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RESEARCH ARTICLE

User behaviors in consumer-generated media under monetary reward schemes

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Abstract

We investigate both the influence of monetary reward schemes on user behaviors and the quality of articles posted by users in consumer-generated media (CGM), such as social networking services (SNSs). Recently, CGM platforms have implemented monetary rewards to incentivize users to post articles and comments. However, the effect of monetary rewards on user behavior merits further investigation. Given that quality articles require more time and effort for preparation, we analyze user-dominant behaviors, including posting and commenting activities, and the quality of posted articles, using different monetary reward schemes. Therefore, we propose a monetary reward SNS-norms game by extending a conventional SNS-norms game, a social networking services model based on evolutionary game theory, and then introduce three monetary reward schemes with different monetary reward timings. We further incorporate efforts to improve the quality and preferences for monetary rewards, psychological rewards, and article quality in the agents, that is, our model of users. We have found that the timing of providing monetary rewards strongly influences the number and/or quality of articles posted using a game with monetary reward schemes on several types of user network structures, including a stochastic block model and an instance of the Facebook network. These results indicate that monetary rewards must be carefully designed in terms of timing and amount, depending on their purpose in the CGM.

Keywords Consumer-generated media · Social networking service · Social media · monetary reward · Public goods game · Genetic algorithm

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Introduction

Globally, the amount of consumer-generated media (CGM) is increasing; consequently, they are an indispensable and effective source of daily communication. They have several purposes, such as establishing and maintaining online social relationships and communities, political debate, and education through the sharing and exchanging of opinions within communities [1]. CGM are underpinned by the vast amount of content users provide. Although it is costly for users to continue posting articles, particularly those of high quality, psychological rewards, which implies satisfying intellectual curiosity, expressing oneself, and belonging to a community [2], are the primary incentive for users to provide content. However, psychological rewards alone might be insufficient to retain several users for long periods. Thus, to develop a CGM that can attract viewers, we must determine why users continue to provide content.

Several studies have explored the underlying mechanisms and reasons why users post content, such as text articles and videos, on *social networking services* (SNSs) and social media platforms [3–5]. Zhao et al. [3] interviewed SNS users to better understand their objectives for using an SNS and its impact on face-to-face physical communications. In addition, Natalie et al. [5] investigated the incentives and motivations of users when posting content by analyzing SNS-posted data using text mining techniques. Some studies have employed an evolutionary game-theoretic approach to analyze the influence of various mechanisms implemented on SNS platforms on user activities. For instance, Toriumi et al. [6] proposed a model of SNS activities using public goods games proposed by Axelrod [7] and reported that meta-comments significantly affect active SNS postings. Subsequently, they introduced an extension of this model, called an *SNS-norms game* by incorporating the characteristics of interactions occurring on an SNS and found that simple, low-cost responses, such as clicking a “Like” button, positively influence user behaviors. Several studies have highlighted the influence of psychological rewards rather than physical or monetary rewards on user behavior.

Moreover, some CGM encourage the posting of articles and comments, persistently or temporarily, by offering users monetary rewards or points similar to these rewards. Some users may become more active and continue to post articles because of monetary and psychological rewards. For example, Rakuten Recipes (https://global.rakuten.com/corp/) is a Japanese online recipe-sharing site operated by the Rakuten Group; herein, users can post and view food recipes. Once a user cooks a meal using the posted recipe, the user can comment on the cooking based on the recipe. By posting recipes and meta-comments, users who post recipes, comments, and meta-comments are rewarded with Rakuten points, which can be exchanged for commercial goods from the Rakuten Market run by the Rakuten Group; thus, it is almost equivalent to monetary rewards. Although monetary rewards can be a potent motivator, we lack sufficient information on the impact of attracting users on the behavioral strategy and the effect of user acquisition on competition from other CGM. However, previous studies based on evolutionary games [6, 8] have predominantly envisaged models that include only psychological rewards and no monetary rewards.

Therefore, this study obtained insights into monetary reward schemes that incentivize users to post more articles and improve their quality. Herein, we analyzed the impact of monetary rewards on user behavioral strategies using an evolutionary game-based approach. In particular, we extended a conventional SNS-norms game for CGM by adding two types of rewards, monetary and psychological, and a parameter indicating the article quality. This type of extended game is called a *monetary reward SNS-norms game*. In addition, we extended our user model, that is, an agent, to include various preferences between monetary and psychological rewards, and the average quality of articles posted. Usui et al. [9] proposed a model that included monetary rewards. We further extended their approach using various monetary reward schemes, whose differences were primarily in the timing of the rewards to users. We conducted more detailed experiments and discussions on how they impact user behaviors. Subsequently, a monetary reward SNS-norms game was played between agents on networks generated by an *stochastic block model* (SBM) and on a network based on actual Facebook data. Experiments with these games revealed that different monetary reward schemes can significantly change the dominant user behavioral patterns, thus reinforcing users to post more or higher-quality articles in the CGM. These results provide insights into the design of monetary rewards that meet the practical objectives of CGM.

Related work

Social media platforms are used for various purposes and have thus been studied from various perspectives. For instance, some studies investigated the benefits of using social media for marketing, particularly for customer acquisition [10–13]. Alalwan [10] aimed to identify and test the central factors related to social media advertising to predict purchase intention. Their results indicated that hedonic motivation, performance expectancy, informativeness, perceived relevance, and interactivity positively influence purchase intention. Kumar et al. [11] examined the impact of firm-generated content (FGC) on social media with a television advertisement and e-mail communication on customer spending, cross-buying, and customer profitability; they found that the benefits of FGC are greater for customers who are more experienced, tech-savvy and frequent users of social media. Toker-Yildiz et al. [12] investigated the relationship between social interaction and marketing actions, and the effectiveness of monetary incentives among these activities. Their findings indicated that monetary incentives significantly impact repeated use, and ignoring this effect may overestimate the impact of social influence on marketing. Arora et al. [13] proposed a mechanism for measuring the influencer index across popular social media platforms using machine learning techniques; they reported that engagement, outreach, sentiment, and growth are key in determining influencers. Moreover, this study suggests that we must identify influencers who propagate key information in various areas, such as e-commerce, social media marketing, viral marketing, and brand management. These findings can be used to design social media platforms for specific marketing purposes.

