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Detecting Chasms and Cracks Using Innovator Scores and Agent Interactions

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ABSTRACT

In chasm theory, it is found from field data that many new products have an initial sales peak followed by a decline. In some cases, this decline lasts for a long period of time, which is named a chasm or crack. In this study, we model the phenomenon using innovator scores and agent-based modelling to understand the factors that cause it. We then conduct a sensitivity analysis of the exogenous variables that determine the behavior of the model. Specifically, we use innovator scores to classify users into innovator theory groups, and build an agent-based model. This study evaluates how cluster connectivity, which represents the word-of-mouth effect between each group, and product recognition range, which represents the advertising effect, affect the chasm or crack phenomenon and new product diffusion. Four scenarios are analyzed with different cluster connectivity and product recognition ranges. Additionally, for each scenario, we perform simulations that consider the interactions between agents and add considerations for new product diffusion measures. Evaluating this model using the behavioral and questionnaire data collected from users of an Online-to-Offline site, it is found that the parameters related to communication in the clusters are factors that cause the occurrence of chasms and cracks.

Keywords: Innovator Theory, Chasm Theory, Agent-Based Modeling, Sensitivity Analysis, Three-Sigma Rule, O2O
JEL Classifications: M31, O39, C63, C38

1. INTRODUCTION

In the context of marketing food and other convenience products with short life cycles, it is important to effectively penetrate the market with new products. According to innovator theory (Rogers, 2003), the life cycle of a new product's penetration is a curve that continuously connects the sales at each point in time. The sales are composed of the following five user groups with different characteristics and behaviors: innovators, early adopters, early majority, late majority, and laggards.

It is said that it is important to disseminate products to innovators and early adopters. However, even if a product is popularized by innovators and early adopters, it often disappears without spreading to the subsequent market. The reason for this is that there is a chasm between the potential buyers in the early market, where innovators and early adopters are the main buyers, and the mainstream market, where the early majority and late majority are the main buyers. Moore (2014) found from field data that for many new products, while initial sales peaks and declines are observed, in some cases the declines are long-lasting. He named the sales plunge that occurs between the early and mainstream markets as a chasm. In addition, he named the sales decline that occurs between innovators and early adopters, between the early majority and late majority, and between the late majority and laggards as a crack, and explains the countermeasures. In fact, while chasm theory is well known in the high-tech field, Moore suggests that chasms and cracks also occur in business-to-consumer markets.

In this study, we develop a model to estimate the groups in innovator theory and to understand the chasm factors by using innovator scores (Iwata et al., 2020) and an agent-based model. In this model, we are able to reproduce chasms in the product diffusion process using data from an Online-to-Offline (O2O) site where users oscillate between online stores on the Web and offline physical stores. In this study, the target market is food and other convenience products. We consider the fact that there are some convenience products that have not been able to spread to early market and have been sold at the end of their lives, for which no sales data remains. Therefore, we speculate that there are many convenience products that have fallen into chasms, as claimed by Moore. If we can understand the chasm factor, then we can penetrate the market more effectively and overcome these by analyzing the evaluation information in the early and mainstream markets when a new product is launched.

In Chapter 2, we explain the traditional group estimation method based on innovator theory and the traditional method for reproducing the product diffusion process and chasms. In Chapter 3, we introduce the group estimation method on innovator theory used in this study. In Chapter 4, we explain the method for the product diffusion process and for reproducing chasms in this study. In Chapter 5, we evaluate the proposed method using actual data and present the results. Chapter 6 concludes this study and discusses future issues.

2. LITERATURE REVIEW

In this chapter, we review the existing research to explain the group estimation method based on innovator theory and the traditional method for reproducing the product diffusion process and chasms.

2.1. Group Estimation Method on Innovator Theory

Traditionally, questionnaire-based data analysis has been used to estimate users with attributes such as innovators and early adopters. For example, methods have been proposed to prepare a self-reporting scale to measure the innovativeness of users. Using this to calculate innovativeness scores from the results of questionnaires allows the estimation of groups that adapt to the classification of the innovator theory (Flynn and Goldsmith, 1993; Goldsmith, 2000; Goldsmith and Flynn, 1992; Uray and Dedeoglu, 1998). In order to understand the timing of product adoption, a method has also been proposed to estimate groups by calculating the relative timing of adoption from questionnaires (Chau and Hui, 1998). Other methods have been proposed that use regression analysis (Laukkanen and Pasanen, 2008; Rossow, 2005; Thøgersen et al., 2010), cluster analysis (Campbell et al., 2012; Saito, 1994), correlation coefficients (Wansink and Kranz, 2013), and self-report measures (Filová, 2015; Plötz et al., 2014).

These methods impose a heavy burden on users to answer a questionnaire. Not all users will do so. Therefore, it is difficult to extract users who fall into the innovator theory-based groups in a large market by using estimation methods that can only target specific users who agree to respond to a questionnaire.

Estimation methods have also been proposed that consider the propagation rate and order of content adoption among users and items mainly for the purpose of using it for product recommendation. The user who adopts the content first is an innovator. For example, methods have been proposed to estimate groups based on the purchase time calculated from the past purchase history (Ichikawa et al., 2013; Kawamae et al., 2007; Rusmevichientong et al., 2004; Sugiyama et al., 2018). A method for estimation using the InfluenceRank algorithm, which is created from past blogs, has also been proposed (Song et al., 2007). In fields other than product recommendation, methods using the innovation diffusion model (Mahajan et al., 1990), innovation maps and penetration maps (Kamakura et al., 2004) have also been proposed.

These methods do not require any explicit input from the user, such as a questionnaire. Since it uses the purchase order of users for a specific product, it is effective in fields where many users purchase the same product (e.g., home appliances).

As a suggestion from previous studies, we use innovator scores (Iwata et al., 2020) to classify users through a method that (1) does not rely on an explicit user input and (2) is applicable to the convenience product market.

2.2. Method for Reproducing the Product Diffusion Process and Chasms

Traditionally, analytical methods based on mathematical models have been used to reproduce phenomena such as the product diffusion process, chasms (Moore, 2014) and saddles (Bulte and Joshi, 2007; Bulte and Stremersch, 2004; Golder and Tellis, 2004; Mahajan et al., 1995). Mathematical models were aimed at empirical generalization, so that the diffusion of a new product or chasm could be described simply at the market level. In these studies, chasm phenomenon can be attributed to causes such as technological change or macroeconomic events; having said that, it can also be explained by user interaction. For example, there is a study that claims that the chasm phenomenon can be explained by information cascade theory (Golder and Tellis, 2004). A small shock to the economic system, such as a small recession, causes a temporary decline in the adoption rate, and the decline will be magnified by information cascade. Another explanation is based on the heterogeneity of the population to be adopted, and the fact that it is divided into two groups. If the speed of product adoption between these two groups is very different and communications between them is weak, sales may decrease temporarily (Bulte and Joshi, 2007). By combining heterogeneity and user interaction, these methods help explain phenomena that do not fit the typical bell-shaped sales curve.

Subsequently, research on agent-based modeling has evolved as follows. For example, some studies have modeled the product diffusion process and chasm phenomenon by referring to various network structures, such as random networks, cellular automata, small-world networks, and power-law distribution networks (Bohlmann et al., 2010; Cho and Blommestein, 2015). These studies argue that the chasm phenomenon is not necessarily something that can be simply described at the market level. They examine how users connect with others in the market and how they respond to information in various network structures. Research issues related to network heterogeneity are addressed using agent-based modeling methods.

