Impact of Monetary Rewards on Users' Behavior in Social Media

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Abstract. This paper investigates the impact of monetary rewards on behavioral strategies and the quality of posts in consumer generated media (CGM). In recent years, some CGM platforms have introduced monetary rewards as an incentive to encourage users to post articles. However, the impact of monetary rewards on users has not been sufficiently clarified. Therefore, to investigate the impact of monetary rewards, we extend the SNS-norms game, which models SNSs based on the evolutionary game theory, by incorporating the model of monetary rewards, the users' preferences for them, and their efforts for article quality. The results of the experiments on several types of networks indicate that monetary rewards promote posting articles but significantly reduce the article quality. Particularly, when the value of the monetary reward is small, it significantly reduces the utilities of all the users owing to a decrease in quality. We also found that individual user preferences for monetary rewards had a clear difference in their behavior.

Keywords: Social media · Consumer generated media · Monetary reward · Social network service · Public goods game

1 Introduction

Many *consumer generated media* (CGM), more generally *social media*, have been developed around the world and have become an influential communication media. They are used for a variety of purposes, including the establishment of online social relationships and communities, and information sharing and exchange within the communities [7]. Generally, CGM is supported by a vast amount of contents/articles provided by users. It is costly for users to post articles, yet the main motivation for users to provide content is the psychological reward, which means to satisfy the desire for self-expression and a sense of belonging to society [9]. Additionally, some CGM have a mechanism that gives users monetary rewards or points that is almost equivalent to monetary rewards for posting articles or comments to promote activity; some users stay active to

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obtain one or both the psychological and monetary rewards. In such diverse situations, it is important to elucidate the reasons why users continue to provide content for the growth of CGM and social media, and to clarify the conditions and mechanisms that make such growth possible.

Many studies have attempted to understand the reasons and mechanisms by which users contribute content to social networking service (SNS) and social media. Natalie et al. [3] analyzed the users' motivation for posting using a text mining technique from posting data in an SNS. Zhao et al. [15] conducted a survey by interviewing SNS users to see their purposes of using SNS and the impact on physical face-to-face communication. Some studies have used evolutionary game theoretic approaches to analyze the impact of various mechanisms of SNS on users. Toriumi et al. [13] modeled the activity in a SNS using Axelrod's public goods games [2] and showed that the existence of meta-comments plays a significant role on the prosperity of SNS. Hirahara et al. [6] proposed the *SNS-norms game*, which incorporates the characteristics of SNSs that cannot be represented by the public goods game, and showed that low-cost responses such as the "Like" button strongly affect users' activities.

Recently, some CGM/social media have introduced monetary rewards or point awarding for article and comments, temporarily or permanently, to attract users. For example, on the Rakuten recipe (https://global.rakuten.com/corp/) which is an online recipe sharing site operated by the Rakuten Group in Japan, the users can post cooking recipes and browse those that have been posted. When users cook meals using the recipes, they can post reports/reviews on the recipes as comments. When users post recipes or comments, they are rewarded with Rakuten points that can be used in their online markets, which makes it a kind of monetary reward. Although such monetary rewards could be powerful incentives, their actual influence on the users' activities and their impact on competition with other CGM are not fully known. However, previous studies [6,13] based on the evolutionary game mainly incorporate only psychological rewards in their models, and do not consider the model of monetary rewards to users.

Thus, we attempt to analyze the impact of monetary incentives on user behavior based on the evolutionary game. More specifically, we extend the SNS-norms game for the CGM by adding a parameter indicating the article quality, as well as two types of rewards corresponding to psychological and monetary rewards. Simultaneously, we extend the user model (agent) by modeling their preferences for rewards and the average quality of the posted articles. The extended SNS-norms game is then performed between agents based on networks represented by a complete graph and networks based on the *connecting nearest neighbor* (CNN) model [14]. Subsequently, we investigate the dominant strategies that the agents learn through the interaction and effect of monetary rewards on the agents' behaviors.

