Effect of online word-of-mouth communication on buying behavior in agent-based simulation

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Abstract. This paper discusses online word-of-mouth communication and uses an agent-based model to investigate the importance of knowledge-based communication for effective diffusion of information. By constructing the model, we focus on three axes: consumer component, number of interaction partners, and consumers' partner selection rules. Consumers are categorized as Early Adopter, Individualist, Trend Maker, or Follower along "information retrieving" and "information outgoing" axes. According to the simulation of our agent-based model with several scenarios, a cascade of buyers plots a S-shaped curve and that the early adopters buy the good first and the trend makers generate word-of-mouth communication and then it comes over the followers. Besides, if people choose partners on the basis of their personal knowledge levels, both efficient and inefficient diffusion of information emerges. Inefficient diffusion occurs in the case that they choose persons with their similar level of knowledge, while more efficient diffusion occurs in the case that with higher level. This insight may indicate the existence of alpha bloggers or signal the emergence of a new regime in Internet-based communication.

Keywords.
Diffusion of information, Consumer Behavior, online word-of-mouth, agent-based simulation

1. Introduction

The explosive growth of the Internet with its enhanced communication capabilities has greatly affected both quantitative and qualitative aspects of word-of-mouth (WoM) communication. Various terms have been coined for WoM communication over the Internet, including "Digital Word of Mouth" (Dellarocas and Narayan, 2006) and "electronic WoM (eWoM)" (Hennig-Thurau et al., 2004). Here, we use "online WoM," the most commonly used term.

In this paper we address some questions. How does the WoM process change in an online environment? How can online WoM be modeled? How does the diffusion of information on the consumption of goods change? What are the key factors affecting the diffusion of information? We formalize and model online WoM communication and use the model to investigate the importance of knowledge-based communication for effective diffusion of information. With traditional WoM communication, random communication might bring about more effective diffusion of information. In contrast, knowledge-based communication may be more effective diffusion with online WoM communication.

1.1 Literature

Various aspects of online WoM communication have been investigated. For example, Hu (2006) observed that online reviews have become a major information source for consumers. Many studies have examined the importance of online product reviews and their effect on sales. For example, Dellarocas (2003) surveyed the progress made in clarifying the new possibilities and challenges resulting from the growth of online WoM. He also discussed important dimensions in which Internet-based reputation mechanisms differ from traditional WoM networks. Conceptual studies of online WoM have described useful frameworks or ideas, such as dispersion (Godes and Mayzlin, 2004), tie strength, homophily, and source credibility (Brown et al., 2007), and the valence of online ratings (Dellarocas et al., 2005).

The main purpose of online WoM studies for both scholars and practitioners of marketing is to collect a large amount of WoM communications and to use online WOM as a revenue forecasting tool (Dellarocas and Narayan (2006)). This is why there are many empirical studies of online WoM related to explaining and forecasting consumer purchasing behavior.

Chevalier and Mayzlin (2006) examined the effect of consumer reviews on the relative sales of books on the Amazon.com and Barnes and Noble web sites. They found that the sales of a book increase if the book's average review score increases and that the effect of negative reviews is greater than that of positive ones. Godes and Mayzlin (2004) showed that a measure of the dispersion of conversations across communities has explanatory power in a dynamic model of TV ratings.

Hu et al. (2006) tested whether online product reviews reveal the true quality of the product by using data from Amazon.com. He found that 53% of the products listed on the site have a bimodal, U-shaped price-quality distribution and that the average score does not necessarily reveal the product's true quality, meaning that the recommendations can be misleading. They assumed that the people who wrote the reviews were either very satisfied with the reviewed product and wanted to brag about their purchase or were very disgruntled and wanted to moan about their misfortune. They built a simple analytical model based on this assumption, the “brag-and-moan model.”

Dellarocas et al. (2005) developed a movie revenue forecasting model, Kuwashima (2006) studied a network analysis on data about a cosmetic word of mouth site, and Smith et al. (2005) found evidence in two empirical studies that suggests that many online consumers seek and accept recommendations in order to effectively manage the great amount of information presented during an online search process.

Many researchers and marketing practitioners have stressed the importance of the effect online WoM has on sales. Most macro models are based on the analysis of data obtained by empirical macro observation without a micro foundation such as consumer behavioral theories and information diffusion information. The behavior of individual consumers thus cannot be captured by using these theories and models.