Further, there is a study that sets up four types of agents (company, product, user, and government) using agent-based modeling.

It examines the inherent interdependence between each agent (Zhang et al., 2011). In the experiment, technology push, market pull, and regulatory push were examined as the mechanisms that accelerate the adoption of products. The simulation results support the idea that a technology push can be an important mechanism to accelerate product diffusion. Market pull, i.e., word-of-mouth, has a positive impact on product diffusion and increased social benefits. Furthermore, this study shows that word-of-mouth leads to an increased willingness to pay for the product, and that the perceived value of the product is enhanced by the word-of-mouth. By contrast, government policies targeting companies have been shown to lead to a reduction in air pollution because of an increased share of eco-innovations.

In addition, most of the studies of agent-based modeling in the product diffusion process and chasm phenomenon have been conducted for high-tech industries (Nomakuchi, 2015a, 2015b; Nomakuchi and Takahashi, 2014; Sakai and Kawai, 2006; Van Eck et al., 2011; Zhang and Nuttall, 2011), but there are also studies for automobiles, biomass fuels, movies, etc. (Broekhuizen et al., 2011; Günther et al., 2011; Kim et al., 2011; İkizler, 2019).

Many studies set up virtual data instead of real data such as market data and questionnaires, and reproduce the product diffusion process and chasm phenomenon with agent-based modeling (Cadavid and Cardona, 2013; Kumar et al., 2009; Nanba, 2017).

As a suggestion to this research from the previous research, creating an agent-based model based on actual data on the diffusion of new products in the convenience product market, it is possible to detect the stage at which a chasm or crack phenomenon occurs in the market and understand the factors behind it.

3. GROUP ESTIMATION METHOD ON INNOVATOR THEORY

When purchasing the product, we use innovator scores (Iwata et al., 2020) as a method to classify users according to how long it has been since the product was launched and how many times they have visited the stores. This is in accordance with the hypothesis that innovators tend to buy products faster and visit stores more often. The classification method of users is as follows.

Clustering is performed based on the relationship between the elapsed time, which is the difference between the date and time when the user purchased the target product (*PD*) and the date and time when the target campaign started (*SD*), and the number of campaign participants (*CP*), which is the number of visits to stores made by the user. For a user set $J = \{1,2,..., n\}$, let $s(j)$ be the ascending order in which $PD_j - SD$ is arranged. Then we have equation (1).

$$PD_{s(1)} - SD < PD_{s(2)} - SD < \cdots < PD_{s(j-1)} - SD < PD_{s(j)} - SD = PD_{s(j+1)} - SD < \cdots < PD_{s(n)} - SD \quad (1)$$

We define users' elapsed time scores *PSS* in equation (2).

$$PSS_{s(j)} = n - j + 1, \left(j = 1, 2, \cdots, n \right) \quad (2)$$

However, if $PD_{s(j)} - SD = PD_{s(j+1)}$, as in (1), then $PSS_{s(j)} = PSS_{s(j+1)} = n - j$. Let $c(j)$ denote CP_j arranged in ascending order. Then we have equation (3).

$$CP_{c(1)} < CP_{c(2)} < \cdots < CP_{c(j-1)} = CP_{c(j)} < CP_{c(j+1)} < \cdots < CP_{c(n)} \quad (3)$$

We define *CPS* for the number of users' campaign participation scores as in equation (4).

$$CPS_{c(j)} = j, \left(j = 1, 2, \cdots, n \right) \quad (4)$$

However, if $CP_{c(j-1)} = CP_{c(j)}$ as in (3), then $CPS_{c(j-1)} = CPS_{c(j-1)} = j - 1$. the innovator scores for user set $J = \{1,2,.., n\}$ is given in equation (5).

$$IS_j = PSS_{s(j)} + CPS_{c(j)}, \left(j = 1, 2, \cdots, n \right) \quad (5)$$

The mean μ_{IS} and standard deviation σ_{IS} of the innovator scores are used to classify user set J into five clusters (IS_{IN}: innovators, IS_{EA}: early adopters, IS_{EM}: early majority, IS_{LM}: late majority, and IS_{LA}: laggards) according to equations (6)–(10).

$$IS_{IN} = \left\{ j \in J | IS_j \geq \mu_{IS} + 2\sigma_{IS} \right\} \quad (6)$$

$$IS_{EA} = \left\{ j \in J | \mu_{IS} + 2\sigma_{IS} > IS_j \geq \mu_{IS} + \sigma_{IS} \right\} \quad (7)$$

$$IS_{EM} = \left\{ j \in J | \mu_{IS} + \sigma_{IS} > IS_j \geq \mu_{IS} \right\} \quad (8)$$

$$IS_{LM} = \left\{ j \in J | \mu_{IS} > IS_j \geq \mu_{IS} - \sigma_{IS} \right\} \quad (9)$$

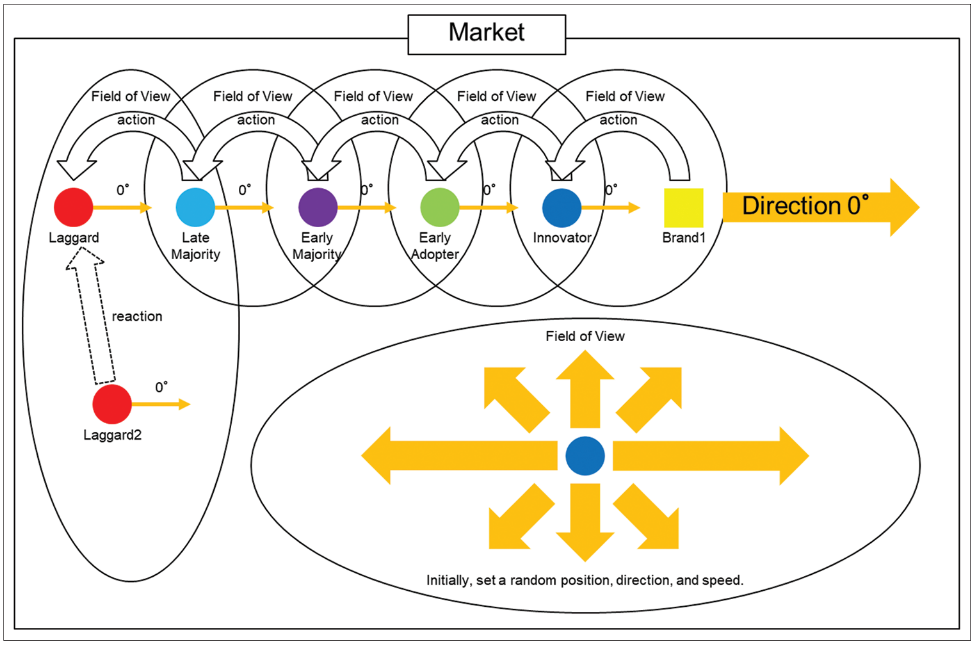
$$IS_{LA} = \left\{ j \in J | \mu_{IS} - \sigma_{IS} > IS_j \right\} \quad (10)$$

4. MODEL FOR DETECTING CHASMS IN THE PRODUCT DIFFUSION PROCESS

In this chapter, we describe a model that can detect chasm phenomena in the product diffusion process of convenience products. An illustration of the agent-based model is shown in Figure 1 below.