2 Related Work

Many studies have investigated the impact of social media on people [1,5,11,12]. For example, Elison et al. [5] examined the relationship between Facebook usage and the formation of social capital from a survey of users (undergraduate students) and the regression analysis using these data. Their results suggested that the use of Facebook was related with measures of psychological well-being and users who experienced lower life satisfaction and lower self-esteem may gain more benefits from Facebook. Adelaniaea al. [1] used a predictive model to test whether community feedback, such as replies and comments, would affect users' posts. The results showed that feedback increased the rate of users' continuous posting. Shahbaznezhad et al. [12] investigated the impact of content on the users' engagement on social media by analyzing posts and responses on two social media platforms and found that these impacts are largely dependent on the type of platform and the modality of the contents. Ostic et al. [11] conducted a survey among students to determine the impact of social media use on psychological well-being, with a particular concentration on social capital, social isolation, and smartphone addiction. Their analysis showed that social media use has a positive effect on psychological well-being by fostering social capital, whereas smartphone addiction and social isolation have a significantly negative effect on the psychological well-being. These studies focus on the interaction and psychological aspects of social media through empirical analysis, and do not analyze the dominant behavior based on rationality. They also did not discuss the effect of monetary rewards on the users' psychological states.

Several studies have investigated the implementation of monetary rewards on social media and their effects on the user's behavior. Chen et al. [4] empirically investigated the impact of financial incentives on the number and quality of content posted on social media in financial markets. They then found that monetary incentives increase the motivation to provide content, but do not improve the quality of the content. López et al. [8] investigated an electronic word-of-mouth called e-WoM and analyzed the types of incentives for opinion leaders to spread information on w-WoM. Their results reported that opinion leaders responded differently to monetary and non-monetary rewards. However, these studies were limited to empirical surveys of specific services and did not indicate whether their results were applicable to other social media. In contrast, our study aims at understanding the impact of monetary incentives in a more general manner. For this purpose, we extend the abstract model of SNS, SNS-norms game, to adapt to the CGM by incorporating the concept of abstracted monetary incentives and the quality of content. Subsequently, we experimentally show the effect of the reward on the content and the behavioral strategies of CGM users.

3 Proposed Method

3.1 SNS-Norms Game with Monetary Reward and Article Quality

The SNS-norms game [6] models three types of user behavior in SNS: article posts, comments on posted articles, and meta-comments (comments on comments). These behaviors come at a cost, but the users can receive psychological rewards from the articles, the comments, and meta-comments. Therefore, a user

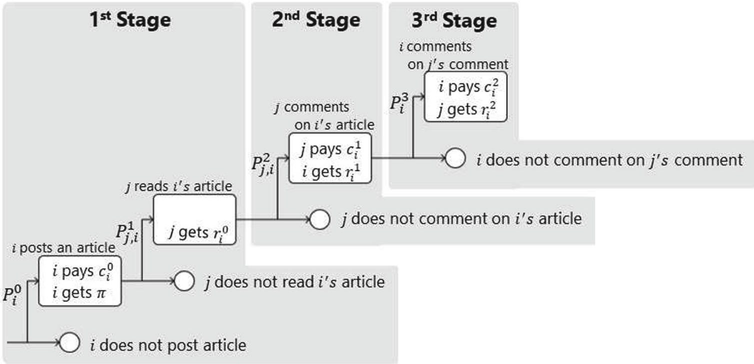


Fig. 1. Flow of SNS-norms game with monetary reward and article quality.

gains the *utility* from the interaction of such behaviors, where utility is the difference between the cost of the user's actions, such as posts and comments, and the psychological rewards as a result of the behaviors of other users. The SNS-norms game runs on a network of agents represented by the graph $G = (A, E)$, where $A = \{1, \ldots, n\}$ is a set of n agents and E is a set of undirected edges between agents, representing the links (or friend relationships) between agents.

We propose the *SNS-norms game with monetary reward and article quality*, by adding two parameters to the SNS-norms game to represent the concept of the article quality and monetary reward as well as the psychological reward that is already modeled in the SNS-norms game. We often refer to the proposed game simply as the extended SNS-norms game. We assume that whenever agent $i \in A$ posts an article, it receives a monetary reward $\pi(>0)$. Furthermore, parameter $Q_i(>0)$ is introduced to represent the quality of an article posted by agent i by assuming that i may obtain a relatively large number of responses to its articles but the chance of article postings will decrease and the cost of the article post will increase if Q_i is large. From the correlation of these parameters, we can observe the impact of monetary rewards on the quality of poseted articles.

