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Retraction

Retracted: Research on Information Propagation Model in Social Network Based on BlockChain

Discrete Dynamics in Nature and Society

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Manipulated or compromised peer review

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] Y. Zhao, S. Bin, and G. Sun, "Research on Information Propagation Model in Social Network Based on BlockChain," *Discrete Dynamics in Nature and Society*, vol. 2022, Article ID 7562848, 14 pages, 2022.

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Research Article

Research on Information Propagation Model in Social Network Based on BlockChain

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With the development of blockchain technology, many new social networks based on blockchain technology have emerged. The unique consensus mechanism and incentive mechanism of blockchain technology makes the law of information propagation in the new social network different from that in the traditional social network. Based on the information propagation characteristics of blockchain social network, this paper considers the influence of opposing groups of opinions, incentive mechanism and user's conformity psychology in blockchain social network, and uses the evolutionary game to define the transfer process and probability between states and puts forward a new information propagation model. This paper analyses the influence of group density, state transition probability, and incentive policy on information transmission trends in the network through simulation experiments. The comparative experiment with the traditional model shows that the model in this paper can describe the propagation behaviour choices of different propagators under different incentive policies, which the traditional model cannot describe. Using the model in this paper to analyse the information propagation of blockchain social networks can effectively inhibit the propagation of inferior information and further build a good network public opinion environment.

1. Introduction

With the rapid development of Internet technology, many social network services (SNS) have emerged, bringing great convenience to people's daily information acquisition. The continuous interaction of social network users makes all kinds of information quickly spread in social networks. Its huge social graph makes the spread and influence of information easily magnified. These characteristics have made social networks an essential platform for individuals and organizations to express public opinion and release information. Building an information dissemination model based on real networks can reflect the information dissemination process in social networks and predict information dissemination trends [1–5]. It helps researchers better understand information propagation laws and provides theoretical support for other research based on information propagation. In the 1960s, Daley and Kendall proposed the DK model [6]. In the research, they found a certain similarity between information propagation and virus propagation in society. Therefore, later information propagation studies mainly refer to the ideas and methods of infectious disease models or directly use existing models to study information propagation. Classical infectious disease models include SI model, SIS model, SIR model [7], SEIR model [8], other propagation models are mainly based on the classic models mentioned above. The infectious disease model abstracts the various populations in the process of virus transmission into different state nodes and abstracts the infection and recovery process of the population into state transitions between nodes. These classic infectious disease models take a fixed value as the probability of transition between states. These characteristics enable infectious disease models to describe the spread of viruses or information among the population to a certain extent.

With the gradual popularization of blockchain technology, research on information dissemination based on blockchain technology has also been carried out one after another. A batch of social networks with blockchain as the underlying architecture represented by Steemit and Mind has been put into operation one after another. This type of social network uses blockchain to record the release and dissemination of information in the social network so that all users' speeches are traceable and challenging to tamper. Furthermore, this type of social network gives economic and community prestige rewards to contributors and disseminators of high-quality content in the community. And it punishes the creators and disseminators of false information and spam. These characteristics make the cost of producing and propagating information higher. Compared with users in traditional social networks, users in this type of social network pay more attention to their comments in the community. They can view all kinds of information released in the community more rationally, thus constructing a new information propagation environment.

However, the traditional social network communication model is difficult to describe the characteristics of information communication in the blockchain environment. Therefore, it is meaningful to study the propagation law of the social network of the blockchain and construct a propagation model.

2. Related Work

This kind of social network based on blockchain technology has attracted many scholars' attention. Many scholars have made prospects for the application of blockchain in information dissemination. Swan M. [9] first discussed the application prospects of blockchain technology in information propagation. Ersoy O. [10] studied information dissemination in the blockchain and proposed a method that combines routing mechanisms and incentive mechanisms to improve information dissemination efficiency in the blockchain significantly. Qiang Ma [11] and others took the Steemit social network as an example to analyse the governance model of network rumours based on blockchain technology. Jia P. [12] used the social network analysis method to explore the characteristics and laws of public opinion information dissemination of specific blockchain social networks and blockchain social networks and concluded that blockchain social networks are scale-free networks.

In addition, some scholars have conducted in-depth research on the practical application of blockchain in social networks. Le Jiang [13] designed a blockchain-based framework for decentralized OSN, using blockchain to provide central control services and separate storage services, improving users' control over their data, and solving user privacy issues leak problem. Chakravorty [14] provide a user-centric, blockchain-enabled social media network that enables true decentralization, security, and traceability of content distribution. In the literature [15], Barbara Guidi gives an overview of the leading blockchain-based online social media platforms, considers users as the system's central role, and then proposes a new model of blockchain-based online social networks. Gyuwon Song [16] proposes a blockchain-based social media notarization service, uses blockchain technology to realize the real archive of social media content and finally proposes a real-time messaging scenario as a proof of concept. These studies have made in-depth studies in the combined application of blockchain and social networks. Scholars use blockchain technology to improve the problems of user privacy data leakage, low data security, high degree of social network centralization, and difficulty in tracking data sources in traditional social network frameworks. Furthermore, these real social networks provide a practical platform for subsequent research on the dynamics of information propagation in blockchain social networks.

In the research of information propagation model, from an empirical perspective, Dan Zhao [17] proposed a conceptual model of public opinion information dissemination in a blockchain environment based on blockchain and information dissemination. Based on network communication and blockchain theory, Gengxin Sun [18] introduced an income-risk matrix and proposed a public opinion communication model for social networks in the blockchain environment. Arquam M. [19] proposes a model for sharing the information securely at the peer level based on blockchain. This model can detect the source of misinformation and information dissemination nodes by applying blockchain technology. Cui Z. [20] also believes that the blockchain has changed the mode of social network information dissemination. This work optimizes the forwarding probability based on the literature [18], adds state nodes, and proposes a new network information Propagation model based on blockchain. However, most of the current research focuses on analysing the application prospects of blockchain technology in information propagation, improving the efficiency of information propagation in the blockchain, and reducing the cost of information storage. Only a few studies have proposed a propagation model for blockchain social networks.

However, in the research mentioned above on information propagation in social networks based on blockchain, the following three issues have not been considered: (1) opposite groups in blockchain social networks and their relative density impact the choice of communication behaviour of other users. (2) What impact will the implementation of different incentive policies on the blockchain social network platform have on users' propagation behaviour. (3) The state transition probability in the existing propagation model takes a fixed value at each moment. Still, the size of different groups in the network is constantly changing, affecting the user's choice of propagation behaviour, which will lead to transitions between states probability changes dynamically. In order to answer the above questions, in the research of this paper, we propose a new information propagation model. Based on the SEIR model, this paper divides propagators into two groups with opposing opinions and calculates the state transition probability of multiple groups at different times through evolutionary games. The difference between this paper and traditional research is that some state transition probabilities in information propagation are regarded as dynamic changes rather than a fixed value in terms of state transition probability calculation. Finally, this paper simulated different incentive policies in the simulation experiment stage to observe their influence on user propagation behaviour choices. This article aims to establish a blockchain-based social network information dissemination model while highlighting the application prospects of blockchain technology in the direction of public opinion guidance and governance to provide references for social platforms and government departments.

3. Information Propagation Model in Social Network Based on Blockchain

3.1. Characteristics of Social Network Information Propagation Based on Blockchain. Before establishing the propagation model, one should first understand how the blockchain affects information propagation in social networks. This article explains the influence of blockchain on information dissemination and user dissemination behaviour from three aspects.

