Research Article

E-Commerce Credit Network Control Strategy from a Critical Perspective

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Credit problems are the main bottleneck in the development of e-commerce. Both the time and degree of e-commerce credit control directly affect its economic benefits. From the perspective of the criticality of complex systems, this paper explores the control node of e-commerce credit behaviour. Implementing control in this node can not only ensure the stable development of the credit network but also optimise the control cost. This paper constructs a credit behaviour model for the four regulatory behaviours of the transaction subject, analyses the evolution law of the credit network, and determines the critical state of the network. Finally, the paper’s empirical analysis and simulation experiments prove that when the false information in the credit network in the empirical data is 32%, the implementation of credit control has an efficient control effect. Nevertheless, 32% is not a universal result; the specific critical point value needs to be recalculated according to the theoretical derivation of the critical point combined with the actual network. These research results can help regulators obtain the highest regulatory return with the lowest regulatory investment.

1. Introduction

According to the general requirements of “developing digital economy and building digital China,” China issued the 14th five-year plan for e-commerce development in 2021. This plan proposed “taking high-quality development as the theme” and taking multiple measures to realise the high-quality development of the e-commerce industry itself. The China Internet Development Report (2021) shows that in 2020, the national e-commerce transaction volume reached 37.21 trillion yuan, with a year-on-year increase of 4.5%, and the number of online shopping users reached 810 million. Moreover, November 11, an ordinary day before 2009, has been established as a landmark Shopping Festival in China. This festival has driven not only the rapid development of China’s e-commerce industry but also the development of logistics, manufacturing, and network technology. However, given these large-scale users, credit problems behind the high transaction volume also arise. According to statistics, during the November 11 period, the return rate of Taobao was more than 20%, that of JD was about 10%, and that of live e-commerce was as high as 60%. In this fierce competition, the lower profits forced e-commerce to lower prices, which further led to the deterioration of the quality of some products. This, in turn, resulted in a high return rate, increasing the costs of e-commerce operators and forming a vicious circle. The e-commerce credit system has the characteristics of a complex system. This paper analyses China’s “new development pattern” by taking the credit behaviour of operators and consumers as the starting point and employing the idea of the “criticality” of complex systems, that is, systems have the best control efficiency when the credit system is in a critical state. This is an important way to promote the “high-quality development” of e-commerce in China.

The difference between e-commerce and traditional commerce is that e-commerce integrates information technology, communication, and business processes,
making the transaction process more convenient. Thus, e-commerce provides a way for individuals and organisations to share information through integration [1]. However, the credit problem of e-commerce has always been a concern of Chinese scholars. In order to better promote the healthy development of new business models in the field of e-commerce, the research group on credit construction in the field of e-commerce in the editorial department of “China credit” carried out in-depth research, collected and sorted a large amount of data, analysed the overall development trend of the e-commerce industry and the general background of the macroeconomic situation, and put forward early-warning and preventive measures for various possible credit risks. At present, the research on e-commerce credit is mainly divided into two mainstream directions: credit evaluation and credit risk. With the rapid development of big data, many e-commerce platforms have made innovations in technology, security, strategy, and other aspects to actively improve their credit level. Nevertheless, they cannot avoid false credit evaluation problems such as bill-swiping, commodity information distortion, and malicious bad evaluation [2]. At first, scholars explored the interactive behaviour caused by competition among business entities in e-commerce. For example, based on game theory and Petri net theory, Liu et al. [3] designed an e-commerce credit risk game mechanism to ensure the local and global optimal utility of individuals and groups. Later, scholars found that the credit risk in e-commerce is not only the result of the game between different sellers but also the result of the game between network traders and managers. Therefore, the government should play the role of macro-control and participate in the game process as a participant so that the game result is close to Pareto optimality [4]. However, by testing Internet consumer purchasing behaviour data collected via a web survey, it is concluded that the presence of a third-party seal did not strongly affect consumers’ trust [5]. Taking Taobao as an example, the second-hand service platform has a direct impact on the quality of Taobao’s service. Zhang and Xixi [6] identified the sensitive factors and key factors of e-commerce credit risk based on Bayesian networks and empirical analysis and concluded that national supervision is one of the key factors. The research methods of e-commerce credit risk are mainly divided into two categories: qualitative investigations of the formation and mechanism of risk from the perspective of law and economics [7, 8] and quantitative analyses of the early-warning model and dynamic-evaluation models of risk from game theory, economic theory, and mathematical methods [9, 10].