Considering the aforementioned cooking recipe site as a baseline CGM model, we divide the set of agents A to two subsets: the set of the *contributor agents* A_p that posts articles and the set of the *browser agents* A_{np} that does not post, where $A = A_p \cup A_{np}$. This is because in this kind of cooking recipe social media, the users are classified into the group whose members post recipes (these users also cook using other users' recipes) and the group whose members only cook using the recipes and report (comment) on it. Agent i ($\in A_p$) has parameters with values ranging from 0 to 1: *posting rate* B_i, *comment and meta-comment rates* L_i, *article quality* Q_i, and *monetary preference* M_i. Here, we assume that Q_i has the lower bound, $Q_{min} > 0$, thus, $0 < Q_{min} \leq Q_i \leq 1$. Agent j ($\in A_{np}$) has only one parameter for the comment rate L_j. The parameter values of B_i, L_i, Q_i and L_j dynamically change with learning to gain more utilities, whereas the monetary preference M_i is randomly determined initially for each agent and does not change in the simulation round. We then define

$$A_{p,\alpha} = \{i \in A_p | M_i < 0.5\} \text{ and } A_{p,\beta} = \{i \in A_p | M_i \geq 0.5\},$$

where $A_{p,\alpha}$ and $A_{p,\beta}$ are the sets of agents preferring psychological reward and agents preferring monetary reward, respectively.

Figure 1 shows the flow of one game round of the extended SNS-norms game. In the first stage of a game round, any agent $i \in A_p$ has a chance to post an article with probability $P_i^0 = (B_i/Q_i) \times Q_{min}$. This probability means that agents that stick to high quality articles have relatively low posting rates because of the elaboration process. Unlike the SNS-norms game, agent i that posted the article pays the posting cost c_i^0 (>0) and gains the monetary reward π. If i does not post the article, i's turn in this game round ends. Then, agent $j \in N_i$ browses the post of i with probability $P_{j,i}^1 = Q_i/s_j$ and obtains a psychological reward r_i^0 (>0), where N_i ($\subset A$) is the set of agents adjacent to i and s_j is the number of articles posted by N_j in the current game round (if $s_j = 0$, we set $P_{j,i}^1 = 0$). Thus, probability $P_{j,i}^1$ indicates that the article with higher quality is likely to be browsed.

The game round then enters the second stage. Agent j that has browsed the article gives i the psychological reward r_i^1 (>0), i.e., post a comment on the article to i with probability $P_{j,i}^2 = L_j \times Q_i$ and pays the cost c_i^1 (>0). In the third stage, i returns a meta-comment to j with probability $P_i^3 = L_i \times Q_i$ only when j gives i the comment, which also reflects the article quality. Here, i pays cost c_i^2 (>0) and gives j the psychological reward r_i^2 (>0). This is where i's turn in the current game round ends. It should be noted that the first stage of each game round proceeds step by step in a concurrent manner to calculate s_j, i.e., after all contributor agents in A_p have posted/have decided to not post, agents in A select and browse some articles with $P_{j,i}^1$.

The cost c_i^0 of posting by the contributor agent i ($\in A_p$) and the psychological reward r_i^0 obtained by browsing the article posted by i are assumed to be proportional to the quality Q_i of that article (Formula (1)). We set the values for the costs c_i^0 c_i^1 and c_i^2 and the psychological rewards r_i^0 r_i^1 and r_i^2 that occur when posting, browsing, commenting, and meta-commenting by referring to Okada et al. [10].

$$\begin{aligned} c_i^0 &= c_{ref} \times Q_i \quad & c_i^1 &= c_i^0 \times \delta \quad & c_i^2 &= c_i^1 \times \delta \\ r_i^0 &= c_i^0 \times \mu \quad & r_i^1 &= c_i^1 \times \mu \quad & r_i^2 &= c_i^2 \times \mu \end{aligned} \tag{1}$$

Note that parameter δ, which represents the ratio of the cost of each stage, and parameter μ, which represents the ratio of the cost to the reward value, were defined sequentially based on the reference value c_{ref}.