The incentive mechanism, consensus mechanism, and characteristics of blockchain that are difficult to tamper with make the information propagation process in blockchain-based social networks different from traditional social networks. First of all, the blockchain is a decentralized distributed ledger. Due to the technical characteristics of the incentive layer in its infrastructure, each node in the blockchain needs to perform data verification to reach consensus and keep accounts. So, it needs to be designed reasonably incentive measures to make each node's interests in the blockchain consistent with the overall consensus. The characteristics of this underlying technology are mapped to the application level: various social network platforms based on blockchain technology issue platform economic tokens for incentives to high-quality content creators and disseminators. These economic tokens can be converted into legal currency through official exchange or offline transactions by users. This kind of incentive brings economic power to platform users' creation. Therefore, users should obtain as many recognitions and token incentives from other users as possible. When expressing their views, users will have a deeper understanding of the background of the event and find evidence to prove their views. While users have regulated their behaviour, social networking platforms can also adjust the token incentive policies to guide platform users effectively.

Secondly, the consensus layer of the blockchain technology infrastructure uses the characteristics of blocks to form consensus in a highly decentralized system efficiently. In the propagation process, users in the blockchain social network platform propagate information to a certain extent. Users can pay for platform tokens to vote on a piece of content to evaluate whether the content is high-quality (or low-quality) information. Moreover, whether the content should be presented first to allow more users to see it expand its dissemination scope, thereby promoting high-quality content to get the token incentives of the platform.

Finally, the data stored in the blockchain is traceable and difficult to tamper with. The blockchain uses timestamps and digital signatures to ensure the stability and reliability of the information stored in the blockchain. The user's propagation behaviour and the content will be stored in the blockchain and cannot be deleted. Even if the user deletes the local record of a piece of information, the information will still be recorded in other distributed ledgers. With this feature, after receiving the information, other users on the social network platform can preliminarily determine the authenticity of the received information by querying the historical release records and historical dissemination records of the user who created (or propagated) the information.

3.2. Blockchain Social Network Information Propagation Model. Based on the SEIR model, this paper considers the opinion opposition groups in the blockchain social network to introduce a new node state. Furthermore, this paper considers the impact of economic incentives and punishments on user communication behaviours through the Bayesian game [21] and evolutionary game [22], redefines the transition probability between states, and proposes a propagation model.

Assuming that there is information T in SNS (T is support or opposition information for a type of topic), according to the actual situation of information dissemination in the blockchain social network, the nodes in the SNS are divided into the following five categories: susceptible node S (*Susceptible*), Wait and see node E (*Exposed*), support node A (*Advocates*), oppose node O (*Objector*), immune node R (*Removed*), support node A and oppose node O are collectively referred to as an infected node I (*Infected*). The S node indicates that the user has not yet touched the information T. The E node indicates that after S contacts the information T, a group is temporarily on the sidelines to maximize its economic benefits. A node represents a node that agrees with the T after the susceptible node contacts the information T and chooses to disseminate supporting information. Node O represents the node that opposes after the susceptible node contacts the information T and chooses to spread the opposing information. R means that the node is no longer affected by the information. The state transition process is shown in Figure 1:

Suppose $S(k,t)$, $E(k,t)$, $A(k,t)$, $O(k,t)$, $R(k,t)$ respectively represent the density of various nodes with degree k at time t, and At any moment: $S(k,t) + E(k,t) + A(k,t) + O(k,t) + R(k,t) = 1$. The transition rules between each state are described as follows:

(1) When node S contacts the target information, S may transform into node A with probability p_{sa}, or transform into node O with probability p_{so}, or choose to wait and see temporarily due to economic incentives and punishments, and transform into node E with probability p_{se}. Among them, p_{sa}, p_{so}, and p_{se} are, respectively, called the support probability, opposition probability, and wait-and-see probability of node S for information.

(2) After node E touches node A again or node O, it may transform into node A with probability p_{ea}, into node O with probability p_{eo}, or into node R with probability p_{er}. p_{ae}, p_{eo}, and p_{er} are called support

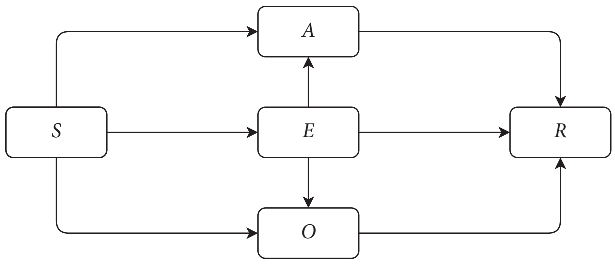

Figure 1: The state transition process of the SEAOR model.

probability, opposition probability, and direct immunity probability of node E.

(3) Node A transforms into node R with the probability p_{ar}, which is called p_{ar} as the immunity probability of node A to target information.

(4) Node O is transformed into node R with probability p_{or}, and p_{or} is called the immunity probability of node O to target information.

(5) When a node becomes node R, its state no longer changes.

$$\begin{cases} \dfrac{\mathrm{d}S(t)}{\mathrm{d}t} = -p_{sa}p_{\mathrm{con}}A(t)S(t) - p_{se}p_{\mathrm{con}}S(t) - p_{so}p_{\mathrm{con}}O(t)S(t), \\ \dfrac{dA(t)}{dt} = p_{sa}p_{\mathrm{con}}A(t)S(t) - p_{ar}A(t) + p_{ea}A(t)E(t), \\ \dfrac{\mathrm{d}E(t)}{\mathrm{d}t} = p_{se}p_{\mathrm{con}}S(t) - p_{ea}A(t)E(t) - p_{eo}O(t)E(t) - p_{er}E(t), \\ \dfrac{\mathrm{d}O(t)}{\mathrm{d}t} = p_{so}p_{\mathrm{con}}O(t)S(t) + p_{eo}O(t)E(t) - p_{or}O(t), \\ \dfrac{\mathrm{d}R(t)}{\mathrm{d}t} = p_{ar}A(t) + p_{er}E(t) + p_{or}O(t). \end{cases} \tag{1}$$

p_{con} is the probability that any random edge in the network is connected to the node of the infected node.

3.3. Construct the Game Matrix. In the model described in 3.1, the state transition probabilities p_{ei}, p_{eo}, p_{er}, p_{ir}, and p_{or} are affected by the social networks' economic incentive and punishment mechanism. In order to describe the propagation behaviour of node E, node A, and node O under economic rewards and punishments, this paper constructs the game matrix based on the Bayesian game.

Assuming that node A, O, and E in the social network are all bounded rational groups, the game matrix is constructed according to the Bayesian game as shown in Table 1:

In the game matrix, x is the probability of node E accepting a message from an infected node. According to 1.1, x is $p_{ea} + p_{eo}$, and $1 - x$ is p_{er}. y and z are the probability of the proponents and opponents disseminating information, respectively. When the infected person no longer disseminates the message, it will be transformed into an immune node.

The definition of each parameter in the game matrix is shown in Table 2:

After node S or node E accepts the message, it transforms into node I (A or O), pays the cost of voting c and obtains it from the economic incentives provided by the community according to the density λ and $(1 - \lambda)$ of A and O in all I Basic income λE, $(1 - \lambda)E$. Node I will obtain its corresponding additional benefits when node I successfully affects healthy nodes, expanding the scope of information dissemination. At the same time, the information transmitted by I may be regarded as inferior content, and I will be punished accordingly, that is, the risk of punishment for the information propagated by I. The income of node A and node O is related to their density in all I. When the density of one party continues to decrease, the information it propagates is eventually recognized as inferior information, and its density will decrease. With the information Expansion of the scope of propagation, the penalty will be greater than its benefits. On the contrary, the density of one party continues to increase, and the information it propagates is ultimately recognized as high-quality content, which will help its density increase. The gains will be more significant than the losses.