Brown et al. (2007) argued that existing interpersonal communication theories may be inappropriate for describing online WoM behavior.

1.2 Aim and Originality

Although the importance of online WoM has been recognized, few studies have analyzed the relationship between online WoM and consumer behavior due to the lack of an operable model. We have developed and calibrated an online WoM model by using an agent-based approach that is based on Roger's theory of diffusion and innovation. The model can be used to investigate the effect of the appearance of new types of consumers such as bloggers.

According to Granovetter (1973) and Putsis et al. (1997), WoM spreads more quickly within communities than across them. Sun et al. (2006) concluded from an analysis of survey data from college students that innovation diffusion theory can be applied to online WoM communication because innovativeness, Internet usage, and Internet social connectivity are significant predictors of online WoM. Hennig-Thurau et al. (2004) used a sample of some 2000 online consumer reviews to examine the structure of such reviews and the motives of the consumers. They found that their desire for social interaction, the existence of economic incentives, their concern for other consumers, and the potential to enhance their self-worth are the primary factors leading to online WoM behavior. Rogers (1983) focused on the diffusion of innovations and developed a framework in which consumers are differentiated into five types (innovators, early adopters, early majority, late majority, and laggards). Our model of online WoM communication is based on innovation diffusion theory and Roger's framework.

Bickart and Schindler (2001) asserted that traditional WoM communication typically consists of spoken words exchanged with a friend or relative in a face-to-face situation. In contrast, online WoM communication typically consists of written words exchanged with strangers in a non face-to-face situation. Sun et al. (2006) compared traditional and online WoM and developed an integrated model to explore the antecedents and consequences of online word-of-mouth. WoM communication is not based on the ex ante valuation but sharing in buyers' experiences. Using the well-known Dentsu’s AISAS model (attention, interest, search, action, share), we characterize online communications as an original formalization.

The main originality of this work is the modeling itself. In this paper, we describe online WoM communication in terms of the consumer population, the number of interaction partners, and their memory period. We also analyze the effect of knowledge-based selection.

1.3 Agenda

Section 2 describes the framework used to develop our model. Section 3 explains how the model was built. Some of the results obtained by using the model are presented in Section 4. Finally, we discuss the effect of online WoM communications, summarize the paper, and mention future work in Section 5.

2. Model Structure

Here we describe the framework used to develop our online WoM model. It encompasses online communication, consumers, and information flows.

How should "online" be modeled? We focus on three axes. First is the consumer component. Yamamoto et al. (2002) proposed a framework for consumer information behaviors as an extension of the model of the Nikkei Institute of Industries and Consumption (2000a,b). They categorized consumers as Early Adopter, Individualist, Trend Maker, or Follower along “information retrieving” and “information outgoing” axes, as shown in Table 1.

Table 1. Consumer information behaviors

<table>
<tr><td colspan="2"></td><td colspan="2">Information Retrieving (Finding)</td></tr>
<tr><td colspan="2"></td><td>Active</td><td>Passive</td></tr>
<tr><td rowspan="2">Information Outgoing (Talking)</td><td>Active</td><td>E</td><td>T</td></tr>
<tr><td>Passive</td><td>I</td><td>F</td></tr>
</table>

Type	Retrieving	Talking	Listening	Buying Goods
E	o	o	o	o
I	o	—	o	o
T	—	o	o	o
F	—	—	o	o

Retrieving: One directly searches for information about goods on the market and find goods with a certain probability.

Talking: One communicates information about goods one has bought to other people.

Listening: One gets information about goods from other people through their talking.

Buying Goods: One buys goods.

E: Early Adopter I: Individualist
T: Trend Maker F: Follower

The spread of the Internet has enabled consumers to not only receive standardized information through mass media but also to distribute their own information proactively. Popularity of the blogs bring that the consumers with passive information outgoing such as Individualists and Followers can become them with active information outgoing. This is why the development of online WoM communications derives the change of consumers' component.

For simplicity, we model agent actions as speaking to other agents rather than as writing (as in a blog) and as listening to other agents rather than as reading (as from a blog). Our model can control agents of various types by using only four behavior rules because of the use of several devices, as described below (a one good model and/ or network topology). This model describes online WoM as an extension of traditional WoM. However, certain situations must be interpreted using an artifice; for example, Individualists are listeners. We might adopt different approach in future work. If we do, we must first add a blogosphere to our model.

