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An incentive mechanism for data sharing based on blockchain with smart contracts☆

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ABSTRACT

Data sharing techniques have progressively drawn increasing attention as a means of significantly reducing repetitive work. However, in the process of data sharing, the challenges regarding formation of mutual-trust relationships and increasing the level of user participation are yet to be solved. The existing solution is to use a third party as a trust organization for data sharing, but there is no dynamic incentive mechanism for data sharing with a large number of users. Blockchain 2.0 with smart contract has the natural advantage of being able to enable trust and automated transactions between a large number of users. This paper proposes a data sharing incentive model based on evolutionary game theory using blockchain with smart contract. The smart contract mechanism can dynamically control the excitation parameters and continuously encourages users to participate in data sharing.

1. Introduction

In the era of big data, digital resources have grown exponentially, and data has become an important strategic resource. At present, the big data industry faces a dilemma referred to as the problem of "data islands". An effective solution to this problem would be to establish a reasonable and effective data sharing model [1]. Today, information disclosure and open sharing of data have become general trends in scientific, and even national, innovation. Numerous studies have shown that data sharing and reuse are conducive to accelerating the dissemination of data resources, by improving the efficiency and quality of work, and enhancing the potential for innovation [2–5].

Although data sharing has varying applications, it provides significant convenience in daily life. However, in the process of data sharing, there are still three problems to be solved: unwillingness to share, fear of sharing, and inability to share [6]. The unwillingness of users to share data is affected by the formation of mutual-trust relationships and the economic utility

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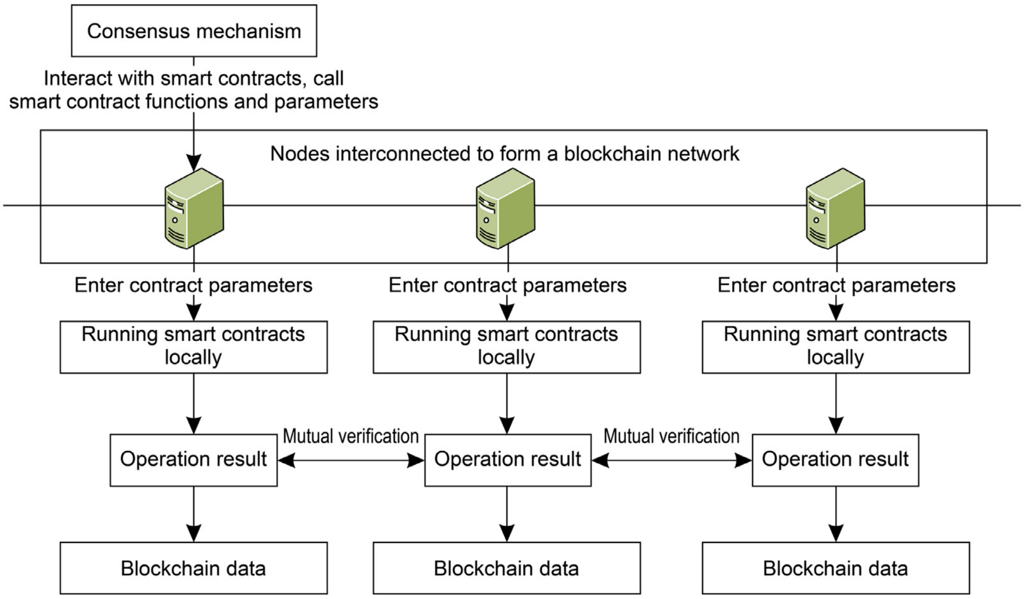

Fig. 1. Execution of smart contracts in blockchain.

of data sharing. However, little research has been conducted on data sharing in the big data era and with the support of blockchain technology.

In this paper, we perform an evolutionary game equilibrium analysis of data sharing in the era of big data, and explore and analyze the evolutionary game process of data sharing. Finally, we obtain four constraints with which to design an adaptive smart contract mechanism that can be used to motivate more users to participate in data sharing.

The remainder of this paper is organized as follows. Section 2 gives a brief overview of related research achievements and explains the research directions explored in related work. It introduces the current state of theory and technology research, and outlines our specific innovations. Section 3 presents our model and its mathematical derivation and analysis, from which we form a smart contract mechanism. Section 4 describes a simulation experiment conducted on the model, and Section 5 presents concluding remarks.

2. Related work

2.1. Blockchain based on smart contracts

Blockchain technology is a distributed, decentralized, and tamper-proof shared ledger technology that allows peer-to-peer transmission [7,8]. Contract terms are enforced, which extend the functionality of the blockchain. The execution of smart contracts is shown in Fig. 1. When a smart contract is called, the nodes in the blockchain run it locally with the parameters. If the result can be mutually verified, it is accepted and added to the blockchain.

Blockchain based on smart contracts has been applied in many scenarios, for example in intelligent medical treatment, and in intelligent devices. The researchers [9] and [10] proposed a multi-layer blockchain architecture based on intelligent contracts for intelligent medical treatment.

2.2. Data sharing and blockchain

Blockchain-based data sharing is also applicable in different scenarios, such as smart medical care, the internet of vehicles, etc.; in these scenarios, blockchain plays different roles. Dong et al. [11] and Yue et al. [12] proposed a framework for securely sharing sensitive data on big data platforms, and [13] designed the Distributed Earth System Scientific Data Sharing Platform (ESSDSP) to integrate scientific data resources and provide users with one-stop data sharing services. In [14], a blockchain-based model applied to smart medical care is proposed along with blockchain ACTS as a data storage index. In terms of generating sharing protocols, [15] H. Desai, proposed a framework for generating intelligent contracts and a custom data sharing protocol generated by this framework. In terms of IoT [16,17] introduced the use of cloud computing in the Internet of Things for data sharing, and in [18], Li L proposed a vehicle information sharing architecture (CreditCoin) applied to the Internet of Vehicles. In terms of artificial intelligence, [19] proposed a framework for identifying false information in a video. In essence, data sharing can greatly reduce duplication of data collection and processing, thereby reducing costs and promoting focus on other tasks.

Table 1
User participation in the data sharing evolution game's payment matrix.