In our model, we set the Market as the space where agents act, and define six types of agents. The six types of agents are *Brand1* (New Product), *Innovator*, *EarlyAdopter*, *EarlyMajority*, *LateMajority*, and *Laggard*. By creating a brand agent, the product design can be easily incorporated into the model. By dividing users into innovators, early adopters, early majority, late majority, and laggards, the willingness to purchase a product introduced into the market and the word-of-mouth effect can be varied for each user. By separating the brand and user as agents, the parameter

Figure 1: Image of agent-based modeling



Direction, which indicates the purchase intention, is updated when information about the brand enters the user's cognitive range (Field of View) and becomes available.

The diffusion process from the new product (*Brand1* agent) to each user agent has the same direction as *Brand1*. The situation related to proceeding to 0° (or the situation related to tracking the new product) is regarded as diffusion. This analogy takes into account any future extensions of the model. *Direction* can express the user's purchase intention as a continuous quantity. The closer it gets to 0°, the higher is the purchase intention. In the initial step of our model, the direction of *Brand1* is 0°, while the direction of the user agent is random. In this model, brand agents and user agents are generated at random positions in the market. User agents buy the new product and make a word-of-mouth "action" to other user agents, while brand agents can influence the purchasing behavior of users through an advertising "action."

In this model, several scenarios are considered in the simulation. In a study by Vuzz Inc. (2015), the word-of-mouth purchasing experience is higher for convenience products than for other products. In addition, advertisements and word-of-mouth are the main recognition channels, while Web-based word-of-mouth is a contact point to the same degree as the real word-of-mouth. However, it is not clear how these word-of-mouth and advertising activities affect chasms in the convenience product market and the diffusion of new products. We believe that word-of-mouth and advertising have a significant impact on the diffusion of a new product and the formation of chasms after the convenience product is introduced to the market. In other words, the influence of word-of-mouth increases when a new product on the market is bundled into a value chain through advertising and the difference between the value that potential buyers demand and that which they actually perceive is sufficiently reduced. This helps with suppressing chasm formation and speeding up diffusion. Therefore, in order to clarify the influence of word-of-mouth and advertising on chasms and the diffusion of new products, this model analyzes the market using the concepts of cluster connectivity (representing the word-of-mouth effect) and product recognition range (representing the advertising effect). We construct the scenarios (S1 to S4) shown in Figure 2 in order to evaluate the impact of high and low cluster connectivity and the wide and narrow range of product recognition on chasms and the diffusion of a new product.

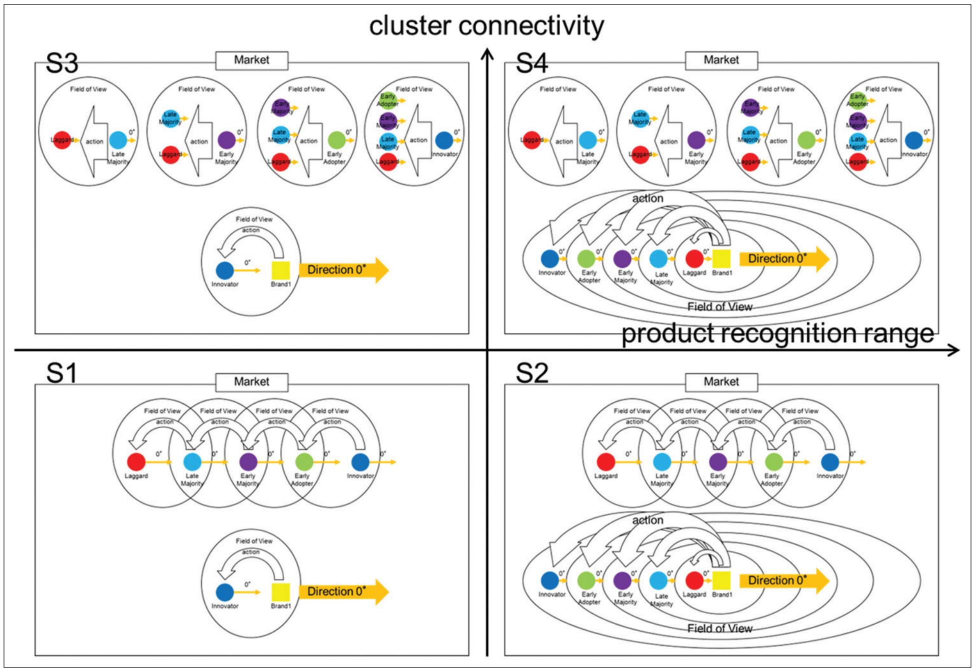
Each scenario represents a market situation, where:

- Users are less influenced both by word-of-mouth and advertising (S1)
- Users are more influenced by advertising and less influenced by word-of-mouth (S2),
- Users are more influenced by word-of-mouth and less influenced by advertising (S3), and
- Users are more influenced both by word-of-mouth and advertising (S4).

Each of these situations leads to the following different user purchasing behaviors:

- S1: Advertising only affects innovators. Word-of-mouth by innovators affects the early adopters, while that by early adopters affects the early majority. Similarly, word-of-mouth by early majority affects the late majority, while word-of-mouth by late majority affects only the laggards
- S2: Advertising affects innovators, early adopters, early majority, late majority, and laggards. Advertised users purchase a new product if their innovativeness value meets or exceeds a uniform random number. If the innovativeness value is below the uniform randomness threshold, users will not purchase the new product
- S3: In the case of innovators' word-of-mouth, the word-of-mouth affects the early adopters, early majority, late majority, and laggards. Word-of-mouth users purchase a new product if their innovativeness value meets or exceeds a uniform random number. If the value of innovativeness is below the

Figure 2: Scenarios based on cluster connectivity and product recognition range



threshold of uniform randomness, the values of similarity of personality and lifestyle of oneself and the innovator are calculated. If the similarity value between a targeted user and the innovator meets or exceeds a uniform random number, the user purchases the new product. If the value of similarity is below the threshold of uniform randomness, the user will not purchase the new product. The similarity value is calculated based on the assumption that users with similar personalities and lifestyles are likely to interact with each other in terms of purchasing behavior

- S4: The influence of advertising is the same as in S2 and the influence of word-of-mouth is the same as in S3.

This chapter is organized as follows: Section 4.1 describes the parameters and flow of the model, while Section 4.2 describes the three-sigma rule for detecting chasms and cracks.

4.1. Parameters and Flows of a Model in Market Space

Table 1 shows the parameters of agent-based modeling.

The size of the Market space is 467 × 467. The market parameters in Table 1 are the number of agents that can be set in the Market space. The diffusion parameter represents the number of diffusions per step for each cluster. For example, the overall number of subtotal diffusions, DIF_2^{st}, per step *st* and the increase or decrease, DIF_3^{st}, of the overall number of subtotal diffusions per step are computed as in equations (11) and (12).

$$DIF_2^{st} = DIF_1^{st} - DIF_1^{st-1} \quad (11)$$

$$DIF_3^{st} = DIF_2^{st} - DIF_2^{st-1} = \left(DIF_1^{st} - DIF_1^{st-1}\right) - \left(DIF_1^{st-1} - DIF_1^{st-2}\right) \quad (12)$$

For the other parameters, the purchasing factor composition ratio $ACTRATIO_t$ of cluster *t* is calculated as in equation (13).

$$ACTRATIO_t = \frac{tN}{ACTR_{act_t}} \quad (13)$$

Where *tN* is the number of each cluster and $ACTR_{act_t}$ is the number of factors in the purchasing behavior of each cluster. We output the number of occurrences of users in each cluster either purchasing based on their own innovativeness or due to similarities to other users.

Table 2 shows the parameters of the new product in our model.

