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Yongjing Xie

Zhihong Li

Xiaoying Xu

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Addressing Wealth Inequality Problem in Blockchain-Enabled Knowledge Community with Reputation-Based Incentive Mechanism

Yongjing Xie [1]
Zhihong Li [2]
Xiaoying Xu [3,*]

*Corresponding author
[1] Postgraduate, South China University of Technology, China, xieyongjing2021@163.com
[2] Professor, South China University of Technology, China, bmzhhli@scut.edu.cn
[3] Associate professor, South China University of Technology, China, bmxyxu@scut.edu.cn

ABSTRACT

An increasing number of online knowledge communities have started incorporating the cut-edge FinTech, such as the token-based incentive mechanism running on blockchain, into their ecosystems. However, the improper design of incentive mechanisms may result in reward monopoly, which has been observed to harm the ecosystems of exiting communities. This study is aimed to ensure that the key factors involved in users' reward distribution can truly reflect their contributions to the community so as to increase the equity of wealth distribution. It is one of the first to comprehensively balance a user's historical and current contributions in reward distribution, which has not received sufficient attention from extant research. The simulation analysis demonstrates that the proposed solution of amending the existing incentive mechanism by incorporating a refined reputation indicator significantly increases the equity of rewards distribution and effectively enlarges the cost of achieving reward monopoly.

Keywords: Blockchain, knowledge community, wealth inequality, incentive mechanism.

INTRODUCTION

Online knowledge communities have become increasingly popular for knowledge sharing and communication (Chen, Baird & Straub, 2019; Liu et al., 2020; Rafiei & Kardan, 2015). Famous examples include Quora, Stack Exchange, and Yahoo Answer. However, the lack of an effective incentive mechanism in these communities has led to the decrease of users' enthusiasm to contribute knowledge, and free-riding behaviors have emerged intensively (Kim & Chung, 2018). According to recent statistics, in most knowledge communities, only 1% of users produce original content, 9% of users contribute by synthesizing or curating content, and 90% of users consume content without contributing (Kwon, 2020).

With the development of financial technologies (FinTech), such as blockchain and the token economy, knowledge communities have started embracing these cut-edge technologies to develop precise incentive mechanisms in a decentralized and autonomous manner. Users who post and discover high-quality content and those who contribute to knowledge dissemination can be economically rewarded (Sun et al., 2019). The token-based incentive mechanisms have shown their effectiveness to some level in promoting contributions in knowledge communities. Typical examples include Steemit (https://steemit.com/), one of the most popular blockchain-enabled and autonomous knowledge communities.

Regardless of their popularity, blockchain-enabled communities are facing great challenges due to the improper design of their incentive mechanisms. In these communities, as a common form, the voting rights of users are weighted by the tokens they have owned. Such mechanism design is good at increasing the effectiveness of decision-making and promoting user contributions at the early stage of the community. However, as the community evolves, a large number of rewards, as well as voting rights, tend to be obtained by a small number of users, who will monopolize the community. As a result, most ordinary users keep contributing knowledge and voting for good content, but they fail to get the corresponding rewards since the rewards are distributed according to the weights of voting rights. In other words, monopoly turns the community from decentralized towards centralized, seriously harming most users' enthusiasm for the community.

The problem of the current incentive allocation scheme has been identified and highlighted by recent studies, and its seriousness can be easily observed from real-world communities. For example, some scholars have found that the decentralization of blockchain-driven platforms, such as Steemit, Swarm City, Bihu, etc., is far below the ideal level, and the incentive system is abused (Guidi, Michienzi & Ricci, 2020). By analyzing the data collected from Steemit on November 12, 2020, we find that only 0.035% of users controlled over 64% of the voting rights, and this figure is still growing. During December 2020, these powerful users took up 74.8% of the total upvoting rewards in the community, but the percentage of posts they upvoted was less than 1%. Therefore, the distribution of tokens in the community does not effectively reflect the level of knowledge contribution of users, which is of primary concern to us.

Obviously, how to resolve the monopoly of incentive allocation is an urgent issue faced by both academia and communities. However, existing studies in this field mostly focus on detecting and preventing some specific speculative actions for monopolizing rewards, such as using voting bots (Li & Palanisamy, 2019; Guidi & Michienzi, 2020). They fail to address the problem in a more holistic manner by considering how to eliminate the association between the voting weights and the tokens accumulated not from community contributions but from purchasing and renting, which we believe is fundamental and critical. In addition, our focus is not on how to achieve the absolutely equal distribution of wealth, as we cannot deny that there are large discrepancies in the level of knowledge contribution of users in the community. Therefore, to fill in the research gap, in this study, we propose to tackle the problem from the angel of equity theory and incorporate the idea from the reputation system to quantify users' contribution when amending the incentive mechanism. Our main objective is to ensure that the key factors involved in users' reward distribution can truly reflect their contributions to the community so as to increase the equity of wealth distribution.