Two pioneering papers in Science and Nature in 1998 and 1999 marked the rise of complex network theory by proposing the small-world network model and scale-free network model. It is precisely because of this topic’s complexity and generality that it has aroused great interest from scholars, both in theoretical research [11–13] and applied research [14]. Wang et al. [15] systematically introduced the relevant basis of complex networks and described the propagation mechanism and synchronization control of complex networks in detail, which is an area of particular interest in many fields. Moreover, Wang et al. [16] constructed a complex network recovery model based on a polar Dalian Tong subgraph boundary and designed network average recovery and optimal recovery strategies. Zhang et al. [17] studied the random synchronization of complex network clusters through fixed time control technology and made a contribution to the theoretical research on the synchronization convergence of complex networks. Zheng et al. [18] constructed a generalised Friedkin model with time-varying parameters to describe the dynamics of stochastic belief systems in complex networks under time-varying constraints.

Several scholars have also sought to identify the criticality component of complex systems [19–21]. In BA networks, the failure of a critical node may pull down the whole network, while the network still functions normally even if any edge breaks down [22, 23]. The problem of the universality of critical exponents in complex networks is studied based on networks built from seismic data sets. These studies show that the critical exponent is not universal in some scale-free complex networks. Therefore, finding the critical point of complex networks has become an issue of great academic interest, and many algorithms for this purpose have emerged [24, 25].

Inspired by both the needs of practical management problems and the literature discussed above, this paper puts forward the control strategy of e-commerce credit networks from the perspective of complex network criticality to ensure the stable operation and efficient management of e-commerce systems. The main contributions of this paper are as follows: (1) proposing the viewpoint of maximising management and control efficiency at the critical point of system evolution, applying it to e-commerce credit networks, and verifying it through mutual confirmation by empirical analysis and simulation experiment; (2) summarising four behaviours of nodes in e-commerce credit networks and constructing the behaviour model of the nodes; and (3) analysing the evolution law of the network based on the node behaviour model and obtaining the critical probability of the system.

The remainder of this paper is organised as follows. In Section 2, the paper analyses the credit behaviour of e-commerce and constructs a credit behaviour adjustment model. In Section 3, the critical state of the credit network is obtained by analysing the evolution law of e-commerce credit networks. In Section 4, the mutual confirmation of empirical data analysis and the simulation experiment is carried out. Section 5 is the conclusion of the article.

2. Analysis of Individual Behaviour Model of E-Commerce Credit Networks

2.1. Problem Analysis. Schelling, the Nobel laureate, argued in his book that “it is precisely the interactions between individuals that lead to a sudden convergence in the behaviour of the whole group.” The famous scientist Philip Ball, in his study of changes in individual behaviour leading to the emergence of group behaviour, argued that “a sudden change in the behaviour of a group is not necessarily the
result of a unanimous demand by all individuals,” and “the more likely it is that the behaviour of a group will automatically change direction, even if the tendency of the individual changes only slightly.” It can be concluded that for a complex adaptive system, changes in the behaviour of just a few individuals can lead to changes in the overall state of the system. The e-commerce credit system studied in this paper is a complex adaptive system in which the behaviour of the participants is random and nonlinear. The information transmission between consumers and operators and the relationship between transactions form an intuitive dynamic network. In this network, the transaction subject is defined as the node in the network and the weight of the arc in the network is defined as the credit size. The resulting credit network is a directed network. The interaction of individual behaviour under the influence of the network makes the network more complex. If we can determine which or how many individuals in the transaction credit network behave in ways that percolate through the entire e-commerce system, we can use this threshold as a reference to achieve reasonable and efficient control over the e-commerce industry’s credit problem.

2.2. Analysis of Individual Connections in E-Commerce Credit Network. China’s e-commerce credit network is a dynamic network. Occasionally, it will show different credit connections, thus forming a directed graph at a certain moment. Therefore, the e-commerce credit network is a graph of a stochastic process. If there is a flow of information at all the points on the graph, including both trustworthy and non-trustworthy information, the e-commerce system is considered to be functioning at that time. When the point where there is a flow of information is very small, if a point is connected to many points, and the flow of information is large, then that point is considered important. Nevertheless, this situation will change over time.