The brand parameter ID_{B1} is the ID of Brand1 agent generated in the Market space. X_{B1} and Y_{B1} represent the physical (e.g., storefront) and spatial (e.g., e-commerce site) locations of *Brand1* in the market. The other parameter, θ_{B1}, is the angle in the Market of *Brand1*, which is 0°. For the diffusion of the different types of user agents aside from *Brand1* agents, we consider the situation in which the agents are moving in the same direction as *Brand1*, toward 0°, or diffusion.

The configuration of the *Brand1* agent for S1 and S3 is as follows:

- It acts in the direction of 0°, communicates the existence of the product to *Innovator* within a field of view = 15. When an innovator who has not yet purchased the product purchases it, it sets *Innovator* to 0°. The field of view is set based on the assumption that innovators are willing to purchase new products.

The configuration of the Brand1 agent for S2 and S4 is as follows.

- It acts in the direction of 0° and communicates the existence of the product to *Innovator* within a field of view = 15,

Table 1: Parameter settings for agent-based modeling

Parameter Type	Meaning	Parameters	Range or Unit or Value
Market parameters	Number of new products	*BRN*	[1,100]
	Number of innovators	*INN*	Positive real number
	Number of early adopters	*EAN*	
	Number of early majority	*EMN*	
	Number of late majority	*LMN*	
	Number of laggards	*LAN*	
Diffusion parameters	Number of diffusions to innovators	IND_i^{st}	i=1 Cumulative diffusions i=2 Subtotal diffusions i=3 Fluctuation in subtotal diffusions
	Number of diffusions to early adopters	EAD_i^{st}	
	Number of diffusions to early majority	EMD_i^{st}	
	Number of diffusions to late majority	LMD_i^{st}	
	Number of diffusions to laggards	LAD_i^{st}	
	Number of diffusions to whole	DIF_i^{st}	
Other parameters	Number of factors in purchasing behavior of innovators	$ACTR_{act_{IN}}$	Positive real number
	Number of factors in purchasing behavior of early adopters	$ACTR_{act_{EA}}$	
	Number of factors in purchasing behavior of early majority	$ACTR_{act_{EM}}$	
	Number of factors in purchasing behavior of late majority	$ACTR_{act_{LM}}$	
	Number of factors in purchasing behavior of laggards	$ACTR_{act_{LA}}$	

Table 2: Parameter settings for new product

Parameter type	Meaning	Parameters	Range or unit or value
Brand parameters	ID	ID_{B1}	[1,100]
	Position in market (X-axis)	X_{B1}	[0,467]
	Position in market (Y-axis)	Y_{B1}	[0,467]
Other parameters	-	θ_{B1}	0°
	Speed of change in position within market	spd_{B1}	[0,1]
	Factors in user purchasing behavior	act_{B1}	{Purchase with user's own innovativeness, Purchase based on similarity to other users, Not purchased}

EarlyAdopter within the field of view = 11.5, *EarlyMajority* within the field of view = 8, *LateMajority* within the field of view = 4.5, and *Laggard* within the field of view = 1. For users who have not yet purchased the product, when the agent makes a purchase, it sets the user to 0°. The field of view is set based on the assumption that innovators are willing to purchase new products. Conversely, laggards set their field of view based on the assumption that they are conservative in purchasing new products.

SPD_{B1} represents the speed of change in the physical (e.g., storefront) and spatial (e.g., e-commerce site) location of *Brand1* in the market. act_{B1} represents the factors in a user's purchasing behavior. The output indicates whether the user made the purchase based on their own innovativeness or similarity to other users.

Table 3 shows the user's parameters in our model.

The user parameters ID_t is the ID of the user agent generated in the Market space. X_t and Y_t represent the physical (e.g., storefront) and spatial (e.g., e-commerce site) locations of the user in the market. The purchase behavior parameter θ_t is the user's angle in the Market space, which is initially a random direction.

The settings for the purchasing behavior of the different user agents in S1 and S2 are as follows:

- Agent *Innovator* communicates the existence of a product to *EarlyAdopter* within the field of view = 3, and sets the angle to 0° if *EarlyAdopter* that has not yet purchased a product makes a purchase
- Agent *EarlyAdopter* communicates the existence of a product to *EarlyMajority* within the field of view = 1, and sets the angle to 0° if *EarlyMajority* that has not yet purchased a product makes a purchase
- Agent *EarlyMajority* communicates the existence of a product to *LateMajority* within the field of view = 1, and sets the angle to 0° if *LateMajority* that has not yet purchased a product makes a purchase.

The settings for the purchasing behavior of the different user agents in S3 and S4 are as followshased a product, purchases it

- Agent *EarlyAdopter* communicates the existence of a product to *EarlyMajority*, *LateMajority*, and *Laggard* within the field of view = 1 and sets user to 0° when a user agent that has not yet purchased the product purchases it
- Agent *EarlyMajority* communicates the existence of a product to *LateMajority* and *Laggard* within the field of view = 1 and

Table 3: Parameter settings for user

Parameter type	Meaning	Parameters	Range or unit or value
User parameters	ID	ID_t	[1, *n*]
	Position in market (X-axis)	X_t	[0,467]
	Position in market (Y-axis)	Y_t	[0,467]
Purchase behavior parameters	Whether or not to purchase (a situation in which user proceeds facing 0° is considered diffusion)	θ_t	[0,360] degrees
	Speed of product information collection	spd_t	[0,1]
	Wide field of view to observe purchase status of other users in market	vw_t	Positive real number
	Number of observed users required as a condition for implementing purchasing behavior	flw_t	Positive real number
	Degree of innovativeness	IS_t	Positive real number
	Factors in user purchasing behavior	act_t	{Purchase with user's own innovativeness, Purchase based on similarity to other users, Not purchased}
Basic attribute parameters	Gender (SA)	gen_t	{Male, Female}
	Age (SA)	age_t	{20s, 30s, 40s, 50s, 60s or older}
	Address (SA)	add_t	{Hokkaido, …, Okinawa}
Consciousness parameters	Purchase store (SA)	str_t	{Convenience store 1, …, Supermarket 17}
	⋮	⋮	⋮
	Important points when purchasing beverages (MA)	ju_t	{Fruit juice, Not selected}
	⋮	⋮	⋮
	Important points when purchasing beverages (MA)	$oth3_t$	{Other, Not selected}

sets user to 0° when a user agent that has not yet purchased the product purchases it.

The settings for the purchasing behavior of the different user agents in S1 to S4 are as follows:

- Agent *LateMajority* communicates the existence of a product to *Laggard* within the field of view = 1 and sets the angle to 0° if *Laggard* that has not yet purchased a product makes a purchase
- A user agent that has not purchased a product recognizes the existence of a product if there are more than flw_t user agents of the same type that have purchased the product in the field of view = vw_t. Then, if a user agent who has not yet purchased a product makes a purchase, the user is set to 0°.

The agent who has not yet purchased the product is modeled to make a purchase decision based on their own innovativeness IS_t or their similarity to other users calculated from the basic attributes and consciousness parameters (questionnaire response results). The probability that user *j* will purchase *Brand1* based on their innovativeness $IS_t^{\theta\neq 0}$ is calculated as in equation (14).

$$\frac{IS_t^{\theta\neq 0}}{\max_{1\leq j\leq n} IS_j} \tag{14}$$

The probability of purchasing Brand1 based on the similarity between agents $\delta_{t,t'}^{\theta\neq 0,\theta=0}$ calculated from the basic attributes and consciousness parameters is calculated as in equation (15).

$$\frac{\delta_{t,t'}^{\theta\neq 0,\theta=0}}{\max \delta_{j,k}} \tag{15}$$

$\delta_{j,k}$ is the similarity between agents *j* and *k*. The flow of the similarity calculation and an example of the calculation method are respectively shown in Figure 3 and Table 4 below.

