of the development of e-commerce in the future.

Figure 1 provides an example of the topological structure of the crowd transaction network, showing the crowd transaction network as a fully distributed unstructured one. According to the six-degrees-of-separation theorem, the social connection between any two strangers is at most six, i.e. a chain of "friends' friends" can connect two people within at most six steps (Milgram, 1967; Jiang, 2013; Li, 2009). Individuals, the government and enterprises can form circles of friends according to the size of the correlation. For example, Jerry is in Linda's degree-one circle of friends while ShouNong is in Linda's degree-two circle of friends, and this is continued till someone is in Linda's degree-six circle of friends. Through the circle of friends of different degrees, the crowd transaction network connects everything all inclusively. Nodes in different circles of friends can interact or trade with each other, cooperatively making decisions more intelligent.

Establishing a transaction credit model in the unstructured crowd transaction network is an urgent problem. The model has to address the defects of current models on existing e-commerce platforms. This paper proposes a model based on the unstructured crowd transaction network. We first construct the transaction credit model based on the crowd transaction network. This model comprehensively considers factors that influence the transaction credit, including transaction evaluation, transaction time, transaction status, transaction amount and transaction times. The transaction status includes transaction

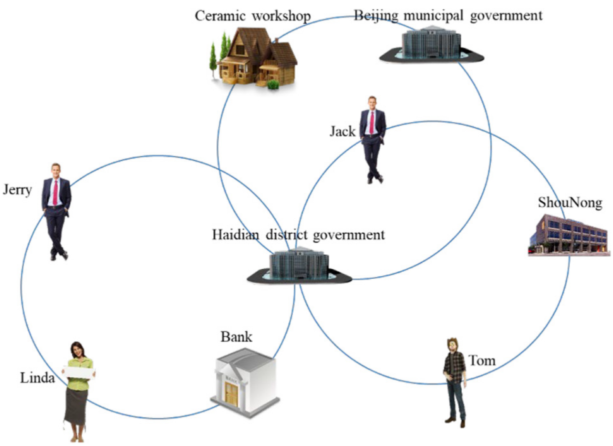


Figure 1.
Topological Structure of the crowd transaction network

failure times and transaction failure amount, which improves the accuracy of transaction credit evaluation. To effectively avoid malicious attacks such as collusion evaluation in the network, this paper divides the recommendation nodes (buyer or seller) into two categories and constructs the recommendation credibility for each type, improving the credibility and accuracy of recommendations. Simulation results show that the model is superior with high accuracy and anti-aggression. Further, according to the characteristics of the transaction flow and the crowd transaction network topology, we develop methods to store and update the transaction credit data.

The remaining of the paper is structured as follows: Section 2 describes the related literature; Section 3 introduces a detailed model of transaction credit evaluation; Section 4 discusses the results through experimental analyses; and Section 5 concludes the paper and discusses future research.

2. Literature review

Although this paper studies the credit problem of the unstructured crowd transaction network, the trust management technology of the e-commerce platform is significantly relevant to this paper. From the perspective of network structure, the crowd transaction network is built on the basis of peer-to-peer (P2P) computer network. The trust management technology of P2P network also has important reference significance for this paper. Therefore, the following will be elaborated from the above aspects.

Amazon uses the average method to calculate the reputation of nodes. This method has strong engineering feasibility and is easy for users to understand (Tian, 2007). However, this method is too simple, treats every transaction equally and is vulnerable to malicious behavior. Domestic e-commerce platforms – JingDong and Taobao – all adopt the accumulative method to evaluate credit, and users can choose one from the good, medium or bad comments for evaluation (Deng, 2012; Zhang, 2017). This method is simple and easy to implement, but the evaluation rules are single, without considering other factors affecting credit and cannot resist the attack of malicious behavior.

In the evaluation of transaction credit, the simple quantitative calculation will provide an opportunity for the fraudulent behavior of the seller. To solve this problem, Xu *et al.* (2007a) constructed the RGTurst credit control model, introduced the transaction amount and penalty factor into the evaluation mechanism, effectively solved the "prisoner's dilemma" problem in the transaction process and then guided both parties to make honest and trustworthy transactions. Liu *et al.* (2012) constructed an open service network model with trust and recommendation relationships. Taking advantage of the properties of "small world", a dynamic trusted service discovery algorithm was proposed to rank the most trustworthy services.

In addition, some scholars have studied the credit mechanism and management of e-commerce. Guo (2012), based on information economics and other theories, constructed the credit mechanism at the "medium" level and made a comparative analysis of the government-oriented system and self-regulation system based on the game theory, but did not give a quantitative model. Yu (2015), Wang (2017) and Li (2019), all adopted indicator analysis method to evaluate seller credit and paid excessive attention to static transaction factors (such as store life, etc.) of sellers and external characteristics (such as website security, etc.) of e-commerce website technology when selecting evaluation indicators, but not considering transaction process factors.