Furthermore, several studies have focused on the impact of social media on the individual behavior of users within society [14–18]. Elison et al. [15] investigated the potential relationship between Facebook usage and social capital development using regression analysis of survey data from undergraduate users. Facebook usage was correlated with psychological well-being; the results indicated that users with lower self-esteem and satisfaction in their lives may benefit more from it. Lovejoy et al. [14] examined how nonprofit organizations use Twitter to communicate on social media. They identified three key Twitter functions: information, community, and action. Ostic et al. [18] surveyed students about the influence of social media use on their psychological well-being with a particular emphasis on isolation from social and smartphone dependence. They found that social media fosters social capital and positively impacts psychological well-being, whereas smartphone addiction and social isolation associated with their use have the opposite effect. Shahbaznezhad, Dolan, and Rashidirad [17] analyzed the effect of content on user engagement on social media by analyzing posts and responses on two CGM platforms and discovered that these effects highly depend on the platform type and content modality. These studies attempted to elucidate the impact of social media in terms of interaction and psychological facets through empirical analysis but did not address rationality-based dominant strategic behavior. Furthermore, they did not discuss the impact of monetary rewards on user behavior.

Several studies have explored the motivation of social media users to generate content [3–6, 19–23]. By analyzing some CGM sites, Yoo and Gretzel [19] investigated the driving forces of a few users who frequently generate content and how they differ from general users who do not post content. They discovered that user personality traits had a significant influence on perceived barriers to content generation motivation. Razmerit et al. [4] identified the factors that encourage and hinder employee participation in enterprise-focused social media based on the social dilemma and self-determination theory. They suggested that the psychological and monetary rewards of helping others encourage participation, whereas availability and trust discourage it. Tang et al. [20] proposed a dynamic structural model to identify the underlying utility function of contributors from observed posting behavior and found that contributors dynamically anticipate the future impact of their decisions on their rewards, such as a desire for exposure, reputation, and revenue sharing. Toubira and Stephen [21] conducted a field experiment in which they exogenously added followers to a group of users for a certain period and compared their posting activities with those of a control group. They discovered that images have greater utility compared with texts for several users.

As the aforementioned studies elucidate, monetary rewards encourage people to contribute or suggest articles, and several studies have investigated the implementation of monetary rewards on social (or online) media and their effect on user behaviors [24–28]. Musutafa and Ali [26] empirically examined the effects of monetary and nonmonetary rewards on self-motivation and reported that monetary rewards are positively correlated with self-motivation. In contrast, Gneezy and Rustichini [24] suggested the complexities of the impact of monetary incentives on human behavior because they confirmed that monetary rewards result in either higher or lower performance. Chen et al. [27] empirically studied the effect of monetary incentives on the quality and number of posts on social media content in financial markets and reported that monetary incentives enhance the motivation to provide additional content but do not improve the content quality. They observed that opinion leaders reacted differently to monetary and nonmonetary rewards. López et al. [28] developed an electronic word-of-mouth communication called e-WoM and analyzed the types of incentives that opinion leaders use to spread information in e-WoM. They observed that such leaders responded differently to monetary and nonmonetary rewards. In addition, Jing et al. [29] investigated the effect of monetary incentives on the prosocial behavior of physicians on an online medical consulting platform. They reported that monetary incentives positively affected prosocial behavior and increased the self-perception of physicians.

However, such studies have been confined to empirical investigations of specific services, and their findings do not apply to other social media applications. In contrast, our study attempted to understand the effect of monetary incentives from a more general and abstract perspective. First, we extended the SNS-norms game, an abstract model of an SNS, to incorporate the notion of content quality and abstracted monetary incentives with associated schemes. Next, using this game, we examined the implications of monetary reward schemes on the content quality of articles posted on CGM, that is, the effort and time spent providing better articles and the behavioral strategies of users.

Proposed model

This section describes our proposed model based on evolutionary games, which is extended by integrating the timing of monetary rewards and the quality of posted articles into the existing model.

SNS-norms game with psychological and monetary rewards and article quality

We proposed a model of user behavior based on psychological and monetary rewards. This model is based on the SNS-norms game [8], which extends the *meta-rewards game* [6] inspired by Axelrod's public goods games [7]. First, we briefly describe the flow of the SNS-norms game. For more information, see [8].

Details of agents

Let $A = \{1, \dots, n\}$ be a set of n agents, where each agent corresponds to a user. The SNS-norms game is played on a network of agents described by the graph $G = (A, E)$, where E is the set of undirected edges between agents, representing a connection or friend relationship on the CGM. Therefore, we denoted the set of neighboring agents of i (i.e., i's friends) as N_i $(\subset A)$. The SNS-norms game includes three types of user (and thus agent) behaviors found on CGM: article posts, comments on posted articles, and meta-comments that correspond to comments on an article. We assumed that agents can read articles and comments posted by neighboring agents in G. Although these behaviors involve cost, agents can obtain psychological rewards from articles, comments, and meta-comments. Therefore, these rewards reflect a sense of satisfaction and connectedness through the information provided to and received from friends.

Agents can derive *utility* through their interactions with such actions. The utility of agent i is the sum of i's psychological reward resulting from the actions of other agents and the monetary reward minus the cost of i's actions, such as posting (including the cost of selecting and reviewing the content and elaborating the text) or commenting. Utility is the subjective degree of satisfaction used to assess an individual's decision to maximize it. Therefore, we assumed that each social media user strategically determines the behaviors that maximize their utility. From the platform company's perspective, high user utility values suggest that the scale of social media is likely to be maintained or even increased. Therefore, any mechanism that increases utility value is valuable to platformers. Hence, from both perspectives, we must investigate the possible mechanisms experimentally demonstrated to enhance the utility.

Agent $i \in A$ has two parameters to determine their behaviors: the *posting rate* B_i denotes the probability of posting an article and the *comment rate* L_i denotes the probability of posting a comment/meta-comment, where $0 \leq B_i, L_i \leq 1$. These parameter values in our evolutionary game were adjusted to maximize their individual rewards using *genetic algorithm* (GA).

Next, we describe the *monetary reward SNS-norms game* and the *article quality*. For $\forall i \in A$, we added three parameters to the SNS-norms game to represent the concepts of *article quality* Q_i, *monetary preference* M_i (where $0 \leq M_i, Q_i \leq 1$), and monetary reward $\pi \geq 0$, as well as the psychological reward previously modeled in the SNS-norms game, as mentioned above. First, we introduced the parameter Q_i, ranging from 0 to 1, which indicates the quality of an article posted by agent i, where a higher Q_i indicates higher article quality. Thus, i posts only an article of quality Q_i or higher. We assumed that if Q_i is high, i can receive numerous comments from the posted articles; moreover, the chance of posting articles decreases because the cost (or effort) required to generate better articles increases. To prevent the repetition of meaningless posts, we assumed that Q_i has a lower bound $Q_{min} > 0$; thus, $0 < Q_{min} \leq Q_i \leq 1$. Parameter M_i expresses the degree of preference for monetary rewards. An agent with a large M_i favors monetary rewards and has a propensity to collect them, whereas a small M_i indicates less adherence to monetary rewards.