4. Behaviour Analysis of Game Participants and Calculation of State Transition Probability

Based on the above game matrix, this paper uses evolutionary games to analyse the behaviour of game participants and calculate the probability of each state transition.

Table 1: Game matrix.

		I			
		$A\cdot\lambda$		$O(1-\lambda)$	
		Propagate y	Not propagate $(1-y)$	Propagate z	Not propagate $(1-z)$
E	Accept x	$(\lambda E-c,\ \lambda E+E_a-c-R)$	$(0,\ \lambda E-c)$	$((1-\lambda)E-c,\ (1-\lambda)E+E_a-c-R)$	$(0,\ (1-\lambda)E-c)$
	Not accept $(1-x)$	$(0,\ \lambda E-c-R)$	$(0,\ \lambda E-c)$	$(0,\ (1-\lambda)E-c-R)$	$(0,\ (1-\lambda)E-c)$

Table 2: Interpretation of Parameters in Game matrix.

Parameters	Parameter interpretation
E	Total incentives provided in the blockchain social network
E_a	Node A influence the additional income of healthy nodes
E_o	Node O influence the additional income of healthy nodes
R	Punishment risk for infected nodes to propagate information
c	The cost of turning healthy nodes into infected nodes
λ	The current density of node A among the infected nodes
x	Probability of node E to accept information
y	Probability of node A propagating information
z	Probability of node O propagating information

4.1. The Behaviour Analysis of Node E and State Transition Probability Calculation. For the node E among the game participants, this paper set u_{E1} as the expected income when the selected strategy is "*Accept*," u_{E2} is the expected income when the selected strategy is "*Not Accept*." $\overline{u}_E$ is the average income when node E selects the above two strategies:

$$\begin{aligned} u_{E1} &= (y\lambda - z\lambda + z)E - (y+z)c, \\ u_{E2} &\equiv 0, \\ \overline{u}_E &= xu_{E1} + (1-x)u_{E2} = xu_{E1} \\ &= x[(y\lambda - z\lambda + z)E - (y+z)c]. \end{aligned} \tag{2}$$

Construct the replicator dynamic equation of the probability when node E selects the strategy "*Accept*" [23]:

$$\begin{aligned} F(x) &= \frac{\mathrm{d}x}{\mathrm{d}t} = x\left(u_{E1} - \overline{u}_E\right), \\ F(x) &= x(1-x)[(y\lambda - z\lambda + z)E - (y+z)c]. \end{aligned} \tag{3}$$

(i) If $(y\lambda - z\lambda + z)E - (y+z)c = 0$, then $F(x) \equiv 0$, that is, regardless of the ratio of the node E that chooses "*Accept*" to the node E that chooses "*Not Accept*," it's the strategy will not change over time. At this time, p_{er} and $p_{ea} + p_{eo}$ remain unchanged.

(ii) If $(y\lambda - z\lambda + z)E - (y+z)c \neq 0$, let $F(x) \equiv 0$, the above formula can get $x = 0$ and $x = 1$ as the two stable points of x. That is, when no mutant chooses the opposite strategy, the ratio of node E choosing a specific strategy (stabilizing at " Accept" or "*Not Accept*") will no longer change. At this time, the derivative of $F(x)$ can be obtained:

$$n\frac{\mathrm{d}F(x)}{\mathrm{d}x} = (1-2x)[y(\lambda - c) + z[(1-\lambda)E - c]]. \tag{4}$$

If $y(\lambda - c) > -z[(1-\lambda)E - c]$, then $\mathrm{d}F(x)/\mathrm{d}x|_{x=0} > 0$, $\mathrm{d}F(x)/\mathrm{d}x|_{x=1} < 0$, So according to the evolutionary stable strategy (*ESS*) [18], $x = 1$ is the equilibrium point. When node E makes a decision, it will tend to choose "*Accept.*" That is, the probability of node E choosing "*Accept*" $(p_{ea} + p_{eo})$ will gradually increase, and the probability of choosing "*Not Accept*" (p_{er}) Will gradually decrease, $F(x)$ is the increase rate of x [19]. If $y(\lambda - c) > -z[(1-\lambda)E - c]$, then $\mathrm{d}F(x)/\mathrm{d}x|_{x=0} < 0, \mathrm{d}F(x)/\mathrm{d}x|_{x=1} > 0$, It can be calculated that $x = 0$ is the equilibrium point. When node E makes a decision, it will tend to choose "*Not Accept.*" The probability of node E choosing "*Not Accept*" will increase and the probability of choosing "*Accept*" will decrease. At this time, $F(x)$ is the decrease rate of x:

$$nx = (1 + F(x))x_0. \tag{5}$$

x_0 is the initial acceptance rate at time t.

4.2. The Behaviour Analysis of Node A and State Transition Probability Calculation. For node A among the game participants. This paper set u_{A1} as the expected income when the selected strategy is "*Propagate*," u_{A2} is the expected income when the selected strategy is "*Not Propagate*." $\overline{u}_A$ is the average income when node A selects the above two strategies.

$$\begin{aligned} u_{A1} &= xE_A + \lambda E - c - R, \\ u_{A2} &= \lambda E - c, \\ \overline{u}_A &= yu_{A1} + (1-y)u_{A2} = y\left(xE_A - R\right) + \lambda E - c, \end{aligned} \tag{6}$$

The above formula can construct a replication dynamic equation of the probability that node A chooses "*Propagate*":

$$F(y) = \frac{\mathrm{d}y}{\mathrm{d}t} = y\left(u_{A1} - \bar{u}_A\right),$$
$$nF(y) = y(1 - y)(xE_A - R). \tag{7}$$

(i) If $x = (R/E_A)$, then $F(y) \equiv 0$, that is, regardless of the ratio of the node A that chooses "*Propagate*" to the node A that chooses "not propagated," its the strategy will not change over time. At this time, p_{ar} remains unchanged.

(ii) If $x \neq (R/E_A)$, let $F(y) = 0$, the above formula can get $y = 0$ and $y = 1$ as the two stable points of y. Similar to node E , the ratio of node A choosing a specific strategy (stabilizing at "*Propagate*" or "*Not Propagate*") will no longer change. We can get the derivative of $F(y)$:

$$\frac{\mathrm{d}F(y)}{dy} = (1 - 2y)(xE_A - R). \tag{8}$$

If $x > (R/E_A)$, $(\mathrm{d}F(y)/\mathrm{d}y)|_{y=0} > 0$, $(\mathrm{d}F(y)/\mathrm{d}y)|_{y=1} < 0$, $y = 1$ is the equilibrium point. When A makes a decision, it will tend to choose strategy "*Propagate*," that is, the probability of A choosing "*Propagate*" will increase. In contrast, the probability of choosing "*Not Propagate*" will decrease. At this time, $F(y)$ is the increase rate of y. If $x > (R/E_A)$, $(\mathrm{d}F(y)/\mathrm{d}y)|_{y=0} < 0$, $(\mathrm{d}F(y)/\mathrm{d}y)|_{y=1} > 0$, $y = 0$ can be obtained as the equilibrium point. When A makes a decision, it tends to choose "*Not Propagate*," that is, the probability of A choosing strategy "*Not Propagate*" will increase. The probability of choosing "*Propagate*" will decrease. At this time, $F(y)$ is the reduction rate of y:

$$ny = (1 + F(y))y_0,$$
$$np_{ir} = (1 - y). \tag{9}$$

y_0 is the initial propagation rate at time t.