User B takes the strategy	User A takes the strategy	
	Participate	Not participate
Not participate	$\gamma\mu ln(1+R)-\tau-C$, $\gamma\mu ln(1+R)-\tau-C$	$\mu ln(1+R)-\tau-C$, $\mu ln(1+R)$
Participate	$\mu ln(1+R)$, $\mu ln(1+R)-\tau-C$	$\mu ln(1+R)$, $\mu ln(1+R)$

2.3. Evolutionary game theory

Evolutionary game theory — a mathematical method used to study and predict the evolution of social interactions — considers individuals to be rational and then analyzes individual policy choices and game equilibria [20,21]. In the evolutionary game, it is important to determine that the concept behind the game equilibrium is the evolutionarily stable strategy (ESS), which is equivalent to the Nash equilibrium but can also be applied to the evolution of individual policies. When a state can be maintained under slight disturbances caused by the dynamic system, it is called a steady state.

In addition to the concept of an evolutionarily stable strategy, evolutionary game theory also considers replicator dynamics (RD). According to conclusions derived from the replication dynamic model, the trend of individual strategy selection in the population can be better predicted. The mathematical formula for competitive growth dynamics in RD is a differential equation that simulates the individual participating in the game, so it can better describe the effective rational trend of an individual's behavior in the population.

Some scholars have used the idea of games to conduct research on data sharing. Ali and Maheswaran [22] studied online data sharing on social networks from a game theory perspective, showing that when blacklisting is introduced as a triggering strategy, sharing conditions become balanced. Kamhoua et al. [23] used game methods to help online social network (OSN) users determine the optimal strategy for data sharing. Yassine et al. [24] proposed a game theory mechanism that balances the benefits of data use and individuals' privacy in deregulated smart grids. Tosh et al. [25] proposed an evolutionary game theory framework to investigate network security information sharing to promote the sharing of cyber threat intelligence between organizations and mitigate the impact of cyber-attacks using a cybersecurity information exchange framework, called CYBEX.

3. Model analysis

The expectation of data sharing is to get more people involved in data sharing. The data sharers can only choose to participate or not in data sharing. The strategy of these two behaviors depends on the bounded rationality of the user with limited information acquisition ability, and continuous learning, through trial and error, to gradually adjust their strategy. Therefore, the game theory of user participation in data sharing can be modeled by evolutionary game theory to find a way to adjust the user's participation in sharing expectations according to the current situation.

3.1. Data sharing based on an evolutionary game incentive (EGI) model

The EGI model is a symmetric user-involved data sharing evolutionary game composed of a quaternion array $G = (P, N, S, U)$ where:

- P represents a population composed of many individuals (users participating in data sharing);
- N represents a collection of individual users;
- S represents a policy space available to the user, where $S = (S_1,\ S_2) =$ (participation, no participation). That is, during the game, each user can choose whether to participate in data sharing.
- U: indicates the payment matrix formed by the two users in a game, as shown in Table 1.

The various situations in the income matrix are discussed separately below.

Case 1: Both users choose not to participate. In such a case, users in the data sharing blockchain platform will not share data. When users are not involved in data sharing, their utility gain only depends on their own investment costs. We use the logarithmic rate of return to calculate the return, which can be expressed using the logarithmic gain function $\mu ln(1+R)$. According to the realistic rationality requirement, $\mu ln(1+R) > 0$, otherwise the user is not willing to make any investment. Therefore, when both users of the interaction choose not to participate in the strategy, their returns are $\mu ln(1+R)$ and $\mu ln(1+R) > 0$.

This is the steady state. According to the nature of the ESS, the ESS must be satisfied, and then four evolutionary stabilization strategies based on the incentive and participation cost conditions are obtained.

Case 2: Both users choose to participate in the strategy. In this case, each user shares data and can also receive data shared by other users to help increase revenue, which reduces the difficulty of solving problems. When users participate in data sharing, benefits are reaped not only from their own investment, but also from the data shared by other users. We regard these two kinds of income as $\gamma\mu ln(1+R)$, which is the common benefit of investment and sharing. Also based on the realistic rationality requirements, the shared benefit must be greater than 1, otherwise the user would have no motivation to share. When sharing data, a user needs to provide the sharing cost $\tau > 0$. Obviously, the data-sharing blockchain platform can provide incentives for all users, but this may result in saturation of such incentives and may also cause the inflation of virtual currency within the data sharing platform. Therefore, we provide an incentive parameter C, referred to as the incentive and participation cost. When both users choose the participation strategy, the benefits of both users is $\gamma\mu ln(1+R) - \tau - C$.

Case 3: One user chooses to participate, and another user chooses not to. This situation describes the risk of participating in data sharing. Users who choose to participate in the strategy join the data sharing blockchain platform and share their own data, but they cannot obtain data from other users, incurring additional costs without additional shared benefits. The nonparticipating user does not pay any price and does not receive any benefit. Therefore, when one user chooses to participate in the strategy and another user chooses not to, the benefit of the user who chooses to participate in the strategy is $\mu ln(1+R) - \tau - C$ and the benefit of the user who chooses not to participate in the strategy is $\mu ln(1+R)$.

3.2. ESS and dynamics analysis

There are only two strategies in the EGI model: participation and nonparticipation. Therefore, in a population consisting of all users, $\theta(t)$ can be set as the hybrid strategy of the population at stage t, where $\theta(t) = (\theta_1(t), \theta_2(t))$. If $\theta_1(t)$ indicates the proportion of users who choose to participate in the policy, then $\theta_2(t) = 1 - \theta_1(t)$ is the proportion of users who do not participate in the policy. For simplicity, $\theta_1(t)$ is denoted as θ in the following. The expected benefit of the user selecting the participation strategy at this stage is Eq. (1)

$$u(s_1,\ \theta(t)) = \ \theta[\gamma\mu ln(1+R) - \tau - C] + \ (1-\theta)[\mu ln(1+R) - \tau - C]. \tag{1}$$

The expected return for choosing not to participate in the strategy is Eq. (2)

$$u(s_2,\ \theta(t)) = \theta(\mu\ln(1+R)) - (1-\theta)(\mu\ln(1+R)). \tag{2}$$

The average expected return of population P in a blockchain platform for data sharing is Eq. (3)

$$\bar{u}(\theta(t),\ \theta(t)) = \theta u(s_1,\ \theta(t)) + (1-\theta)u(s_2,\ \theta(t)). \tag{3}$$