References to the power-law distribution in the market structure of e-commerce are verified based on the market share data of e-commerce in China from 2007 to 2013 and in the United States from 2004 to 2013. The e-commerce credit network is an open system with a growth mechanism, and the connection between each principal is a preferential connection mechanism based on the size of the revenue. Therefore, the e-commerce credit network can be described by the scale-free network model as follows:

- Suppose 1: the ecommerce credit network is regarded as composed of many subsystems including a variety of both consumer subsystems and operator subsystems. Consumer subsystems of the same type engage in a cooperative game. A noncooperative adaptive game is carried out between the consumer subsystem and operator subsystem, between the operator and operator subsystem [26].
- Suppose 2: the topological structure of the e-commerce credit network is stochastic and dynamic. The individual determines the game object according to the rule of maximising his own profit and makes the priority connection [27].

Under the above hypothesis, it is possible to set the initial condition \((t=0)\). The network is composed of \(n_0\) isolated nodes. After each time step \(t\), a new node is added to the network, the node with \(n(n < n_0)\) edges. The probability that a new node will connect to the existing node \(i\) in the network is

\[
P_i = \frac{k_i}{\sum_{j=1}^{n} k_j},
\]

where \(n_0\) is the total number of nodes in the current system. After time interval \(t\), the algorithm generates a network with \(N = n_0 + t\) nodes and \(nt\) edges. It can be assumed that the degree \(k_i\) of node \(i\) changes continuously with respect to time \(t\) and is expressed as \(k_i(t)\). Then, for any node \(i\), the change of degree \(k_i(t)\) satisfies the following dynamic equation:

\[
\frac{\partial k_i(t)}{\partial t} = A\Pi(k_i) = A \frac{k_i}{\sum_{j}k_j},
\]

The total degree of the network is \(\sum k_j = 2nt\), and the change of the total degree of the network at each time step is \(\Delta k = n\). Therefore, with \(A = n\), equation (1) can be transformed into

\[
\frac{\partial k_i}{\partial t} = \frac{k_i}{2t}.
\]

Combined with the initial conditions, the initial degree of each node entering the system is \(k_i(t_0) = n\), where \(t_0\) is the time when the \(i\)th node joins the system:

\[
k_i(t) = n^t \left(\frac{t}{t_0}\right)^{0.5}.
\]

Then, for any node \(i\), the probability that degree \(k_i(t)\) is less than degree \(k\) is \(P(k_i(t) < k)\):

\[
P(k_i(t) < k) = P\left(t_i > \frac{n^2t}{k^2}\right).
\]

Since the point is added in the same time interval, the probability of adding point \(i\) at time \(t\) is

\[
P(t_i) = \frac{1}{n_0 + t}.
\]

By combining formulas (5) and (6), we obtain

\[
P\left(t_i > \frac{n^2t}{k^2}\right) = 1 - \frac{n^2t}{k^2(n_0 + t)}.
\]

Therefore, there are

\[
P(k) = \frac{\partial P(k_i(t) < k)}{\partial k} = \frac{2n^2t}{n_0 + t} \frac{1}{k^3},
\]

when \(t \to \infty\), \(P(k) \sim (2n^2/k^3)\).

Remark 1. In the proof process, every time step \(t\) passes, a new node will be added into the network, where the new node can be a consumer or an operator. If a new consumer is added, it will connect with other consumers to obtain the
evaluation information of a product or it can connect with the operator to complete the transaction. If a new operator is added, it will establish a connection with consumers to complete the transaction and will connect with other operators to complete the noncooperative adaptive game process. It should be noted that trust is generated once a connection is established.

2.3. Construction of Individual Behaviour Model of E-Commerce Credit Network. In an e-commerce credit network, consumers of the same product can be determined as having a cooperative relationship through the mutual reference process of evaluation information, which can be described as a cooperative adaptive game. There is no cooperative relationship between consumers of different products, which is reflected in the boundless connection in the network. Both consumers and operators pursue their own maximum benefits and engage in the behaviour of interest competition with each other. Therefore, they can be described as a noncooperative adaptive game. The topology of this network is dynamic, which is reflected not only in the change of game strategy but also in the dynamic selection of game objects.