A simulation analysis based on a real-world dataset collected from Steemit has shown that our proposed solution can reduce the Gini Index of upvoting rewards distribution by 53% and increase the correlation coefficient between users' historical contributions and their upvoting rewards by eight times, without losing the consideration on their current contributions to determining the total rewards of the posts they have upvoted. Moreover, the simulation results also indicate that the proposed solution has created a huge barrier to achieving a rewarding monopoly.

In summary, the novelty and contributions of our work lie in the following: (1) We are among the first to amend the incentive mechanism design in blockchain-enabled knowledge communities by comprehensively considering the trade-off between users' historical and current contributions in reward distribution; (2) We enrich the relevant research of equity theory by expanding its application scenarios to a specific form of Decentralized Autonomous Organizations (DAOs) which has a distinctive character of a strong link between users' property and voting rights; (3) Our validation approach of combining empirical analysis with incentive mechanism simulation based on a real-world dataset collected from Steemit provides implications for the practice of blockchain-enabled incentive mechanism design.

RELATED WORK

This section reviews and discusses related work to our study. First, we summarize the literature on the impact of incentive mechanisms on knowledge contribution that motivates our work. Then, we review the literature on equity theory, which is the theoretical foundation of our work, and its applications on incentive mechanism design. Finally, we discuss some of the recent work on the reputation systems that are the main approach we adopt to solve the problem.

Impact of Incentive Mechanism on Knowledge Contribution

For online knowledge communities, motivation is the key to driving users to participate in knowledge sharing. Motivation theory has been widely used to explain users' online participation behavior (Roberts et al., 2006; Huang et al., 2018). Motivation theory divides motivation into two types, including intrinsic motivation and extrinsic motivation (Ryan & Deci, 2000). To motivate individuals to share their knowledge in online communities, the method of financial rewards is a typical approach (Zhao, Detlor, & Connelly, 2016; Kuang et al., 2019). A great deal of previous research has investigated the influence of external motivation on knowledge contribution. For example, Ryan and Deci (2000) emphasized the importance of external motivation. In their seminal article, they demonstrated that economic rewards provided not only extrinsic motivation but also enhanced intrinsic motivation. Chen, Chang, and Liu (2012) had taken a different approach by focusing on the influence conditions of motivation, incentive mechanism, and satisfaction on knowledge sharing behavior. Their studies had concluded that the incentive mechanism was a significant predictor of the knowledge acquisition motivation of virtual community members.

Overall, these studies indicate that external incentive has a positive effect on enhancing users' willingness to contribute knowledge. Therefore, a proper design of incentive mechanisms in the knowledge community plays an important role in the development of the community. Although these studies have highlighted the importance of economic incentives on knowledge contributions, they have not considered the impact of incentive equity, which is the focus of our work.

Application of Equity Theory in Incentive Distribution

Although economic incentives have been found to have a positive effect on enhancing users' knowledge contribution, some studies have also found that if the distribution of wealth is unequal, it will hinder knowledge sharing, which is related to equity theory. The first systematic study of equity theory was reported by Adams (1963). Equity theory tries to explain people's perception, evaluation, and behavioral judgment of equity. There is a large volume of published studies describing the relationship between the equity of the distribution of economic incentives and the willingness to share knowledge. An empirical study on investigating the motivations behind people's intentions to continue knowledge sharing in open professional virtual communities implied that justice factors appear to be important in leading to higher satisfaction levels (Wolfe & Loraas, 2008; Chiu et al., 2011). Furthermore, Mirkovski et al. (2019) empirically proved that users' sense of equity in obtaining incentives in the community has a moderating effect on the relationship between users' psychological motivation and their willingness to share information.

These studies have summarized the importance of ensuring the equity of incentive distribution to the sustainability of online communities, and they have confirmed the applicability of equity theory in a related context. However, they do not provide any specific solution to avoid the inequity of incentive distribution, nor do they keep track of the recent development of the blockchain-enabled incentive mechanisms, which is the focus of our work.

Incentive Distribution Based on Reputation System

To ensure the equity of the incentive distribution of the community, the biggest challenge we face is how to quantify the level of user contribution to the knowledge community. We borrow the idea from the reputation system to formulate our solution. The reputation system is an interactive mechanism, which is the result of a long-term dynamic repeated game of users (Gong & Fan, 2019). A reputation score is an indicator used by the online knowledge community to represent the historical performance of users (Wei, Chen & Zhu, 2015). In recent years, there has been an increasing amount of literature on the combinations of reputation systems and incentive mechanisms. For example, Zhao, Yang, and Li (2012) and Thanasis and George (2010) showed that the establishment of a reputation system based on an incentive mechanism could promote more real feedbacks and, in return, could form a more reliable and trustful reputation system. Gong and Fan (2019) indicated that compared with the incentive model without reputation mechanism, the optimal dynamic model combining the reputation mechanism with the explicit incentive mechanism could not only realize Pareto improvement and increase the incentive intensity, but also improve the level of information sharing efforts in social networking services.

