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User's Position-Dependent Strategies in Consumer-Generated Media with Monetary Rewards

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***Abstract*—Numerous forms of consumer-generated media (CGM), such as social networking services (SNS), are widely used. Their success relies on users' voluntary participation, often driven by psychological rewards like recognition and connection from reactions by other users. Furthermore, a few CGM platforms offer monetary rewards to users, serving as incentives for sharing items such as articles, images, and videos. However, users have varying preferences for monetary and psychological rewards, and the impact of monetary rewards on user behaviors and the quality of the content they post remains unclear. Hence, we propose a model that integrates some monetary reward schemes into the SNS-norms game, which is an abstraction of CGM. Subsequently, we investigate the effect of each monetary reward scheme on individual agents (users), particularly in terms of their proactivity in posting items and their quality, depending on agents' positions in a CGM network. Our experimental results suggest that these factors distinctly affect the number of postings and their quality. We believe that our findings will help CGM platformers in designing better monetary reward schemes.**

***Index Terms*—Social media, Consumer-generated media, Monetary reward, Agent-based simulation, co-evolution.**

I. Introduction

Consumer-generated media (CGM), such as *social networking services* (SNS) and review sites, have become integral to society. Contrary to traditional media outlets like television and newspapers, which disseminate information unilaterally from a few companies or government entities, CGM flourishes owing to the voluntary participation of its users. This fact seems unreasonable because voluntarily posting items, such as articles, images, and videos, to the media incurs, more or less, psychological, financial, and temporal costs. Thus, it is natural to assume that there is some incentive for most users to continue their participation. Thus, it is crucial to analyze the effect of different types of incentives to attract more users.

In general, the common incentives for contributing to CGM are psychological rewards for fulfilling their need for belonging, self-expression, and self-approval [1] in virtual connections on the Internet. To realize these, numerous CGMs include "Like" buttons, comments, stamps, and other features that present responses among users. Moreover, some media, such as YouTube, offer a few types of engagements that provide opportunities for monetary rewards, such as reward program points, advertising revenues, or sponsorship deals with well-known brands as incentives for participating to post more quality items.

Our study has adopted an evolutionary game-theoretic approach because we believe that it is suitable for a formal analysis of how user behavioral strategies are influenced by the incentives provided by CGM and their positions within social networks. To investigate the effect of monetary rewards on the number and quality of posted items, Usui et al. [2] introduced a few schemes for monetary rewards to the game theoretic model representing SNS [3]. They also show that by appropriately providing monetary rewards, users attempt to improve the quality of the items they post. Although users' behavioral strategies in a CGM are partly determined based on their positions in the networks, such as normal users and influencers with many followers, these studies overlook the users' positions in the social networks because they used the conventional *genetic algorithm* (GA) on a CGM network.

Therefore, we investigate how users' behaviors vary depending on their positions when a monetary reward scheme is introduced in CGM. For this purpose, we use the *multiple-world genetic algorithm* (MWGA) [4], which is a *co-evolutionary* algorithm by extending the conventional GA, to ensure that all agents (users) can examine different behavioral strategies with neighbors that also have various strategies in the same network structure. we experimentally demonstrate the manner in which agent strategies concerning the posting/comment rates and the quality of their items vary depending on their degrees, that is, the number of friends/followers, and on agents' preferences for monetary or psychological reward. We believe that our findings on the effects on agents' behaviors will help in the design of future CGMs to improve item quality by adopting a monetary rewards scheme.

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II. Related Work

Studies on CGMs have been widely conducted. Dhir et al. [5] identified that psychological self-efficacy and the users' habits affect the use of the Facebook "Like" button from the perspective of *behavioral intention theory*. Several studies focused on the influence of monetary rewards on users' behaviors in CGM. Cvijikj et al. [6] found that monetary rewards for users on Facebook actively increased the number of comments, while it led to a decrease in passive responses such as the use of "Like" buttons.