4.3. The Behaviour Analysis of Node O and State Transition Probability Calculation. For node O among the game participants. This paper set u_{O1} be the expected income when the selected strategy is "*Propagate*," u_{O2} is the expected income when the selected strategy is "*Not Propagate*." $\overline{u}_O$ is the average income when node O selects the above two strategies.

$$nu_{O2} = (1 - \lambda)E - c,$$
$$n\overline{u}_O = zu_{O1} + (1 - z)u_{O2} = z\left(xE_O - R\right) + (1 - \lambda)E - c, \tag{10}$$

The above formula can also construct a replication dynamic equation of the probability that node O chooses "*Propagate*":

$$F(z) = \frac{\mathrm{d}z}{\mathrm{d}t} = z\left(u_{O1} - \overline{u}_O\right),$$
$$F(z) = z(1 - z)(xE_O - R), \tag{11}$$

(i) If $x = (R/E_o)$, then $F(z) \equiv 0$. Regardless of the node O ratio that chooses "*Propagate*" to the node O that chooses "*Not Propagate*," its strategy will not change over time. At this time, p_{or} remains unchanged.

(ii) If $x \neq (R/E_O)$, let $F(z) = 0$, we can get $z = 0$ and $z = 1$ as the two stable points of y. The ratio of node O choosing a specific strategy (stabilizing at "*Propagate*" or "*Not Propagate*") will no longer change. We can get the derivative of $F(z)$:

$$\frac{\mathrm{d}F(z)}{\mathrm{d}z} = (1 - 2z)\left(xE_O - R\right). \tag{12}$$

If $x > (R/E_O)$, $(\mathrm{d}F(z)/\mathrm{d}z)|_{z=0} > 0$, $(\mathrm{d}F(z)/\mathrm{d}z)|_{z=1} < 0$, $z = 1$ is the equilibrium point. O will tend to choose strategy "*Propagate*." The probability of O choosing "*Propagate*" will increase. The probability of choosing "*Not Propagate*" will decrease. At this time, $F(z)$ is the increased rate of z. If $x < (R/E_O)$, $(\mathrm{d}F(z)/\mathrm{d}z)|_{z=0} < 0$, $(\mathrm{d}F(z)/\mathrm{d}z)|_{z=1} > 0$, $z = 0$ is the equilibrium point. When O makes a decision, it tends to choose "*Not Propagate*," that is, the probability of O choosing strategy "*Not Propagate*" will increase. The probability of choosing "*Propagate*" will decrease. At this time, $F(z)$ is the reduction rate of z:

$$nz = (1 + F(z))z_0,$$
$$np_{or} = (1 - z), \tag{13}$$

z_0 is the initial propagation rate at time t.

Through the evolutionary game theory and the above calculations, this paper can get the trend and function of the transition probabilities p_{er}, p_{ar}, and p_{or} at time t. The participants in the above game are node E and all infected nodes I, so the changing trend of transition probabilities p_{ei} and p_{eo} when node E selects "*Accept*" cannot be determined only through the above calculation. When node E selects the strategy "*Accept*":

(i) If node E chooses to accept the information propagated by A, it can be known that its income is $\lambda E - c$ through the game matrix

(ii) If node E chooses to accept the information propagated by O, through the game matrix, its income is $(1 - \lambda)E - c$

λ is the density of node A in all nodes I at the current moment, and $(1 - \lambda)$ is the density of node O in all nodes I at the current moment. Therefore, under the condition that E selects "*Accept,*" its income is related to the density of A and O among all infected nodes. Mapping to reality reflects the phenomenon that bounded rational individuals in real social networks will suppress their suspicion when facing popular beliefs. This phenomenon is called the conformity psychology [24]. Youhong Wan [25] combined the initial transmission rate of information and the propagator density at each moment and described the influence of herd effect on the probability of information transmission. Based on the above existing research and the actual situation of this paper. This paper can respectively get the dynamic change equations of the transition probabilities p_{ea} and p_{eo} under the condition that E selects "*Accept*":

$$
\begin{aligned}
np_{ea}\left(p_{ea}^{t-1}, A[t]\right) &= \left(1 - p_{er}\right) \cdot \frac{p_{ea}^{t-1}}{p_{ea}^{t-1} + p_{eo}^{t-1}} \cdot e^{A[t]}, \\
np_{eo}\left(p_{eo}^{t-1}, O[t]\right) &= \left(1 - p_{er}\right) \cdot \frac{p_{eo}^{t-1}}{p_{ea}^{t-1} + p_{eo}^{t-1}} \cdot e^{O[t]},
\end{aligned}
\tag{14}
$$

Among them, p_{ea} and p_{eo} represent the probability that node E is transformed into node A or node O at the current moment. p_{ea}^{t-1}, p_{eo}^{t-1} are the probability of node E transforming into node A or node O at the last moment, $A[t]$, $O[t]$ represents the current moment node A or node O density. According to p_{ea}^{t-1}, p_{eo}^{t-1} and the communicator density coefficient $e^{A[t]}$, $e^{O[t]}$, calculate p_{ea} and p_{eo} at the current moment.

5. Simulation Experiment and Result Analysis

This section first explored the topological characteristics of social networks based on blockchain with actual data. Then, this paper conducted computer simulation experiments and analyses under different parameters. According to the behaviour analysis of game participants and the calculation of state transition probability in Section 3, We know that the incentive mechanism and people's conformity psychology in the blockchain social network will affect the propagation behaviour of different groups. The expected income of users is related to their basic income E, propagation costs c, the penalty risk of propagation R, and additional income of propagation. And the density of different infected persons affects their basic income and additional income. Therefore, adjusting the above parameters will have an impact on the density changes of various nodes. Due to the relatively short information dissemination time, this article does not consider the dynamic changes of the network scale in subsequent experiments.

5.1. Analysis of Topological Characteristics of Social Network Based on Blockchain. Wenyi Xiao et al. proposed a Sean model for content recommendation, compared with the CF algorithm and other content-based recommendation methods on the data set constructed on the blockchain social platform Steemit, and achieved good results [26]. This article uses its public Steemit user relationship data set to build a complex network. The network topology is shown in Figure 2. The graph contains 7242 nodes and 273942 edges. The colour and size of the node represent the degree of the node. If the colour of the node is darker and the size is larger, the degree of the node is about greater.

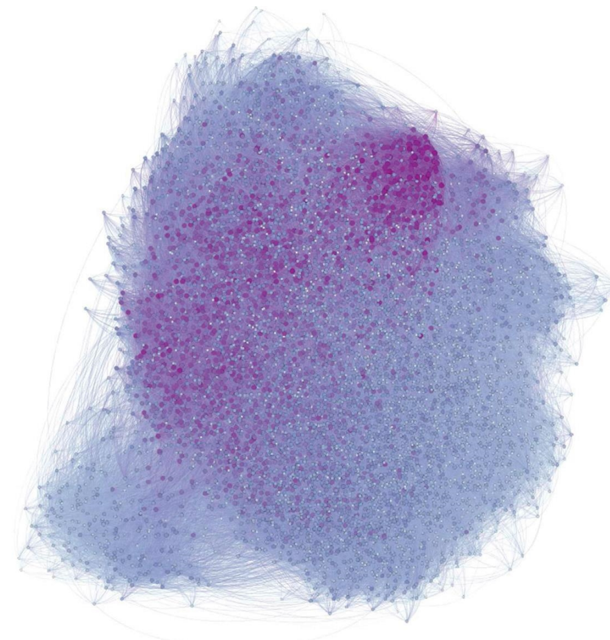

Figure 2: User relationship network of social network based on blockchain.