Monetary reward schemes

Next, we introduced three monetary reward schemes: S1, S2, and S3, depending on when the monetary reward $\pi(\geq 0)$ is provided to an agent who posts an article by considering the phases in SNS-norms games [8].

S1—Reward when an article is posted: Whenever agent $i \in A$ posts an article, i receives monetary reward π, which was already defined in Usui et al. [9].

S2—Reward when an article posted is read:After i posts an article, if it is read by a neighboring agent in N_i, i receives π.

S3—Reward when the article poster posts a meta-comment:After i posts an article and receives a comment on it, if i posts a meta-comment to the received comment, i receives π for each meta-comment.

We did not introduce the monetary reward scheme when a neighboring agent posts a comment because its effect is almost identical to scheme S2.

Subsequently, we investigated the impact of monetary rewards on the posting rate B_i, comment rate L_i, and quality of posted articles Q_i depending on the value of π and the adopted schemes. Although we can provide some reward to an agent when posting a comment, we focused only on the reward to an article poster because we aimed to investigate its effect on the number and quality of articles, which also affects the costs of preparing/posting articles. Note that $\pi = 0$ indicates no monetary reward for the CGM platform.

Monetary preference of agents

As a CGM model based on the previously mentioned cooking recipe website, the set of agents A is divided into two disjoint subclasses: the set of *browsing agents* A_{np} that reads articles and posts only comments and the set of *contributor agents* A_p that can post articles, comments, and meta-comments, where $A_{np} \cap A_p = \emptyset$ and $A = A_{np} \cup A_p$. This is because only some users, that is, contributor agents, post recipes, whereas other users, browsing agents, only cook using the recipes and then report (comment) on them. Contributor agents also cook using other agents' recipes and comments. Therefore, the behavior of contributor agent i ($\in A_p$) is characterized by four parameters: B_i, L_i, Q_i, and M_i, whereas that of the browsing agent j ($\in A_{np}$) is characterized by only one parameter, L_j.

Agent i changes the parameter values of B_i, L_i, Q_i, and L_j dynamically using the GA to maximize the total utility. However, we assumed that the monetary preference M_i is underlying, and thus, it is determined randomly for each agent before each experimental run and remains constant. Thus, we defined the two sets using the following equation:

$$A_{p,\alpha} = \{i \in A_p \mid M_i < 0.5\} \text{ and } A_{p,\beta} = \{i \in A_p \mid M_i \geq 0.5\}, \tag{1}$$

where $A_{p,\alpha}$ and $A_{p,\beta}$ denote the sets of agents who prefer psychological and monetary rewards, respectively.

Flow of monetary reward SNS-norms game

Figure 1 shows the flow of one round of the monetary reward SNS-norms game. In the first stage of a round, contributor agent $i \in A_p$ posts an article with probability P_i^0, where

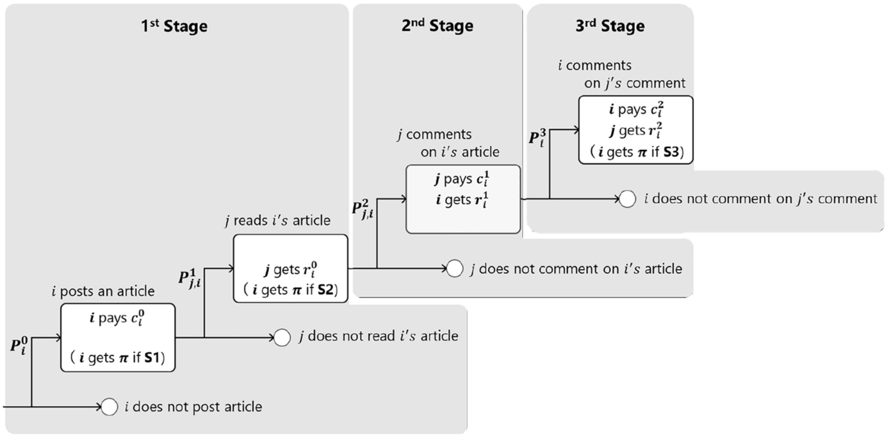


Fig. 1 Flow of monetary reward SNS-norms game with article quality

$$P_i^0 = B_i \times \frac{Q_{min}}{Q_i}. \tag{2}$$

This posting probability factors in that a contributor agent committed to high-quality articles will have a relatively low posting probability owing to the costly process of elaboration. Thus, agent i that has posted the article should pay cost c_i^0 (> 0) proportional to its quality, as defined later. Agent i may receive monetary reward π at this stage only if the monetary reward scheme is S1. If i decides not to post an article, it is the end of the turn for i in the game round (no monetary reward is given). Next, another agent $j \in N_i$ browses the article of i with probability $P_{j,i}^1 = Q_i/s_j$ and then receives a psychological reward r_i^0 (not r_j^0), where s_j is the number of articles received from the agents in N_j in the current round of the game. Furthermore, if the monetary reward scheme is S2, i receives π as a monetary reward. Note that $P_{j,i}^1 = 0$ if $s_j = 0$. The reward r_i^0 is proportional to Q_i and is defined later. Thus, the definition of probability $P_{j,i}^1$ indicates that higher-quality articles are more likely to be browsed by neighboring agents.

In the second stage (Fig. 1), agent $j \in N_i$ that browses the article posts a comment on the article to i with probability $P_{j,i}^2 = L_j \times Q_i$ and then pays cost c_i^1 (> 0). This comment provides a psychological reward r_i^1 (> 0) to i. In the third stage of the game, as illustrated (Fig. 1), i may respond with a meta-comment to $j \in N_i$ with probability $P_i^3 = L_i \times Q_i$, which also reflects article quality. This meta-comment corresponds to the psychological reward r_i^2 (> 0) to j, and agent i pays cost c_i^2 (> 0). Furthermore, if the monetary reward scheme is S3, i receives monetary reward π. This is the end of i's turn in the current game. Note that to calculate s_j in the game flow, a round proceeds concurrently stage-by-stage, which implies that after all contributor agents in A_p have posted or have decided not to post in the first stage, each agent in A browses the articles selected with probability $P_{j,i}^1$.