The utility u_i of agent i obtained for a round of the game is calculated by

$$u_i = (1 - M_i) \times R_i + M_i \times K_i - C_i. \tag{2}$$

It should be noted that C_i is the sum of the costs paid by i, R_i is the sum of the psychological rewards of i and K_i the sum of the monetary rewards; therefore, for example,

$$C_i = c_o + \gamma_i^c \times c_i^1 + \gamma_i^{mc} \times c_i^2,$$

where γ_i^c and γ_i^{mc} are the number of comments and meta-comments that i posted during the current round. Note that because the agents in A_{np} receive no monetary reward, we set $M_j = 0$ for $j \in A_{np}$, which is identical to the utility defined in the SNS-norms game.

3.2 Evolutionary Process

Let a generation consist of four game rounds. At the end of each generation, all agents apply the genetic algorithm to learn parameters B_i, L_i, and Q_i for $i \in A_p$ and L_i for $i \in A_{np}$, using U_i, the sum of the utilities in the generation calculated by Eq. (2) as the fitness value. For this purpose, all parameters are encoded as 3-bit numbers that can express integer values from 0 to 7. We then correspond them to fractions $0/7, 1/7, \ldots,$ or $7/7$ for B_i, L_i and $1/8, 2/8, \ldots,$ or $8/8$ for Q_i, by setting Q_{min} as $1/8$. Thus, each agent has a 9-bit gene.

The process of evolution consists of three phases: parent selection, crossover, and mutation. In the parent selection phase, agent i chooses two agents as parents for the child agent that will be at the same position in the network G in the next generation. The parents are chosen from the same type of agents in $A_{p,\alpha}$, $A_{p,\beta}$, or A_{np} using roulette selection. Therefore, if $i \in A_{p,\alpha}$, for example, $j \in A_{p,\alpha}$ is chosen as its parent with the probability Π_j using roulette selection;

$$\Pi_j = \frac{(U_j - U_{min})^2 + \epsilon}{\sum_{k \in A_{p,\alpha}} (U_k - U_{min})^2 + \epsilon},$$

where $U_{min} = \min_{k \in A_{p,\alpha}} U_k$ and ϵ is a small positive number to prevent division by zero. We set $\epsilon = 0.0001$ in our experiments.

In the crossover phase, uniform crossover is applied, i.e., the value of one of the parent genes is adopted as the next gene for each bit. Finally, in the mutation phase, each bit of the new gene generated by the crossover is reversed with a small probability of mr ($\ll$1). The agents with the new genes play the game in the next generation on the same network, and this is repeated until the G generation.

4 Experiments

4.1 Experimental Settings

We conducted the experiments to explore the changes in behavioral strategies and utilities of the contributor and browser agents in networks of friendships, as well as the impact of the posters' concerns for article quality when a monetary reward for article posting is introduced in CGM. The impact on the behavioral

Table 1. Network characteristics.

Description and parameter	Complete graph	CNN-model network
Number of agents, $n = \|A\|$	80	400
Number of agents preferring psychological reward, $\|A_{p,\alpha}\|$	20	100
Number of agents preferring monetary reward, $\|A_{p,\beta}\|$	20	100
Number of browser agents, $\|A_{np}\|$	40	200
Transition probability from potential edges to real edges, u	–	0.9
Average degree	79	20.3
Cluster coefficient	1	0.376