In this study, the minimum point of each evaluation item was set to 0, while the maximum point was set to 1. The process of point allocations for the options was performed according to the number of options and the content of the options. Based on this, the similarity points between users were calculated. For example, if a certain basic attribute corresponds to a gender rating item in a single-answer questionnaire, the points for each option are set to 1 for male and 1 for female. Points are also awarded if the users' answers match each other. For example, if a questionnaire item is a multiple-answer questionnaire and corresponds to the evaluation item of an important point when purchasing beverages, the points for each option are set to the same value and the allocation process is applied so that the maximum points equal 1 when all answers match.

SPD_t represents the speed with which a user collects product information. act_t represents the factors in the user's purchasing behavior. The output indicates if a user has made the purchase based on their own innovativeness or similarity to other users.

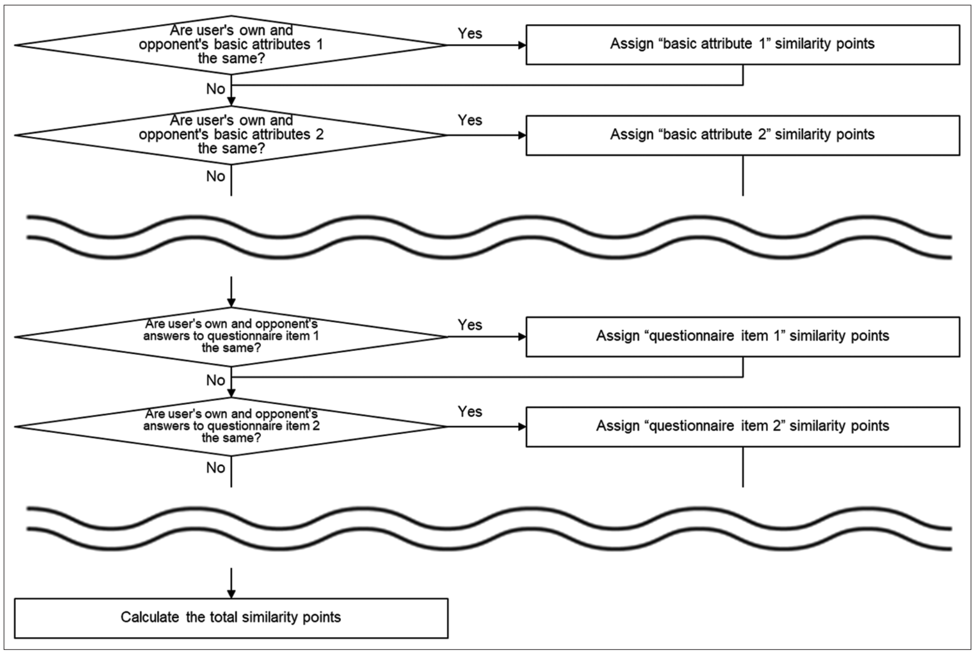
The flow of the brand agent is shown in Figure 4 below (Note that Figure 4 also represents the flow of S2 and S4).

1. Initially, set position and speed to random, while direction is 0°
2. When there are unpurchased agents around (in the field of view), the brand agent decides whether to make the unpurchased agent the same angle (θ = 0°) as itself, based on the purchase probability calculated from the innovator scores of the unpurchased agent. This is done by generating a uniform

Table 4: Similarity calculation method

Evaluation items	Answers and similarity points										
Gender (SA)	Male 1	Female 1									
⋮	⋮	⋮									
Important points when purchasing beverages (MA)	Fruit juice 1/11	Alcohol content 1/11	Type of flavor 1/11	Word-of-mouth 1/11	Brand 1/11	Compatibility with food 1/11	Price and cost performance 1/11	Buzz 1/11	Functionality 1/11	Do not usually purchase beverages 1/11	Other 1/11

Figure 3: Flow of similarity calculations



random number (z~U(0,1)) between 0 and 1 at each iteration step and comparing it to the purchase probability, after which the direction is updated. Specifically, it is set to 0° in the cases shown in equations (16)-(20).

$$\frac{IS_{IN}^{\theta\neq0^\circ}}{\max_{1\leq j\leq n} IS_j} \geq z \tag{16}$$

$$\frac{IS_{EA}^{\theta\neq0^\circ}}{\max_{1\leq j\leq n} IS_j} \geq z \tag{17}$$

$$\frac{IS_{EM}^{\theta\neq0^\circ}}{\max_{1\leq j\leq n} IS_j} \geq z \tag{18}$$

$$\frac{IS_{LM}^{\theta\neq0^\circ}}{\max_{1\leq j\leq n} IS_j} \geq z \tag{19}$$

$$\frac{IS_{LA}^{\theta\neq0^\circ}}{\max_{1\leq j\leq n} IS_j} \geq z \tag{20}$$

Here $IS_{IN}^{\theta\neq0^\circ}$, $IS_{EA}^{\theta\neq0^\circ}$, $IS_{EM}^{\theta\neq0^\circ}$, $IS_{LM}^{\theta\neq0^\circ}$, and $IS_{LA}^{\theta\neq0^\circ}$ are the respective innovator scores of innovators, early adopters, early majority, late majority, and laggards who have not purchased the product.

Thus, the flow of each type of user agent is shown in Figure 5 below.

1. Initially, set a random position, direction, and speed
2. The agent that has not purchased the product decides whether or not to take the same angle (θ = 0°) as the agent that has purchased the product based on the purchase probability calculated from the innovator scores $IS_t^{\theta\neq0^\circ}$ and if the number of agents that have purchased the same type of product in the surrounding (field of view variable vw_t) are above a certain number (number is variable flw_t). This is done by generating a uniform random number (z~U(0,1)) between 0 and 1 at each iteration and comparing it to the purchase probability, after which the direction is updated. Specifically, it is set to 0° in the case shown in equation (21).