Unlike the SNS-norms game, 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 in a game round are defined by referring to Okada et al. [30] as follows:

$$\begin{aligned} c_i^0 &= c_{ref} \times Q_i, & r_i^0 &= c_i^0 \times \mu, \\ c_i^1 &= c_i^0 \times \delta, & r_i^1 &= c_i^1 \times \mu, \\ c_i^2 &= c_i^1 \times \delta, & r_i^2 &= c_i^2 \times \mu, \end{aligned} \tag{3}$$

where c_{ref} denotes the reference value for the cost and reward; μ denotes the ratio of the cost to the reward value; and δ denotes the ratio of the cost in each stage. These costs and psychological rewards are proportional to the quality Q_i of the article.

The utility that agent i gains during a round is denoted as u_i, which is obtained as follows:

$$u_i = M_i \times K_i + (1 - M_i) \times R_i - C_i, \tag{4}$$

where K_i and R_i denote the sum of the monetary and psychological rewards of i, respectively; and C_i denotes the sum of the costs paid by i. Therefore, if contributor agent i posts an article, comments, and meta-comments during the latest round, the sum of the costs is

$$C_i = c_i^0 + \gamma_i^c \times c_i^1 + \gamma_i^{mc} \times c_i^2, \tag{5}$$

where γ_i^c denotes the number of comments and γ_i^{mc} denotes the number of meta-comments posted by i. Note that $M_j = 0$ for $j \in A_{np}$, which is identical to the utility defined in the SNS-norms game, because a browsing agent does not receive monetary rewards.

Evolutionary computation process

We assumed that each contributor agent has four chances to post an article during one generation; that is, one generation has $4 \times |A_p|$ rounds of the game. After each generation, we used the GA for all agents to evolve the parameter values of B_i, L_i, and Q_i for $i \in A_p$ and the value of L_i for $i \in A_{np}$ based on the fitness value U_i. We defined U_i as the sum of the utility u_i in the latest generation, calculated using Eq. (4). To encode these parameter values for the GA, each is represented by a 3-bit number with values of $0, 1, \ldots$, and 7. Subsequently, each integer maps to a fraction, $0/7, 1/7, \ldots$, or 7/7 for B_i, L_i, and $1/8, 2/8, \ldots$, or 8/8 for Q_i by assuming $Q_{min} = 0.125$ (= 1/8). Therefore, contributor agents have a 9-bit gene and browsing agents have a 3-bit gene.

The evolutionary process in GA consists of parent selection, crossover, and mutation phases. First, agent i chooses two agents as parents in the parent-selection phase, which produce a child agent that will be placed at the same position in G during the next generation. To maintain the type of agent, the parents of i are chosen through roulette selection from among the same type of agents in A_{np}, $A_{p,\alpha}$, or $A_{p,\beta}$. For example, if $i \in A_{p,\beta}$, $j \in A_{p,\beta}$ is chosen as its parent according to the ratio described by the distribution $\{\Pi_j\}_{j \in A_{p,\beta}}$, where

$$\Pi_j = \frac{(U_j - U_{min,\beta})^2 + \epsilon}{\sum_{k\in A_{p,\beta}}(U_k - U_{min})^2 + \epsilon} \tag{6}$$

where $U_{min,\beta} = \min_{k\in A_{p,\beta}} U_k$, We introduced a small positive number, ϵ, to avoid division by zero (as described in the next section, $\epsilon = 0.0001$ in our experiments).

Next, a uniform crossover is applied to all the genes in the crossover phase. Each bit of the following gene is determined by random bitwise selection from the parent genes. Finally, after the crossover phase, the new gene is inverted bitwise with a small probability of m_p ($\ll 1$) during the mutation phase. During the next generation, the produced child agent of i with the new genes plays the monetary reward SNS-norms game at the same location as i in G. This is repeated until g_{end} is reached, where $g_{end} > 0$ is an integer that indicates the *maximal generation number* in our experiments.

Experiments and discussion

Experimental settings

We investigated the dominant behavioral strategies and earned utilities of the contributor and browsing agents in the networks, as well as changes in the interest of the contributing agents in article quality when different monetary reward schemes were adopted in CGM. The overall behavioral strategy was identified by analyzing the average values of the posting rate B_i, comment rate L_i, and article quality Q_i for all agents. Subsequently, to examine the effect of network structures for interactions between agents on the agents' evolving strategies, agents conducted games on the networks generated by SBM [31] (hereafter, we call this class of network em SBM networks) and the Facebook (ego) network [32].

We conducted two experiments: the first (Exp. 1) assumed interactions in the SBM networks, whereas the second (Exp. 2) assumed interactions on the Facebook network. The characteristics of these networks are listed in Table 1.

We used SBM networks to identify the baseline characteristics of users' behavioral strategies in various monetary reward schemes in this game. Subsequently, we

Table 1 Parameter values and network characteristics

Description & Parameter	SBM network	Facebook network
Number of agents, $\lvert A\rvert = n$	80	4039
Number of agents preferring psychological reward, $\lvert A_{p,\alpha}\rvert$	20	1010
Number of agents preferring monetary reward, $\lvert A_{p,\beta}\rvert$	20	1010
Number of browsing agents, $\lvert A_{np}\rvert$	40	2019
Average degree	16.21	43.69
Cluster coefficient	0.375	0.606

Table 2 Parameter values for GA and cost/reward ratio

Description	Parameter	Value
Maximal generation number	g_{end}	1000
Probability of mutation	m_p	0.01
Reference value for cost and reward	c_{ref}	1.0
Ratio of cost to reward value	μ	8.0
Cost ratio between game stages	δ	0.5

used the Facebook network to verify the similarities and differences in the users' behavioral strategies generated based on the real user interaction structure from those in artificial networks, such as SBM networks.

To compare the experimental results, the number of nodes (i.e., agents) in the SBM network was set to $n = 80$, which is identical to that used by Usui et al. [9]. Further, we set up three communities: *Comm.* 1, *Comm.* 2, and *Comm.* 3, whose populations were 20, 25, and 35, respectively, and each type of agent was proportionally allocated to browsing agents, contributor agents preferring a psychological reward, or contributor agents preferring a monetary reward according to the population of the communities. These communities were then connected based on the block matrix, which was set as

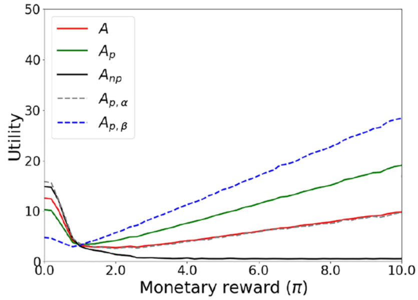
$$\begin{array}{cc} & \begin{array}{ccc} \mathit{Comm.}\ 1 & \mathit{Comm.}\ 2 & \mathit{Comm.}\ 3 \end{array} \\ \begin{array}{c} \mathit{Comm.}\ 1 \\ \mathit{Comm.}\ 2 \\ \mathit{Comm.}\ 3 \end{array} & \begin{pmatrix} 0.5 & 0.05 & 0.05 \\ 0.05 & 0.5 & 0.05 \\ 0.05 & 0.05 & 0.5 \end{pmatrix} \end{array}, \tag{7}$$

where each element in this matrix indicates the edge probability of two different agents conditional on their community memberships. The parameter settings of these SBM networks were partly determined by referring to the approach of Lee and Wilkinson [33]. The number of agents on Facebook was $n = 4039$. We set the populations $A_{p,\alpha}$, $A_{p,\beta}$, and A_{np} in the SBM and Facebook networks as listed in Table 1. The value of M_i for $\forall i \in A$ was initially determined for each run under the conditions listed in Table 1.