As discussed above, these existing studies have provided both theoretical and empirical supports to our idea of incorporating users' reputations in incentive mechanism design. However, none of them have considered the application of user reputation in increasing community equity. Therefore, our work is aimed to implement a more comprehensive incentive mechanism design that considers users' reputations for addressing the shortcomings caused by an inequity.

MODEL DESCRIPTION

Description of Key Variables

In the following, we will identify and introduce the key variables involved in our model, including *Voting Power, Weighted Power*, *Vesting Shares*, *Rshares*, Δt, P_{SP} ,$P_{curator}$.

Voting Power **(V_P)**

Voting Power is a variable designed to restrict the abuse of upvoting rights by users in order to maximize their profits. When a user's *Voting Power* is low, his/her votes will carry less influence, resulting in fewer voting rewards. The community recharges a user's *Voting Power* by a maximum of 20% every day, with an upper bound of 100%. The recharge of *Voting Power* starts right after each vote in the following manner:

$$V_P = min\left\{V_{P0} + \frac{20\%}{24\times60\times60} \times t_0, 100\%\right\} \tag{1}$$

where VP_0 is the last *Voting Power*. t_0 is the elapsed seconds from the last vote of the curator.

Weighted Power **(W_P)**

Weighted Power means a user's level of preference for a post. It can be calculated by Eqs. (2):

$$W_P = V_P \times \frac{|W|}{100\%} \tag{2}$$

where *W* is the weight that he/she can set for his/her vote, from 1% to 100%. This weight is positive for upvote and negative for the downvote.

Vesting Shares **(V_S)**

Vesting Shares represents the worth of a vote. The value of *Vesting Shares* is not only related to the number of effective *Steem Power* a user holds but also related to the total *Vesting Shares* and total *Steem Power* of the community. It can be calculated as:

$$V_S = \frac{SP}{TV_{fs}} \times TV_s = \frac{SP_1 - SP_2 + SP_3}{TV_{fs}} \times TV_s \tag{3}$$

where SP is effective *Steem Power* the user holds, SP_1 is the *Steem Power*, the user, holds, SP_2 is the *Steem Power* of outgoing delegation, SP_3 is the *Steem Power* of receiving the delegation, TV_s is the total *Vesting Shares* of the community, and TV_{fs} is the total *Steem Power* of the community.

Rshares (RS)

Rshares reflect a user's contribution to the growth of a post's rewards. It can be positive or negative, depending on whether the user upvotes or downvotes the post. It can be calculated by Eqs. (4):

$$RS = \begin{cases} +V_S \times 10^6 \times \frac{\frac{W_P+c}{d}}{100\%} & \text{for upvote} \\ -V_S \times 10^6 \times \frac{\frac{W_P+c}{d}}{100\%} & \text{for downvote} \end{cases} \tag{4}$$

where c and d, which are used to control the decreasing rate of *Weighted Power*, are set to 0.0049 and 50 respectively in Steemit.

Δt

Δt is a variable designed to reflect the early voting penalties. If curators vote for a post within the first 5 minutes after the post is created, a certain portion of their rewards will be deducted and sent to the author.

$$\Delta t = \begin{cases} \frac{t}{5} & \text{for } t < 5min \\ 1 & \text{for } t \geq 5min \end{cases} \tag{5}$$

where t is the time of upvote after posting, Δt is the portion of their curation reward that remained for the curator.

$\boldsymbol{P_{SP}}$

$$P_{SP} = \frac{RS_T}{R_c} \times R_b \tag{6}$$

where P_{SP} is the total payout of the post, RS_T is the total *Rshares*, R_b is the reward balance of the community, and R_c is the recent claims, i.e., the total *Rshares* of all posts that have not been settled yet.

$\boldsymbol{P_{curator}}$

$P_{curator}$ is the reward for a single curator. Up to 50% of the total payout is awarded to curators who upvote the post as a reward for discovering the content. The remaining 50% is awarded to the authors. Eqs. (7) is the original upvoting reward distribution scheme.

$$P_{curator} = 0.5 \times RS_T \times \frac{R_b}{R_c} \times \frac{\frac{RS'+RS}{\sqrt{RS'+RS+2s}} - \frac{RS'}{\sqrt{RS'+2s}}}{\frac{RS_T}{\sqrt{RS_T+2s}}} \times \Delta t \tag{7}$$

where RS' is the *Rshares* accumulated by the post before the curator votes, s equals 2×10^{12} in Steemit.