Zheng et al. [28] proved that the necessary and sufficient condition for the complex system structure to remain stable is that all agents are familiar with the strategies of other agents in the subsystem, the income is maximised, and the optimal income converges to a certain interval. Moreover, Zheng [29] proved that when time-scale switching occurs, the topology of the agent will change. As a result, the optimal strategy does not exist, but from the perspective of the whole complex system, the optimal strategy of the agent satisfies the Poisson distribution. Based on the above conclusions, this paper constructs the behaviour model of the transaction subject in the e-commerce credit network so that each behaviour subject in the e-commerce credit network is an agent. First, in a short time-scale, the agent needs to judge whether it is in a cooperative game or a noncooperative game. Then, it must consider both its own strategy and its neighbour’s strategy so as to determine its own strategy and adjust its behaviour:

\[
b^j_i(a_i | \omega) = \arg \max_{a_i \in A_j} \pi^j_i(a^j_i, g) + \epsilon^j_i. \tag{9}\]

In the formula, \(j_i\) is the \(j^{th}\) agent in the \(i^{th}\) subsystem, \(\pi\) is the income in the short time-scale, \(a_i\) is the strategy of agent \(j_i\), which belongs to strategy set \(A\), \(a\) is the resource size (parameter) corresponding to strategy \(a_i\), \(g\) represents the topology structure of the game of agent \(j_i\), \(a_i\) is the adjusted strategy of agent \(j_i\), and \(\epsilon\) is noise.

Next, we discuss the adjustment behaviour of agents in the e-commerce credit network system in the following cases:

(1) In the process of e-commerce transactions, cooperative and noncooperative games are carried out, so the following two game behaviours can be established:

(a) Create a new game with agents in other subsystems:

\[
P\left(\pi\left(a^j_i, a^k_i\right) + \epsilon^j_i \geq \pi\left(a^h_i, a^l_i\right) + \epsilon^l_i, \quad \forall i \notin N^j_i(\omega)\right). \tag{10}\]

(b) The new game created by the agent in the same subsystem is as follows:

\[
P\left(\pi\left(a^h_i, a^k_i\right) + \epsilon^j_i \geq \pi\left(a^j_i, a^l_i\right) + \epsilon^l_i, \quad \forall i \notin N^j_i(\omega)\right). \tag{11}\]

where \(N\) represents the set of all neighbours of agent \(j_i\) and \(N^j_i\) represents the set of agent \(j_i\) and all its neighbours.

(2) In the process of an e-commerce transaction, when the consumer and the operator complete a transaction, the consumer will no longer choose the operator when purchasing the commodity again. Here, this is called deleting an old game behaviour:

\[
P\left(\pi\left(a^j_i, a^k_i\right) + \epsilon^j_i \leq \pi\left(a^j_i, a^l_i\right) + \epsilon^l_i, \quad \forall i \notin N^j_i(\omega)\right). \tag{12}\]

(3) In the process of an e-commerce transaction, when the operator completes the first transaction with the consumer, a game is established with the new agent:

\[
P\left(\pi\left(a^j_i, a^N_{i+1}\right) + \epsilon^j_i \geq \pi\left(a^j_i, a^N_{i+1}\right) + \epsilon^l_i, \quad \forall i \in i(\omega)\right). \tag{13}\]

(4) In the process of an e-commerce transaction, when the operator cannot continue to operate due to business- or product-related problems or the consumer does not conduct a transaction within a certain period, the agent exits the system:

\[
P\left(\sum_{i \in N^j_i} \pi\left(a^j_i, a^k_i\right) + \epsilon^j_i \leq \sum_{l \in N^j_i} \pi\left(a^l_i, a^k_i\right) + \epsilon^l_i\right). \tag{14}\]

To summarise, the description of agents’ behaviour can determine whether the system is running normally through the connection between different agents. When agents choose different connection strategies according to the priority connection mechanism, the system’s topology will also change. Zheng (2019) concludes that the agent strategy is the mapping of the system structure and provides research ideas that can be used for reference. Next, the criticality of the credit network is analysed using the evolution law of the credit network topology.