In order to explore the topological characteristics of social networks based on blockchain, this experiment used Gephi software to analyse further the topological characteristics of the network on this data set. This experiment respectively generated WS network, BA network and ER random network with a similar number of nodes and the average degree to the complex network formed by the blockchain mentioned above social network. Their average clustering coefficient and average shortest path are shown in Table 3.

This experiment can see that the average clustering coefficient of the blockchain social network is 0.060, which is smaller than the average clustering coefficient of the WS network. However, the two are still in the same order of magnitude, which shows that the blockchain social network still has a high clustering coefficient. In addition, the average path length of a complex blockchain network is about 3.225, which is approximately log N (N is the number of nodes). According to the definition of the WS model introduced by Duncan Watts and Steven Strogatz [27]. The blockchain social network conforms to the characteristics of the WS network.

Figure 3 shows the degree distribution of the complex network of the blockchain. According to the degree distribution graph, this paper examines the degree of fit of the degree distribution curve and the power-law distribution in the experiment to determine whether the blockchain social network has scale-free characteristics. The results show that p value = 0.00 is less than the significance level (5%), so the blockchain social network does not have prominent scale-free characteristics [28].

5.2. The Impact of Node Density on the Information Propagation of Blockchain Social Networks. In this experiment, different parameters are selected to make the expected

Table 3: Average clustering coefficient and average shortest path of different networks.

Network	Average clustering coefficient	Average path length
This network	0.060	3.225
WS network	0.096	2.855
BA network	0.036	2.363
ER network	0.009	2.470

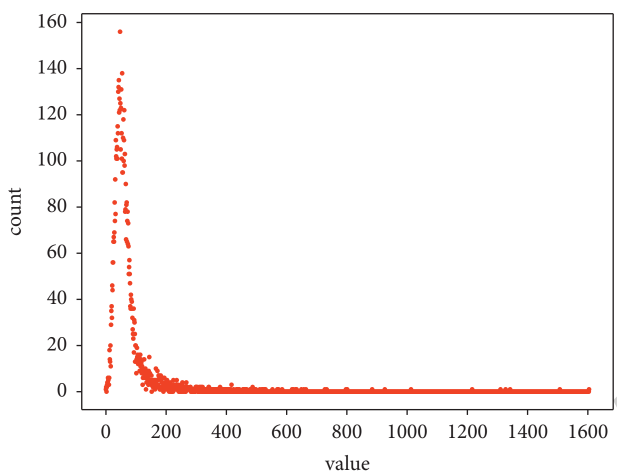

Figure 3: Degree distribution of social networks based on blockchain.

return of the infected node greater than 0 or less than 0. Then, in this experiment, different initial density ratios of node A and node O are set, and the system evolution process is shown in Figure 4.

As shown in Figure 4, no matter in which case, nodes S and E will reach a stable state before $t = 20$. Among them, S contacts the target information with the contact rate $A(t) + O(t)$ and transforms into A, O, E with the probabilities p_{sa}, p_{so}, and p_{se} respectively, so it shows a continuous downward trend in the whole evolution process. After S is transformed into E, E will contact the information again with $A(t) + O(t)$ at time t. The increasing amount of E is greater than the decreasing amount, and the overall trend is increasing. Approximately when $t > 8$, the density of A and O increases, and the probability that E will contact the target information again increases. The increase in the density of node E is less than its decrease, and the overall trend is decreasing and finally reaches a steady state. When the initial density is greater for nodes A and O, the density when it reaches a steady-state is also greater. Through simulation experiments, it is found that $A(t)/O(t) \approx 2.08$ is the dividing line:

(i) When $(O(t)/A(t)) > (1/2.08)$, the density of A and O are both greater than 0 when they reach the steady-state. At this time, both parties will stick to their opinions. Regarding the economic incentive mechanism of the blockchain, it can be seen from the evolutionary game inference part of Chapter 4 that at this time, nodes A and O will believe that their expected benefits of persisting in propagation are greater than 0. Because of the influence of this incentive mechanism, the probability that A and O persist in propagating information will increase. It can be seen that under the influence of economic incentives, users in blockchain-based social networks have higher propagation enthusiasm than traditional social networks.

(ii) When $(O(t)/A(t)) < (1/2.08)$, that is, when the initial density difference between the two parties is significant, the A density of the larger initial density is greater than 0 when it reaches the steady-state. After node O persists in propagating information for some time, since its income is less than the cost, the density of node O will keep decreasing and tend to zero. In the process of information propagation, node A believes that the expected benefit of persisting in propagation is greater than zero. In contrast, node O thinks that the expected income of persisting in propagation is less than the cost and risk of propagation. Affected by the economic incentives and penalties of the blockchain, the probability of node A persisting in propagating information increases, while the probability of node O persisting in propagating information decreases, and the reduced probability increases as the density of group O decreases. From **(b)**, **(c)**, **(d)** in Figure 4, we can see that the smaller the initial density of node O, the smaller its peak value (peak values are 0.16, 0.09, 0.04 in turn), and the time for the entire network to reach the steady-state The shorter (the time to reach steady-state is 67, 43, 33, respectively). Due to economic incentives and punishments, users in blockchain social networks behave more rationally when propagating information. On the one hand, it is easier to highlight high-quality information in the social network, and on the other hand, it can suppress the propagation of low-quality information.

5.3. The Influence of State Transition Probability on Information Propagation. The density of S and E and the speed and trend of change have an important influence on the time for A and O to reach the steady-state and then influence the time for the entire system to reach a steady state. It is specifically embodied in the values of transition probabilities p_{se}, p_{sa}, p_{so}, p_{ea}, and p_{eo}. Due to p_{ea} and p_{eo} are calculated through dynamic change equations based on the expected income of node E at time t, only the values of p_{se}, p_{sa}, and p_{so} need to be adjusted. Set $p_{sa} = p_{so}$ and take the probability $p_{se} = (0.2, 0.4, 0.6, 0.8)$, the changing trend of the density of node S and node E with time is shown in Figure 5.