Apart from these empirical studies, there are studies from an evolutionary game theoretic perspective to identify the behaviors of users in CGMs [2], [3], [7]. Toriumi et al. [7] found that CGMs share characteristics with public goods game [8] and proposed the *meta-reward game*, which is a dual problem with Axelrod's *meta-norms game*. Subsequently, they showed that meta-comment, that is, comment-return or comment on the comment, plays a crucial role in incentivizing voluntary activities. Subsequently, the meta-reward game was modified to *SNS-norms game* [3] to fit the nature of CGM and further extended to *SNS-norms game with monetary reward and article quality* (SNS-NG/MQ) to investigate the effect of monetary rewards by identifying the common dominant behavioral strategy for all agents. However, unlike ours, they overlooked the diverse strategies depending on the positions of users in the network.

III. Preliminary

A. SNS-norms game and agent network

The SNS-norms game [3] is an abstract model for the agents' behaviors with strategies in an SNS/CGM. Let graph $G = (A, E)$ be a CGM network, where $A = \{a_1, a_2, \ldots, a_N\}$ is the set of N agent nodes (or simply agents), each of which corresponds to a user in the CGM, and E is the set of edges connecting two agents. Thus, edge $(a_i, a_j) \in E$ represents the connection, referring to the relationship between agents such as friends. We denote the neighboring agents of a_i, $N_{a_i} = \{a_j \in A \mid (a_i, a_j) \in E\}$. Each agent a_i has two parameters, posting rate B_i, comment/meta-comment rate L_i, $(0 \leq B_i, L_i \leq 1)$, to control its behavioral strategy. These parameter values evolved through the interaction with neighboring agents in G using GA such that they can gain more fitness values, which are the total rewards they earn. The SNS-norms game represents the sequence of events from the posting of an item on the SNS to the viewing and commenting by followers and the return as meta-comments by the poster. From these flows, the agent pays some costs and obtains psychological rewards. Note that all rewards described here are psychological rewards and no physical materials or monetary rewards are provided.

B. Multiple-world GA

MWGA is an extension of the GA to facilitate co-evolutionary learning within a network of agents. It allows agents in MWGA to explore various strategies in parallel worlds that are replicated. First, in MWGA, W (≥ 1) networks, $G^l = (A^l, E^l)$ (for $1 \leq l \leq W$), are duplicated from G; therefore, $A^l = A$ and $E^l = E$. For agent a_i in G, the set of its copies (clones) is denoted by $\mathcal{S}_i = \{a_i^1, \ldots, a_i^W\}$ whose element is called a *sibling agent*. Assuming that sibling agent a_i^l has its strategy in the l-th world G^l, all sibling agents of a_i experience interactions with their neighboring sibling agents, which also have different strategies at the same relative position. This suggests that each a_i^l has different values of posting rate B_i^l and comment/meta-comment rate L_i^l, which are expressed by 3-bit binary genes, ranging from $0/7$ to $7/7$.

Similar to the conventional GA, MWGA consists of three stages; (parents) selection, crossover, and mutation, to create genes for the next generation, but its selection stage is distinctive. Unlike GA, in which the gene of a_i is likely to be inherited from its and neighboring agents, the gene of a_i^l $(1 \leq l \leq W-1)$ in MWGA is inherited from $\mathcal{S}_i$, which had another experience at the same position, according to the values of the fitness function. MWGA enables agents to learn location-specific strategies because each agent evolves using its experience as $\mathcal{S}_i$. Moreover, the W-th world, G^W, is a test world to confirm the optimal strategies of all agents that are usually selected from the different worlds. The detailed encoding in our model will be explained in Section IV-B.

IV. Proposed Model and Methodology

We propose the *SNS-norms game with monetary reward and article quality* (SNS-NG/MQ) to investigate the effect of monetary rewards on the behaviors of agents and the quality of the item they post, which are article, image, or video content. The main differences from the previous model [2], [9] are that it did not consider the uniqueness of its standpoints and differences in behavioral strategies of neighbors. Therefore, in the previous model, genes were inherited from the agents with different standpoints. This seems acceptable when all agents are uniform like a complete graph, but the actual network structures are far from the complete graph. Thus, We extended their model to ensure that it can be used with all type of networks. Further, we eliminated our unnecessary agent types in our model because our main goal is to examine differences in behavioral strategies with standpoints, that is, places in the network, and unnecessary agent types hinder this analysis. Specifically, the main reason for introducing such unnecessary agents in previous studies was that they assumed a CGM in which a large proportion of agents do not post an item and only view it. Our research does not need to take this into account supecifically, since agents in positions where such behaviour would be optimal can also converge on their unique strategies. Our contribution enables us to determine the most effective monetary reward scheme for agents at the places. Conversely, as CGM managers also aim to encourage activity from specific types of agents, they can design reward schemes that are appropriate for these target groups.