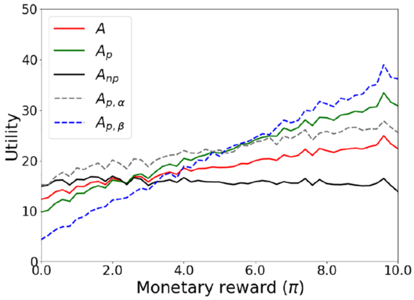
Table 2 lists the values of the parameters used in the GA and monetary reward of the SNS-norms game. We set $\delta = 0.5$ and $\mu = 8.0$ based on Okada et al. [30]. The results of the experiments are the averages of 100 independent runs, each of which had $g_{end} = 1000$ generations.

Experimental result—stochastic block model

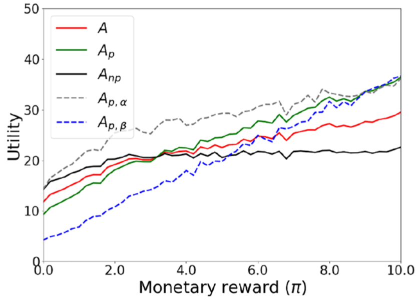
Figure 2 plots the *average utility* for each agent type; that is, A (all agents, red line), A_p (contributor agents, green line), A_{np} (browsing agents, black line), $A_{p,\alpha}$ (contributor agents preferring psychological rewards, gray dotted line), and $A_{p,\beta}$ (contributor agents preferring monetary rewards, blue dotted line) in the SBM networks under monetary reward schemes S1 (Fig. 2a), S2 (Fig. 2b), and S3 (Fig. 2c) with various



(a) S1 (when posting an article)



(b) S2 (when the article is read)



(c) S3 (when posting a meta-comment)

Fig. 2 Average utility U and monetary reward π in SBM networks

monetary reward values π. Here, the value of π was set from 0 to 10.0 in increments of 0.2. The average utility in these graphs was calculated using the utilities received in the final generation (thus, the g_{end}-th generation). Therefore, for example, the average utility of all agents in $A_{p,\beta}$ was calculated as

$$\mathcal{U} = \frac{1}{|A_{p,\beta}|} \sum_{i \in A_{p,\beta}} U_i^{g_{end}}, \tag{8}$$

where U_i^g denotes the received utility of i in the gth generation ($1 \leq g \leq g_{end}$). Note that $\pi = 0$ corresponds to when there is no monetary reward in the game.

First, let us examine the utility of A, A_p, and A_{np} in monetary reward scheme S1 (Fig. 2a). This figure shows that the utility of all types of agents decreases sharply with an increase in π from $0 \leq \pi \leq 1$ and then increases gradually with an increase in π. Browsing agents prefer CGM with no monetary reward scheme S1. This indicates that a small monetary reward negatively affects the satisfaction of all types of users; to improve this, relatively larger monetary rewards are required. Although contributor agents can receive monetary and psychological rewards, we found that their utilities are smaller than in situations without monetary rewards unless if π is large (≥ 6.0). Moreover, a comparison between the results of $A_{p,\alpha}$ and $A_{p,\beta}$ revealed that the utility of $A_{p,\alpha}$ is always lower than that of the CGM without a monetary reward (i.e., $\pi = 0$), although the utility of $A_{p,\beta}$ appreciates this reward. These results are mostly consistent with our previous experiments, except that the utility was considerably lower even when π was large in a complete graph [9].

In contrast, the abovementioned characteristics differed from those of the other monetary reward schemes, S2 and S3. Figure 2b and c shows that the average utility of all agents A increases with an increase in π. Looking closely at Fig. 2b, the utility of the contributing agents increases as π increases in S2, although the utility of the browsing agents remains almost unchanged (or decreases slightly). Interestingly, contributor agents that prefer psychological rewards ($A_{p,\alpha}$) earn more utility than contributors that prefer monetary rewards ($A_{p,\beta}$) when $\pi \leq 5$. This tendency was more pronounced in S3 (Fig. 2c), where the agents in $A_{p,\alpha}$ almost always gains more utility than those in $A_{p,\beta}$. Comparing the utility of the browsing agents, they earned more in S3 than in S2, although the difference was negligible. These results indicate that monetary reward schemes affect the behavioral strategies of agents depending on their preferences.

Evolved behavioral strategies in SBM networks

Based on the experimental results described in the previous subsection, we analyzed the relationships between monetary reward π and the evolved parameter values of agents in the monetary reward schemes. We plotted the average values of posting rate B, comment rate L, and article quality Q in Fig. 3 in monetary reward schemes S1, S2, and S3, where these average values are calculated using B_i, L_i, and Q_i evolved in the final generation, similar to $\mathcal{U}$.

First, Fig. 3a indicates that although the difference is small, monetary reward scheme S1 increased the number of article posts the most; however, Fig. 3c shows that as the monetary reward π increased, article quality rapidly declined. This phenomenon indicates that contributor agents, particularly those in $A_{p,\beta}$, post several low-quality articles at a lower cost to receive more monetary rewards. However, the browsing agents in A_{np} earned only small rewards because of the low-quality articles and thus could not obtain utility (see Fig. 2a). Furthermore, Fig. 3b shows that the agents had relatively low comment rates in S1; therefore, the contributor agents received lower psychological rewards from the comments to an article post, which left the utility of the agents in $A_{p,\alpha}$ low (Fig. 2a).