The dynamic equation of replication in the evolutionary game of users participating in data sharing is Eq. (4)

$$\begin{aligned} F(\theta) = \dot{\theta} &= \theta[u(s_1,\ \theta(t)) - \bar{u}(\theta(t),\ \theta(t))] \\ &= \theta(1-\theta)\{u(s_1,\ \theta(t)) - u(s_2,\ \theta(t))\} \end{aligned} \tag{4}$$

which can be simplified to Eq. (5)

$$F(\theta) = \dot{\theta} = \theta(1-\theta)[\theta(\gamma-1)\mu\ln(1+R) - \tau - C]. \tag{5}$$

Let $F(\theta) = 0$, Eq. (5) with up to three stable states [25], which are

$$\theta_1^* = 0, \tag{6}$$

$$\theta_2^* = 1, \tag{7}$$

$$\theta_3^* = \frac{\tau + C}{(\gamma-1)\mu ln(1+R)}. \tag{8}$$

The steady state represented by (8) may be the same as the steady state represented by (6) or (7).

According to the nature of the ESS, a steady state must be stable to small disturbances in the dynamic system. In fact, this situation can satisfy the necessary conditions for the stability theorem in the differential equation to be established. Let θ^* be the steady state; then, it must satisfy $F'(\theta^*) < 0$. Four ESSs based on incentive and participation cost conditions C were obtained.

Condition 1: If $0 < C < (\gamma - 1)\mu ln(1+R)$ and $(\tau + C) < (\gamma - 1)\mu ln(1+R)$, then θ_1^* and θ_2^* are ESSs for users to participate in data sharing evolutionary games and θ_3^* is not an ESS.

Condition 1 shows that if the proportion of the population initially choosing to participate in the strategy is less than θ_{thres}, then the ESS tends to be non-participation, because the gain from the system is sufficient to force the entire group to move to the sharing strategy.

Condition 2: If $0 < C < (\gamma - 1)\mu ln(1+R)$ and $(\tau + C) \geq (\gamma - 1)\mu ln(1+R)$, then θ_1^* is the only ESS for users participating in the data sharing evolutionary game and θ_3^* does not hold.

Condition 2 indicates that users will not participate in data sharing regardless of the initial participating strategy group.

Condition 3: If $C > 0$ and $C \geq (\gamma - 1)\mu ln(1+R)$, then θ_1^* is the only ESS for users to participate in the data sharing evolutionary game and θ_3^* does not hold.

Condition 3 indicates that, owing to the high cost of data sharing, the evolutionary strategy of populations will be to adopt a non-participation strategy.

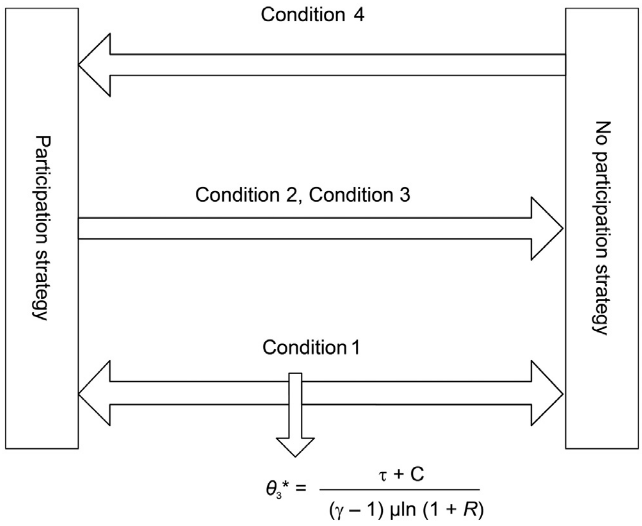

Fig. 2. ESS trend of the EGI model.

Condition 4: If C < 0 and $(\tau + \text{C}) \leq 0$, then θ_2^* is the only ESS for users to participate in the data sharing evolutionary game. θ_3^* is not established.

Condition 4 indicates that regardless of the initial scale value, the ESS of the population will be the participation strategy.

ESS is not unique to users participating in the data sharing evolutionary game. Both participation and nonparticipation strategies have the potential for evolutionary stability, depending on which of the above conditions is met. To clearly illustrate that users participate in the data sharing evolutionary game with two potential ESSs that depend on the above conditions, Fig. 2 summarizes the ESS trends based on Conditions 1–4. We can see that both the participation and nonparticipation strategies may be ESSs, depending on the initial proportion of users who choose to participate in the strategy. These ESSs can be used as triggers for appropriate data sharing incentives and costs.

The above discussion illustrates the changing trend of the evolutionary stable structure based on blockchain data sharing. The factors affecting the trend change are the incentive/participation cost and the proportion of the population that initially chooses to participate in the strategy. Therefore, modeling the incentive/participation costs based on the above four conditions is critical to establishing and maintaining an effective blockchain platform for data sharing. These conditions not only indicate that ESS is achievable, but also show how incentive/participation costs promote user participation in data sharing; they additionally indicate that incentive/participation costs are an important factor in improving users' revenue through sharing.

Therefore, to allow the blockchain platform for data sharing to coexist with users, the user can take advantage of data sharing, and enable the blockchain platform for data sharing to advantageously manage users participating in data sharing. This establishes a dynamic incentive mechanism based on the EGI model, which can encourage more users to participate in data sharing, as shown in Fig. 3. At the beginning of the game k, the initial number of users participating in data sharing is very small. According to the analysis, using conditions 4, incentives can be given instead of charging participation costs to encourage and motivate more users to move toward the participation strategy. Once the proportion of users participating in data sharing exceeds a certain threshold θ_{thres_k}, then using condition 1, the blockchain platform for data sharing can now be implemented without any external incentives. Moreover, at this time, the blockchain platform for data sharing can impose a specific cost on the user. The same process is repeated to iteratively apply a set of participation costs until a set of participation costs is successfully charged or until the maximum phase of the game phase is reached. Therefore, the dynamic incentive/participation cost mechanism can maximize user participation, enabling more users to participate in data sharing, and experience the benefits of data sharing.