Model Construction

In Steemit, Steem Power is similar to equity in a company, which reflects how much influence a user has in the community. Holders of Steem Power can not only receive dividends but also influence the value of posts. However, *Steem Power* is not a good indicator for users' past contribution since users can acquire a large amount of *Steem Power* in a short time through leasing or purchasing. *Steem Power* soon becomes the key factor of causing upvoting reward monopoly. Based on this, one might reckon that the simplest solution would be to remove purchased/rented tokens from the incentive system. However, as a cryptocurrency, the free exchange in the market is one of the basic characteristics of tokens, so it is not reasonable to do that. From another perspective, this study is aimed to alleviate the inequality of community upvoting rewards distribution indicated by the *Gini Index*, and at the same time, to balance users' historical contributions and their current contribution to determining the total rewards of the post, respectively, when distributing the upvoting rewards.

In order to achieve the above objectives, we need to introduce more variables to indicate the aspects being considered in upvoting reward distribution. First of all, the reputation system of the community plays an important role in promoting user participation in knowledge-sharing activities by quantifying users' past contributions to the community, which can fulfill our requirements. Therefore, the first main amendment of the upvoting rewards is to incorporate a user reputation indicator. However, the total rewards for the author of a post and all the curators who upvote this post are determined by the *Rshares* of these curators. In other words, the *Rshares* of a curator indicates his/her current contributions to the total rewards of a post. A curator's *Rshares* should not be totally ignored when distributing the rewards. Otherwise, it will badly harm fairness and will lower users' willingness to upvote a post. Therefore, by making a tradeoff, we propose to incorporate both the reputation indicator and the *Rshares* of users, reflected as their corresponding proportions, into the upvoting reward calculation. The proportions are determined in an experimental way that will be introduced later.

The detailed amended upvoting reward calculation is illustrated in Algorithm 1. Specifically, a curator's upvoting reward for a post will be calculated by two steps: (1) Calculate the total rewards for this post upon Eqs. (1-6); (2) Calculate the specific reward that can be allocated to the curator. Our upvoting reward amendments are made upon Eqs. (7) which is the original upvoting reward distribution scheme of Steemit. Firstly, we split the total rewards into two parts. One part is for the users' historical contribution indicated by their reputation, and the remaining part is for their current contribution indicated by their *Rshares*. We define a new variable $PR \in [0,100\%]$, i.e., the proportion of reputation reward, to control the proportion of rewards assigned to the reputation aspect, and then $1 - PR$ indicates the proportion of rewards assigned to the *Rshares* aspect.

Algorithm 1: Optimized upvoting reward distribution algorithm

Input: the total votes of the post *N*, the serial number of the curator *i*, the proportion of reputation reward $PR, VP_i, W_i, SP_i, TV_s, TV_{fs}, R_b, R_c, \Delta t\_i, H \in \{0,1\}$, the reputation score of the curator RU_i.

Output: Upvoting reward of the curator $P_{\text{curator\_}i}$.

$RS_T \leftarrow 0$; $RS' \leftarrow 0$; $RS_0 \leftarrow 0$; $RD_T \leftarrow 0$; $RD' \leftarrow 0$; $RD_0 \leftarrow 0$;
for all $i \in [1,N]$ do
    $WP_i = VP_i * |W_i|$;
    $VS_i = SP_i * TV_s / TV_{fs}$;
  if H=0 // upvote
      $RS_i = +VS_i * 10^6 * (WP_i + 0.49\%)/50$;
  else // downvote
      $RS_i = -VS_i * 10^6 * (WP_i + 0.49\%)/50$;
  if RU_i<=25
    RD_i=0;
  else
    $RD_i = RU_i * (RU_i - 25)$; // the reputation indicator of the curator *i*
  for all $j \in [1,N]$ do
      $RS_T \leftarrow RS_T + RS_j$;// the total *Rshares* of the post after a week
      $RD_T \leftarrow RD_T + RD_i$; // the total RD of curators who upvote the post after a week
  for all $k \in [0,i\text{-}1]$ do
      $RS' \leftarrow RS' + RS_k$;// the total *Rshares* accumulated by the post before the curator *i* votes
    $RD' \leftarrow RD' + RD_k$; // the total RD of curators before the curator *i* votes
    $P_{sp} = RS_T * R_b / R_c$;
  $WS = ((RS' + RS_i)/sqrt(RS' + RS_i + 2s) - RS'/sqrt(RS' + 2s))/(RS_T/sqrt(RS_T + 2s)$;
  $WD = ((RD' + RD_i)/sqrt(RD' + RD_i + 2s) - RD'/sqrt(RD' + 2s))/(RD_T/sqrt(RD_T + 2s)$;
    $P_{\text{curator\_}i} = 0.5 * P_{sp} * (WS * (1 - PR) + WD * PR) * \Delta t\_i$;
  return ($P_{\text{curator\_}i}$);
  end if
  end for
end for