Table 2. Values of experimental parameters

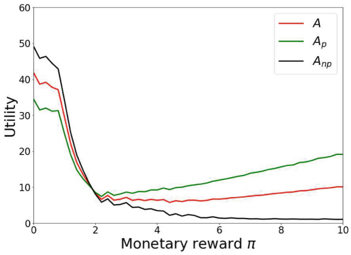
Description	Parameter	Value
Generation length	G	1000
Mutation probability	mr	0.01
Cost ratio between game stages	δ	0.5
Ratio of cost to reward value	μ	8.0
Reference value for cost and reward	c_{ref}	1.0

strategy is determined from changes in the average values of the posting rate B_i, comment rate L_i, and article quality Q_i for all agents. We also investigate the influence of different network structures among agents on the results. Therefore, we conducted experiments assuming interactions on the complete graph (Exp. 1) and the networks generated by the CNN model [14] (Exp. 2). The number of nodes (i.e., agents) in the complete graph was set to $n = 80$, whereas the number of nodes in the CNN-model network was set to $n = 400$. Other parameter values and the characteristics related to the generated networks are listed in Table 1. The cardinal numbers of $A_{p,\alpha}$, $A_{p,\beta}$, and A_{np} are also listed in Table 1.

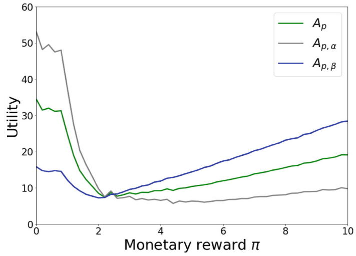
The parameter values in our experiments are listed in Table 2. Note that δ and μ were set to 0.5 and 8.0, respectively, in accordance with Okada et al. [10]. The results of this experiment are the averages of 100 experimental trials using different random seeds. In the graphs shown below, the red, green, black, gray, and blue lines represent the averages of all agents A, posting agents A_p, browser agents A_{np}, contributor agents who prefer psychological rewards $A_{p,\alpha}$, and $A_{p,\beta}$, agents who prefer monetary rewards, respectively.

4.2 Experimental Result – Complete Graph

The results of the first experiment (Exp. 1) of the agent's behavioral strategy in the complete graph are shown in Fig. 2, where Fig. 2a plots the averages of the



(a) All agents



(b) Contributor agents

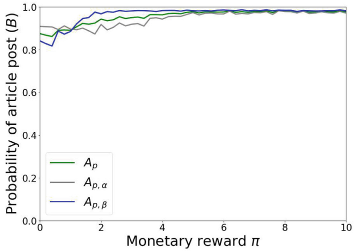
Fig. 2. Utility and monetary reward in complete graph.

evolved utilities for A, A_p, and A_{np}, for the monetary reward π, and Fig. 2b plots the averages of the evolved utilities of $A_{p,\alpha}$ and $A_{p,\beta}$. Remarkably, Fig. 2a reveals that the utility of all types of agents tended to decrease, whereas π increased from 0 to 2.2 After that, when π increased from 2.2 to 10, the utility of the contributor agents A_p begins to trend upward, whereas the graph of the browser agents A_{np} decreases further. The average for all agents is slightly increasing, but this tendency might depend on the ratio of $|A_p|$ to $|A_{np}|$.

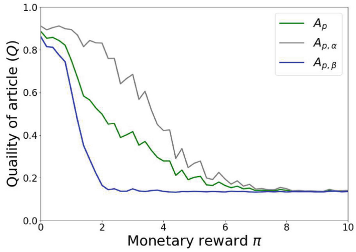
To determine the cause of the decline in utility in the range of $\pi \leq 2.2$, we plotted the relationship between the monetary rewards and agents' behavioral parameters in Fig. 3. It should be noted that all agents have the comment rate L_i, whereas the posting rate B_i, the article quality Q_i and the probability of article post P_i^0 are the parameters that only the contributor agents have. We omit the subscripts of these parameters, such as B, L, Q and P^0, to express their average values.

The change in these parameters seems to occur owing to the users' attitudes toward the quality of the articles they post. Figure 3a shows that the article posting rate B increased albeit only slightly, as the monetary reward increased. When $\pi = 0.0$, it shows that the posting rate B was between 0.8 and 0.9, with higher values for agents $A_{p,\alpha}$ that prefer psychological rewards. However, at approximately $\pi = 1.0$, the value of B of the agents in $A_{p,\beta}$ increases. Then, in the range of $\pi \geq 5.0$, the value of B of all agents were close to 1.0. It can be inferred that the introduction of monetary rewards leads to the promotion of article posting, but the effect is not large and the types of users that benefit from it are different.