Many works have had an in-depth discussion on the trust of P2P networks. In the early stage of the study, Aberer and Despotovic (2001) proposed a trust evaluation mechanism based on global reputation. In this system, nodes can complain to other nodes, and then the P2P system continuously collects the complaint information and calculates the reputation of each node. However, this mechanism cannot effectively resist malicious attacks. Based on Aberer and Despotovic (2001) study, Kamvar *et al.* (2003) proposed an EigenRep model which obtained the credibility of nodes by iterating between them. In a secure and trusted network without malicious attack, this model can reflect the real behavior of nodes to a large extent. However, this model also has some defects: it needs a group of *priori* trusted nodes, which is difficult to achieve in an open environment. And the trust value of this model is calculated each time the whole network iteration is required, which leads to high communication cost of the whole network. The model uses structured DHT (distributed hash table) strategy to select the unique node to place the trust value, which is prone to a single-point failure problem. Dou *et al.* (2004) improved EigenRep, but they did not consider the efficiency of the model. They did not give a quantitative model to solve the problems of security and convergence. This model also uses the structured DHT strategy for distributed storage of trust values, so there is the single-point failure problem. Xiong and Liu (2004) proposed the PeerTrust model, which considered factors such as transaction satisfaction, transaction quantity, transaction credibility, transaction context and transaction community environment, and it also proposed a structured trust calculation method. However, the model did not explain how these factors are established, how conspiracy attacks cannot be resisted and the complexity of the structure of recommendation credibility. Jiang and Li (2007) proposed a P2P e-commerce trust model based on reputation. This model considered relatively comprehensive trust factors, and it aggregated the local reputation and global reputation of nodes into the comprehensive trust of nodes. However, the model is complex, and the engineering maneuverability is poor. Li *et al.* (2007) proposed a trust model based on similarity weighting in the P2P environment and improved the trust model based on recommendation given by Dou, which adopted a global iteration model similar to EigenRep. However, it is difficult for the model to resist malicious attacks, required the nodes to have good computing power and the data storage and updating program is complex, so the engineering operability is low. Liu *et al.* (2013) proposed a trust network-based trust computing method. In the trust network, service trust and recommendation trust constructed the social relations between users. The influences of interaction number, time, reputation, service trust and recommendation trust are comprehensively considered in trust computing and propagation in trust network. It's a general method but should be modified with specific parameters in e-commerce.

However, there are still some remaining problems on which literature has insufficient discussions. Most research on the credit problems of e-commerce is on the legal system and transaction processes, which are all measures to improve the credit system. Existing credit evaluation models pay too much attention to the static factors of trading subjects and e-commerce platform technology, but these pay less attention to the transaction itself. The lack of comprehensive consideration of transaction process factors, or the simple quantitative calculation during evaluating of transaction credit, leads to the lack of accuracy and the lack of resistance to malicious attacks for the credit evaluation model.

3. Transaction credit model based on the crowd transaction network

In the crowd transaction network, when buyers have purchase demands, they need to search for corresponding commodities in the crowd transaction network with six degrees of separation. Then, they can accurately match and get a list of recommended commodities. When buyers browse their desired products, before making the purchase decision, they need to check the seller's credit information and the product's evaluation information in the crowd transaction network, and then calculate the seller's credit. After the transaction completion, the buyer evaluates the seller, calculates the seller's transaction credit and updates it and then releases the evaluation and relevant credit data to the circle of friends. Such process is summarized in Figure 2.

The above process design shows that the transaction credit based on the crowd transaction network is the premise of credible and secure transactions. Therefore, the model is able to accurately measure the seller's fulfillment of the transaction agreement and to resist malicious attacks in the network.

3.1 Model setup

3.1.1 Transaction evaluation. Existing studies (Hennig-Thurau *et al.*, 2004; Liu, 2006; Gupta and Harris, 2010) show that before making transactions, users of e-commerce platforms usually refer to purchase and evaluation records of other users, which can play an important role in making the purchase decisions of future buyers. Transaction evaluation is the direct manifestation of the seller's performance and an important factor to evaluate seller's credit. We use the continuous evaluation method in this paper. Buyers' evaluation on the sellers varies within the range of [0,1], which not only reflects the buyer's real thoughts but is also easy to distinguish.

3.1.2 Transaction times. The seller's performance of the transaction agreement is the expression of the transaction subject's behavior, which varies with different time stages. According to the recency effect, the closer the transaction is to the current time, the better it can reflect the seller's transaction credit (Ha, 2004). Unfortunately, at present, most e-commerce platforms ignore this effect, leading to malicious behaviors such as the seller fraud, periodic fraud, etc. This paper considers using the time decay effect to distinguish the historical transactions. The closer/further the transaction is to the current time, the greater/smaller the impact on transaction credit. To reduce the computational complexity and storage load, we use the decay factor of the time window, γ, to measure the time decay effect, as shown in equation (1).

$$\gamma = e^{-\vartheta \times \cdot T} \tag{1}$$

where $\vartheta \in (0, 1]$ is the attenuation coefficient; $\Delta T = T_{\mathrm{now}} - T_{\mathrm{transaction}}$ is the difference between the time window at the current moment and the time window at the transaction time.