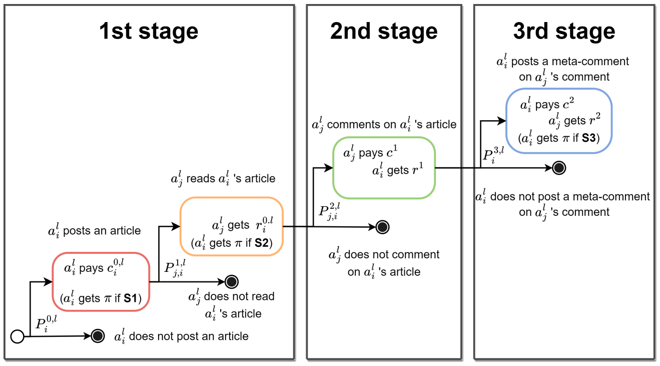


Fig. 1: One game round of SNS-NG/MQ

A. Agents in network

As in the SNS-norms games, agents have interactions with neighboring agents in $G = (A, E)$. In addition to the behavioral parameters B_i and L_i for $a_i \in A$, we introduce another parameter Q_i, $(0 < Q_{min} \leq Q_i \leq 1)$, denoting the item quality [2], relating to the willingness of agent a_i to spend to improve the quality of their items. We presume that quality items are more likely to receive comments and this reduces posting frequency because of the effort they involve. Note that Q_{min} is the minimum value of quality and, unlike B_i and L_i, $Q_i > 0$.

We also introduce parameter M_i $(0 \leq M_i \leq 1)$ to express the preference for monetary reward. As we believe that this preference is intrinsic and constant, we set it as a constant value after it is defined initially for a_i. Subsequently, agents are classified into the following two types of agents:

$$V_\alpha = \{a_i \in A \mid M_i < 0.5\}, V_\beta = \{a_i \in A \mid M_i \geq 0.5\} \quad (1)$$

Thus, V_α and V_β are the sets of agents that relatively prefer either psychological or monetary rewards, respectively.

B. SNS-norms game with monetary reward and article quality

Agent a_i^l on $G^l = (A^l, E^l)$ $(1 \leq l \leq W)$ performs the SNS-NG/MQ with its neighboring agents. It is similar to the process involved in the SNS-norms game but is modified to consider the quality of items and monetary rewards. One game round is illustrated in Fig. 1, in which three types of monetary reward schemes, $S1$, $S2$, and $S3$, are shown, but only one of them is implemented for each game episode [9]. In these schemes, monetary reward π (≥ 0) is offered to a_i^l when:

- $S1$: Agent a_i^l has posted an item
- $S2$: The item posted by a_i^l is viewed by a neighboring agent; and
- $S3$: Agent a_i^l returns a meta-comment to the comment from one of its neighboring agents.

Therefore, it is feasible for a_i^l to earn multiple π in $S2$ and $S3$. We assume that monetary rewards are provided by the platformer of the CGM. Note that $\pi = 0$ means that no monetary rewards are adopted; this scheme is denoted by $S0$.

As in the SNS-norms game, SNS-NG/MQ represents the flow from posting to meta-commenting and agents incur and get cost and psychological reward. Although in the SNS-norms game, user actions such as posting and commenting are determined by the parameters B and L, in SNS-NG/MQ, thier actions are further determined by considering quality of items Q and they can recive monetary reward at the appropriate time for each adopted scheme. To find out about the game flow, cost and reward, refer to our full version (https://arxiv.org/abs/2310.04805). Afte single game, agent a_i^l cauclurates utility u_i^l like following:

$$u_i^l = (1 - M_i) \times R_i^l + M_i \times K_i^l - C_i^l, \quad (2)$$

where R_i^l, K_i^l, and C_i^l are the summed psychological rewards, monetary rewards, and cost provided to/incurred a_i^l in the game. This utility is used as the fitness value in MWGA, and thus, all agents attempt to increase their utilities.