To determine the reputation reward, the main problem that we need to deal with is how to design a suitable reputation indicator for reward distribution. To quantify a user's historical contributions, Steemit uses a variable *Reputation Number* that is directly correlated with the user's *Rshares* received by users for their posts and comments, as is shown in Eqs. (8), to address the wide-range problem of the *Reputation Number,* Steemit applies a logarithm transformation to generate a new indicator *RU.* But it goes from one extreme to the other, making the difference of reputation among users very tiny so that it cannot significantly differentiate the users' historical contributions. With this regard, this study defines a new variable, reputation indicator *RD* in Eqs. (9). Through this nonlinear relationship, the historical contribution level of users can be reflected more reasonably. The effectiveness analysis of this part of improvement will be further discussed later.

$$RU = (log^{Reputation\ Number} - a) \times b + Initial\ Score \tag{8}$$

$$RD = RU \times (RU - Initial\ Score) \tag{9}$$

Where *RU* represents the user's reputation score, *a* and *b*, which are used for controlling the growth rate of *RU*, are both set to 9 in Steemit. *Initial Score* is the user's initial reputation score. Steemit sets the *Initial Score* to 25. When *RU* is lower than the initial reputation score of 25, *RD*=0, indicating that the user does not contribute to the community.

The next problem is how to distribute rewards among all the curators who upvote the same post. The proposed allocation method is similar to Steemit's original calculation method in Eqs. (7), which adopts upvoting rewards gradually declining with upvoting time. The main difference is that the reputation part needs to be taken into account. Specifically, two nonlinear formulas of *WD* and *WS* in Algorithm 1 are respectively used in this paper to represent the reputation indicator *RD* of the curator and the *Rshares* of his/her contribution to participate in the income distribution. Where, RS' represents the total *Rshares* contained in a post before the curator i upvotes the post; RS_i means that the *Rshares* contributed by the curator i; s is a constant, is equal to 2×10^{12}; RD_T represents the total reputation indicator *RD* of all the curators of the post; *RD'* means that the total *RD* contained in the post before the curator i upvotes the post; RD_i represents RD contributed by the curator i; Thus, the upvoting reward $P\_curator$ of each curator in the post can be calculated.

SIMULATION RESULT

This section will first describe how to determine the proper value of PR, *i.e.*, the proportion of rewards assigned to the newly introduced reputation indicator based on simulation analysis. Generally, the value of PR is determined by making a tradeoff between the equity of reward distribution and the importance attached to users' historical and current contributions. Furthermore, we will report the assessment results on the effectiveness of the proposed solution by comparing the equity distribution and the cost to achieve reward monopoly before and after the amendment.

We use the distributional equality metric *Gini Index* (Wang et al., 2020) to measure the equality of the upvoting rewards distribution in the community. *Gini Index* is defined as:

$$Gini\ Index = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}|P(curator_i)-P(curator_j)|}{2n^2\bar{x}} \tag{10}$$

where $P_{curator\_i}$ is the upvoting reward of user i ($i \in$ [1,2, … , n]). $P_{curator\_j}$ is the upvoting reward of user j ($j \in$ [1,2, … , n]). $\bar{x}$ is the average absolute difference of the upvoting reward of all users. A lower *Gini Index* indicates greater equality, with 0 representing perfect equality.

To quantify the real influence of users' historical and current contributions on reward distribution, we use $R(RS, P_{SP})$ $(0 \leq R(RS, P_{SP}) \leq 1)$ to denote the correlation coefficient (Fieller, Hartley & Pearson, 1957) between users' $Rshares$, *i.e.*, their current contributions to determining the total rewards of a post, and their own upvoting rewards P_{SP}:

$$R(RS, P_{SP}) = \frac{cov(RS, P_{SP})}{\sqrt{var(RS) \times var(P_{SP})}} \tag{11}$$

where $R(RS, P_{SP})$ is the correlation coefficient between the users' *Rshares* and their own upvoting rewards P_{SP}. $cov(RS, P_{SP})$ represents the covariance between the users' $Rshares$ and their own upvoting rewards. $var(RS)$ and $var(P_{SP})$ represent the variance of the users' *Rshares* and their own upvoting rewards, respectively.

Similarly, we use $R(RD, P_{SP})$ $(0 \leq R(RD, P_{SP}) \leq 1)$ to denote the correlation coefficient between users' historical contribution and their upvoting rewards.

Dataset

We collected the ten posts in the popular list on November 22, 2020, in Steemit randomly, as shown in Table 1 below. These posts received a total of 494 upvotes.