$$\frac{IS_t^{\theta\neq0^\circ}}{\max_{1\leq j\leq n} IS_j} \geq z \tag{21}$$

Figure 4: Brand agent flow

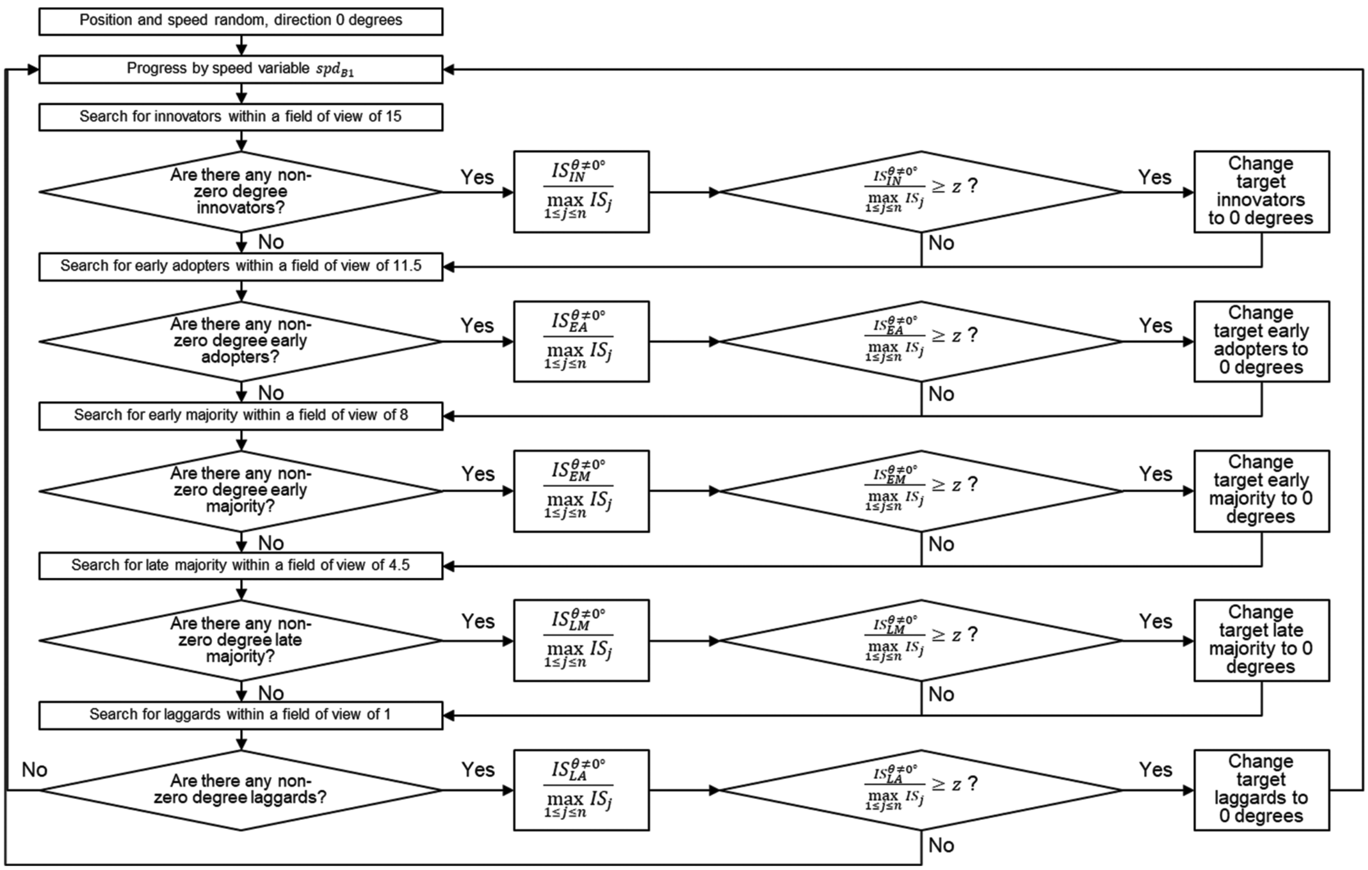
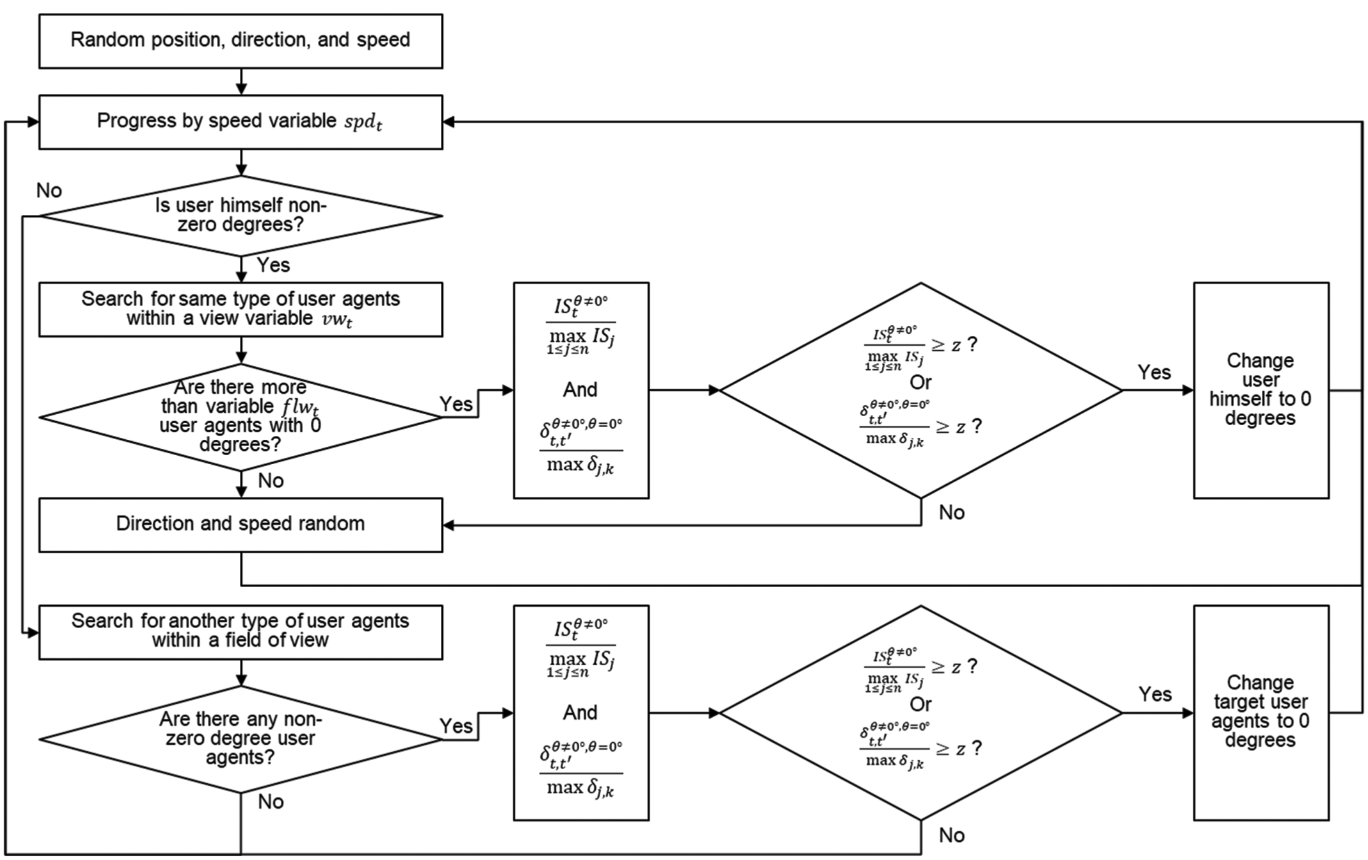


Figure 5: Flow of each type of user agent



Here, t is the user agent of each cluster from innovators to laggards.

3. If the agents who have not purchased the product do not change to the same angle (θ=0°) as described above, the purchase probability is calculated based on the similarity between the agents $\delta_{t,t'}^{\theta\neq 0°,\theta=0°}$ calculated from (i) the basic attributes of the agents who have not purchased the product and the agents who have purchased the product, and (ii) the results of their questionnaire responses. Based on this probability, decide whether to change to 0° or not. This is done by generating a uniform random number (z~U(0,1)) between 0 and 1 at each iteration and comparing it to the purchase probability, after which the direction is updated. Specifically, it is set to 0° in the case shown in equation (22).

$$\frac{\delta_{t,t'}^{\theta\neq 0°,\theta=0°}}{\max \delta_{j,k}} \geq z \tag{22}$$

where $\delta_{j,k}$ is the similarity between agents j and k.