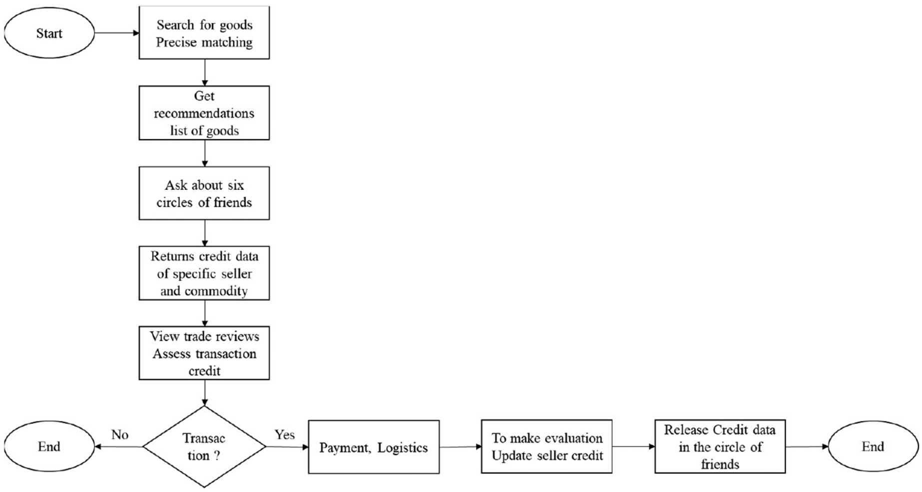


Figure 2.
Process of transaction

According to the distance from the current time, the time window is marked as: T_1, T_2, . . ., T_w, where T_w is the nearest time window to the current time. The last moment of each window is denoted as T_{end_1}, T_{end_2}, . . ., T_{end_w}, where T_{end_w} is the last time in the time window closest to the current time.

3.1.3 Transaction amount. In the process of e-commerce transactions, receipts and payments are separated in time. Before product delivery, the seller has to pay certain commodity money in advance as the "accounts receivable." Higher transaction amount results in greater "accounts receivable" – such "accounts receivable" can partially reflect the seller's ability to fulfill the transaction contract. On the other hand, some sellers accumulate transaction credit rapidly through small transactions. After obtaining enough transaction credits, they turn to sell overpriced commodities. Such behavior is one of the common cheating methods of sellers. For these two reasons, this paper introduces the transaction amount into the transaction credit model: larger/smaller the transaction amount means greater/smaller the impact on the transaction credit. We use a weight coefficient of transaction amount to measure the influence of amount, as shown in equation (2).

$$\omega_k = \frac{m_{wk}}{M_w} \tag{2}$$

where ω_k is the weight coefficient of amount of the kth transaction to the transaction credit; m_{wk} is the transaction amount of the k^{th} transaction in the w^{th} time window; and $M_w = \sum_{k=1}^{n} m_{wk}$ is the total amount of transactions between the buyer and seller in the w^{th} time window.

3.1.4 Transaction status. Transaction status refers to the final status of the transaction, including transaction success and transaction failure. When a transaction fails, the defaulting subject should be identified according to the reasons of the failure. For the defaulting subject, its transaction credit should be reduced. This paper sets the penalty factor for transaction failure, and it comprehensively considers the number of transaction failures and the amount of transaction failures. Equation (3) calculates φ, the weight coefficient of transaction failure.

$$\varphi = \frac{f_w}{1 + \left[e^{1-(z+g_w)}\right]} \tag{3}$$

where the binary variable $f_w = \begin{cases} 0, & \textit{no failure record in } w^{\text{th}} \textit{ window} \\ 1, & \textit{failure record in } w^{\text{th}} \textit{ window} \end{cases}$; z is the number of failed transactions within the w^{th} time window; and g_w is the level of the total amount of failed transactions within the w^{th} time window.

Owing to the wide variation range of transaction amount, this paper uses transaction amount level to replace the quantity of transaction amount, as shown in Table I.

3.1.5 Direct transaction credit. Through modeling and analysis of the influencing factors of transaction credit, we calculate D_{ij}, the direct transaction credit of seller j relative to buyer i in the time window T_w in equation (4).

$$D_{ij} = \sum_{k=1}^{n} C_k \times \omega_k - \left(\sum_{k=1}^{n} C_k \times \omega_k\right) \times \varphi \tag{4}$$

where $C_k \in [0,1]$ buyer i's evaluation of seller j on the kth transaction; ω_k is the weight coefficient of the transaction amount for the k^{th} transaction, defined in equation (3); φ is the weight coefficient of transaction failure, defined in equation (2); and n is the number of transactions between buyer i and seller j in the time window T_w.