The second axis of our framework is the number of interaction partners. Consumers using the Internet are expanding the number of their interaction partners. In our model, network topology is referred to as “consumer interactive relationship”; therefore, the number of links increases through online WoM communications.

The third axis is related to consumer memory. With offline WoM, the diffusion of information depends on consumer memory, which is finite. In contrast, the openness and externality of memory on the Internet, such as in blogs, results in consumer WoM information being retained semi-permanently. That is, consumer memory is lengthened.

In addition to these three axes, we model how consumers communicate with each other. The total amount of consumer attention has a limit in spite of their expanding communicative capability. What criteria do they use to choose their interaction partners? We give a consumer a tag of one-dimensional level of knowledge and test the effect of the tag under the assumption that all tags are visible to all consumers. Do consumers communicate with disregard to the tags or with regard to the class of tags? Do they tend to communicate with partners with a similar level of knowledge?

3. Model building

On the basis of the conceptual model described above, we developed an agent-based model of online WoM communication. The consumers are agents, the interaction partners are links, and there is one consumption good. There are four types of agents, and every type has a different informative behavior rule (Table 1).

The agent network is a small-world network. Compared with various other topologies (two-dimensional torus grid, small-world, scale-free, and random), the small-world network has several advantages for our purpose. The Internet may make a communication network a random and dynamic one. However, we focus on the scope of potential communication partners. This makes it hard to treat a dynamic network. A torus-type network would not be appropriate for analyzing the diffusion of information, and a scale-free network would not be appropriate for distributing different agent types because of the inhomogeneous number of links. A tree-type network may be effective for modeling information propagation in an organization, but a hierarchical online community is unrealistic. Therefore, we use a small-world network a la Watts and Strogatz (1998) for modeling agent informative behaviors. First, every node is connected to its neighbors in a one-dimensional torus grid. Second, all edges reconnect to the other edges with probability p. If $p = 0$, the network is a grid network; if $p = 1$, it is a random network. Here, $p = 0.1$.

How do agents behave? They can perform three types of informative actions and one type of buying action: retrieving, talking, and listening and buying goods. In retrieving, two types of agents (E and I; see Table 1) can get information about a consumption good with a particular probability. If one agent obtains the information, the amount of information the consumer retains increases by a particular value. In talking (or blogging), an agent chooses one of its neighbors and talks about its consumption experience after buying the good. In listening, an agent who listened to a speaker obtains a particular amount of information. For simplicity, we assume that a receiving agent chooses a neighbor agent, and if the chosen agent can send information, i.e., it is type E or T, then the information can circulate among the other agents. Moreover, partner selection can be bound by the knowledge level, as explained later. Finally, in buying goods, an agent buys the good when the total amount of information it has received exceeds a particular value. In formulating the effect of online communication, the agent type, the number of neighbors (links), and the available duration of agent memory are the model parameters.

A simulation using this model proceeds as follows. First, a network is set up that consists of nodes and links as agents and their potential communication partners. Next, agents are characterized by behavioral type and knowledge level. Then, in each period, the type E and I agents retrieve information about the good, the type E and T agents talk to a partner, and all agents have an opportunity to buy the good.

How do agents decide whom to choose among their potential interaction partners? We assume that people tend to select the person who is the most similar level or who has the highest level of knowledge about the good. We call this "knowledge-based selection."

The parameters for the simulation we ran were set as shown in Table 2.

Table 2. Parameter Settings for Simulation

a) Fixed Parameters

No. of agents	1000
No. of time periods	4000
Probability of finding when retrieving	0.001
Amount of information found	2.0
Total amount of information in WoM communication*	40.0
Threshold amount of information to buy a good**	Type (E,I,T,F) = (4,6,8,18)
Knowledge level	Type (E,I,T,F) = (0.5–1.0, 0.5–1.0, 0.25–0.75, 0–0.5)

b) Variable Parameters

No. of links	2, 4, 8, 20
Available duration of agent memory	40, 200, 800
Population of agent types	
p1) normal case**	(E,I,T,F) = (0.14, 0.22, 0.35, 0.29)
p2) online case	(E,I,T,F) = (0.36, 0, 0.64, 0)
Criterion for partner selection***	
c1) Random	P(i) = 1
c2) Similar level preference	P(i) = 1 - |(my level) − (i's level)|
c3)High level preference	P(i) = (i's level)

*Amount of information in an agent’s WoM is obtained by dividing 40.0 by Available duration of agent memory.