4. If the unpurchased agent is not acted upon by the purchased agent, it randomly changes its direction and speed.
5. When the agent who has already purchased the product has another agent who has not yet purchased the product around it (the size of the field of view is set for each agent), it decides whether or not to make the agent who has not yet purchased the product change to the same angle (θ=0°) as itself based on the purchase probability calculated from the innovator scores $IS_t^{\theta\neq 0°}$ of the agent who has not yet purchased a product. Specifically, it is set to 0° in the case shown previously in equation (21).
6. If the agents who have not purchased the product do not change to the same angle (θ=0°) as described above, the purchase probability is calculated based on the similarity between the agents $\delta_{t,t'}^{\theta\neq 0°,\theta=0°}$ calculated from (i) the basic attributes of the agents who have not purchased the product and the agents who have purchased the product, and (ii) the results of their questionnaire responses. Based on this probability, decide whether to change to 0° or not. Specifically, it is set to 0° in the case shown previously in equation (22).

4.2. Method for Detecting Chasms or Cracks

In this study, the three-sigma rule is used to detect chasms or cracks.

If $D=\left\{DIF_3^1, DIF_3^2, \cdots, DIF_3^{st}, \cdots, DIF_3^m\right\}$ is the data of the increase or decrease in the number of subtotal diffusions, then from (12), the mean μ_D=$E[D]$ s as shown in (23).

$$E\left[D\right]=\frac{1}{m}\sum_{st=1}^{m}\left(\left(DIF_1^{st}-DIF_1^{st-1}\right)-\left(DIF_1^{st-1}-DIF_1^{st-2}\right)\right) \tag{23}$$

The variance $V[D]$ and standard deviation $\sigma_D=\sqrt{V\left[D\right]}$ are shown in (24) and (25), respectively.

$$V\left[D\right]=E\left[\left(D-E\left[D\right]\right)^2\right]=\frac{1}{m-1}$$
$$\sum_{st=1}^{m}\left(\left(DIF_1^{st}-DIF_1^{st-1}\right)-\left(DIF_1^{st-1}-DIF_1^{st-2}\right)-E\left[D\right]\right)^2 \tag{24}$$

$$\sqrt{V\left[D\right]}=\sqrt{\frac{1}{m-1}\sum_{st=1}^{m}\left(\begin{pmatrix}DIF_1^{st}-\\DIF_1^{st-1}\end{pmatrix}-\begin{pmatrix}DIF_1^{st-1}-\\DIF_1^{st-2}\end{pmatrix}-E\left[D\right]\right)^2} \tag{25}$$

The three-sigma rule is one of the outlier detection methods, where DIF_3^{st} is an outlier when the increased or decreased value of the subtotal diffusion number DIF_3^{st} satisfies the condition in (26).

$$DIF_3^{st} \geq \mu_D + 3\sigma_D \tag{26}$$

When using this method to detect chasms or cracks, the mean and standard deviation are calculated from the data set giving the frequency of the increase or decrease of the subtotal diffusion number for each step. The chasm or crack threshold is given in (27), which is the mean reduced by three times the standard deviation.

$$DIF_3^{st} \leq \mu_D - 3\sigma_D \tag{27}$$

If the value of the increase or decrease in the number of subtotal diffusions is observed to be below the threshold, then a chasm or crack is identified.

In the three-sigma rule, when the number of steps is small, it is easy to detect a chasm or crack. In our agent-based model, since all agents are generated in the initial step, the range of values for the increase or decrease in the number of subtotal diffusions is large in the first few steps. However, we do not think it is appropriate to conclude that a chasm or crack has occurred at those values. Therefore, for the definition of a chasm or crack in this study, the cases in which chasms or cracks occur are defined as those in which the increase or decrease in the subtotal diffusion number of each step is less than or equal to μ_D–$3\sigma_D$ after six steps.

Figure 6 shows an example of the increase or decrease in the subtotal diffusion number of a new product, where the vertical line drawn marks the case where a chasm or crack is detected.

5. EXPERIMENT

As experimental data, we used behavioral data and questionnaire data collected by DO HOUSE Inc. The behavioral data contains information such as product name, user ID, date and time of purchase, and the number of campaign participations for the target product purchased by target users visiting an O2O site and physical stores. The questionnaire data is obtained by conducting questionnaires on users who are targets of the behavioral data collection. The data was collected in November 2018, and the number of users analyzed was 17,450. The target of this study was a beverage brand that included a new product at the time and had a relatively large number of purchasers among convenience products. The number of brand agents was set to 87 and the number of each user agent was generated based on the results of the innovator scores calculation. In addition, each of the variables, vw_t and flw_t,to determine if each user agent would implement the purchasing behavior were set as shown in Table 5.

After this, simulations were conducted on four scenarios for each condition of each variable in the model. Figure 7 shows the subtotal diffusion numbers for the new product in the four scenarios.

The uppermost line in the graph is the overall subtotal diffusion number. The shape of the curves is similar in S1 and S3, and in S2 and S4, respectively; the speed of diffusion is different in each scenario. In this sense, we can say that cluster connectivity and

Table 5: Condition 1 of the experiment

	Innovator	*Early Adopter*	*Early Majority*	*Late Majority*	*Laggard*	Total
Field of View (vw_t)	2	2	2	2	2	
Number of Observed Users (flw_t)	1	1	2	3	3	
Average Innovator Scores	32,906	27,421	20,503	13,902	6,605	
Ratio (%)	2.0	15.4	31.7	33.9	17.0	100.0
Number of Users	345	2,685	5,534	5,912	2,974	17,450

Figure 6: Example of increase/decrease in the subtotal diffusion number of the new product

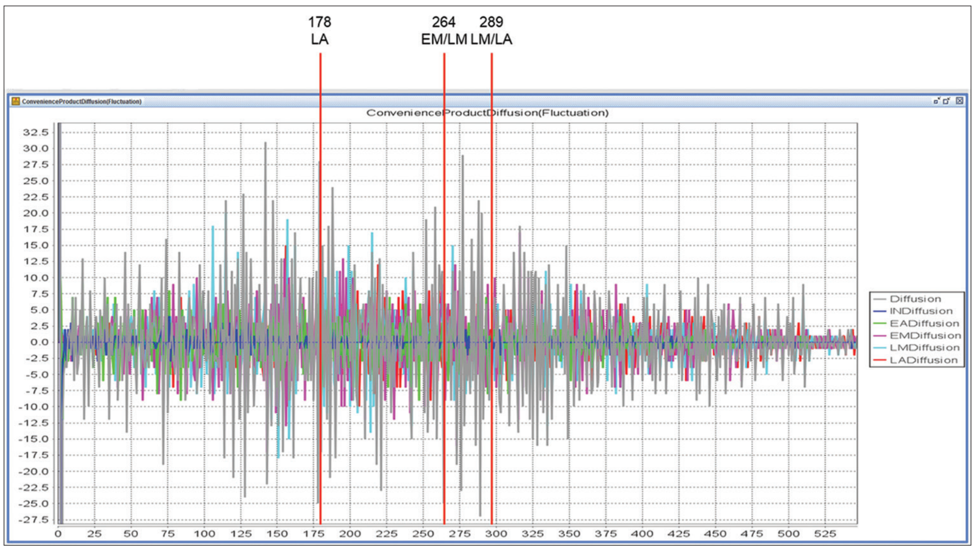
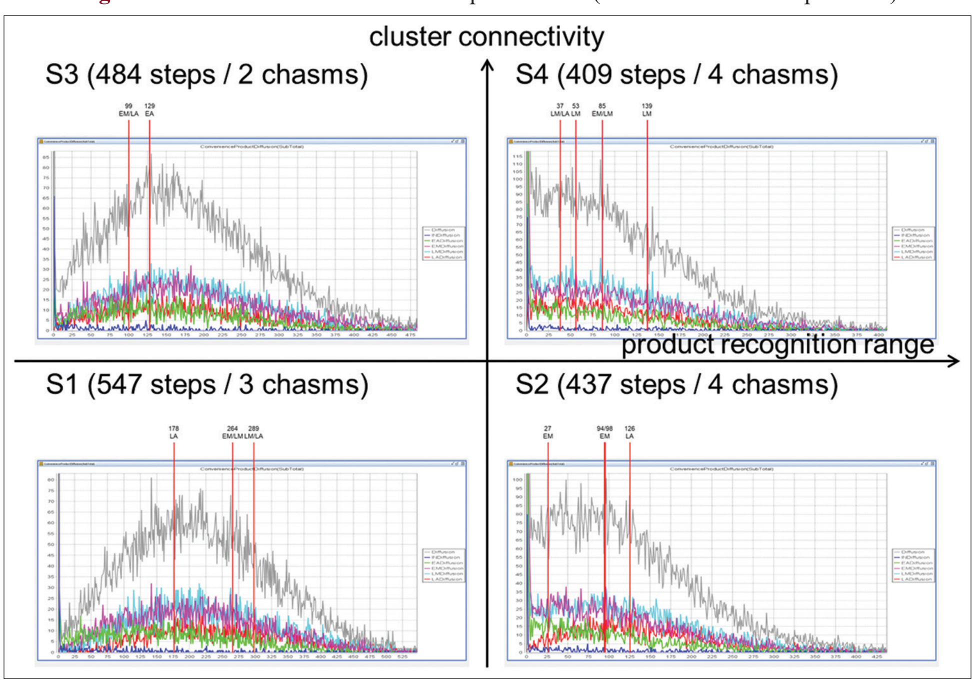