Equation (4) calculates the transaction credit within the time window. To improve the accuracy and effectiveness of transaction credit, this paper adopts an iterative method of the time window to calculate the seller's current direct transaction credit, as shown in equation (5).

$$D_{ij} = \mu \times D_{ij}^{\left(T_{\mathrm{end}_{w'}}\right)} + (1-\mu) \times D_{ij}^{(T_w)} \tag{5}$$

where $D_{ij}^{\left(T_{\mathrm{end}_{w'}}\right)}$ is the direct transaction credit of seller j relative to buyer i at the last moment of the time window with transaction history, in addition to the current time window; $D_{ij}^{(T_w)}$ is the direct transaction credit of seller j relative to buyer i in the current time window; and μ is the historical transaction credit-weighting coefficient. The calculation of μ needs to take the influence of transaction time and transaction amount into account, as shown in equation (6).

$$\mu = \frac{1}{2} \times \left(\frac{\gamma}{1+\gamma} + \frac{\gamma \times M_{ij}^{\left(T_{\mathrm{end}_{w'}}\right)}}{M_{ij}^{(T_w)}} \right) \tag{6}$$

where $M_{ij}^{(T_w)}$ is the cumulative transaction amount of buyer i and seller j up to the current time; and $M_{ij}^{\left(T_{\mathrm{end}_{w'}}\right)}$ is the cumulative transaction amount of buyer i and seller j up to the time window with historical transactions, in addition to the current time window.

To avoid the rapid improvement or decline of seller's transaction credit, the convergence rate of direct transaction credit is controlled by equation (7).

$$D_{ij}^{'} = 0.5 + \tau_1 \times \left(D_{ij} - 0.5\right) \tag{7}$$

where N_{ij} denotes accumulative total transaction number between buyers i and sellers j; and $\tau_1 = e^{-\left(\frac{1}{N_{ij}}\right)}$. Note that $\lim_{N_{ij}\to\infty} \tau_1 = 1$, effectively controls the rate of convergence, preventing the seller from improving credit value quickly through a few trading days.

3.1.6 Recommend transaction credit. The recommendation node refers to the node that has transacted with the target seller j. In this paper, recommendation nodes are divided into two categories. One is recommendation node l, which has transaction histories with buyer i. The other is the recommendation node s, which have no transaction histories with buyer i. By integrating the direct transaction credits of target seller j relative to these two recommendation nodes, R_{ij}, the recommended transaction credit of target seller j relative to buyer i is calculated in equation (8).

Transaction failure amount (yuan)	Transaction failure amount level
(0, 100]	1
(100, 300]	2
(300, 500]	3
(500, 1,000]	4
(1,000, 3,000]	5
(3,000, 5,000]	6
>5,000	7

Table I. Transaction failure amount

$$R_{ij} = \begin{cases} \delta_1 \times \sum_{l=1}^{L}\left(\eta_l \times D'_{lj}\right) + \delta_2 \times \sum_{s=1}^{S}\left(\eta_s \times D'_{sj}\right), & recommendation\ node \\ 0.5, & not\ recommendation\ node \end{cases} \tag{8}$$

where δ_1 and δ_2 are the recommendation weight Coefficients 1 and 2, respectively; η_l and η_s are the recommendation credibility of l and s, respectively; and L and S are the numbers of recommendation nodes l and s, respectively.

Among the above notations, the transitivity of transaction credit is used to obtain the recommendation credibility of recommendation node l, as shown in equation (9):

$$\eta_l = \frac{D'_{il}}{\sum_{l=1}^{L} D'_{il}} \tag{9}$$

The recommended node s recommended credibility, using the difference between the direct transaction credit of seller j relative to buyer i and the direct transaction credit of seller j relative to recommended node s. If the difference is very big, recommend node s and buyers' point on the same thing has a very big difference, and then the recommended value of s is given a small weight, as shown in equation (10):

$$\eta_s = 1 - \sqrt{\left(D'_{ij} - D'_{sj}\right)^2} \tag{10}$$

δ_1 and δ_2 are the recommendation weights of these two types of recommendation nodes, and the weights represent the degree of trust in these two types of recommendation node sets. Buyers can set the weight according to their own strategies, or consider the influence of transaction amount. It is believed that the greater the transaction amount between the recommendation node set and seller j, the greater the weight will be. As shown in equation (11):

$$\delta_1 = \frac{\overline{M_L^{(T_w)}}}{\left(\overline{M_L^{(T_w)}} + \overline{M_S^{(T_w)}}\right)} \quad \text{and} \quad \delta_2 = \frac{\overline{M_S^{(T_w)}}}{\left(\overline{M_L^{(T_w)}} + \overline{M_S^{(T_w)}}\right)}, \tag{11}$$

where $\overline{M_L^{(T_w)}}$ is the average of cumulative transaction amount of all recommendation node l and seller j (by the current time); $\overline{M_S^{(T_w)}}$ is the average of cumulative transaction amount of all recommendation node s and seller j (by the current time).