From Figure 5, we can see that the larger the value of p_{se}, the longer it takes for node S and node E to reach the steady state. Because the actual probability of S transforming into A and O is determined by the contact rate p_{con} and $A(t), O(t)$, and the actual probability of S transforming into E has nothing to do with $E(t)$. Therefore, the smaller the p_{se}, the slower the change of S and E, and the longer it takes to reach

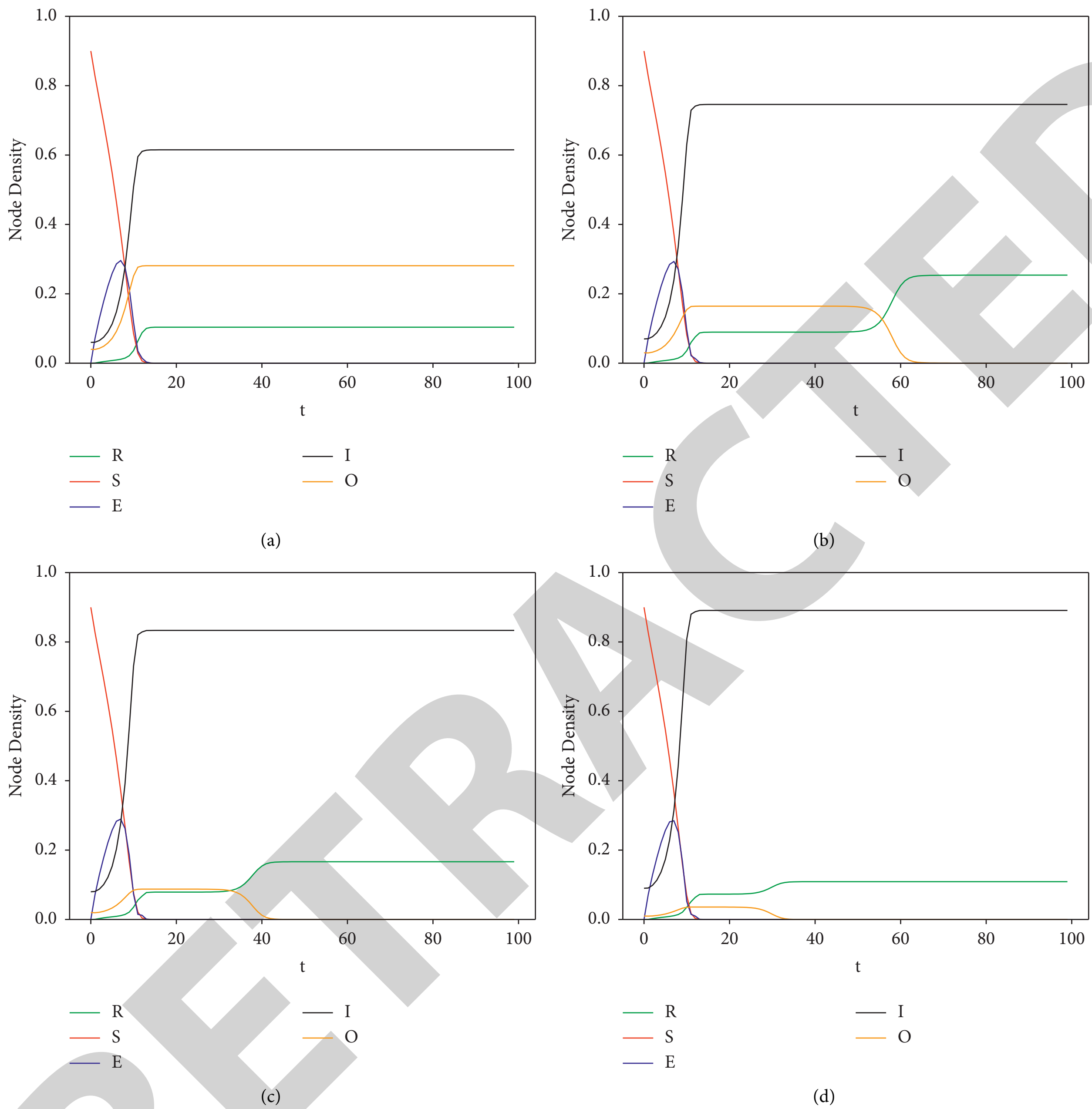

FIGURE 4: The influence of the initial density ratio of A and O on the density of various nodes. (a) $(O(0)/A(0)) = 4/6$. (b) $(O(0)/A(0)) = 3/7$. (c) $(O(0)/A(0)) = 2/8$. (d) $(O(0)/A(0)) = (1/9)$.

a steady state. Moreover, because only S can be transformed into E, the smaller p_{se} is, the smaller the peak value of node E in the evolution process.

5.4. The Impact of Incentive Policies on Blockchain Network Information Dissemination. In the process of information dissemination in the blockchain social network, the economic benefits of nodes A, O, and E have a decisive influence on their dissemination behaviour. Therefore, it is necessary to study the communication behaviour of various groups under different economic incentive policies. According to the simulation results in 5.2 and 5.3, to highlight and compare the changing trend of node A and node E, shorten the time for the whole to reach steady-state, and facilitate calculation, This experiment select parameters $(O(0)/A(0)) = (2/8)$ and $p_{se} = 0.8$ in subsequent experiments.

In this experiment, the first incentive policy makes the expected return (expected income minus expected risk) of nodes E, A, and O always less than 0. The changing trend of each node is shown in Figure 6.

We can see from Figure 6 that because the total income is less than the risk and the initial density of node O is small, the expected return of node O is always less than 0. Hence, its density decreases rapidly and reaches a steady state. Because

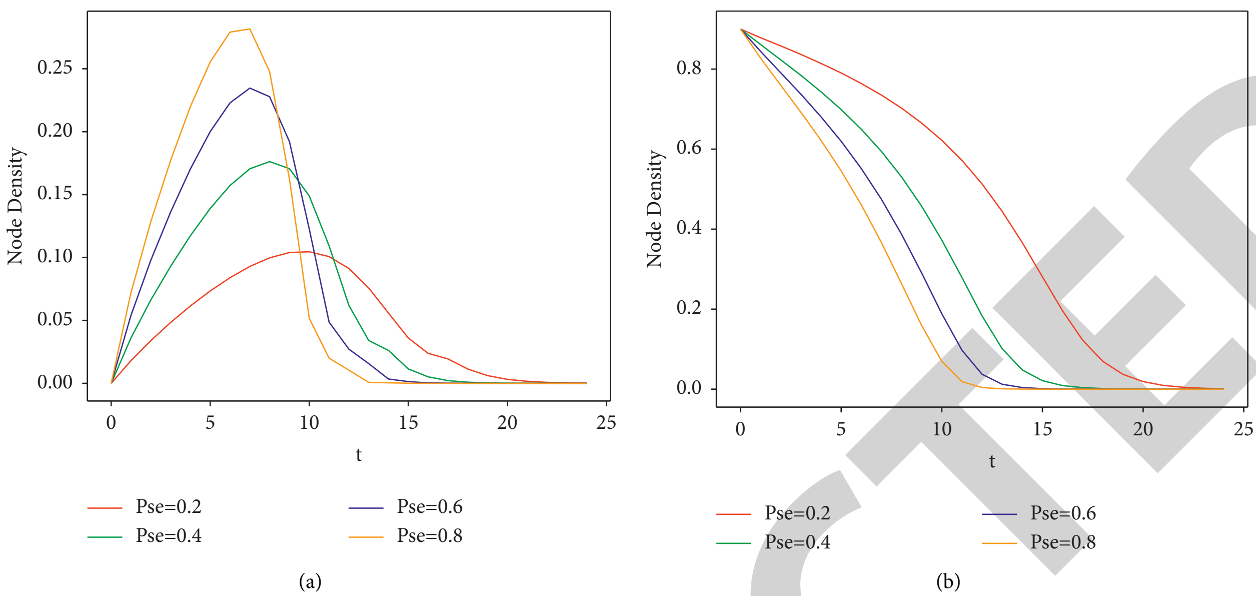

FIGURE 5: The influence of different p_{se} on the evolution trend of node S and node E. (a) The evolution trend of node E, (b) The evolution trend of node S.