Table 1: Data statistics

Statistic	Average	Standard Deviation	Minimum	Maximum
Number of upvotes of the post	49.4	16.0	20.0	71.0
Post rewards/*Steem Power*	87.2	48.8	25.0	195.5
Author rewards/*Steem Power*	45.2	25.1	12.5	97.9
Curator rewards/*Steem Power*	0.8	5.0	0.0	74.6
Reputation score	56.9	16.3	-0.9	80.7
Number of effective *Steem Power* of curator	113941.7	784306.9	0.0	10094907.0

Equity of Reward Distribution

Based on the above dataset, we can obtain the correlation coefficient between users' historical contribution and their upvoting rewards $R(RD, P_{SP}) = 0.07$, the correlation coefficient between the users' *Rshares* and their own upvoting rewards $R(RS, P_{SP}) = 0.98$ and $Gini\ Index = 0.95$ before the upcoming reward amendment. The high *Gini Index* indicates that the current inequity level of upvoting reward distribution is extremely high in the community. Moreover, the unbalanced values between $R(RD, P_{SP})$ and $R(RS, P_{SP})$ confirm that the upvoting reward distribution is mostly determined by the users' current *Rshares*, which can be easily obtained through purchasing or renting, but has little to do with their past contributions.

In order to achieve the target that the upvoting rewards distribution of the posts can truly reflect users' contributions, we incorporate a refined reputation indicator RD into the upvoting incentive distribution scheme. Figure 1 depicts the results of comparing the correlation coefficients between the reputation and rewards when using the proposed indicator RD and the original indicator RU respectively, under different proportions of reputation reward PR. The results show that the proposed RD is able to enlarge the correlation coefficient between reputation and rewards, which is consistent with our expectation and validates the design of the RD indicator.

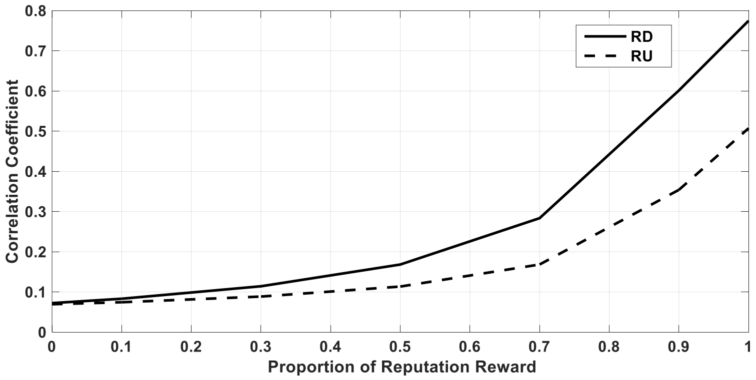


Figure 1: Comparison of reputation-reward correlation coefficients using RD and RU

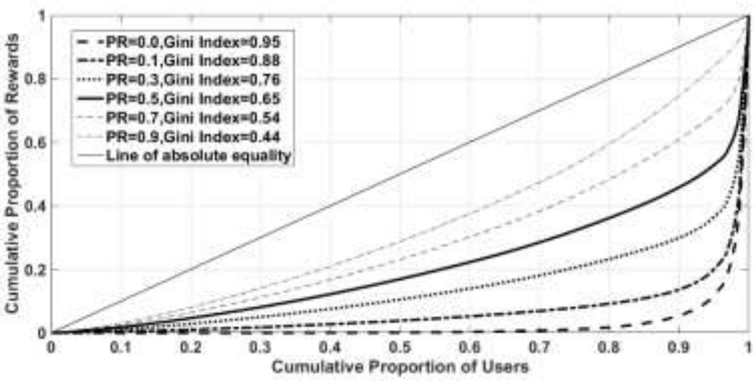


Figure 2: Lorenz curves and *Gini index* with different *PR* values

Figure 2 shows the Lorenz curves and their corresponding *Gini Index* when different proportions of reputation rewards PR are set. It can be seen from the results that when more proportions of rewards PR are allocated to the reputation aspect, the inequity level of reward distribution decreases dramatically. Such results demonstrate the effectiveness of our proposed amendment by considering the reputation aspect.

However, it should be noted that achieving absolute equity is not the ideal situation. As mentioned earlier, besides considering users' historical contributions to the community, we should also differentiate each user's efforts in determining the total rewards of a post so that they could be effectively motivated to upvote high-quality content. Although a more comprehensive mechanism of how to make a trade-off between a user's historical and current contributions can be further discussed, to simplify the analysis, here we assume that a user's historical and current contributions are equally important. Following this assumption, we aim to find an equilibrium point of the correlation coefficient between users' historical contribution and their upvoting rewards $R(RD, P_{SP})$ and the correlation coefficient between the users' $Rshares$ and their own upvoting rewards $R(RS, P_{SP})$ by varying the proportion of reputation reward PR, and the results are depicted in Figure 3. It is intuitive that $R(RD, P_{SP})$ increases while $R(RS, P_{SP})$ decreases along with the increase of PR in a non-linear manner. When the proportion of reputation reward $PR = 0.89$, the equilibrium point can be found and $R(RD, P_{SP}) = R(RS, P_{SP}) = 0.58$, and $Gini\ Index = 0.44$. In the following analyses, we keep the same setting that PR=0.89.