3. Criticality of E-Commerce Credit Network System

3.1. E-Commerce Credit Network System Model. We define a constructional stochastic process \(M(0, 1)\) whose density
function is \( f(x) = 2x, \ x \in [0, 1] \), and take the independent identically distributed random variables \( r_k \), \( 1 \leq k \leq l[E[\pi]]n \), where \( l \) indicates the subsystem number. Then, we rank the random variables in ascending order \( 0 < R_1 < \cdots < R_l[E[\pi]]n \) with \( W_{ij} = R_i[E[\pi]](\sum_{j=1}^{n} R_{ij} + j) \), \( 1 \leq j \leq n \), \( 1 \leq i \leq l \), and \( \sum_{j=1}^{n} R_{ij} = n \).

The generation process of the e-commerce credit network \( C^{(n)} \) can be described as follows: given \( l[E[\pi]]n \) random variables \( L_{j,i,r} \) that are uniformly distributed and independent of each other on \( R_{[E[\pi]](j,i)+r, \} \) agent \( j_i \) sends \( E[\pi] \) edges to agent \( t_{j,i,r} \).

### 3.2. Evolution Law of E-Commerce Credit Network

In the e-commerce system, the behaviour of the transaction subject mainly depends on its own transaction history, the seller’s information about the products searched, and other buyers’ evaluations of the seller. They can be described by their own history policy, local topology, and “neighbour” policy, respectively. As a result of this interaction, very complex nonlinear behaviour emerges from the network. At the same time, the irrational behaviour of some individuals may lead to the rapid collapse of the whole credit network. The literature [13] has proposed that “interest is the psychological basis of credit transmission.” From the perspective of interest, this paper analyses the critical problem of the collapse of the e-commerce credit network. Starting from \( W_{ij} \), the probability that agent \( j_i \) sends agent \( j \) a connection to agent \( t_{j,i,r} \) is zero:

\[
P_1(t_{j,i,r} = t) = \begin{cases} \frac{w_i}{W_j}, & 1 \leq t \leq j, \\ 0, & \text{other.} \end{cases}
\]

(15)

or the probability that agent \( j_i \) deletes the connection to agent \( t_{j,i,r} \) is zero:

\[
P_2(t_{j,i,r} = t) = 1 - P_1(t_{j,i,r} = t) = \begin{cases} 1 - \frac{w_i}{W_j}, & 1 \leq t \leq j, \\ 0, & \text{other.} \end{cases}
\]

(16)

The agent’s six behaviours mentioned above, adjusting behaviours according to the change of strategy, creating new game behaviours in the same subsystem, creating new game behaviours with agents in other subsystems, deleting an old game behaviour, establishing game behaviours with newly entered agents, and quitting the system behaviour, occur with probability \( q_1, q_2, \ldots, q_6 \), respectively. Therefore, it is possible to set the priority connection mechanism and the priority deletion mechanism as \( \Pr_1 = \left( \frac{q_2 + q_3}{q_4} \right) / q_4 \), \( \Pr_2 = \left( \frac{q_4 + q_6}{q_4} \right) / q_4 \), respectively; these mechanisms occur independently. The priority connection mechanism refers to the cooperative object that the newly entered agent preferentially selects to maximise its own benefit. Meanwhile, the interaction of this connection causes a dynamic change in the network.

The probability that node \( t_{j,i,r} = t \) is selected and connected to node \( j_i \) is as follows:

\[
P(t_{j,i,r} = t) = \begin{cases} \frac{q_4 + q_5}{q_2} + \frac{q_3 - q_2 + q_5}{q_1} \frac{w_j}{W_j}, & 1 \leq t \leq j, \\ 0, & \text{other.} \end{cases}
\]

(17)

When a new transaction subject enters or the connection of the old transaction subject changes, the old connection will break, a new connection will be generated, and the structure of the e-commerce credit network will change. In accordance with the priority connection and deletion mechanisms mentioned above, \( (q_4 + q_6) n/q_2 \) connections will be deleted and \( (q_4 + q_5) n/q_2 \) connections will be added. It can be seen from equation (17) that the strategy of the agent mainly depends on \( W_{ij} \).

With the rapid development of e-commerce, the number of agents in the system (network) is also increasing. Here, the degree of \( n \) agents is normalised and denoted as \( 1 \). The degree of agents that are preferentially connected is \( x \), and the degree of agents that are preferentially deleted is \( 1 - x \). Obviously, \( x > 0.5 \) for an e-commerce credit system and agents can only fall in this interval or not. This random event only has two mutually exclusive results, so the random variable is a binomial classification variable that meets the binomial distribution.