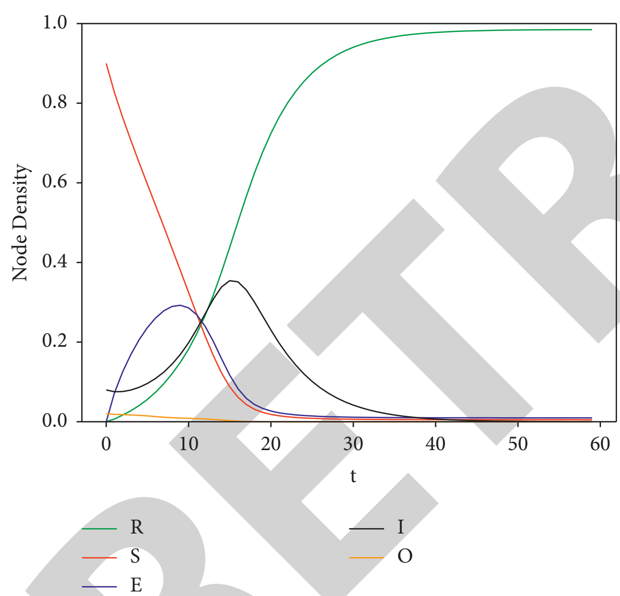

FIGURE 6: System evolution trend when incomes are always less than risks.

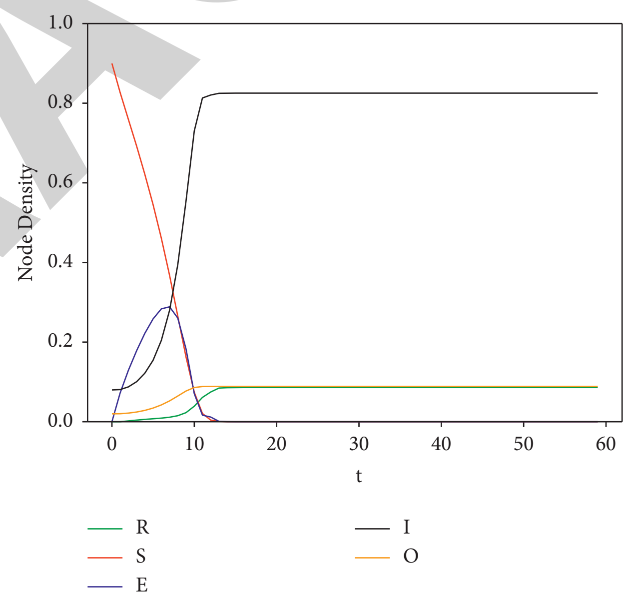

FIGURE 7: System evolution trend when incomes are always greater than risks.

the initial density of node A is relatively large, the expected income of node A can still offset its expected risk within a period after the start of the propagation. Therefore, the density of node A will increase during the period after the start of the propagation. As the densities of nodes S and E continue to decrease, the expected benefit of nodes A's continuous propagation also decreases, and ultimately it is less than the expected risk. Therefore, the density of node A begins to decrease after some time and finally reaches a steady state.

Then, the second incentive policy makes the expected return of nodes E, A, and O always greater than 0. The changing trend of each node is shown in Figure 7.

It can be seen from Figure 7 that because the propagating income of nodes E, A, and O is always higher than the risks, the densities of nodes A and O will rise in a short period and will not decrease, and eventually reach a steady state.

The third incentive policy makes the expected return of nodes E, A, and O may be greater than 0 or less than 0 at any time during the propagation to the steady-state. The changing trend of each node is shown in Figure 8.

According to Figure 8: When the relationship between the spreading benefits and risks of groups E, A, O is unknown, the density of infected nodes with a relatively small initial density decreases after a short period and tends to

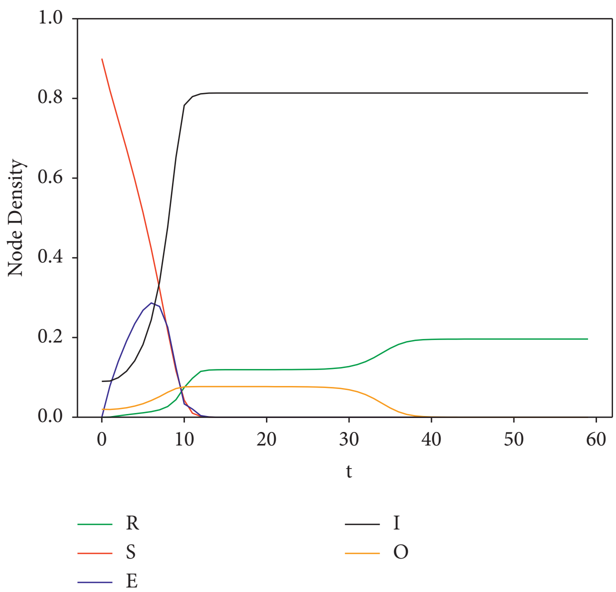

FIGURE 8: System evolution trends when the magnitude of incomes and risks are uncertain.

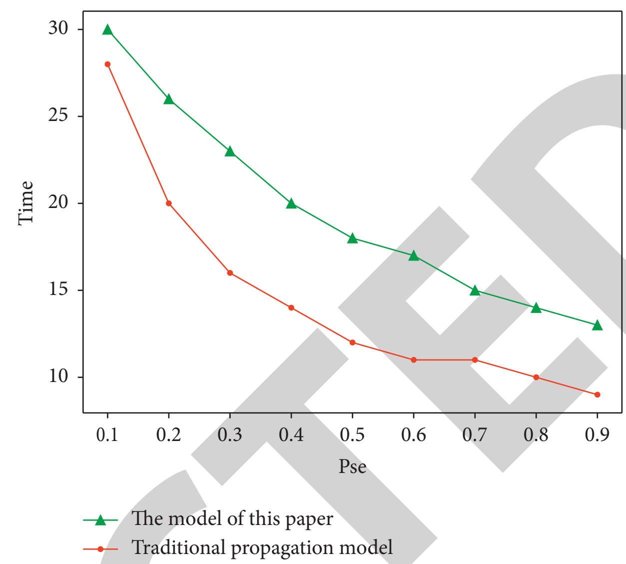

FIGURE 9: The time required to reach the maximum range of information propagation.

zero. In the final network, only a group of infected nodes with a large initial density and node R.

5.5. Comparative Experiment. The economic incentives and punishments of the blockchain social network make users more cautious and rational in choosing propagation behaviour when receiving information. But the traditional social network model can hardly reflect this characteristic. In order to highlight the advantages of the model proposed in this article, this experiment selects the traditional social network communication model without media in the literature [29], which has similar node states and state transition processes to the model in this article. This experiment compares this model with the model in this paper. It selects the time required for the maximum spread of information and the density difference of different propagators as evaluation indicators.

This paper takes the time required to reach the maximum range of information dissemination as an evaluation indicator. The longer the time to reach the maximum spread range under the same parameter conditions, the longer the time for users to think and choose the spreading behaviour in the spreading process, instead of not thinking about it and spreading it casually after receiving the information. It shows how sane users in the network are when propagating. The probability P_{se} has an important influence on the time for A and O to reach the steady-state. That is to say, P_{se} influences the time for reaching the maximum propagation range. The experiment takes $P_{se} \in (0, 1)$, and the comparison of the time to reach the maximum propagation range is shown in Figure 9 Shown:

It can be seen from Figure 9 that regardless of the value of P_{se}, the time for the model in this paper to reach the maximum propagation range is always greater than the time for the traditional propagation model to reach the maximum propagation range. When the value of P_{se} is different, the time for the model in this paper to reach the maximum propagation range is at least 7% higher than the traditional propagation model, and the maximum is 54% higher. It shows that users spend longer and more rationally thinking when choosing propagation behaviours after users receive information. By comparing the time when the information reaches the maximum spread range, it is shown that the model in this paper can better express the influence of the incentive mechanism of the blockchain-based social network on the spreading behaviour of users compared with the traditional propagation model.