3.3. Smart contract mechanism based on the EGI model

To allow the data-sharing blockchain platform to coexist with users, we establish a dynamic incentive and participation cost mechanism based on the EGI model to encourage more users to participate in data sharing. At the beginning of the game, the initial number of users participating in data sharing is very small. Using Condition 4, incentives can be given to motivate more users to move toward the participation strategy. Once the proportion of users participating in data sharing exceeds a threshold, using Condition 1, it is possible to ensure that the blockchain platform for data sharing is self-sustaining in terms of participation strategies, and no external incentives are required. Moreover, at this time, the blockchain platform for data sharing can impose a specific cost on the user. The same process is repeated to iteratively apply a set of participation costs until a set of participation costs is successfully charged or until the maximum phase of the game phase is reached.

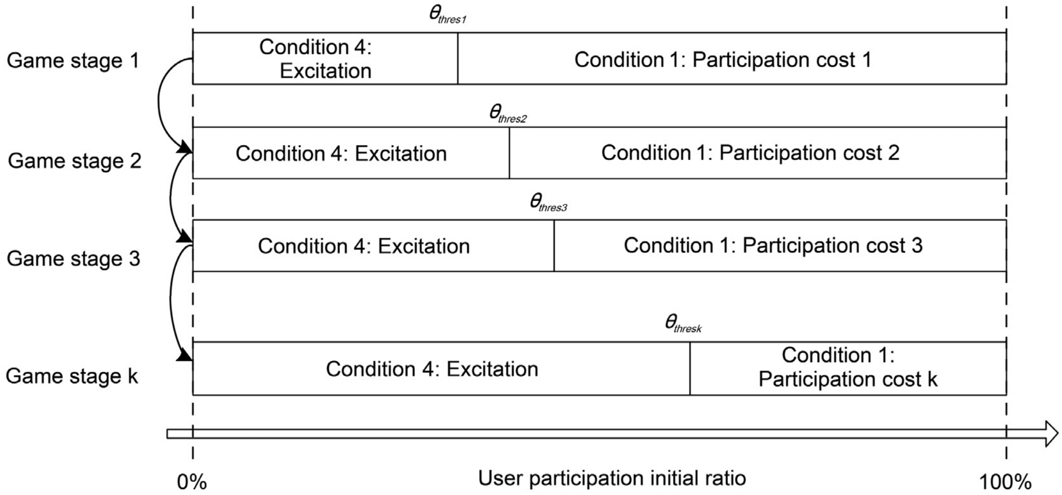

Fig. 3. Dynamic incentive/participation cost mechanism.

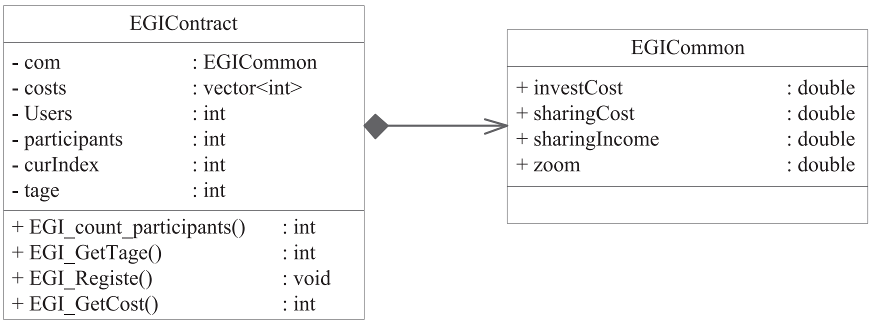

Fig. 4. Template mechanism for smart contracts.

Thus, the dynamic incentive and participation cost mechanism can maximize user participation, enabling more users to participate in and experience the benefits of data sharing. To this end, we provide a smart contract template mechanism based on the EGI model in the form of a UML class diagram, as shown in Fig. 4.

Because the EGI model considers all participating users to be essentially the same, the parameters of all participants are the same. The deployment of smart contracts requires the initialization of the basic parameter *com* and the ordered incentive and participation cost set *costs*[]. The parameter *com* contains four basic parameters: *investCost, sharingCost, sharingIncome,* and *zoom*, which are the investment cost parameter *R*, shared cost parameter τ, shared benefit parameter γ, and scaling parameter μ in the EGI model. The cost set *costs*[] contains an incentive parameter *cost*[0] with a set of participating cost parameters $costs[i]\,(i > 0)$, *costs*[0] for excitation parameters, and *costs*[*i*] for participation cost parameters. According to the EGI model, excitation parameter *cost*[0] satisfies $costs[0] < 0$ and $costs[0] + sharingCost < 0$; the participation cost parameter *costs*[*i*] satisfies $sharingCost < cost[i] < (sharingIncome - 1) * Zoom * log(1 + sharingCost)$. The global variables that need to be dynamically maintained are:

- ***Users*:** Number of registered users
- ***participants*:** The number of participating users in the current game phase
- ***curIndex*:** Index of the participation cost set used in the current phase
- ***stage*:** The stage of the current game

The method *EGI_GetTage()* is used to obtain the current game stage, which is convenient for users to query and can be called at any time. The method *EGI_Registe()* is called when the user registers, and the user is incremented to update the variable.

The method *EGI_GetCost()* is called when the user participates in data sharing, and is used to dynamically adjust the incentive and participation cost parameter and return the incentive and participation cost parameter that should be applied to the current user. Its pseudocode is shown in Algorithm 1, where *GETP(n)* represents the threshold for calculating the current game phase.

Assuming that the smart contract for data sharing is *ShCon*, when the user participates in data sharing, *ShCon* calls the *EGI_GetCost*() method of the *EGIContract* smart contract. It first calculates the current user participation ratio and determines

Algorithm 1 EGI_GetCost().

input: null
output: Incentive and participation cost parameters that should be applied to the current user

```
function EGI_GetCost()
  curP ← participants / Users;
  if curIndex > maxK then
    costIndex = curIndex;
    return cost[costIndex];
  end if
  if curP > 0.95 then // default setting, user saturation participation ratio
    tage++;
    curIndex ++;
    participants ← 0;
    curP ← 0;
  end if
  thresP ← GETP(curIndex);
  participants ++;
  if curP > thresP then
    return costs[curIndex];
  else
    return cost[0];
  end if
end function
```

Table 2
Parameter settings.