C. Multiple-world GA for SNS-NG/MQ

The co-evolutionary learning algorithm, MWGA, is applied such that each agent evolves its behavioral strategy specified by B_i, L_i and Q_i (more precisely, B_i^l, L_i^l and Q_i^l in the l-the world). Its use for SNS-NG/MQ is almost identical to that for the SNS-norms game described in Section III-B except Q_i^l that does not appear in the SNS-norms game. Q_i^l is also encoded by 3-bit gene whose values correspond to $1/8$ $(= Q_{min})$, $2/8, \dots, 8/8$.

One generation is defined as N_{gen} (≥ 1) games and one episode consists of g (≥ 1) generations. The fitness value U_i^l of a_i^l used for the selection after each generation is the sum of u_i^l obtained in the SNS-NG/MQ. The selection, crossover, and mutation processes are performed as follows:

1) Selection: Two parents of each agent $a_i^l \in A^l$ $(1 \leq l \leq W-1)$ are itself and one sibling agent in $\mathcal{S}_i^{-l} = \mathcal{S}_i \setminus \{a_i^l\}$ selected using the *roulette wheel selection*, that is, agent $a_i^k \in \mathcal{S}_i^{-1}$ is selected with the probability Π_i^k:

$$\Pi_i^k = \frac{(U_i^k - U_{i,min})^2 + \varepsilon/(W-1)}{\sum_{v_i^k \in A_i^{-l}} (U_i^k - U_{i,min})^2 + \varepsilon}, \quad (3)$$

where $U_{i,min} = \min_{v_i^k \in A_i^{-l}} U_i^k$. Value ε $(\ll 1)$ is a positive value to avoid zero division (we set $\varepsilon = 0.00001$).

Meanwhile, agent $a_i^W \in A^W$ in the next generation is set to one of the sibling agents $\mathcal{S}_i$ with the highest utility U_i, and the crossover is not applied. Therefore, the W-th world consists of agents with the highest utilities in all worlds.

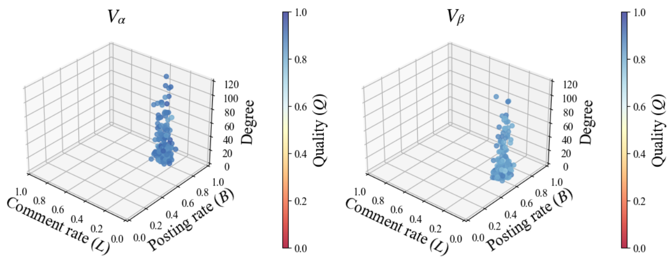
2) Crossover: In l-th $(1 \leq l \leq W-1)$ worlds, the gene of the child is composed of the selected parents using the *uniform crossover* of the selected parents.

3) Mutation: To prevent falling into a local optimum, it is done by flipping each bit of the 9-bit gene of each agent in A^l for $1 \leq \forall l \leq W$ with a *mutation probability* m, where $0 \leq m \leq 1$.

Finally, the outcome in each generation from MWGA is defined as the results of the W-th world.

TABLE I: Parameter values in experiments

Description	Parameter	Value
Number of agents	$N = \|A\|$	400
Number of agents preferring psychological reward	$\|V_\alpha\|$	200
Number of agents preferring monetary reward	$\|V_\beta\|$	200
Reference value for cost and psychological reward	c_{ref}	1.0
Ratio of cost to psychological reward	μ	8.0
Cost ratio between game stages	δ	0.5
Number of worlds in MWGA	W	10
Number of games in a generation	N_{gen}	4
Number of generations (episode length)	g	1000
Probability of mutation	m	0.01