In the process of model building, this paper uses game theory to describe the impact of economic incentives on users' communication behaviour. In the model of this paper, part of the propagation probability is a time-varying parameter. However, the traditional dissemination model does not consider the influence of the economic incentives of the blockchain. Its dissemination probability can only be set as a fixed parameter during a simulation experiment of simulating dissemination, which leads to the fact that even if there are few disseminators of information at the beginning, the information has a wide range of influence. This paper compares the maximum propagation range of information in the traditional model and our model under different initial parameters. The results are shown in Table 4.

The sensitivity of the traditional model to the change of the initial parameters is relatively weak, and the maximum propagation range of node O is the minimum of 0.3215 and the maximum of 0.3694. When the initial density of node O is 0.01, the proportion of node O in all infected nodes is 0.1, and its maximum density is 0.3147 under the propagation simulation of the traditional propagation model. When the initial density of node O is 0.09, its maximum density is 0.3694 under the propagation simulation of the traditional propagation model. It means that in a community with an initial number of 10,000 people (assuming that the total number of

Table 4: Comparison of the maximum propagation range achieved by the traditional model and the model node O of this paper.

Initially the density of node O	Maximum density of node O in traditional model	The maximum density of node O in our model
0.01	0.3147	0.0360
0.02	0.3215	0.0878
0.03	0.3283	0.1654
0.04	0.3353	0.2848
0.05	0.3425	0.4536
0.06	0.3497	0.6300
0.07	0.3557	0.7600
0.08	0.3625	0.8438
0.09	0.3694	0.8996

people in the community will not change dynamically) if there are 900 people initially disseminating information *o*, there will be up to 3,694 people disseminating information *o* in the process of dissemination; When there are 100 people disseminating information *o* initially, there will still be a maximum of 3147 people who will become the disseminators of information o during the entire dissemination process. In the model of this paper, when the initial density of node O is 0.01 during the whole propagation process, its maximum density is 0.0360. When the proportion of node O among all infected nodes is 0.9, it has a maximum density of 0.8996 during the propagation process. It can be seen that if the influence of economic incentives on the transmission probability is not considered and the transmission probability is set as a fixed parameter, the model will be less sensitive to the initial infected person density. Eventually, there will be a phenomenon that even though the initial values of the infected person are pretty different, the final propagation range is not much different. The model in this paper effectively improves this phenomenon due to the use of a partially time-varying propagation probability.

Blockchain social networks use incentive mechanisms to highlight high-quality information and suppress poor-quality information. To a certain extent, the blockchain social network can use its incentive mechanism to encourage users to suppress the spread of inferior information. The suppression effect can be expressed by the density difference of different information disseminators when the information reaches the maximum dissemination range. Whether the model can describe this effect is also an indicator to evaluate whether the model is reasonable. In the blockchain environment, due to economic incentives, users will be more cautious in choosing the propagation behaviour rather than propagating information casually when they receive it. And when users frequently contact a particular type of opinion, they are more inclined to choose to spread this type of opinion. Thus, the proportion of various propagators at the beginning of the propagation will have an important influence on the propagation behaviour of users after contacting the information. This experiment selects the initial density ratios of different types of communicators and observes the density difference of different information communicators when the information reaches the maximum spread range. The comparison between the model in this article and the traditional communication model is shown in Figure 10:

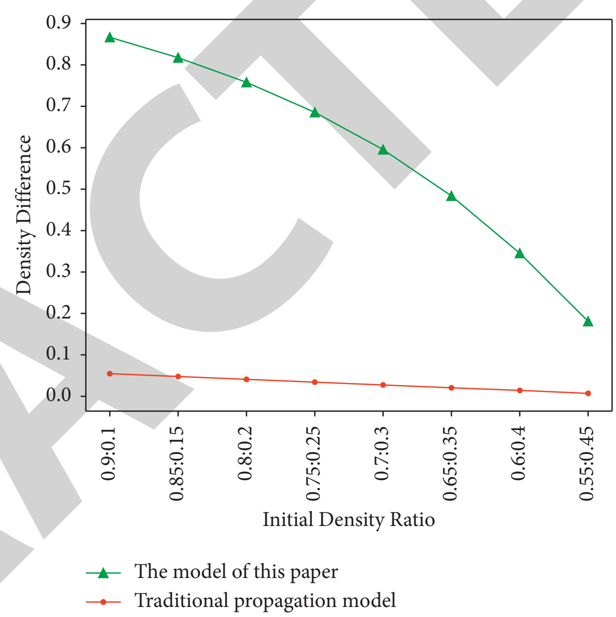

Figure 10: The density difference of different types of propagators when the information reaches the maximum spread range.

When the maximum spread range is reached, even if the density of inferior information propagators is initially low, the scale of propagation of this type of information in the traditional propagation model is still large. The maximum difference in the density of the two types of propagators is 0.054, and the minimum is 0.007. It is not easy to describe the impact of blockchain's economic incentives on information propagation. In the simulation results of this model, the maximum density difference between the two types of information is about 0.866, and the minimum density difference is 0.18. It shows that the model in this paper can better describe the highlighting or inhibiting effect of the blockchain on different information than the traditional propagation model.

The above experimental results show that the economic incentives given to users by the blockchain social network can profoundly affect the propagation behaviour of users in the social network. Economic income can significantly stimulate users' enthusiasm for information propagation. The economic punishment mechanism coexisting with incentives can also enable users to remain rational and suspicious when facing different information and not readily believe in false and poor-quality information. And the model in this paper can better reflect the advantages of blockchain social networks than traditional communication models.

6. Conclusions

This paper considers the impact of blockchain technology on social networks based on the traditional social network propagation model. It abstracts the opposition groups in social networks into "support nodes" and "opposition nodes." Then, this paper uses the evolutionary game theory to define the state transition probability and establish an information dissemination model based on the blockchain social network. This paper first analyses the influence of group density on the information propagation of the blockchain network in the experimental part. Then, it analyses the influence of the state transition probability on the group density in the network and the time required to reach the steady state. Finally, it focuses on verifying the influence of the incentive policy of the blockchain social network the role of social network users' propagation behaviour. The experimental conclusions are as follows: (1) The unique incentive mechanism of the blockchain social network can significantly enhance the user's enthusiasm for dissemination and highlight high-quality content. The punishment mechanism enables users to maintain a certain degree of rationality when choosing their propagation strategies and curb the propagation of false information. (2). The model in this paper can control parameters to simulate different incentive policies and more intuitively describe the impact of incentive policies on information propagation. The application of blockchain technology in social networks provides new ideas for the governance of online public opinion. The model in this article can reference government departments to use blockchain technology to governance and guide online public opinion in the future.

It should be pointed out that this study has certain limitations: (1) in the model of this paper, a small part of the state transition probability still adopts a fixed value. (2) In reality, the intensity of the incentives for users to disseminate information on various social platforms is decreasing with time. But this diminishing effect is not considered in this article. Both aspects are issues that we need to consider and resolve in the future.

Data Availability

Previously reported Steemit data were used to support this study and are available at https://doi.org/10.1145/3292500.3330965. These prior studies (and datasets) are cited at relevant places within the text as references [26].

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Acknowledgments

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