Conditions	Parameters				
	γ	μ	R	τ	C
Condition 1	3	5	4	1	4
Condition 2	3	5	4	6	14
Condition 3	3	5	4	6	18
Condition 4	3	5	4	1	−3

whether the current participation cost is the largest, then returns the maximum participation cost. Otherwise, the algorithm determines whether the user participation ratio in the current game stage tends to be saturated (i.e. greater than 95%). If saturated, it enters the next stage of the game, resets the number of user participants and level of user participation, and selects a small participating cost that is not used in the participating cost set. Then, the threshold of the current stage is recalculated and compared with the user participation ratio. If the user participation ratio is less than the threshold, the incentive parameter is returned; otherwise, the current participation cost is returned.

This system includes a blockchain network, and when users want to enter the blockchain network for data sharing, EGI functions— EGI_Regist on the blockchain will be invoked, as shown in Fig. 5. When the user wants to share the data, the function EGI_Cost is called to request the excitation cost.And through function EGI_Cost, it returns the incentive cost to the user.

4. Experimental evaluation

In this section, by setting different values of γ, μ, R, τ and C, "we verify the role of user participation in the ESS as well as verify the incentive mechanism in the data sharing evolutionary game. The experiment is divided into two groups: the values of the game parameters set in the first set of experiments satisfy Conditions 1 to 4, respectively, and then changes in the data sharing are observed for users participating in the evolution curve; the second group changes C under different initial user ratios, demonstrating the role of the incentive mechanism in the evolution of data sharing participation during the game.

The experimental environment is an Intel (R) Core (TM) i5-3470 CPU @ 3.20 GHz, 4Gb RAM, 64-bit win7 operating system, and the software used is MATLAB 6.5.0.180913a Release 13.

For the first set of experiments, to satisfy Conditions 1 to 4, respectively, shared benefit $\gamma = 3$, scaling parameter $\mu = 5$, investment amount$R = 4$, sharing cost τ and participation cost C all change. The settings for each condition are shown in Table 2.

For the second group of experiments, to explain the role of the incentive mechanism and how it promotes the data sharing user's choice of participation strategy, we set the following parameters to the following values: shared benefit $\gamma = 3$, scaling parameter $\mu = 5$, investment amount $R = 8$, , and sharing cost $\tau = 2$. In Condition 1, $0 < \mathrm{C} < 9.89$ and in Condition 4, $\mathrm{C} < -2$. Thus, for Conditions 1 and 4, we give the participation evolution curve against the ratio of different initial selections of data sharing participation strategies and the participation evolution curves under different excitation parameters

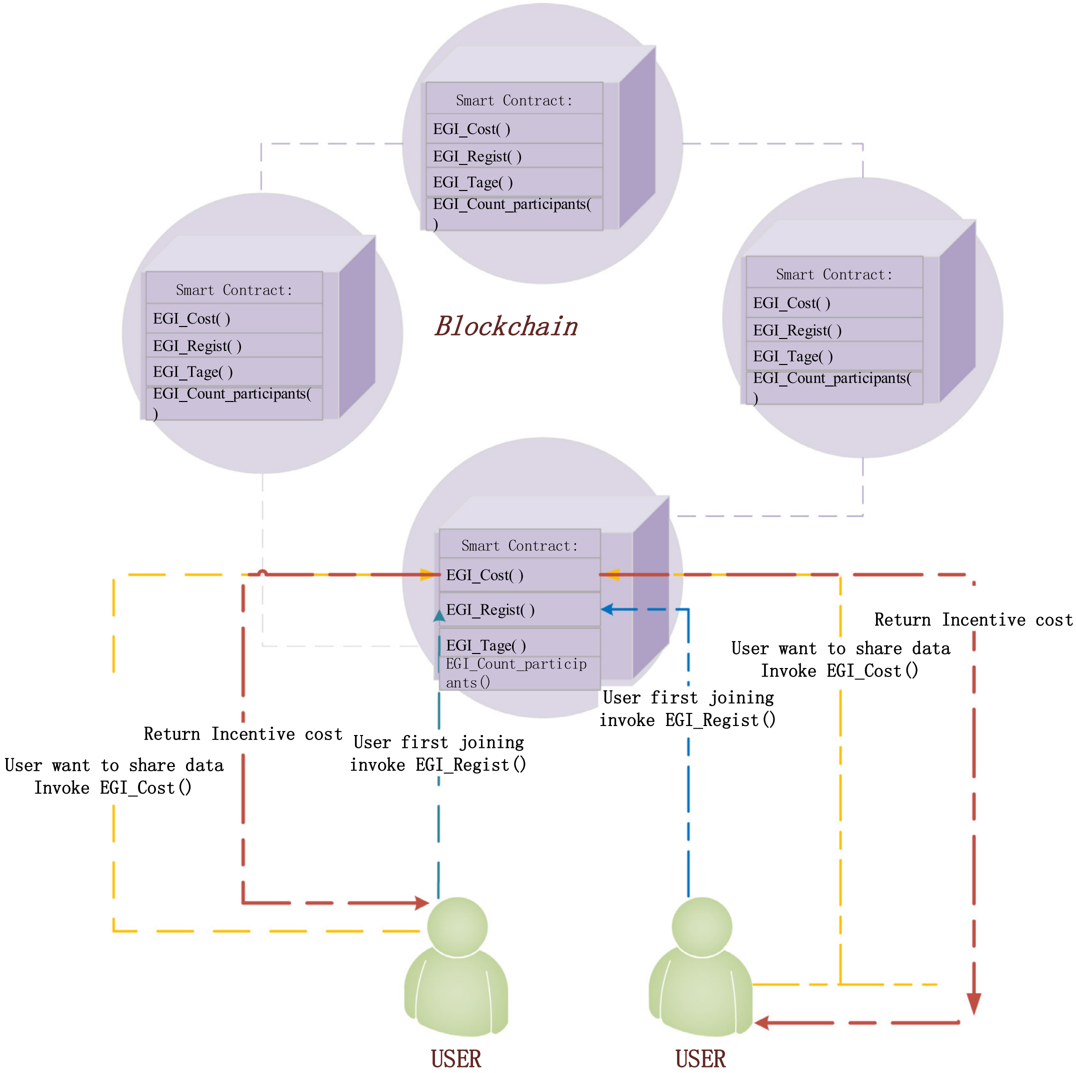

Fig. 5. The system diagram of Smart contract mechanism based on the EGI model.