(a) $S0$ V_α

(b) $S0$ V_β

Fig. 2: Strategy parameters and agent's degree (GA)

V. Experiments and Discussion

A. Experimental setting

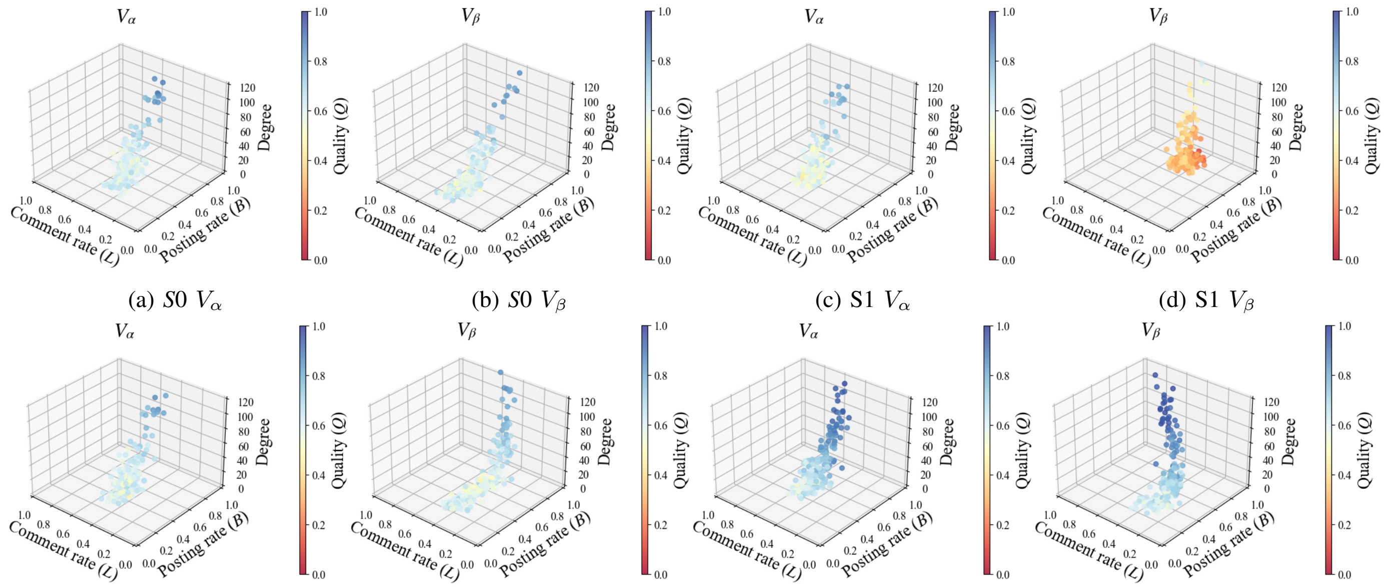
We conducted the experiments of SNS-NG/MQ to investigate the agents' individual and diverse behavioral strategies using MWGA and compared these results with those by the naive GA as used in the previous study [2] to investigate the difference when overlooking the places in a CGM network. We also investigated the impact of monetary reward schemes, the reward value π on agents' strategies, and the number of posts depending on their places in the network. In particular, we focused on the degrees of the network because it shows the number of friends. We used the network based on the CoNN model whose conversion rate $u = 0.9$. If nothing is stated, $\pi = 1.0$. The other parameter values are listed in Table I. These values are taken from the previous study [2]. Because the result of MWGA is the outcome of the W-th world, we simply denote their parameters such as B_i $(= B_i^W)$, L_i $(= L_i^W)$, and Q_i $(= Q_i^W)$. The averages of these parameters are denoted by B, L, and Q. The data shown below are the results of 100 experimental runs. If you require in-depth information regarding the experiment, please refer to the full version.

B. Distribution of behavioral strategies with GA and MWGA

The distribution of behavioral strategies of agents in V_α (preferring psychological reward) and V_β (preferring monetary reward) in scheme $S0$ (no monetary reward is provided), when agents learned their strategies with GA [2], is plotted in Fig. 2. This figure indicates that agents in V_α and V_β respectively, learned, regardless of their degrees, the almost identical strategies that were specified by the values of B, L, and Q. It also shows that agents in V_α were more cooperative (higher B, L and Q as shown in Fig. 2a) than those in V_β (Fig. 2b) because only psychological rewards are the incentive to participate in a CGM.