Similar to direct transaction credit, this paper uses the $\tau_2 = e^{-\left(\frac{1}{L+S}\right)}$ to control the convergence rate of the recommended transaction credit.

3.1.7 Comprehensive transaction credit. Comprehensive transaction credit is the integration of direct transaction credit and recommended transaction credit, which not only takes into account the views of buyers themselves but also refers to the views of other nodes, making the credit evaluation results accurate and comprehensive. As shown in equation (12):

$$T_{ij} = \alpha \times D'_{ij} + \beta \times R'_{ij} \tag{12}$$

where T_{ij} is the comprehensive transaction credit of seller j relative to buyer i; α and β are direct transaction credit weight coefficient – the recommended transaction credit weight coefficient.

Note that as the key in the process of comprehensive transaction credit calculation, $\alpha + \beta = 1$. On the one hand, buyers can set their own weights; on the other hand, the weight can be determined according to the transaction amount and transaction times with the seller, as shown in equation (13).

$$\alpha = \frac{1}{2} \times \left(\frac{M_{ij}^{(T_w)}}{M_{ij}^{(T_w)} + \overline{M_{LS}^{(T_w)}}} + \frac{N_{ij}}{N_{ij} + \overline{N_j}} \right) \quad \text{and} \quad \beta = 1 - \alpha, \tag{13}$$

where: $M_{ij}^{(T_w)}$ is the cumulative transaction amount of buyer i and seller j (up to the current time); $\overline{M_{LS}^{(T_w)}} = \frac{\sum_{k=1}^{L+S} M_{kj}^{(T_w)}}{L+S}$ is the average value of the cumulative transaction amount between the recommendation node and seller j (up to the current time); N_{ij} is the cumulative transaction times of buyer i and seller j; and $\overline{N_j} = \frac{\sum_{k=1}^{L+S} N_{kj}}{L+S}$ is the average value of cumulative transaction times between the recommendation node and seller j.

3.2 Storage and update of the credit data

The crowd transaction network is an unstructured network with six degrees of separation. According to the characteristics of its topological structure and transaction process, this paper adopts the "buyer + circle of friends" mode to store the credit data. Such mode fully uses the computing the storage ability of the internet, and it also solves the failure problem of using a single node. After the transaction, the buyer evaluates the seller, calculates and updates its direct transaction credit according to historical transaction records and then releases the evaluation and relevant credit data to the circle of friends. Therefore, each node should have two credit data tables, namely, direct credit data table and the circle-of-friends credit data table.

Direct credit data table is used to record the transaction history of the sellers who have the transactions with this node, which is kept by the buyer himself. Table II shows the structure of direct credit data table. The circle-of-friends credit data table records the credit data received from circle of friends, which records the credit information and evaluation information of the sellers who have been trading with friend nodes in circle of friends. The data in this table are used to give feedback to the credit query request. Table III shows the circle-of-friends credit data. Figure 3 shows the specific storage process.

Direct credit data table is update by a replacement mode. When a transaction with a certain seller is present, if the record of the seller already exists in the direct credit data table, the transaction is directly updated on the old record. Otherwise, the transaction is recorded in the direct credit data table. By adopting the updating method, the data in the table can be guaranteed to be up-to-date, and the storage space is saved.

To reduce the storage space of the node, the circle-of-friends credit data table has a certain capacity and only retains the credit data records of the most recent period (such as three months). When the latest credit data are received from the circle of friends, if the capacity of the credit data table is full, the credit data record which is farthest from the current time is deleted and the new credit data record is stored. If the capacity of the credit data table in moments is not full, the latest credit data records are imported directly to the data table. This update can ensure that the records of credit information in the circle-of-friends credit data table are always updated.

Table II.
Direct credit data table

Seller ID	Transaction window	Last transaction window	Value evaluation	Transaction times	Transaction amount	Window transaction amount	Cumulative transaction amount	Failure times	Failure amount	Direct transaction credit
BID1	T1	T1'	C1	N1	m1	M1'	N1	z1	F1	D1
BID2	T2	T2'	C2	N2	m2	M2'	N2	z2	F2	D2
BID3	T3	T3'	C3	N3	m3	M3'	N3	z3	F3	D3
…	…	…	…	…	…	…	…	…	…	…

Regarding to the search of the credit data, many mature methodologies have been widely used, e.g. the flooding method (Wang, 2001), and the combination of wide and deep search method (Kalogeraki *et al.*, 2002; Xu *et al.*, 2007b). This paper does not discuss the details.

4. Simulation

This section verifies the accuracy and anti-aggression of transaction credit model through simulation experiment. The simulation experiment was carried out on NetLogo (see http://ccl.northwestern.edu/netlogo), which is a prevalent multi-agent simulation modeling tool in the field of artificial intelligence.

