Relationship between online word-of-mouth communication
and consumer behavior

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Abstract
Online word-of-mouth communication was studied using a model that focuses on consumers’ informational behavior in terms of “information retrieving” and “information sending.” This model was previously used in studies of the basic mechanisms of the winner-takes-all phenomenon and consumption concentration. We applied the model to online word-of-mouth communication by assuming heterogeneity across consumers in terms of individual informative actions. Consumers were assumed to communicate with other consumers selectively using one of three policies: random selection, similar-level selection, and higher-level selection. A basic simulation showed that the most effective policy for selecting communication partners depends on the characteristics of the goods under consideration. An agent-based simulation showed that an effective word-of-mouth policy also depends on the characteristics of the goods under consideration. These findings clarify how consumers deal with cognitive limitations in the face of the massive amount of information now available.

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" [3] and "electronic WoM (eWoM)" [6]. Here, we use "online WoM,” the most commonly used term.

Bickart and Schindler [2] asserted that traditional WoM typically consists of spoken words exchanged with a friend or relative in a face-to-face situation. In contrast, online WoM typically consists of written words exchanged with strangers in a non-face-to-face situation. According to Granovetter [4] and Putsis [12], WoM spreads more quickly within communities than across them. Sun et al. [14] concluded from an analysis of survey data from college students that innovation diffusion theory can be applied to online WoM because innovativeness, Internet usage, and Internet social connectivity are significant predictors of online WoM.

WoM communication related to consumer issues is not based on ex-ante valuation but on sharing buyers' experiences. Hennig-Thurau et al. [6] used a sample of about 2000 online consumer reviews to examine the structure of such reviews and the motives of the reviewers. 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 the posting of on-line reviews.

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. Rogers [13] 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). Sun et al. [14] compared traditional and online WoM and developed an integrated model to explore the antecedents and consequences of online word-of-mouth.

Using the well-known Dentsu AISAS model (attention, interest, search, action, share), we characterize online communications using an original formalization. Our model of online WoM communication is based on innovation diffusion theory and Roger's framework. The main originality of this work is the model itself. We model online WoM communication in terms of the consumer population, the number of interaction partners, and their memory period. We developed and calibrated our online WoM model by using an agent-based approach that is based on Roger's theory of diffusion and innovation. Using this model, we analyzed the effect of knowledge-based communication partner selection. The analysis results show that the model can be used, for example, to investigate the effect of the appearance of new types of consumers such as bloggers.

In this paper, we address several questions. How is the WoM process different in an online environment? How should we model the effects of online communication? How does WoM change the diffusion of information related to the consumption of goods? What are the key factors affecting the diffusion of such information? What criteria do consumers use to select...
communication partners? How do consumers respond to an expansion of the communication space by the introduction of online communication? While random communication might bring about more effective diffusion of information with traditional WoM, investigation using our model of online WoM showed that knowledge-based WoM communication may bring about more effective diffusion.

2. Informational Consumer Behavior Model

We adopted an informational consumer behavior model based on Roger's information diffusion model [13]. We classified consumers into four types ("Early Adaptor," "Trend Carrier," "Individualist," and "Follower") by using two axes: "information retrieving" and "information sending." An "Early Adaptor" is one who actively undertakes information retrieval and communication. A "Trend Carrier" is one who actively undertakes communication but is passive in the area of information retrieval. An "Individualist" is one who actively undertakes information retrieval but is passive in the area of communication. A "Follower" is one who is passive in the areas of both information retrieval and communication. These consumer behavior patterns are summarized in Table 1.

Table 1. Consumer information behaviors (See [11])

<table>
<thead>
<tr>
<th>Type</th>
<th>Retrieving (Finding)</th>
<th>Sending (Talking)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Active</td>
<td>Passive</td>
</tr>
<tr>
<td>E</td>
<td>o</td>
<td>o</td>
</tr>
<tr>
<td>I</td>
<td>o</td>
<td>—</td>
</tr>
<tr>
<td>T</td>
<td>—</td>
<td>o</td>
</tr>
<tr>
<td>F</td>
<td>—</td>
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</tr>
</tbody>
</table>

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

Sending (information): One communicates information about goods one has bought to other people.