Table 3
Verification Condition 1 incentive mechanism program parameters.

Test items	Parameters		Test items	Parameters	
	C	θ		C	θ
Test 1	0	0.05	Test 9	5	0.05
Test 2	0	0.45	Test 10	5	0.45
Test 3	0	0.75	Test 11	5	0.75
Test 4	0	0.95	Test 12	5	0.95
Test 5	2	0.05	Test 13	8	0.05
Test 6	2	0.45	Test 14	8	0.45
Test 7	2	0.75	Test 15	8	0.75
Test 8	2	0.95	Test 16	8	0.95

of the same initial selection of participation strategy. The parameters of the verification incentive mechanism for Conditions 1 and 4 are shown in Tables 3 and 4 below.

The value of the game parameters in Fig. 6 satisfies Condition 1 and the user proportion threshold of the initial selection participation strategy $\theta_{thres} = (\tau + C)/((\gamma - 1)\mu \ln(1 + R)) \approx 0.31$. As can be seen from Fig. 6(a), when the initial participation ratio is 35%, the users participating in the interaction constantly adjust their strategies through learning and imitation.

Table 4
Verification Condition 4 incentive mechanism program parameters.

Test items	Parameters		Test items	Parameters	
	C	θ		C	θ
Test 1	−5	0.3	Test 4	−10	0.3
Test 2	−5	0.6	Test 5	−10	0.6
Test 3	−5	0.9	Test 6	−10	0.9

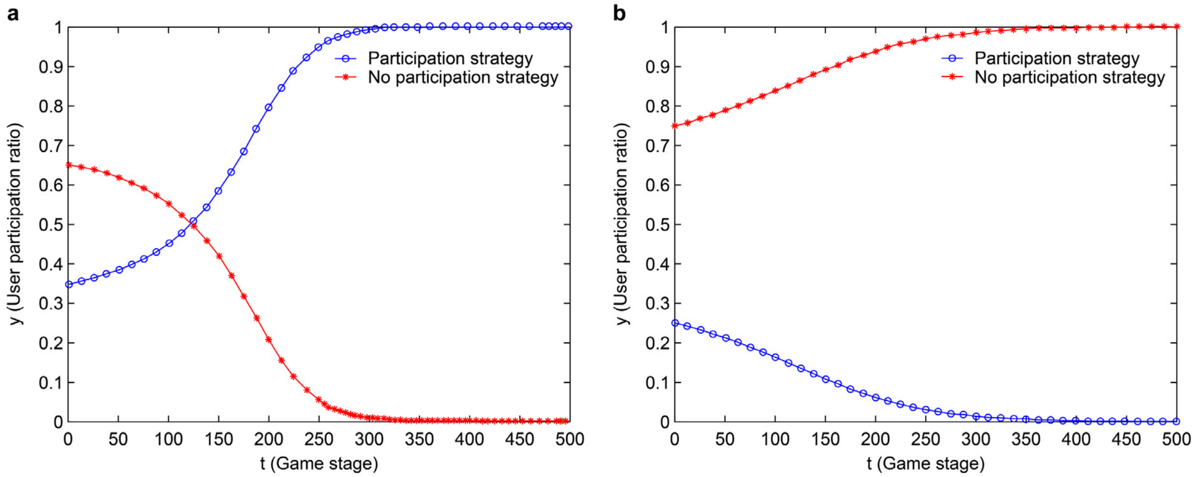

Fig. 6. EGI excitation model evolution curve (Condition 1).

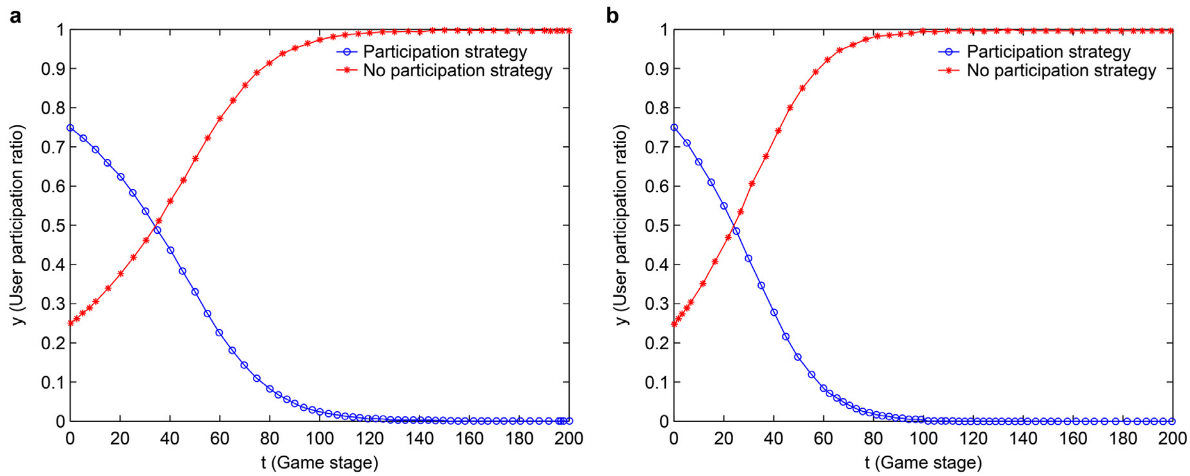

Fig. 7. EGI excitation model evolution curve (Condition 2 and 3).

After multiple games, they finally choose to participate. The proportion of users of this strategy is stable at $\theta_2^* = 1$. As can be seen from Fig. 6(b), when the initial participation ratio is 0.25, after multiple games, the proportion of users who finally choose to participate is stable at $\theta_1^* = 0$. Therefore, when the proportion of users who initially choose to participate in strategy θ^* is below the threshold, most other users tend not to participate; however, when the proportion is above the threshold, users tend to participate. The values here of 25% and 35% are less than 50%, indicating that the number of people participating in data sharing is small. More than 50% means that the number of people sharing data is large, and close to saturation.