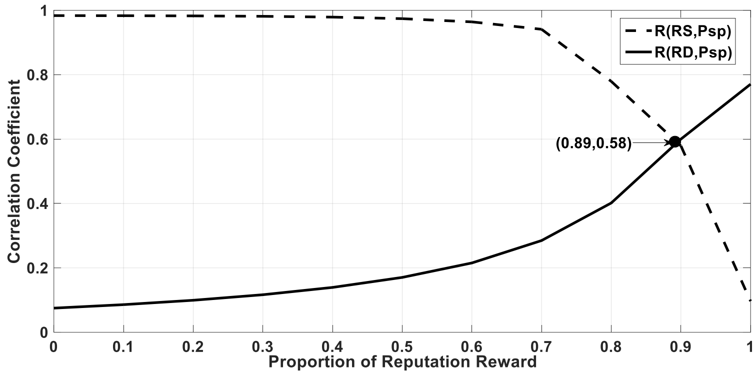
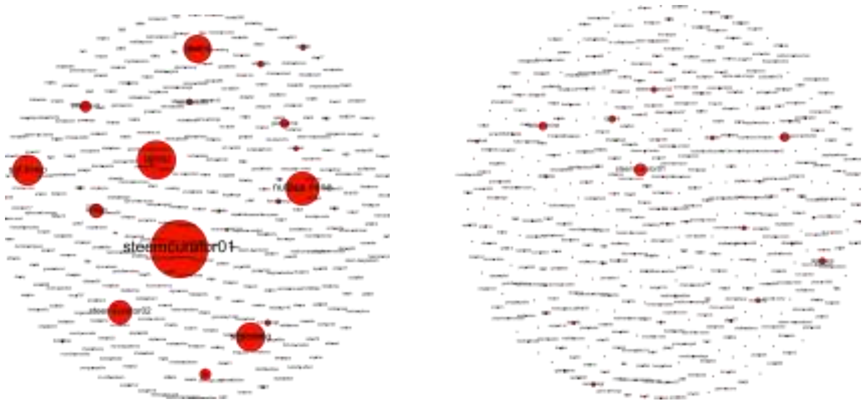


Figure 3: The equilibrium between $R(RD, P_{SP})$ and $R(RS, P_{SP})$

Figure 4 compares the users' upvoting reward distributions of the 494 users in our dataset before and after the amendment. It can be seen from the figure that the upvoting reward distribution of the community becomes more equal after introducing the proposed reputation indicator, although we still give weights to the users' current contributions indicated by their *Rshares*.



(a) Before amendment (b) After amendment

Figure 4: Distribution of rewards for upvoting

Cost of Monopoly

The above analysis has demonstrated the effectiveness of our proposed amendment in addressing the inequality problem of upvoting reward distribution. To further assess the capability of the proposed solution in resisting upvoting reward monopoly, in this section, we evaluate and compare the costs that a user has to pay in order to achieve monopoly before and after the amendment.

Following Avin et al. (2019), we regard obtaining 50% of a post's total upvoting rewards as a monopoly of upvoting rewards, and we then analyze the efforts a user should make to achieve such status by assuming 20 active users are voting together on a post. Here we define active users as those who post, comment, or upvote at least once a month. Statistical analysis of historical data shows that the average reputation indicator *RD* of active users is around 350, and their average amount of *Steem Power* them is around 1000. We set the *RD* and *Steem Power* of the 20 simulated users to the two average values.

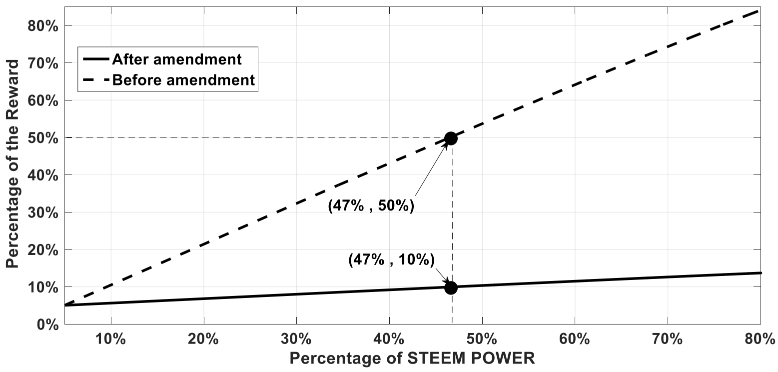


Figure 5: The impact of increasing the percentage of *Steem Power* on the upvoting reward distribution

We simulate two simple strategies a user may adopt to achieve monopoly. One is the reputation of the user remains the same, and he/she gains control over reward distributions purely by accumulating *Steem Power*. As is shown in Figure 5, with the original incentive mechanism, this user can get 50% of the upvoting rewards of the post if the proportion of his/her *Steem Power* reaches 47% of the total *Steem Power* of all users who upvote the post. After the amendment, even this user controls 47% of the total *Steem Power*, and he can get only 10% of the total rewards. Overall, it can be seen that after the amendment, with the accumulation of *Steem Power*, the control power over reward distribution does not increase significantly. In other words, our proposed amendment has effectively increased the cost and set the barriers for achieving a monopoly.