Receiving (information): One receives information about goods from the other people; listening in the case of offline communication and watching in online case.

Buying Goods: One buys goods.

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

2.1. Diversification of information and concentration of consumption

Okada [10] investigated the diversification of information and the concentration of consumption by using an informational consumer behavior model. Here we reproduce the essence of his study.

He investigated whether the ongoing development of information networks is bringing about a diversification or a concentration of consumer selectiveness. Intuitively, it can be said that development on the economic level should give rise to a wide variety of goods that consumers need. In turn, a wide variety of needs gives rise to production on a limited scale of a wide variety of goods and thus forms a basis for one-to-one marketing.

The continuing growth of the Internet is increasing the quantity and variety of information that individuals can access. This is changing society from one in which the mass media distributes information in a monodirectional manner to one in which individuals distribute it in a bi-directional manner. As a consequence, even the needs of consumers in very small markets give rise to markets in and of themselves, enabling today's consumers to select from a wide variety of goods and information. Examples of such small-size markets are auction markets between consumers such as eBay and Internet shopping malls such as Rakuten in Japan. In short, the development of bi-directional (interactive) information networks is generating a society in which the scale of consumption is becoming ever more widespread and varying.

At the same time, a new economy, the "digital economy," has emerged through the development of information technology and information networks. The digital economy has its own set of unique economic laws. A winner-take all society has emerged as a byproduct of the digital economy, and this is a society in which particular winners have monopoly power in a particular market. For example, Microsoft with its Windows™ monopolizes the operating system market worldwide. This is because network externality is a prime factor in the digital economy. In addition, there is a well-known winner-take-all phenomenon that is occurring due to long-established physical economic laws in the full-scale economy: the more goods a firm can produce, the lower their price, which enables the firm to become a winner in its market. For example, McDonald's became a winner in the fast-food market through mass production and cost management.

Some winner-take-all phenomena observed in markets affect neither network externalities nor the economies of scale. For example, in the music and movie software markets, consumption is becoming concentrated. To anticipate the behavior patterns consumers will follow in the future, we must analyze
the development of Internet mechanisms that affect diversification or concentration of consumption, especially the role of information channels between individuals. Thus, we focus our attention on information channels between individuals in information networks. These channels provide communication links such as face-to-face communication, e-mail, and communication over the Web. We hypothesize that increasing the number of information channels will significantly affect winner-take-all phenomena in the music and movie software markets.

Against this background, we constructed a model of consumer purchasing and communication behavior to better understand the manner in which an increase in the number of information channels affects consumer behavior.

Figure 1. Gini coefficient vs. no. of information channels (see [15])

2.2. Agent Simulation and Results

Okada [10] simulated consumer behavior by changing the composition of consumer agents and information channels in order to determine the relationship between an increase in the number of information channels and the winner-take-all phenomenon. He used the Gini coefficient as the metric for the latter. Figure 1 shows the relationship between an increase in the number of information channels and the coefficient. Case 1 is a society with many trend carrier consumers. Case 2 is a society with many follower consumers. Case 3 is a typical consumer composition.

To answer the question of whether increasing the number of information channels in the information network society diversifies or concentrates consumption variety, he constructed a consumer behavior model that takes communication behavior into account. Using this model, he showed that the winner-take-all phenomenon occurs depending on the relationship between consumer composition patterns and the number of available information channels.

1. In a market with many follower consumers, an increase in the number of information channels induces the winner-take-all phenomenon.
2. In a market with many trend carrier consumers, the winner-take-all phenomenon occurs when there are few information channels. However, consumption becomes more diversified as the number of information channels increases.

These results are summarized in Table 2.