**Population of agent types and threshold amount of information to buy a good were derived from data of Nikkei Institute of Industries and Consumption (2000a).

***P(i) means probability before normalization that an agent chooses age

In Table 2, the "probability of finding when retrieving" and “amount of information found” means the probability of that an agent finds the information in a simulation period directly and the amount of the information about the good when finding. If the probability is set too small, the simulation will be quite long because there is little chance that the agent will find the information. If it is set too large, many buying actions are saturated quickly. We thus set the value empirically.

We define that an agent buys a good when one's amount of information exceeds a certain threshold. The threshold values are based on empirical data about the timing of buying them for every type of consumer. Likewise, the abundance ratio of types is based on empirical data (Nikkei, 2000a).

What we should discuss on is about a balance weight of the information when searching for goods directly and when using information received by WoM. We set the former value to 2.0 and the latter to 40.0 in our simulation. For example, if the available duration of agent memory is set to 100 periods, agents can talk to other agents (as they read the agent's blog in the blogosphere) for up to 100 periods after buying, and the amount of information they can receive is 0.25 (40.0 divided by 100.0 is 0.25) . The knowledge levels for the four types of agents are also set empirically, so we can tune these parameters using more sensitive analysis in the future.

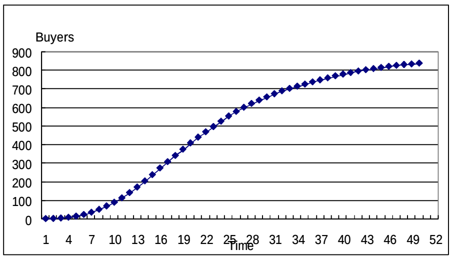
4. Simulation Results

We simulated our agent-based model using several scenarios. In each one, the simulation was run 100 times with different random seeds. We used quadruplet notation for comparable scenarios: (L,M,P,C), which means (no. of links, available duration of memory, population of agent types, method used to choose partner). First, the model was verified by using a basic scenario and observing the effect of online communication. Then, the results using the basic scenario were compared with those using knowledge-based selection and online communication.

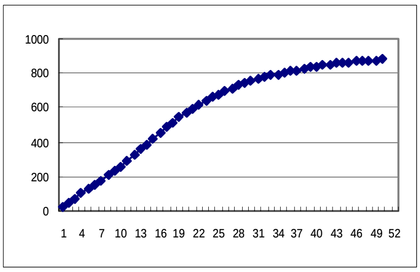
In the verification using the basic scenario, we set (L,M,P,C) = (4,200,p1,c1). Figure 1 shows (a) the number of buyerswith time series, (b) the number of information receivers with time series, (c) the each type of purchase time, and (d) the amount of information circulating in the population. You can confirm that a cascade of buyers plots a S-shaped curve and that the early adopters buy the good first and the trend makers generate WoM communication and then it comes over the followers.

In our model, agents communicate with other agents by WoM over a fixed period of time (agents' available duration of memory) after they buy goods. This is because the blogs written by purchasers keep the other peoples' attention at fixed periods.

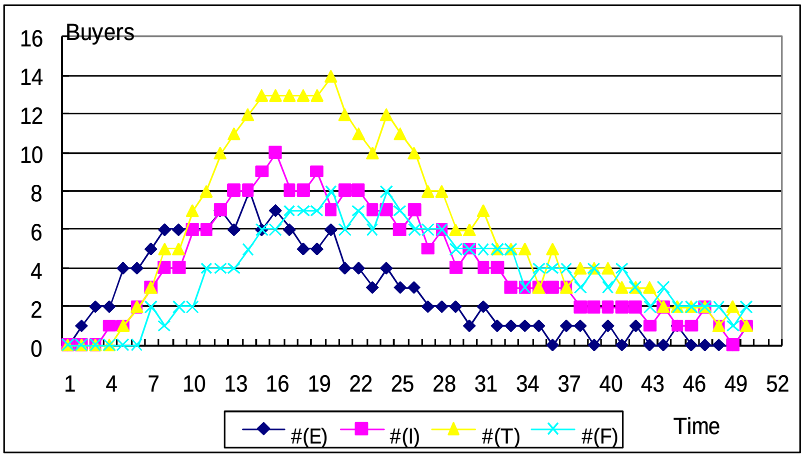
Besides, a certain amount of information needs for purchasers to buy goods. As a result, the diffusion of information decreases over time.