The values of the game parameters in Fig. 7(a) and (b) satisfy Conditions 2 and 3, respectively. It can be seen from the results of these two experiments that regardless of whether the initial proportion of users participating in data sharing is 75% or 25%, after multiple game stages, users eventually tend not to participate. Therefore, for Conditions 2 and 3, regardless of the initial participation ratio, there is a tendency to not participate in the strategy.

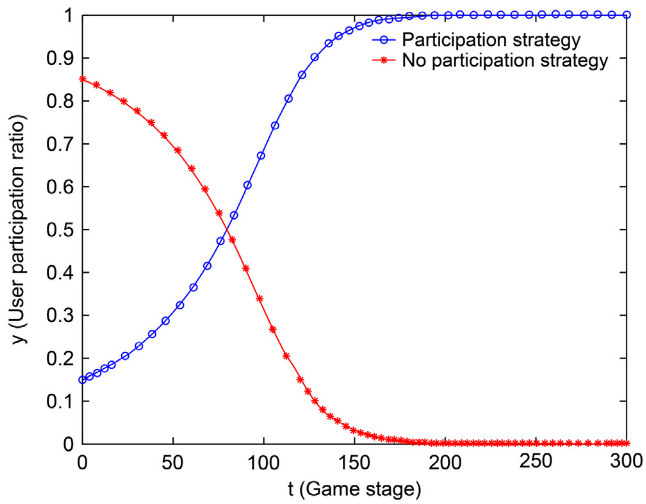

Fig. 8. EGI excitation model evolution curve (Condition 4).

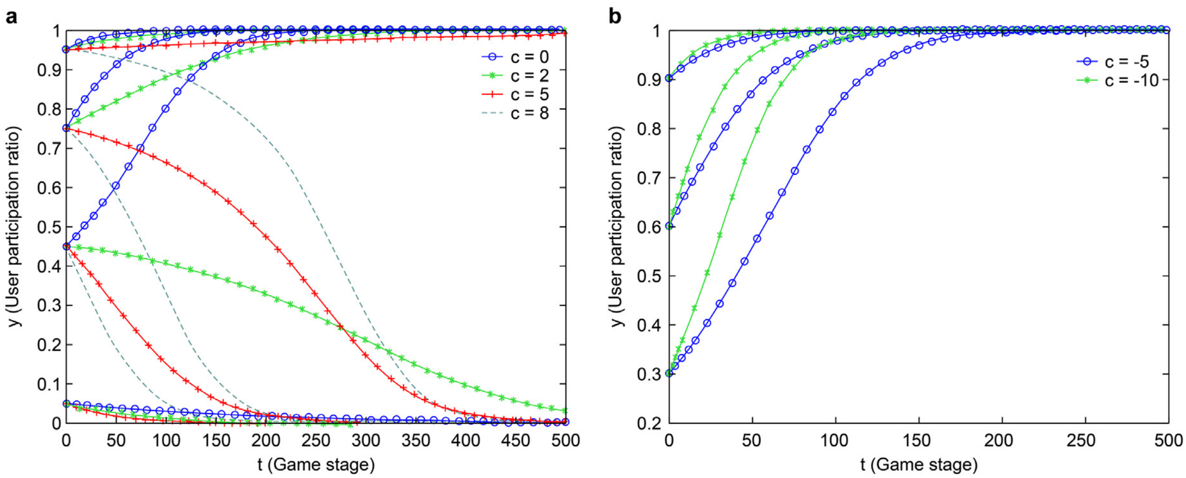

Fig. 9. EGI excitation model evolution curve.

The values of the game parameters in Fig. 8 satisfy Condition 4. It can be seen from the experimental results that when the initial proportion of users participating in data sharing is 85%, after multiple game stages, users eventually tend to participate in the strategy. Even if the initial proportion of users participating in data sharing is 15%, users will eventually tend to participate in the strategy. Therefore, regardless of the initial participation ratio, there is a tendency to participate.

The value of the game parameters in Fig. 9(a) satisfy Condition 1. Note that the curves intersecting the y-axis at different points (representing the initial proportion of the data sharing participants) have different colors. According to Condition 1, different participation costs C result in different user participation proportional thresholds θ. When C $= 0$, $\theta \approx 0.18$; when C $= 2$, $\theta \approx 0.36$; when C $= 5$, $\theta \approx 0.64$; and when C $= 8$, $\theta \approx 0.91$. As can be seen in Fig. 9(a), different incentive and participation costs affect the user's choice of ESS. At the same time, for the evolution curve of the selected participation strategy, the initial proportions of users are compared, and the higher the initial proportion of users, the faster the remaining users will choose to participate in the strategy. Therefore, within the controllable range of incentive and participation cost C (i.e. Condition 1 being satisfied), the participation cost can be gradually increased to encourage more users to participate in data sharing.

The value of the game parameters in Fig. 9(b) satisfy Condition 4. As can be seen from (a), regardless of incentive and participation cost C (as long as Condition 4 is met) and the initial proportion of users, the end user's ESS tends to be participation in the strategy. Therefore, for Condition 4, the incentive and participation cost provided is reasonable.

The EGI incentive model dynamically adjusts the incentive/participation cost to facilitate user participation in data sharing. When the number of users participating in data sharing begins to decrease, if there is no incentive adjustment mechanism, users will likely continue to decrease, eventually leading to the failure of the data sharing network. The incentive adjustment mechanism increases the participation of users by increasing incentives, and maintains the scale and activity of users sharing networks, thus ensuring that a balance is achieved between the user participation level of the data sharing network and the network maintenance cost.

5. Conclusion

In summary, this paper proposed a smart contract-based incentive method to maintain the level of user participation, by dynamically adjusting incentives and participation costs, which should encourage users to actively share data. A high level of user participation is very important to a data sharing system, and future research should also consider how user-shared data size and data quality can impact to the incentive adjustment required.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

Shichang Xuan: Conceptualization, Methodology, Writing - original draft. **Li Zheng:** Methodology, Software, Writing - original draft. **Ilyong Chung:** Writing - review & editing. **Wei Wang:** Data curation, Validation. **Dapeng Man:** Formal analysis, Validation. **Xiaojiang Du:** Writing - review & editing. **Wu Yang:** Supervision. **Mohsen Guizani:** Writing - review & editing.