<table>
<thead>
<tr>
<th>Information channels</th>
<th>Trend carriers</th>
</tr>
</thead>
<tbody>
<tr>
<td>Few</td>
<td>Diversification</td>
</tr>
<tr>
<td>Many</td>
<td>Concentration</td>
</tr>
</tbody>
</table>

Table 2. Effect of number of information channels and of trend carriers on consumption (See [15])

3. Online Word-of-Mouth Communication Model

The model we developed encompasses heterogeneity of consumers, effects of online communication, and selection of communication partner (See [11]).

3.1. Heterogeneity of Consumers

Heterogeneity of consumers focuses on two types of informative behaviors: information retrieving and information sending. Information retrieving means searching for and finding information about a good in a market. Information sending means sharing one's experiences by talking to others in traditional (offline) communication or writing about them (e.g., in a blog) in online communication.

On the basis of these actions, we categorize consumers into four types (Early Adopter, Individualist, Trend Maker, or Follower), as shown in Table 1 again.

3.2. Effects of online communication

How should we model the effects of online communication? We describe the effects from three points of view.

An increasing number of communication partners is the first effect. 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.
The second effect is about the distribution of consumer population. 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. The popularity of blogs has enabled consumers passive about information sending (Individualists and Followers) to become active information senders (Early Adopters and Trend Makers). As a result, the development of online WoM has changed the distribution of consumer population.

The third effect 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 expanded.

We can better understand the diffusion of information by consumers and their purchasing behaviors by using these three effects of online communication.

3.3. Selection of Communication Partners

As is well known, the total amount of consumer cognition (especially attention) has a limit in spite of expanding communicative capabilities. Therefore, what criteria do consumers use to select communication partners? To address this question in our simulation, we assigned each consumer a one-dimensional fixed visible tag. The tag can be interpreted as carrying some kind of meaning, e.g., the consumer's knowledge level, the consumer's degree of authority, or the consumer's preference for goods.

Moreover, we defined three policies for selecting a communication partner. Random selection is used by consumers who are information receivers (listening to offline WoM or viewing blogs in online WoM). Similar-level selection is when consumers select as a partner someone with a tag value close to their own. High-level selection is when consumers select as a partner someone with a higher tag value.

To validate this approach, we tested by simulation the relationship between the type of goods involved and the effective policy on selective communication.

4. Agent Simulation

On Using the basic idea of the model described above, we developed an agent-based model of online WoM. The consumers are agents, and the communication partners are links. There is one kind of infinite consumption good. The network is a shuffle one with a dynamic network topology in which agents always have different communication partners. The number of partners is fixed in every simulation.

How do agents behave? They can perform three types of informative actions and one type of buying action: retrieving, sending, and receiving information about goods and buying goods. In retrieving, two types of agents (E and I; see Table 1) can get information about consumption goods with a particular probability. If one agent obtains the information, the amount of information the consumer retains increases by a particular value. In sending, an agent chooses one of its neighbors and sends that neighbor its consumption experience after buying the good. A receiving agent obtains a particular amount of information. For simplicity, we assume that each receiving agent chooses one of its neighbor agents, and, if the chosen agent can send information, i.e., it is type E or T, the information can circulate among the other agents. Moreover, partner selection depends on their visible tags, as explained above. Finally, an agent buys the good when the total amount of information it has received for that good exceeds a particular value. In formulating the effect of online communication, the number of neighbors (links), the distribution of agents, and the available duration of agent memory are the model parameters.

A simulation using this model proceeds as follows. First, agents are characterized by information behavioral type and a tag. Then, in each period, a network is set up that consists of nodes (agents) and links (their potential communication partners). Next, the type E and I agents retrieve information about the good, the type E and T agents send their experiences to their partners, 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 communicate selectively, as explained above. We call this "tag-based selection."

The parameters for the simulation were set as shown in Table 3. The "probability of finding when retrieving" and "amount of information found" are the probability that an agent finds the information in a simulation period directly and the amount of information found about the good. If the probability is set too small, the simulation will be quite long because there is less chance that the agent will find the information. If it is set too large, many buying actions lead to quick saturation. We thus set the value appropriately for tuning the model. Moreover, we put a cap on the total amount of information in WoM communication because we assume that the consumer's attention is limited, as discussed above.