The distribution of behavioral strategies of agents learned with MWGA in scheme $S0$, $S1$, $S2$, or $S3$ is plotted in Fig. 3. This clearly shows a different trend from that in Fig. 2, that is, their strategies varied according to their degrees (the number of friends/followers) in the network even under scheme $S0$ and even if agents are of the same type. Figures 3a and 3b show that agents in V_α and V_β have a similar comment rate L, and the agents with high degrees in V_α have a higher posting rate B_i and higher quality Q_i. Agents with lower degrees in V_β posted items with a lower rate (B_i) and their quality value Q_i was relatively lower. This is because agents with high degrees had more chances to receive comments from their neighbors, raising the posting rate B_i. They also improved the quality to receive more comments, which brought more psychological rewards. In contrast, agents with lower degrees post relatively poor-quality items as few comments were expected. We believe that these results are intuitively acceptable, as agents' behaviors are naturally influenced by the behaviors and numbers of their neighbors, particularly the cooperative behavior of commenting. Note that we conducted the same experiments using GA in $S1$, $S2$, and $S3$, but their results were also uniform; the detailed results were identical to those in the previous study [2].

Let us assess the results of behavioral strategies with MWGA when monetary rewards were adopted. For example, if we compare Figs. 3c and 3d ($S1$), agents in V_β in $S1$ were likely to post more items, but their quality values Q_i were significantly lower than those of agents in $S0$. Meanwhile, distributions of B_i of agents in V_α in $S0$ and $S1$ were almost identical but the values of Q_i of agents in V_α were slightly lower than those in $S0$. In particular, agents with lower degrees posted more low-quality items. Therefore, we could say that $S1$ provided an incentive for agents to increase the number of items by decreasing the quality, particularly those with



(a) $S0$ V_α (b) $S0$ V_β (c) S1 V_α (d) S1 V_β

(e) S2 V_α (f) S2 V_β (g) S3 V_α (h) S3 V_β

Fig. 3: Distribution of strategy parameters and agent's degree (MWGA)

low degrees preferring monetary rewards (V_β). Their strategies were reasonable because they could gain monetary reward π only by posting any items. Although the results are not shown owing to the page limitation, the average psychological reward and utility of agents in V_α considerably decreased.

Next, we compare Figs. 3e and 3f ($S2$) with Figs. 3a and 3b ($S0$). There is no significant difference in these schemes except that agents in V_β had slightly higher B_i. This is because the poster's monetary rewards when being viewed are not accompanied by psychological rewards, only viewer agents gain psychological rewards, such that only agents in V_β are more likely to encourage posting items. Meanwhile, all agents in V_α and V_β increased the values of B_i and Q_i in scheme $S3$ as shown in Figs. 3g and 3h. This situation is desirable because all agents attempt to post more items with better quality. The monetary reward for meta-comments is tied to the psychological reward that the first item poster gained from the received comments. If the quality of an item is high, both monetary and psychological rewards can be obtained with high probability. This can be an incentive for posting quality items. Moreover, agents with a high degree in V_β considerably increased L_i over those in V_α, because the responses by meta-comments are only the way to gain monetary rewards; this is an incentive to increase L_i.

VI. Conclusion

In this study, we investigated the impact of monetary rewards on agents' activities and how differently agents' activities are affected depending on their places in a CGM network. For this purpose, we improved the SNS-NG/MQ by eliminating unnecessary parts and then identified the agents' appropriate behaviors using MWGA. We adopted three monetary reward schemes and discovered that they affect agents' behaviors differently. Our results indicate that the agents with high degrees were more likely to be affected by certain monetary reward schemes and by appropriately setting the schemes, all agents can improve the quality of items they post without reducing the frequency of posting despite the cost of quality items. Our model is useful for analyzing rational strategies for individual standpoints for specific schemes of monetary rewards by setting appropriate reward values.

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