In contrast to S1, Fig. 3c indicates that monetary reward schemes S2 and S3 could maintain high article quality Q, and Fig. 3a shows that they could maintain a high posting rate, B. The comment rate L in S2 was slightly higher than that in S1 (Fig. 3b), and article quality was significantly higher than that in S1. However, article quality remained almost unchanged (or slightly decreased) as the monetary reward π increased (Fig. 3c). In monetary reward scheme S3, agents could increase the comment rate and article quality to a higher level than in other schemes as monetary reward π increased. As monetary reward was given to a contributor agent when it posted a meta-comment to a received comment, the browsing agents in A_{np} were also credited with high psychological rewards. Thus, all agents in A_p and A_{np} were

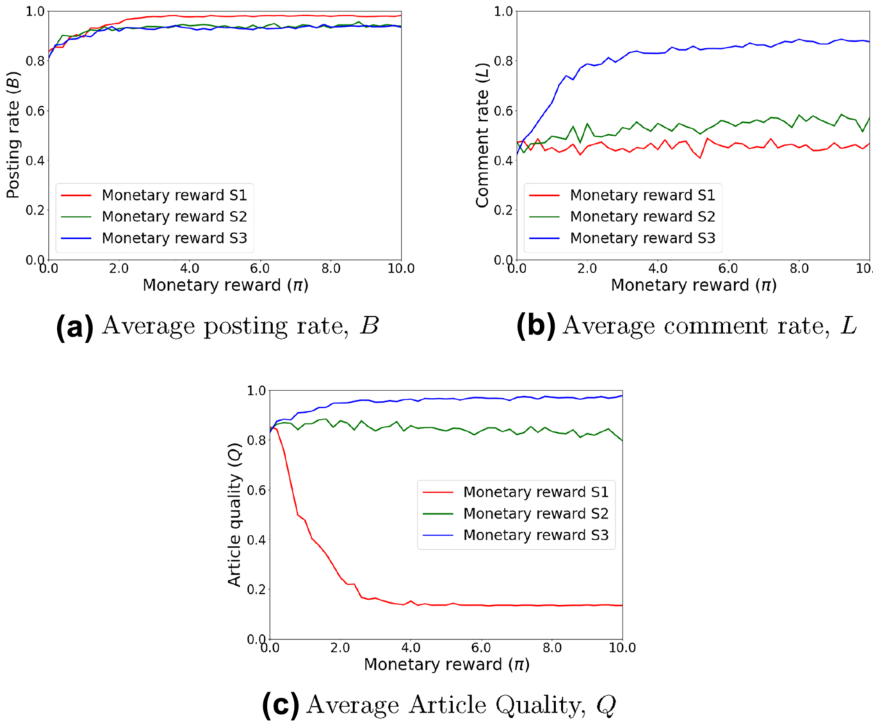


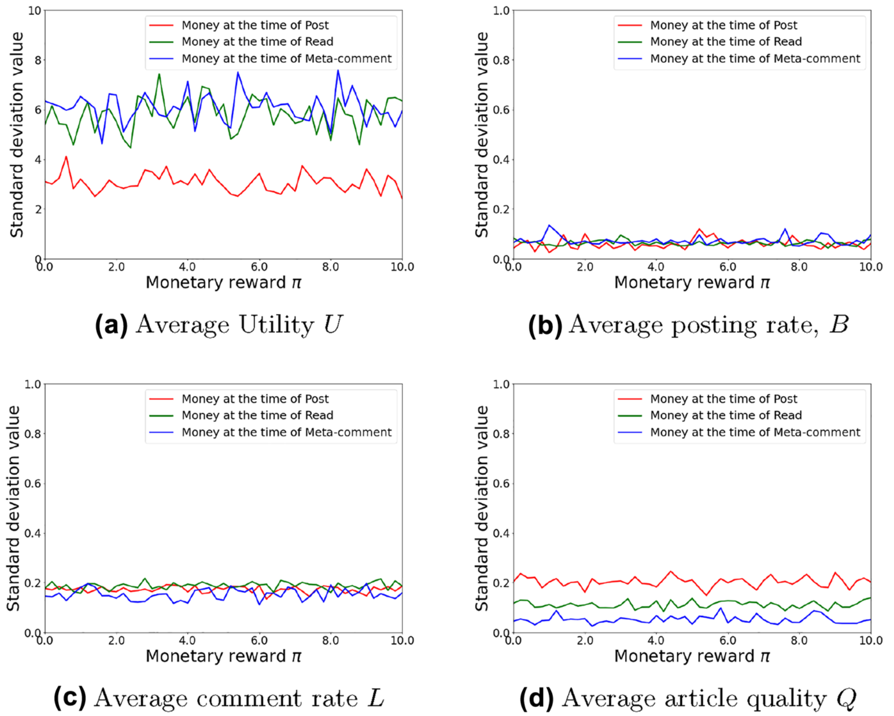
Fig. 3 Behavioral strategy of agents in SBM networks

enhanced to provide both comments and meta-comments. However, Fig. 3 shows that within the range of $\pi > 2.0$, the effect of increasing monetary rewards became smaller and dulled; therefore, a relatively small monetary reward was sufficient to incentivize users to post and comment on articles.

The trends shown thus far are stable. The standard deviations of the experimental results of 100 trials in the SBM network are shown in Fig. 4. These figures show that the standard deviations were small in all cases. The utility graph (Fig. 4a) shows a slightly larger variation, but this is due to the variation in the three parameters B, L and Q. In addition, this figure also shows the data of A, having A_p and A_{np}, which are slightly different owing to the different characters caused by A_{np}, $A_{p,\alpha}$, and $A_{p,\beta}$.

Experimental result—Facebook network

To increase accuracy, we conducted the same experiments with a network generated on a real social media platform to verify that our previous results can be observed in non-artificial networks. Figure 5 plots the relationship between monetary reward π and the average utility of each type of agent on a Facebook network for monetary reward schemes S1, S2, and S3. This figure indicates that the behavioral tendencies of agents in the Facebook network were fairly consistent with those of agents in the



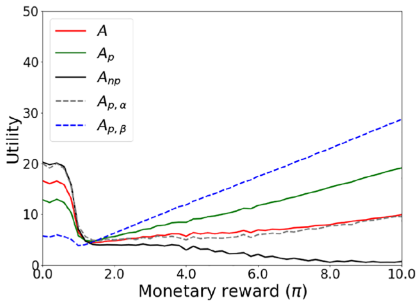
(a) Average Utility U **(b)** Average posting rate, B

(c) Average comment rate L **(d)** Average article quality Q

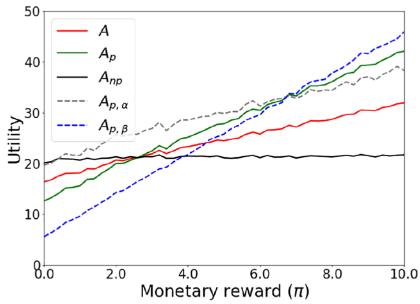
Fig. 4 Standard deviation values for key experimental results (Exp. 1)

SBM networks in Exp. 1, but more pronounced. For instance, although the transitions of the average utility of all types of agents to monetary rewards were similar to those in Exp. 1 in scheme S1 (Fig. 5a), the average utility of the agents in $A_{p,\alpha}$ was larger than that in Exp. 1 for S2 and S3 (see Fig. 5b and 5c). This indicates that the structure of this Facebook network instance was likely to increase the utility of agents who place importance on psychological rewards. Figure 5a also indicates another difference: when π is small ($\pi \leq 0.8$) in S1, the monetary reward is independent of agents' behavior in the Facebook network.