On the contrary, the other strategy is that a user may achieve monopoly by purely accumulating reputation rather than *Steem Power*. The reputation of a user is a reflection of the *Rshares* he/she has obtained by posting and receiving upvotes from other users. In order to increase the reputation value, the user should make other users with sufficient *Rshares* upvote his/her own posts in a short time through bribery. The cost a user should pay to lift his/her reputation can be measured by the total *Steem Power* of those users under his/her control. Figure 6 depicts the relationship between the percentage of controlled *Steem Power* of the community by a user and the percentage of rewards he/she can obtain through lifting his/her reputation value. It can be seen from the results that the cost of lifting a user's reputation value is extremely large. Even in an extreme case that a user could make every other user upvote his post in order to lift his reputation, he/she could only obtain less than 30% of the upvoting rewards. Considering the huge costs, it is obviously uneconomical to pursue a monopoly through accumulating reputation. In this aspect, the effectiveness of the proposed reputation-based incentive mechanism can be further verified.

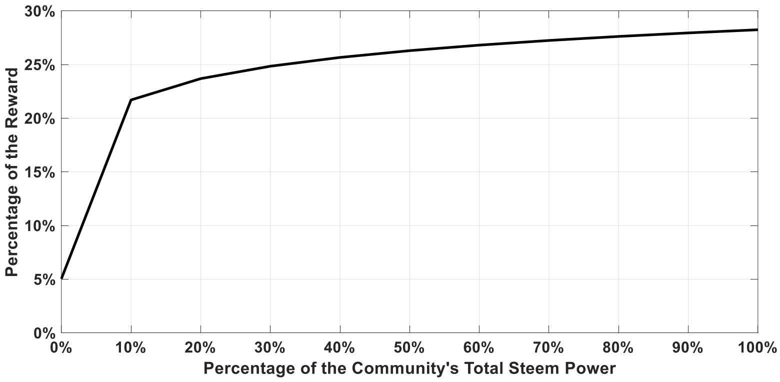


Figure 6: The impact of improving reputation indicator *RD* on the upvoting reward distribution

CONCLUSION

The incentive mechanism based on tokens plays an important role in the blockchain knowledge communities. However, if the incentive mechanism design is not reasonable, a large proportion of rewards may be monopolized by a small number of users, and the platform will tend to be centralized. Moreover, most ordinary users keep contributing knowledge, but they fail to get the corresponding payoff so that their sense of unfairness increases and their enthusiasm to contribute knowledge declines. This is a general phenomenon in blockchain-driven platforms, which has been mentioned by several scholars (Beck, Müller-Bloch & King, 2018; Li & Palanisamy, 2019; Wang et al., 2020). Steemit is one such typical case. This study has found that the existing incentive mechanism in Steemit can reflect the users' contributions to the growth of a post's total rewards, but such contributions can be largely related to the tokens purchased or rented from the external market and fail to reveal the users' real knowledge contributions to the community.

In order to address this problem, we take into account the users' historical performance in knowledge creation and dissemination without ignoring their contributions to the growth of the posts' rewards. By taking a tradeoff, we find the optimal proportion of rewards allocated to the reputation aspect that reflects a user's historical contributions. The simulation results show that our proposed solution can reduce the *Gini Index* of upvoting rewards distribution by 53% and increase the correlation coefficient between user's historical performance and reward by eight times. In addition, we also analyze the costs that a user needs to pay if he/she wants to monopolize the distribution of upvoting rewards. The simulation results indicate that after implementing the proposed amendment to the incentive mechanism, it becomes infeasible to achieve upvoting reward monopoly by accumulating either *Rshares* or reputation values.

However, due to the incompleteness of data and simplified research methodology, there are still several limitations of this work that are worth mentioning. First, this study only constructs a static upvoting reward simulation model. Future work may attempt to build more complex dynamic network models, which will be helpful to depict the behavior of users more accurately. Second, the dataset used in this simulation model contains only 500 users. Subsequent studies can try a larger user sample to verify the effectiveness of the proposed solution. Third, we amend the incentive mechanism of the community by introducing the reputation system, with the assumption that the reputation system is not abused in the long run. However, this assumption may be violated with some speculative strategies, which may need further investigations.

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