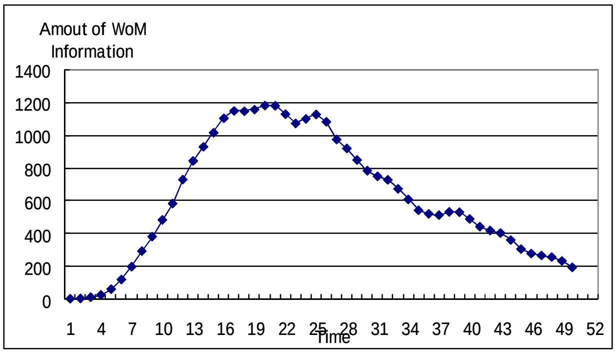
(a) No. of buyers



(b) Information receivers



(c) No. of buyers of each type



(d) Amount of information

Fig. 1. Simulation Results for Basic Scenario (4,200,p1,c1)

To observe the effect of online communication, we set l to be an element of (2, 4, 8, 20), m be one of (40, 200, 800), and p be one of (p1, p2). Table 3 and Figure 2 shows the total number of buyers for all 24 cases (L,M,P,C) = (l,m,p,c1). The results indicate that an increase in the number of links or an increase in the number of speakers increases the number of buyers while a reduction in the available duration of memory reduces the number of buyers.

Table 3. Total number of buyers for 24 cases (l,m,p,c1)

	l = 2	l = 4	l = 8	l = 20
(m,p) = (40,p1)	715	828	933	997
(m,p) = (200,p1)	731	838	933	995
(m,p) = (800,p1)	712	801	893	979
(m,p) = (40,p2)	943	994	1000	1000
(m,p) = (200,p2)	973	998	1000	1000
(m,p) = (800,p2)	935	992	999	1000

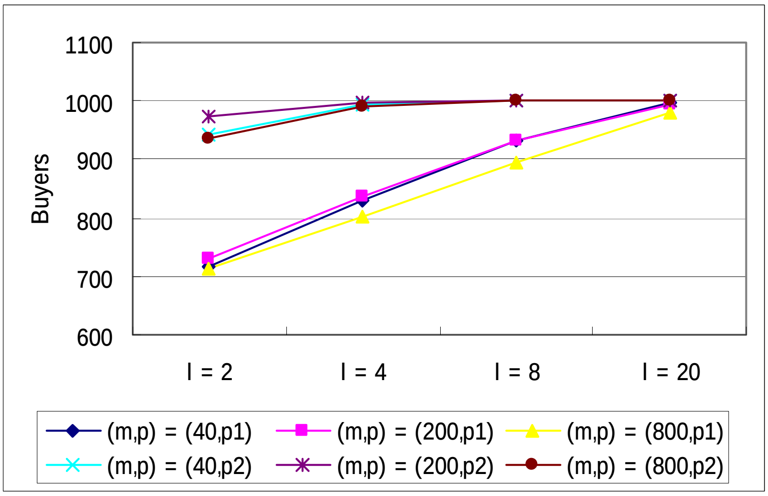


Fig. 2. Total number of buyers for 24 cases (l,m,p,c1)

Finally, we tested the effect of knowledge-based selection. Table 4 and 5 and Figure 3 shows the total number of buyers throughout the simulation for the 24 cases of (L,M,P,C) = (l,m,p,c2) and the 24 cases of (L,M,P,C) = (l,m,p,c3). These observations indicate that total number of buyers depends on rules of agent's selection. If a selection rule is a knowledge-based selection with similar level preference, the total number of buyers is less than a case with random selection. In contrast, many agents can buy the good under the selection with high level preference for all the cases except that of less number of links

Table 4. Total number of buyers for 24 cases (l,m,p,c2)

	l = 2	l = 4	l = 8	l = 20
(m,p) = (40,p1)	682	750	853	977
(m,p) = (200,p1)	666	731	830	961
(m,p) = (800,p1)	646	711	792	894
(m,p) = (40,p2)	859	977	999	1000
(m,p) = (200,p2)	846	977	999	1000
(m,p) = (800,p2)	803	959	998	1000

Table 5. Total number of buyers for 24 cases (l,m,p,c3)

	l = 2	l = 4	l = 8	l = 20
(m,p) = (40,p1)	737 +	868 +	971 +	999 +
(m,p) = (200,p1)	723	854 +	968 +	999 +
(m,p) = (800,p1)	711	837 +	958 +	999 +
(m,p) = (40,p2)	914	996	1000	1000
(m,p) = (200,p2)	911	996	1000	1000
(m,p) = (800,p2)	884	994	1000	1000

+: Total number of buyers of the case is larger than that of (c1) case.