According to the quality of service provided, all nodes in the network are divided into four categories: honest service nodes, dishonest service nodes, random service nodes and oscillating service nodes. The honest service nodes always provide honest service. Dishonest service nodes always provide dishonest service. Random service nodes sometimes provide honest service; other times provide dishonest service. Quality of service provided by oscillating service nodes has periodicity, i.e. one period of time to provide honest service, the next period to provide dishonest service and so on.

According to the quality of evaluation, the nodes in the network are divided into honest evaluation nodes, exaggerated evaluation nodes, collusion evaluation nodes and denigration evaluation nodes. The honest evaluation node's evaluation of the transaction object is always true. Exaggerated evaluation node always exaggerates the evaluation of the transaction object. The evaluation of the collusion evaluation nodes to their collusion partners is high, but the evaluation of the nodes other than the collusion partners is low. The denigration evaluation node's evaluation of the transaction object is always low.

In the simulation experiment, this paper sets a service quality parameter, *service-quality* (represented by r), to achieve the above evaluation strategy. The service quality of the honest service node is represented by this parameter, so the honest evaluation node's evaluation of the honest service node is r. An exaggerated evaluation node is given to the transaction object according to the exaggeration factor, *exaggeration*; for example, the evaluation of an honest service node is given to $\{r + exaggeration \cdot (r - 0.5)\}$. The collusion evaluation node's evaluation of its collusion accomplices is r, while the evaluation of non-collusion accomplices is $1 - r$. The evaluation of denigration evaluation node to its transaction object is $1 - r$. It is assumed that the service provided by any node can be evaluated accordingly.

Seller ID and commodity ID	Evaluation buyer ID	Transaction time	Value evaluation	Text evaluation	Cumulative transaction amount	Transaction times	Direct transaction credit
BID1_CID1	UID1	t1	C1	A1	M1	N1	D1
BID1_CID2	UID2	t2	C2	A2	M1	N1	D1
BID2_CID1	UID3	t3	C3	A3	M2	N2	D2
...	...	...	...	...	...	...	...

Table III. Circle-of-friends credit data table

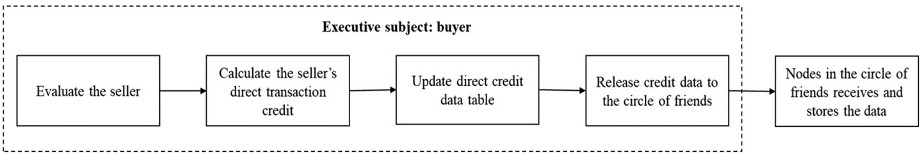


Figure 3. Storage process of credit data

4.1 Experimental analysis of accuracy

Because we want to only verify the accuracy of direct transaction credit calculation, all nodes are set as honest evaluation nodes. Experimental results are shown in Figures 4, 5 and 6.

Figure 4 shows the direct transaction credit trend chart; 4(a) is under time window $T = 10$ and 4(b) is under time window $T = 5$. The longer the time window, the more transactions in the time window. By comparison, it can be found that the larger the time window T is, the slower the direct transaction credit's convergence will be. This is because the larger the time window is, the greater the influence of historical transaction data on the direct transaction credit will be. Before the convergence, the direct transaction credit obtained from historical trading data is relatively low.

It can be seen from Figure 4 that the direct transaction credit proposed in this paper has a good ability to distinguish, and the direct transaction credit of the four types of nodes has

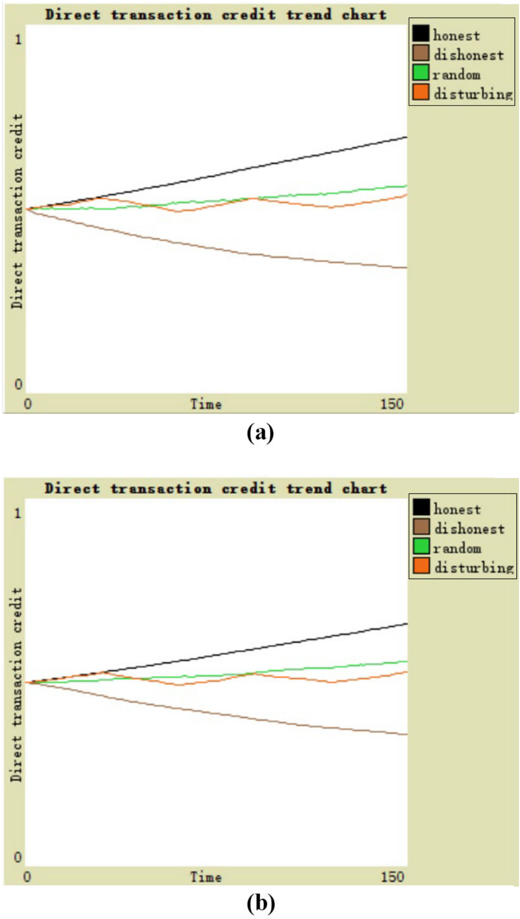


Figure 4.
Direct transaction credit trend chart

Notes: (a) Time window $T = 10$; (b) time window $T = 5$

different evolution trends. Honest service node's direct transaction credit is continuously improved by providing honest service. The direct transaction credit of dishonest service node decreases continuously because of providing dishonest service. The direct transaction credit of random service node and oscillating service node is between honest service node and dishonest service node. The direct transaction credit of oscillating service node oscillates continuously with the oscillating cycle. This shows that the direct transaction credit in this paper has high accuracy.