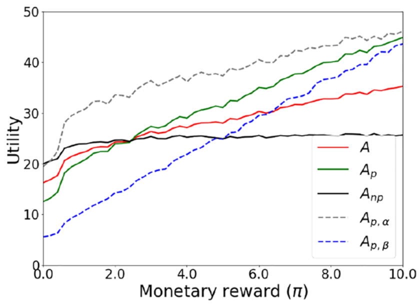
The average values of posting rate B, comment rate L, and article quality Q in Exp. 2 for monetary reward schemes S1, S2, and S3 are plotted in Fig. 6. As shown in Fig. 6a, no differences in the average posting rates between S1, S2, and S3. Meanwhile, Fig. 6b and c shows that the monetary reward scheme S3 was the most effective at increasing the article quality and comment rate of agents in the Facebook network, even with a small π. In monetary reward scheme S1, the opportunity to obtain monetary rewards is only at the time of article posting, and its attainment is attributed only to the voluntary actions of the contributor agents. By contrast, the contributor agent has the most opportunities to obtain monetary rewards in the monetary reward scheme S2 because it can obtain monetary rewards for the number of neighboring agents that read the article it posts. In monetary reward scheme S3, because a monetary reward is obtained for the number of meta-comments to comments on an



(a) S1 (when posting an article)



(b) S2 (when the article is read)



(c) S3 (when posting a meta-comment)

Fig. 5 Utility and monetary reward in Facebook Ego network

article, there are fewer opportunities to receive monetary rewards than in S2. However, the meta-commenting behavior of a contributor agent is enhanced by the monetary reward, which also increases the psychological rewards for browsing agents, thus incentivizing comments. This cascading effect may improve the overall activity of CGM.

Discussion

Herein, we summarize the impact of each monetary reward scheme on user behavior. First, monetary reward scheme S1 negatively affects user behavior. To understand this situation, we investigated how the monetary reward value π affects the number of posted articles and the average of the received psychological rewards, R_i, in each monetary reward scheme during the final generation. The results are presented in Fig. 7a and b. These figures show that when S1 was introduced into the CGM, the number of posted articles was high, whereas the average psychological reward was extremely low. This phenomenon led to a low average utility for all users (Figs. 2 and 5a). This is because agents obtain monetary rewards for posting more articles by reducing the article quality. Here, browsing agents, which correspond to

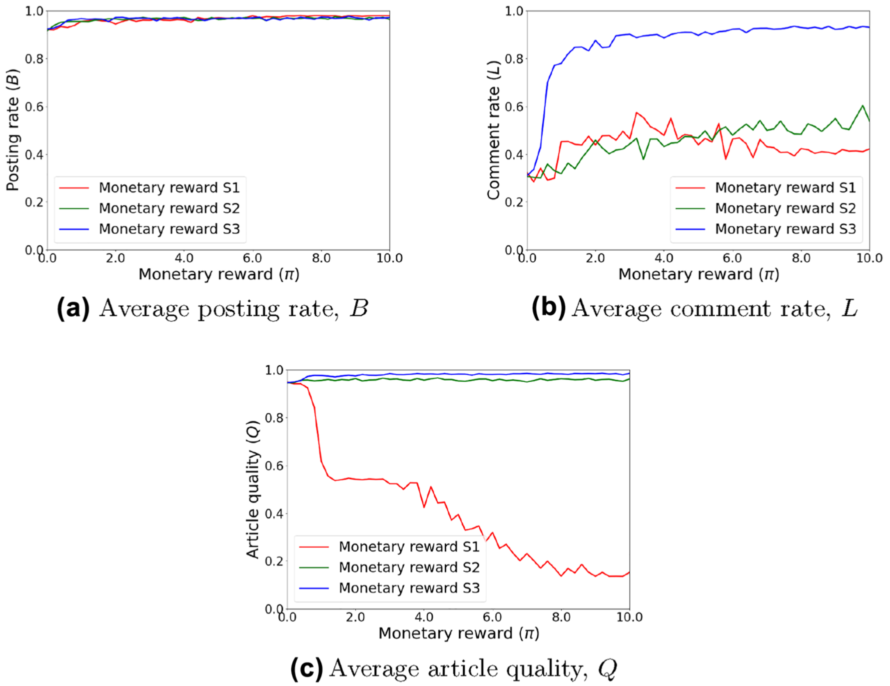


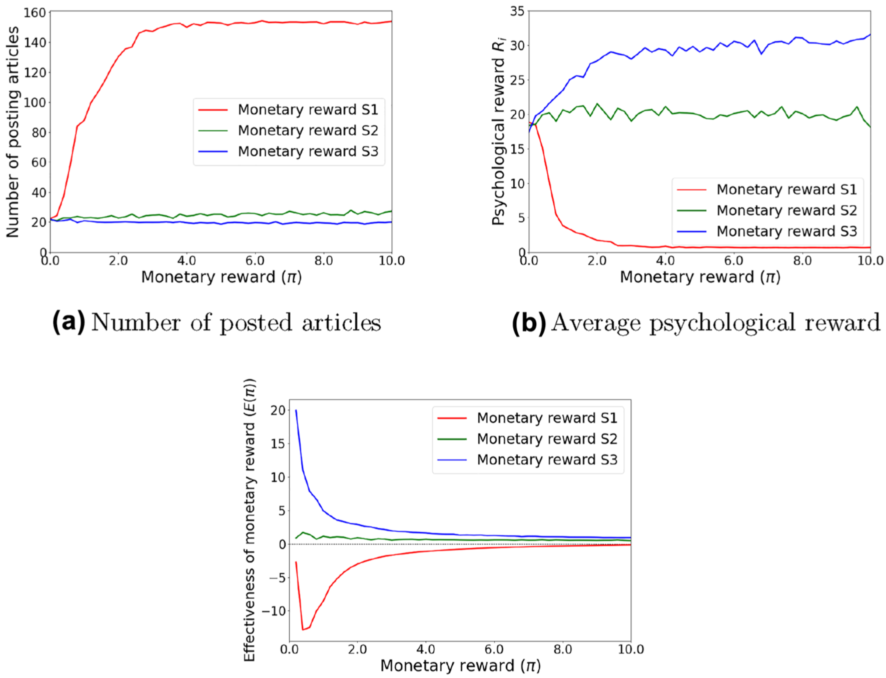
Fig. 6 Parameters and monetary reward of agents in Facebook Ego network

users who do not post articles, are rewarded less because of the low-quality content and consequently stop commenting. Hence, all the agents received extremely low psychological rewards, as shown in Fig. 7b.