An agent buys a good when the amount of information it has about that good exceeds a certain
threshold set by using the framework of Dentsu's AISAS model. The threshold values are based on empirical data for the timing of buying the goods for every type of consumer. The ratio of types is also based on empirical data [7][8].

Table 3. Parameter Settings for Simulation (See [11])

<table>
<thead>
<tr>
<th>a) Fixed Parameters</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>No. of agents</td>
<td>1000</td>
<td></td>
</tr>
<tr>
<td>No. of time periods</td>
<td>100</td>
<td></td>
</tr>
<tr>
<td>Probability of finding when retrieving</td>
<td>0.1</td>
<td></td>
</tr>
<tr>
<td>Amount of information found</td>
<td>1.0</td>
<td></td>
</tr>
<tr>
<td>Total Amount of information in WoM communication</td>
<td>40.0</td>
<td></td>
</tr>
<tr>
<td>Threshold amount of information to buy a good*</td>
<td>(E,I,T,F) = (4,6,8,18)</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>b) Variable Parameters</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>No. of links</td>
<td>2, 4, 8, 20</td>
<td></td>
</tr>
<tr>
<td>Available duration of agent memory</td>
<td>10, 20, 40</td>
<td></td>
</tr>
<tr>
<td>Distribution of agent types</td>
<td></td>
<td></td>
</tr>
<tr>
<td>d1) normal case*</td>
<td>(E,I,T,F) = (0.14, 0.22, 0.35, 0.29)</td>
<td></td>
</tr>
<tr>
<td>d2) online case</td>
<td>(E,I,T,F) = (0.36, 0.64, 0)</td>
<td></td>
</tr>
<tr>
<td>A level of tag**</td>
<td></td>
<td></td>
</tr>
<tr>
<td>t1) ordinal case</td>
<td>Type (E,I,T,F) = (0.5–1.0, 0.5–1.0, 0.25–0.75, 0–0.5)</td>
<td></td>
</tr>
<tr>
<td>t2) nominal case</td>
<td>Type (E,I,T,F) = all on (0.0 – 1.0)</td>
<td></td>
</tr>
<tr>
<td>Criterion for partner selection***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>c1) Random</td>
<td>P(i) = 1</td>
<td></td>
</tr>
<tr>
<td>c2) Similar level preference</td>
<td>P(i) = 1 - (my level - (i's level))</td>
<td></td>
</tr>
<tr>
<td>c3) High level preference</td>
<td>P(i) = (i's level)</td>
<td></td>
</tr>
</tbody>
</table>

*Distribution of agent types and threshold amount of information to buy a good were derived from data of Nikkei [7][8].
**An agent has its own tag initially and the range of the tag depends on two cases. All the tags are given values in uniform distribution within their ranges.
***P(i) means probability before normalization that an agent chooses age.

We need to achieve an appropriate balance between searching for goods directly and using information received by WoM for searching. On the basis of a preliminary experiment, we set the weight of the former to 1.0 and the latter to 40.0 in our simulation.

For example, if the available duration of agent memory is set to 10 periods, agents can talk to other agents (by reading their blogs) for up to 100 periods after buying, and the amount of information they can receive is 4.0 (40.0 divided by 10 is 4.0). The range of the tags for the four types of agents was set appropriately for tuning the model so that we can tune these parameters using more sensitive analysis in the future.

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,D,C; i.e., no. of links, available duration of memory, distribution of agent types, policy used to choose partner). First, the model was verified by using a basic scenario and observing the effect of online communication. The results of this basic scenario were then compared with those using tag-based selection.

4.1. Verification

In the verification using the basic scenario, we set (L,M,D,C) = (8, 10, d1, c1). Figure 2 shows the number of buyers against the time series. Note that the average values for 100 different random seeds are shown of the figures hereafter. The cascade of buyers forms an S-shaped curve: the Early Adopters buy the good first, then the Trend Makers generate WoM communication, and finally the Followers buy it.