In contrast, we can observe from Fig. 3b that the quality of articles decreased significantly as the monetary reward increased. This shows that $A_{p,\beta}$ dropped rapidly and remained at approximately 0.14 when $\pi \geq 2.2$. As π increased from 0 to 8.0, the article quality of the agents in $A_{p,\alpha}$ declined slowly and then maintained the value of approximately 0.14 as in $A_{p,\beta}$ when π was even larger than 0.8. Figure 3c shows that there is no significant change in the comment rate L; however, if we consider it closely, we can observe that as the monetary reward increases, the L of the contributor agents increased, whereas that of the

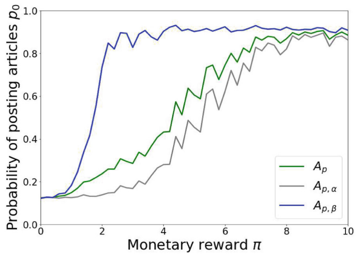


(a) Posting Rate (B).



(b) Quality of Article (Q).

(c) (Meta-)Comment Rate (L).



(d) Probability of Article Post (P^0).

Fig. 3. Behavioral parameter values in complete graph.

browser agents decreased slightly. This difference in the trend across the agent types kept the average comment rate L for all agents at approximately 0.45.

As a result of changes in these parameters, the probability P^0 of the article posts in the game varied as in Fig. 3d. As the value of the monetary reward increases, the contributor agents that prefer the monetary reward reduce the quality of their articles more rapidly than the increase in the monetary reward and instead adopt the strategy to post articles more frequently. Additionally, we can observe that the agents that prefer psychological rewards try to maintain the quality of the articles and do not increase the number of posts. However, further increases in monetary rewards led to a decline in quality.

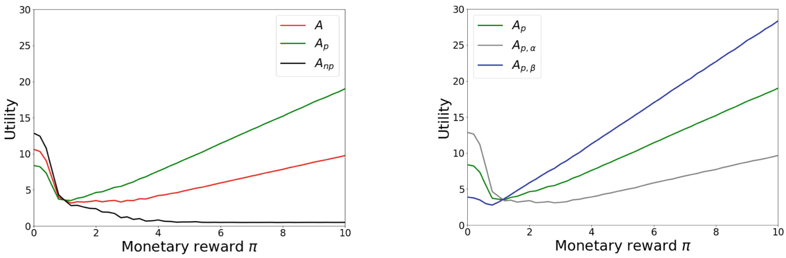
From these results, we deduced that the decrease in the overall utility by giving monetary rewards π was mainly due to the decrease in the quality of article Q. A significant decrease in the quality Q of the posted article resulted in a significant decrease in the utility gained by the browser agents. Particularly, when $0 \leqq \pi \leqq 2.2$ (see Fig. 2), that is, when there is a monetary reward but its value is small, it leads to a drop in utility. As the decline in the article quality Q began to subside ($\pi \geq 2.2$), the contributor agents in A_p increased their utilities to the extent that the monetary reward they obtained increased. In contrast, the comment rate L of the browser agent A_{np} reduced, and the probability of the comments and meta-comments, P^1, which considers the effect of Q, dropped significantly, and the utility did not turn to increase. This lowered the activity of the browser agents.

4.3 Experimental Results – CNN-Model Network

Figure 4 plots the relationship between the average value of the utility and the monetary reward π. We found that the experimental results on the CNN-model networks were similar to those on the complete graph, i.e., the average utility dropped considerably when the monetary reward was given at a small value but gradually increased as the monetary reward value was set to higher values. According to Fig. 5, which shows the evolved parameter values for the user's behavior on the CNN-model networks, the behavioral strategies show that the agents posted more articles, but their qualities decreased, similar to those in the complete graph.