In contrast to S1, as shown in Figs. 3c and 6c, agents could maintain high article quality Q in monetary reward schemes S2 and S3. This was done primarily to obtain psychological (Fig. 7b) and monetary rewards, particularly because monetary rewards operate as prompts for psychological rewards. Although the agents in these schemes have a high posting rate of B (Figs. 3a and 6a), the number of posted articles was not extremely high (Fig. 7a) because we assumed that contributor agents require more time to find and write high-quality articles.

Comparing the experimental results in the S2 and S3 schemes, S3 is preferable from the user satisfaction perspective because it increases the average utility of all agents by increasing the article quality to a higher level. Here, evidently, S3 enhanced meta-commenting because it provides monetary rewards to agents. This incentivizes agents to post comments and work to increase the article quality to increase the number of comments, which leads to a significant increase in the comment rate L, as shown in Figs. 3b and 6b and an increase in the psychological reward, as shown in Fig. 7b. The scheme, that is, S1, S2, or S3, depends on the policy of CGM administrators to either increase the number of posted articles or improve their quality.

Finally, we discuss the effectiveness of monetary rewards from a CGM platform perspective. Each scheme introduced in this study has different timings for providing



(a) Number of posted articles

(b) Average psychological reward

(c) Monetary effectiveness for increased utility

Fig. 7 Relationship between monetary rewards and other parameters (Exp. 1)

monetary rewards, and the frequency of rewards given to agents differs significantly. Therefore, even if the value of the monetary reward π given at one time is identical, the amount of money consumed by the CGM provider/administrator differs, depending on the monetary reward scheme. As the average utility value is the key indicator of the monetary reward SNS-norms game, we calculated the effectiveness $E^{\mathrm{S}n}(\pi)$ of the monetary reward in terms of this increased value when the monetary reward scheme is Sn ($n = 1$, 2, or 3) with reward π, as follows:

$$E^{\mathrm{S}n}(\pi) = \frac{\mathcal{U}^{\mathrm{S}n}|_{\pi} - \mathcal{U}^{\mathrm{S}n}|_{\pi=0}}{\sum_{i\in A_p} K_i/|A_p|} \left(= |A_p| \cdot \frac{\mathcal{U}^{\mathrm{S}n}|_{\pi} - \mathcal{U}^{\mathrm{S}n}|_{\pi=0}}{\sum_{i\in A_p} K_i} \right), \tag{9}$$

where $\mathcal{U}^{\mathrm{S}n}|_{\pi}$ denotes the average utility $\mathcal{U}$ when the monetary reward scheme is Sn with reward π. Therefore, $\mathcal{U}^{\mathrm{S}n}|_{\pi=0}$ is the average utility with no monetary reward. Note that $\sum_{i\in A_p} K_i$ is the total monetary reward given to all contributors.

The values of $E^{\mathrm{S}n}(\pi)$ when $\pi > 0$ in the final generation are shown in Fig. 7c. Evident from the figure, $E^{\mathrm{S}1}(\pi)$ was always negative, which implies that scheme

S1 negatively affects the user's utility; in contrast, $E^{S3}(\pi)$ was positive, particularly when π was not large. This implies that scheme S3 is cost-effective. Therefore, offering a large reward, */pi* is not advisable. Therefore, the CGM administrator should design the monetary reward scheme and the value of monetary rewards by considering the expected outcome.

The novelty of this study is that we proposed three monetary reward schemes, S1, S2, and S3, and showed that S3 is the most effective as it improves the quality of articles and thus increases their utility for users, which may be valuable to CGM platformers. In these results, particularly when adopting S2 and S3, it is assumed that agents can be sufficiently rewarded through interactions with neighboring agents. Therefore, if the connectivity between agents is sparse and sufficient interactions are not established, the results might differ.

Conclusion

We proposed a monetary reward SNS-norms game, which extends the SNS-norms game and models CGM by introducing parameters corresponding to article quality and rewards. In addition, we introduced three monetary reward schemes depending on when the rewards were given to the agents. Next, we analyzed the effect of these schemes on agent behavior, who prefer psychological or monetary rewards, from the perspective of their utility (i.e., agent satisfaction) on SBM networks based on the simulated experiments. These experiments revealed that scheme S3, which provides a monetary reward to a meta-comment of the contributor agent who posted the original article, allows article quality to remain high and provides the highest utility to all types of agents by offering both psychological and monetary rewards. However, scheme S3 could not increase the number of article posts because we assumed that high-quality articles required effort and time. Furthermore, we conducted the same experiment on the Facebook network, which reflects the real interaction structure, to show that these claims are not limited to artificial networks. Similar results were obtained for both network types.

Although some CGM, such as the example recipe site described in "Introduction", may have multiple timings to provide monetary rewards, we introduced three different monetary reward schemes independently to clarify the most effective timing. Therefore, in future, we plan to conduct experiments combining these schemes. In addition, because the experiments described in this study were conducted on a fixed network, we could not introduce the aspects of user acquisition and release. In future, we would like to conduct experiments to observe the dynamic changes in the network structure and number of users to investigate the impact of monetary rewards on the acquisition of users and the quality of articles posted on the CGM.

Another important future study would be to confirm the theoretical and simulation results obtained using real data. Real data should include information on the number of posts per user and their quality over a given period of time. The quality of the postings could be, for example, the number of views/reads or the number of comments, depending on the form of the CGM services and must be defined considering the nature of each service. We believe that collecting such data for certain periods in which a monetary reward scheme was introduced and those in which it was not, and comparing the differences would support this study's findings.

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Availability of data and materials The dataset used in this study is available from the http://snap.stanford.edu/data. This code is available online at https://github.com/usui324/SocialMediaSimulation.

Declarations

Conflict of interest All the authors state that there is no conflict of interest.

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