![Figure 2. Simulation Results for Basic Scenario (8,10,d1,c1) (See[11])](image)
differentiated into five types (innovators, early adopters, early majority, late majority, and laggards). Our model of online WoM can reproduce the diffusion of innovations and Roger's framework.

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 limitations of consumer attention.

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 attention of other people for a fixed period. Moreover, people need a certain amount of information before they buy goods. As a result, the diffusion of information decreases over time.

From the viewpoint of information diffusion, our model is comparable to the conventional Bass [1] 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.

### 4.2. Effects of tag-based selection

We determined the effects of tag-based selection with the distribution of tags assigned to agents (i.e., consumers). To simplify our analysis, we simulated only two types of tag in the online case: TAG = t1 and t2. The online cases were (8, 20, d2, c) in (L,M,D,C) notation, where c is one of (c1, c2, c3).

Figure 3 show the total number of buyers for the six online cases at period 60. The total number of buyers depended on the policy used for communication partner selection, C. For TAG = t1, the total number of buyers was the highest when the policy was higher-level selection. For TAG = t2, the total number of buyers was the highest when the policy was similar-level selection.

How do consumers respond to an expansion of the communication space by the introduction of online communication? To answer this question, we tested tag-based communication partner selection. The agents tended 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 own limited attention span.

Finally, we discuss the relationship between types of goods (personal computers or hobby goods, for example) and the selection of an effective policy. How can we interpret our finding that information retrievers (Early Adopters and Individualists) had higher tag values than the others? For TAG = t1, the tag can be regarded as a special skill, knowledge, or personal authority about a certain type of good, such as laptop computers, real estate, or educational services. Simulation showed that when the agents tended to communicate with others who had higher tag values, their purchasing behavior was faster than with the other two policies. We attribute this to the emergence of highly knowledgeable consumers such as alpha bloggers in the online space.

Furthermore, when tags from a uniform distribution were assigned to the agents, the similar-level selection policy produced the best performance: that is, the goods were bought the most quickly. Example goods for this case include hobby and art products and information about sightseeing areas because the tags had a nominal scale. The similar-level selection policy suggests a kind of compartmentalizing communication style observable in communities such as social network services (SNSs).

A theoretical hypothesis, such as one that prescribes a best selection policy, depends on the features of the good. It not only describes specific phenomena that are observed in SNSs but also shows that alpha bloggers have some beneficial insights for practitioners. For example, the best method for WoM
communication in the PC industry is likely different from that in the tourism industry, and remarkable users may also differ between industries.

5. Discussion
Our simulation of the effects of online WoM communication among consumers by using an agent-based model showed that the four types of consumers we defined on the basis of their information behaviors are analogous to Roger's five types of innovation. Consumers were assumed to communicate with other consumers selectively using one of three policies: random selection, similar-level selection, and higher-level selection. The model reproduced the diffusion of purchasing behavior as described by Rogers, and simulation showed that the most effective policy for selecting communication partners depends on the characteristics of the good under consideration. It also showed that increasing the number of communication partners and changing the distribution of consumers positively affects purchasing behavior while increasing consumer memory through such technologies as blogs does not. These findings help clarify how consumers deal with their cognitive limitations in the face of the massive amount of information now available.

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 [5], these models have various disadvantages, such as a complex network topology, a discrete information, and homogeneous nodes. Our approach to choosing partners with particular labels is similar to social tagging [9]. However, social tagging is more related to the evolution of cooperation than to the diffusion of information. Moreover, understanding the effect of the different partner selection policies on consumer performance is the key to deriving practical insights. For example, how should online WoM be utilized for diffusion of innovation?

The primary limitation of this study is the model itself. The connection between consumer behavior and information diffusion is too weak. It must be enhanced and made more suitable for actual processes. A more sophisticated model should be able to forecast the performance of actual consumption markets. Since the aim of this study is to develop a simple operational model of online WoM communication, we plan to verify the model using empirical data.

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References