Figure 5 shows the relationship between transaction amount and direct transaction credit. Taking the honest service node as an example, it can be seen from the figure that the larger the transaction amount is, the larger the direct transaction credit will be and the faster its convergence rate will be. On the contrary, the smaller the direct transaction credit will be and the slower its convergence rate will be. This also verifies the relationship between transaction amount and transaction credit analyzed above, and at the same time, to a large extent, it can avoid the problem that sellers accumulating credit through small transactions and then cheats through large transactions.

Figure 6 shows the relationship between the number of failed transactions and direct transaction credit. Taking oscillating service node as an example, it can be seen from the figure that, with the increase in transaction failure probability, its direct transaction credit is continuously decreasing. When transaction fails owing to the reason of the sellers, the

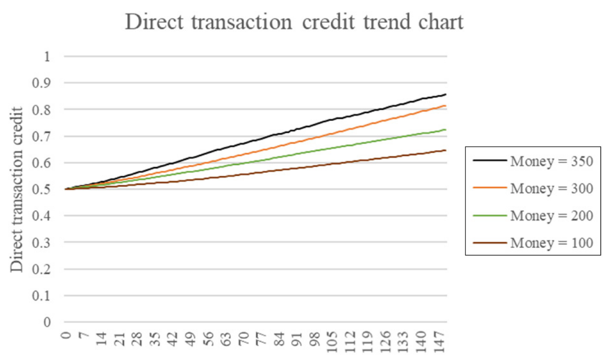


Figure. 5.
Impact of transaction amount

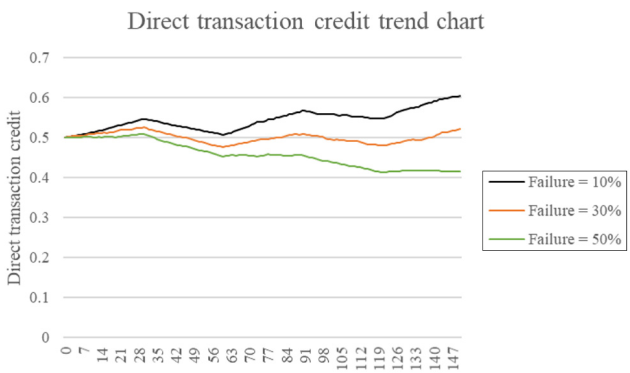


Figure 6.
Impact of failed transactions

transaction credit will be punished, and the more times the transaction fails, the greater the punishment, which can effectively avoid the malicious behavior of the sellers.

4.2 Experimental analysis of anti-aggression

This experiment investigates the anti-attack ability of transaction credit model under different proportions of malicious evaluation nodes. Experimental results are shown in Figures 7 and 8.

Figures 7 shows how the trend of comprehensive transaction credit changes; 7(a) is when the proportion of malicious nodes were 20 per cent, 7(b) is 50 per cent and 7(c) is 80 per cent. The transaction credit model shows good ability to resist attacks, in the presence of malicious evaluation of the transaction in the network can still to distinguish the different types of service node, makes their comprehensive transaction credit have different trends and has little to do with the intensity of malicious attacks. In particualar, when the malicious evaluation become the mainstream in the transaction network (with 80 per cent malicious nodes), honest service nodes' comprehensive transaction credit decreases because of malicious evaluation, but the transaction credit model is still able to distinguish the different type of service node, the honest service nodes' comprehensive transaction credit is still at a relatively high level. This further confirms the anti-aggression of the transaction credit model.

To further verify the anti-aggression of the transaction credit model, this paper sets up a comparative test. The comparison model (represented by ARM model) sets the recommendation credibility of all recommendation nodes to be the same. It can be seen from Figure 8 that honest service nodes' comprehensive transaction credit is at a higher level and rising under this model. However honest service nodes' comprehensive transaction credit under ARM model is at lower levels and rising very slowly, because it cannot be effective against malicious attacks, such as collusion evaluation, denigration evaluation and exaggeration evaluation.