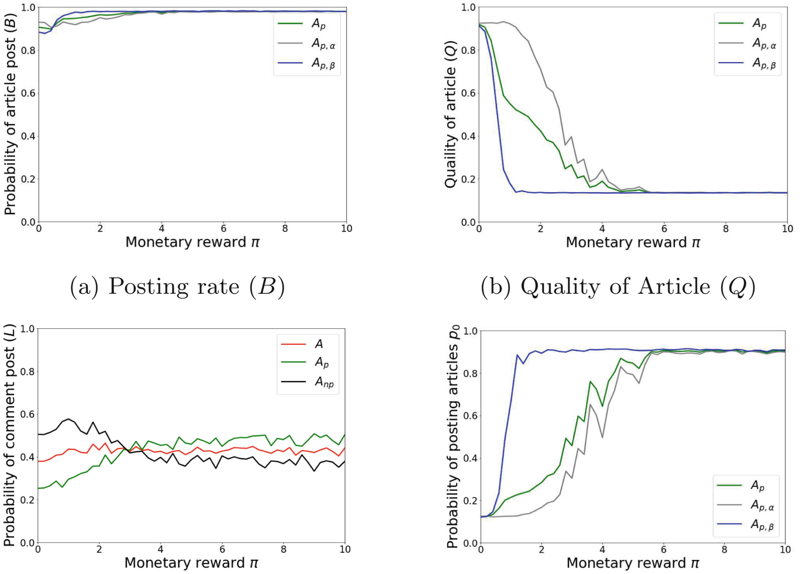
There are also differences between the two experiments: the average utility of the contributor agents in A_p in the CNN-model network was minimized when the monetary reward was quite small, i.e., $\pi = 1.2$, whereas in the complete graph it was minimized when $\pi = 2.2$. In the complete graph, the average utility values did not change much in the utility value when π was between 0 and 1.0, indicating that the agents in the CNN-model network were more sensitive to the monetary rewards.

Comparing Fig. 2 and Fig. 4, the average utility when $\pi = 0$ (when the monetary reward was not implemented) was considerably smaller than that on the complete graph. Therefore, as shown in Fig. 2a, the utility of the contributor agents in particular could not exceed that when $\pi = 0$, even when the monetary rewards were increased. However, the monetary rewards increase the utility only for contributor agents in $A_{p,\beta}$ who prefer monetary rewards (Fig. 2b). Meanwhile, the results on CNN-model networks (Fig. 4a) show that the utility of the contributor agents tends to be larger when the monetary reward is $\pi \geq 4.0$. Particularly, the utility of agents in $A_{p,\beta}$ increases than that when $\pi = 0$, even for small π values (Fig. 4b). Suppose that there are two CGM platforms with and without monetary rewards. Then, the platforms are likely to be chosen differently depending on the user preferences in the CNN-model networks, whereas in the complete graph, all users may remain in the media without monetary rewards. However, for browser agents who only browse and comment on articles,



(a) All agents (b) Contributor agents

Fig. 4. Utility and monetary reward in CNN-model networks.



(a) Posting rate (B)

(b) Quality of Article (Q)

(c) Comment Rate (L)

(d) Probability of Article Post (P^0)

Fig. 5. Behavioral parameter values in CNN-model networks.

monetary rewards are irrelevant, and they tend to concentrate on CGM without monetary rewards owing to the higher quality of articles.

5 Conclusion

We proposed an extension of the SNS-norms game, a game that models a CGM, by introducing parameters expressing the monetary rewards and article quality. We then analyzed the optimal behavior for the users given the monetary rewards in CGM/social media using evolutionary computation. These experiments suggested that monetary rewards can be an incentive for posting in terms of the number of posts. However, if the design of the monetary rewards is insufficiently considered, the contributor agents will focus on obtaining monetary rewards and neglect the quality of the articles they post, which will have the effect of a reduction in the utility of society as a whole. This suggested that large monetary rewards are necessary to increase the utility of the society, but the quality of the articles remains low. We also conducted our experiments on the CNN-model networks and the results showed the same trend regardless of the network structures. However, users on the CNN-model network were more sensitive to the effect of monetary rewards.

In the future, we plan to investigate the effect of rewards that reflect quality, such as monetary rewards that vary according to the number of browsing. We also plan to model other types of CGM to investigate users' activities.

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