### 3.3. Critical State of E-Commerce Credit Network Evolution

Assume that agents in the system have the following sequence: \( 1, 2, \ldots, \mathcal{C}_n, \mathcal{C}_n \), \( n + 1, \ldots, \mathcal{C}_n, \mathcal{C}_n + 1, \ldots, n_{\text{peripheral}} \).

Imagine that there is a critical probability \( c_0 \) such that when \( c < c_0 \), the e-commerce credit system meets the robust process, that is, there are at least two large components to ensure that the system is connected. When \( c \geq c_0 \), the e-commerce credit system will face collapse and the system will no longer be connected, that is, there will be no credit transmission. Therefore, determining \( c_0 \) is necessary for effective control of the e-commerce credit system. Next, we seek to identify this critical probability \( c_0 \).

The e-commerce credit system satisfies process \( \Gamma \): introduce function \( \mathcal{L}_0(a) = 0 \), make \( \mathcal{R}_0(a) = \begin{cases} 1, & 0 < a < a_0 \\ 0, & a_0 < a \leq 1 \end{cases} \), and make \( (\mathcal{L}_0, \mathcal{R}_0) = F((\mathcal{L}_0, \mathcal{R}_0)) \).

Since whether the initial node \( v_0 \) can transmit credit directly depends on whether it is deliberately attacked, it can be set as a function of \( c, \sigma(c) = \sigma(1, c) \). It is easy to see that when \( 0 < c < c_0, \sigma(c) > 0, \mathcal{L}_0(a) \) and \( \mathcal{R}_0(a) \) are nonzero. Therefore, the following equations hold:
\[
\inf_{a \in A} L(a) \leq I(a) = \frac{1}{2^{|d_i^*| + 1}} \int_{u}^{a} \frac{1}{\sqrt{\pi}} \left( |\pi|I(\beta) + (|\pi| + 1)R(\beta)\right) d\beta \leq \sup_{a \in A} \inf_{a \in A} R(a) \leq R(a).
\]

The critical probability can be obtained by transforming the integral form into differential form

\[
c_0 = \frac{q_1 - q_4}{1 + \delta_n(q_1 + q_2 - q_5)} \inf_{a \in A} \pi - 1
\]

Control of e-commerce credit requires the investment of extensive human and financial resources. When the power of investment is insufficient, the e-commerce system will suffer from slow development or the disintegration of credit and subsequent collapse. Conversely, when a large amount of regulatory power is invested, it is necessary to consider whether the ratio of input to output is reasonable. If the economic cost of input supervision is greater than the economic value created by e-commerce, it will be detrimental to economic development. Therefore, \(c_0\) describes whether the e-commerce system is under the condition of appropriate credit regulation (i.e., whether it meets the critical condition for steady development). If the ratio of untrustworthy system participants is less than \(c_0\), regulation can be reduced. However, once the bad-faith proportion of the population is greater than the \(c_0\), the e-commerce system is at risk of collapse and regulation must be stepped up.

4. Numerical Simulation

4.1. Data Collection. In this section, the market research method and network data collection method are used to investigate the online shopping experience. For the market research method, the probability value of individual adjustment behaviour is obtained statistically based on the relevant questionnaire of individual behaviour designed in Section 3. During the investigation, a total of 500 questionnaires were sent out; 479 responses were received, 436 of which were valid after identification. The network data collection method was set based on the results of the questionnaire. Network data were collected through the Taobao, Tmall, and Jingdong online shopping platforms. The information collected mainly included the following phrases: [4] “the n-th buy,” “repo,” and other words, for the same product with no other subjects with new game behaviour; “very poor,” “regret,” and other words; and “good,” “reasonable price,” and other words, meaning that the product will have the possibility of repurchase [5]; according to information about “what else did the buyer of this product buy” provided on the website, a total of 15,966 pieces of information were collected, corresponding to 11,923 nodes.

Through statistical analysis of the above data, the average degree of the credit network is 3.45, the supremum is 3.67, and the infimum is 3.01. Therefore, the probability of credit transmission between entities in the credit network is 0.45, and the probability of disconnection is 0.12. According to the critical probability formula in Section 2.3, the critical probability of this process is 0.32. In other words, among the 15,966 pieces of information collected above, if more than 15,966 \(*\ 0.32 = 6,069.12\) pieces of information are untrustworthy information, the e-commerce credit system will collapse. If regulatory measures are added before this point is reached, the likelihood of e-commerce credit system collapse will be reduced. Alternatively, if the system is allowed to develop without regulation, the e-commerce credit system will eventually collapse.