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References

[1] Wang Z, Tian Y, Zhu J. Data sharing and tracing scheme based on blockchain. In: 2018 8th international conference on logistics, Informatics and Service Sciences (LISS); 2018. p. 1–6.
[2] Ali M, Nelson J, Shea R, Freedman MJ. Blockstack: a global naming and storage system secured by blockchains. In: Proceedings of the 2016 usenix annual technical conference (USENIX ATC '16); 2016. p. 181–94.
[3] Confais B, Lebre A, Parrein B. Performance analysis of object store systems in a fog/edge computing infrastructures. In: 2016 IEEE international conference on cloud computing technology and science (CloudCom); 2016. p. 40–79.
[4] Klems M, Eberhardt J, Tai S, Härtlein S, Buchholz S, Tidjani A. Trustless intermediation in blockchain-based decentralized service marketplaces. In: International conference on service-oriented computing. Cham: Springer; 2017. p. 731–9.
[5] Mukherjee M, Matam R, Shu L, Maglaras L, Ferrag MA, Choudhury N, et al. Security and privacy in fog computing: challenges. IEEE Access 2017;5:19293–304. doi:10.1109/ACCESS.2017.2749422.
[6] Chowdhury MJM, Colman A, Kabir MA, Han J, Sarda P. Blockchain as a notarization service for data sharing with personal data store. In: 2018 17th ieee international conference on trust, security and privacy in computing and communications/12th ieee international conference on big data science and engineering (TrustCom/BigDataSE); 2018. p. 1330–5.
[7] Nguyen QK, Dang QV. Blockchain technology for the advancement of the future. In: 2018 4th international conference on green technology and sustainable development (GTSD); 2018. p. 483–6.
[8] Liu L, Xu B. Research on information security technology based on blockchain. In: 2018 IEEE 3rd international conference on cloud computing and big data analysis (ICCCBDA); 2018. p. 380–4.
[9] Chang EY, Liao S, Liu C, Lin W, Liao P, Fu W, Mei C, Chang EJ. "DeepLinQ: distributed multi-layer ledgers for privacy-preserving data sharing,". In: IEEE international conference on artificial intelligence and virtual reality (AIVR); 2018. p. 173–8.
[10] Cha SC, Chen JF, Su C, Yeh KH. A blockchain connected gateway for BLE-based devices in the internet of things. IEEE Access 2018;6:24639–49. doi:10.1109/ACCESS.2018.2799942.
[11] Dong X, Li R, He H, Zhou W, Xue Z, Wu H. Secure sensitive data sharing on a big data platform. Tsinghua Sci Technol 2015;20(1):72–80. doi:10.1109/TST.2015.7040516.
[12] Wang X, Li K, Li H, Li Y, Liang Z. Consortium DNS: a distributed domain name service based on consortium chain. In: 19th international conference on high performance computing and communications; ieee 15th international conference on smart city; ieee 3rd international conference on data science and systems (HPCC/SmartCity/DSS). IEEE; 2017. p. 617–20.
[13] Zhu Y, Liu R, Min F, Song J. Research on earth system scientific data sharing platform based on SOA. Geo Inform Sci 2009;11(1):77–83. doi:10.1109/WCSE.2009.28.
[14] Kang J, Yu R, Huang X, Wu M, Maharjan S, Xie S, Zhang Y. Blockchain for secure and efficient data sharing in vehicular edge computing and networks. IEEE Internet of Things Journal 2019;6(3):4660–70. doi:10.1109/JIOT.2018.2875542.
[15] Desai H, Liu K, Kantarcioglu M, Kagal L. Adjudicating violations in data sharing agreements using smart contracts,. In: IEEE international conference on internet of things (iThings) and ieee green computing and communications (GreenCom) and ieee cyber, physical and social computing (CPSCom) and IEEE smart data (SmartData); 2018. p. 1553–60.
[16] Khan MA, Khaled S. IoT security: review, blockchain solutions, and open challenges.. Future Gener Comp Sy 2018;82:395–411. doi:10.1016/j.future.2017.11.022.
[17] Almadhoun R, Kadadha M, Alhemeiri M, Alshehhi M, Salah K. A user authentication scheme of IoT devices using blockchain-enabled fog nodes. In: IEEE/ACS 15th international conference on computer systems and applications (AICCSA); 2018. p. 1–8.
[18] Li L, Liu J, Cheng L, Qiu S, Wang W, Zhang X, Zhang Z. Creditcoin: a privacy-preserving blockchain-based incentive announcement network for communications of smart vehicles. IEEE Transactions on Intelligent Transportation Systems 2018;19(7):2204–20. doi:10.1109/TITS.2017.2777990.
[19] Hasan Haya R, Khaled S. Combating deepfake videos using blockchain and smart contracts. IEEE Access 2019;7:41596–606. doi:10.1109/access.2019.2905689.
[20] Phelps S, Wooldridge M. Game theory and evolution. IEEE Intell Syst 2013;28(4):76–81. doi:10.2307/1425844.
[21] De S, Nau DS, Gelfand M. Using game theory to study the evolution of cultural norms. CoRR 2016. Available from: https://arxiv.org/pdf/1606.02570.pdf.

[22] Ali B, Maheswaran M. A game theoretic analysis of blacklisting in online data storage systems. In: 2009 IEEE global telecommunications conference; 2009. p. 1–7.
[23] Kamhoua CA, Kwiat KA, Park JS. A game theoretic approach for modeling optimal data sharing on online social networks. In: 2012 9th international conference on electrical engineering, computing science and automatic control (CCE); 2013. p. 1–6.
[24] Yassine A, Shirehjini AAN, Shirmohammadi S. Smart meters, big data: game theoretic model for fair data sharing in deregulated smart grids. IEEE Access 2015;3:2743–54. doi:10.1109/ACCESS.2015.2504503.
[25] Tosh D, Sengupta S, Kamhoua CA, Kwiat KA. Establishing evolutionary game models for CYBer security information EXchange (CYBEX). J Comput Syst Sci 2018;98:27–52. doi:10.1016/j.jcss.2016.08.005.

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