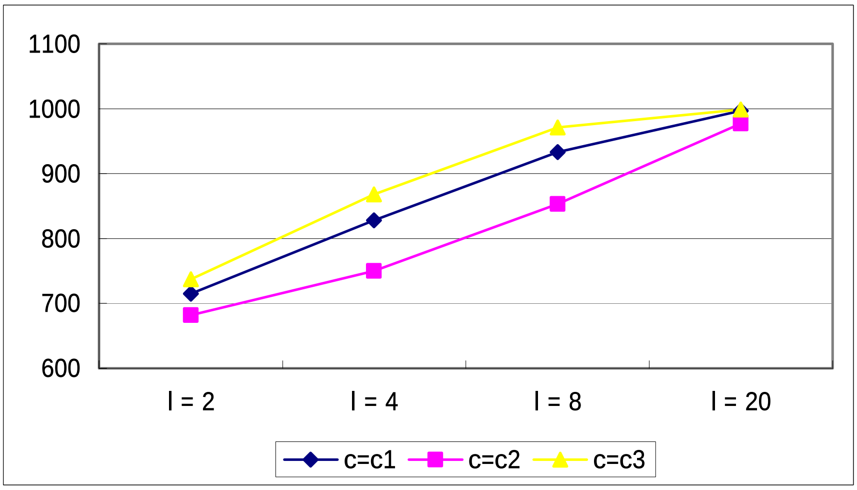


Fig. 3. Total number of buyers for 12 cases (l,40,p1,c)

5. Discussion

Our agent-based simulation reproduced a simple diffusion of information generated among four information behavioral types of consumers: Early Adopters, Individualists, Trend Maker, and Followers. This model has a micro foundation and therefore provides several mechanisms for modeling the purchasing actions by consumers and the effects of online WoM communications.

The simulation results showed that the online communication we defined has a positive effect on both the number of buyers and the diffusion of information by WoM. They provide insight into the essence of online communication. If online communication is regarded as a means of increasing both the number of potential interaction partners by the spread of the Internet and the ease of information transmission by such means as blogs, it promotes the diffusion of information. On the other hand, if online communication is regarded as a means of providing a semi-permanent memory space, it may bring less diffusion because of the limitation of consumer attention.

From the viewpoint of information diffusion, our model is comparable to the traditional Bass (1969) diffusion model. This model describes consumption behavior as a differential equation that is defined as the total of personal action for innovation plus the total of personal action for imitation. This model reproduces time series behavior for consumption that follows an S-shaped curve. Our study can thus be considered an extension of the Bass model. However, the Bass model does not take into account consumer types.

How do consumers respond to an expansion of communication spaces by online communication? We tested knowledge-based selection for communication partner selection. In the policy we used, people tend to restrict the number of their interaction partners depending on the personal attributes, such as knowledge level and confidence, of potential partners in order to deal with their limited span of attention. The results suggest that, if people choose partners on the basis of their personal knowledge levels, both efficient and inefficient diffusion of information emerges. Inefficient diffusion occurs in the case that they choose persons with their similar level of knowledge, while more efficient diffusion occurs in the case that with higher level. This insight may indicate the existence of alpha bloggers or signal the emergence of a new regime in Internet-based communication.

Comparing our model with other approaches, we see that the phenomenon of diffusion is similar to osmotic agent penetration. While there have been studies using percolation models (Grimmett, 1989), these models have limitations, such as a complex network topology, a discrete type of amount of information, and homogeneous nodes. Our approach to choosing partners with particular labels is similar to social tagging (Nowak and Sigmund, 1998). However, social tagging is more related to the evolution of cooperation than the diffusion of information.

The primary limitation of this study may exist the inside of our modeling itself. According to the AISAS framework, actual online WoM is generally related to searching rather than talking or writing. The connection of the consumer behavior model and the diffusion of information will be enhanced and made more suitable for the actual process in future work. We will be able to expand one good model; however, the essence of the mechanism might not be changed in spite of its complexity. A more sophisticated model should be able to forecast the performance of actual consumption markets. The aim of this study is to develop a simple operational model of online WoM, so model verification using empirical data is planned. We also plan to improve the network structure.

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