Remark 2. Pasten et al. [23] found that the critical indices of some scale-free networks are not common when analysing the types of networks constructed from seismic data. Based on the derived critical probability formula, this paper calculates that when there is 32% false information in the credit network, the e-commerce system will face collapse if the system is not controlled. Next, the following two problems are verified by simulation experiments. First, we evaluate whether the simulation results are consistent with the theoretical derivation. Then, we investigate whether 32% is a universal threshold.

4.2. Simulation Analysis. We created an agent-based model in NetLogo with three agent types: consumer, operator, and regulator. This model represents a novel setting for a simulation experiment. For the process of supervision, the method of trustworthy supervision was adopted. This method is reasonable in our context. For example, for reports between peers, the supervisor will pay a certain reward to the informant. Assuming that the initial number of nodes of the credit network is 10, the relevant parameters of the credit network are given according to the data collected above. The connection probability of nodes in the network is given according to the equation [30]. The nodes’ degree distribution in the network is shown in Figures 1 and 2. In Figure 1, the abscissa is “degree” and the ordinate is “of nodes.” In Figure 2, the abscissa is log (degree) and the ordinate is “log (of nodes).”

Next, we simulate control in different credit network evolution stages. The simulation results are shown in Figures 3–5. The abscissa represents the percentage of the evolution time of the three simulation groups in the abscissa diagram.

4.3. Results Analysis. The simulation results show that when the credit network was initially formed, everyone joined the system in accordance with the principle of honesty and trustworthiness. As the system evolved, untrustworthy groups gradually appeared. At this time, the number of
corresponding trustworthy groups decreased. Because we designed the trustworthy person as the supervisor in the simulation process, the sum of the number of supervisors and trustworthy persons is the actual number of trustworthy persons. When the proportion of false information in the credit network is 21.52%, supervision is carried out to avoid the collapse of the system and gradually control the number of dishonest groups so as to make the system continue to develop steadily. When the proportion of false information is 72%, the false information leads to system collapse. Through the simulation results, it can be seen that the system is out of control and eventually leads to collapse. When the proportion of false information is 31.64%, the supervision has higher efficiency than that of 21.52% and will not lead to system collapse; this is essentially consistent with the calculation results of our above empirical data. Therefore,
controlling at the critical point plays a strong role in the stability of the credit network and the efficiency of control.

Finally, we conduct a large number of simulation experiments by adjusting the average degree of network nodes, the number of initial dishonest groups, network scale, and other parameters. We find that while the network critical point does not always stay near 32%, it meets equation (19).

5. Conclusion

E-commerce has the characteristics of remoteness, record changeability, and subject complexity, which lead to more complex and prominent credit problems. Successful e-commerce requires not only trust between e-commerce transaction subjects but also a fair e-commerce transaction platform. It is unrealistic to solve the credit problem of e-commerce in a short time. First, doing so requires not only sound laws, regulations, and systems but also increased human supervision. Second, the biggest difference between e-commerce and traditional transactions is that e-commerce is strongly dependent on information technology. As a result, the security and fraud challenges that arise with information technology will also arise for e-commerce. Currently, the main problems in China’s e-commerce credit system include the general lack of credit awareness and credit ethics, the imperfect internal e-commerce credit management system, the inadequate credit intermediary service, the lack of effective laws, reward and punishment mechanisms, and the publication of false, unhealthy, and even illegal business information on the Internet. These problems are mainly manifested in the disclosure of users’ privacy, information asymmetry on both sides of the transaction, frequent network fraud, and the continual emergence of illegal pyramid schemes.

By establishing the behaviour model of e-commerce traders, this paper analyses the evolution law of the e-commerce credit system, determines the critical state of the system based on complex system theory, and obtains the critical probability for system control. When we control the management strength within this critical range, we can both ensure the stable operation of the e-commerce system and reduce the economic costs of supervision. In addition to enriching the critical theory of complex systems, this result provides a basis for the practice of credit management in China’s e-commerce industry.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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