5. Conclusion

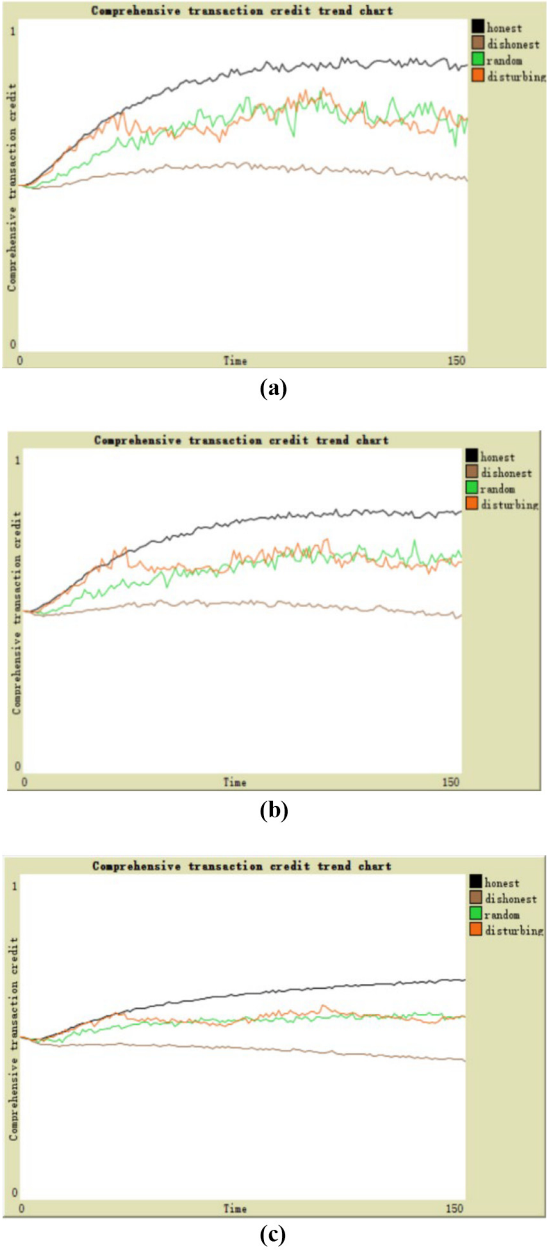
Motivated by the common problems existing in current transaction credit models such as the one-sided measurement, low accuracy and insufficient anti-aggression solutions, this paper studies the transaction credit model based on the unstructured crowd transaction network.

The approach comprehensively considers the influencing factors that affect the transaction credit, including the transaction evaluation, transaction time, transaction status, transaction amount, transaction times, etc., improving the accuracy of the transaction credit evaluation. To reduce the negative impact of malicious attacks such as the collusion evaluation, the study divides the nodes (buyer or seller) into two categories and constructs the recommendation credibility based on each type. The simulation results show that such mechanism increase both the credibility and the accuracy of the recommendation.

This paper proposes a "buyer + circle of friends" storage method, which fully uses the ability of computing and storage of all nodes. Compared with the centralized storage method or using a single node for storage, our proposed method completely avoids a significant disadvantage of these methods – when the storage nodes have malfunction, or go offline, or quit the network, the credit data are inaccessible or the entire network is down.

However, owing to the complexity of the network and the difficulty of the trust issue, there still exist some shortcomings that need further discussions in the future.

- *Evaluating the buyers' transaction credit*: This paper focuses on the transaction credit modeling for sellers. Although the analysis of the transaction behavior also applies to the buyers in this paper, the credit modeling of buyers may involve the influence of different factors and analysis methods, because the purpose and positon of the transaction about



Notes: (a) With 20% malicious nodes; (b) with 50% malicious nodes; (c) with 80% malicious nodes

Figure 7.
Trend of comprehensive transaction credit changes

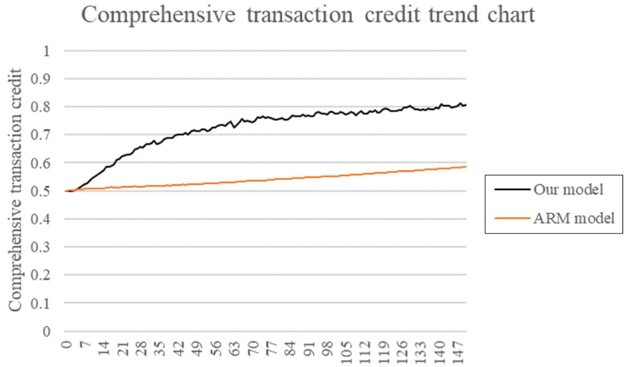


Figure 8. Comparison with ARM model

buyer and the seller is different and the transaction behavior made is also different in the process of specific transactions. In addition, although buyers are at a disadvantage of asymmetric information, opportunism may occur for the sake of interests. Therefore, the next research direction is to evaluate the buyer's transaction credit.

- *Semantic analysis of the transaction evaluation*: Although this paper comprehensively considers the factors affecting the transaction credit in the transaction process, it does not consider the text comments in the transaction evaluation. As an important part of transaction evaluation, text comments in transaction evaluation are an important measurement scale for the performance of the seller's transaction agreement in addition to numerical evaluation. Therefore, it is necessary to conduct semantic analysis on transaction evaluation and discuss its impact on transaction credit.

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