Figure 7: Number of subtotal diffusions per scenario (Condition 1 of the experiment)



the product recognition range are two factors that affect the speed of diffusion of a new product.

In a market structure of users with low cluster connectivity, the speed of diffusion is slow and takes time to reach the market. This is because in a market with high cluster connectivity, the purchase decision of one user facilitates communication and increases the purchase probability of other users in the market. By contrast, a market with low cluster connectivity increases the purchase probability of a limited set of users who are connected to the product purchasing user. This information does not spread efficiently in the market.

In contrast to cluster connectivity, the product recognition range changes the shape of the curve as well as the speed of diffusion. In other words, the wider the product recognition range, the greater the number of purchases at the initial stage, and the higher the probability of a purchaser appearing at an early stage; particularly in contrast to a simultaneous market with a narrower product recognition range.

Looking at the purchasing factor composition ratio, $ACTRATIO_t$, of each cluster, more than 95% of the innovators in S1 to S4 purchase based on their own innovativeness, while less than 70% of the laggards purchase based on their similarity to other users. In other words, the closer the user is to an innovator, the better they recognize the new product through communication from other users and advertisements, making it more likely that the user purchases the product on their own. It was also found that the more laggard the user is, the less likely they were to be influenced by advertising, making it more likely for the user to purchase a new product only when influenced by communication.

Next, based on the simulation results, the three-sigma rule was used to detect chasms or cracks. Among the trials conducted for the four scenarios, we were able to detect chasm three times at S1 in Figure 7, where the vertical line was drawn. The clusters with particularly small increases or decreases in the number of subtotal diffusions in each chasm were laggards at 178 steps, early majority and late majority at 264 steps, and late majority and laggards at 289 steps. Additionally, four chasms were detected in S2, two chasms in S3, and four chasms in S4.

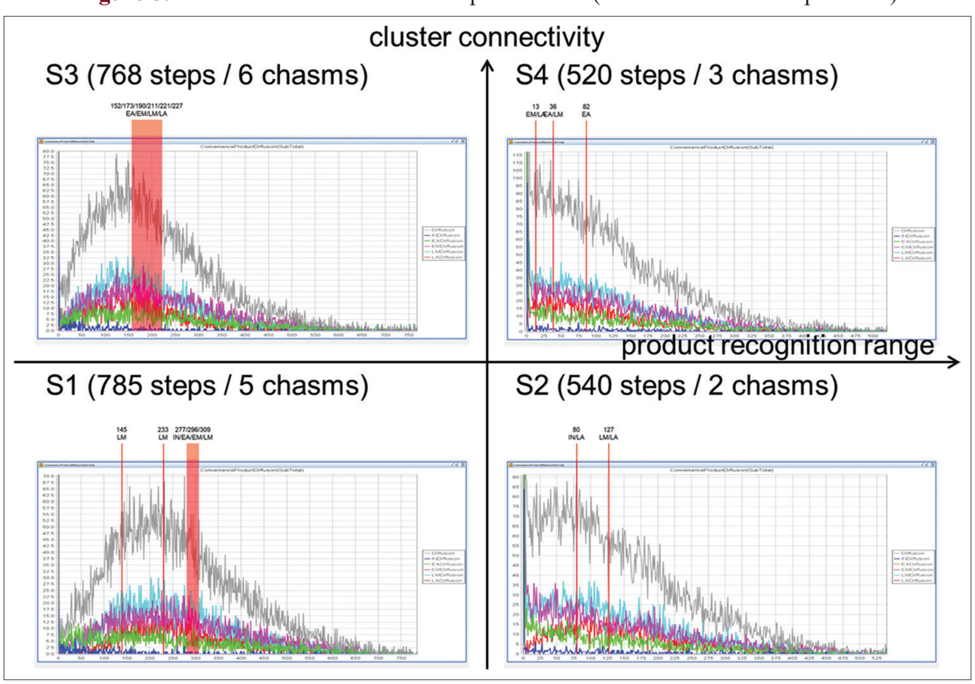
Next, as a sensitivity analysis, we conducted an experiment in which each variable in the model was varied and the number of times a chasm was detected was measured. Our sensitivity analysis examined the effect of the parameters vw_t and flw_t on the number of occurrences of a chasm or crack. Each variable was set as shown below in Table 6.

An experiment was conducted to measure the number of times a chasm was detected by changing the variable vw_t to 1 and flw_t to 10 for early adopters and early majority. Figure 8 shows the subtotal diffusion numbers for the four scenarios of the new product according to Condition 2 of the experiment.

Table 6: Condition 2 of the experiment

	Innovator	*Early Adopter*	*Early Majority*	*Late Majority*	*Laggard*	Total
Field of View (vw_t)	2	1	1	2	2	
Number of Observed Users (flw_t)	1	10	10	3	3	
Average Innovator Scores	32,906	27,421	20,503	13,902	6,605	
Ratio (%)	2.0	15.4	31.7	33.9	17.0	100.0
Number of Users	345	2,685	5,534	5,912	2,974	17,450

Figure 8: Number of subtotal diffusions per scenario (Condition 2 of the experiment)



From Figure 8, it can be seen that when the value of vw_t is small and that of flw_t is large, the number of occurrences of chasms and cracks increases. Comparing with Condition 1 of the experiment, a concentration of chasms and cracks is observed in a short period of time, especially in S1 and S3.

Finally, an experiment was conducted to measure the number of times a chasm was detected by changing the variable vw_t to 1 and flw_t to 10 for innovators, early adopters, early majority, late majority, and laggards. Each variable was set as shown below in Table 7.

Figure 9 shows the subtotal diffusion numbers for the four scenarios of the new product according to Condition 3 of the experiment.

From Figure 9, it is observed that the number of occurrences of chasms and cracks increases.

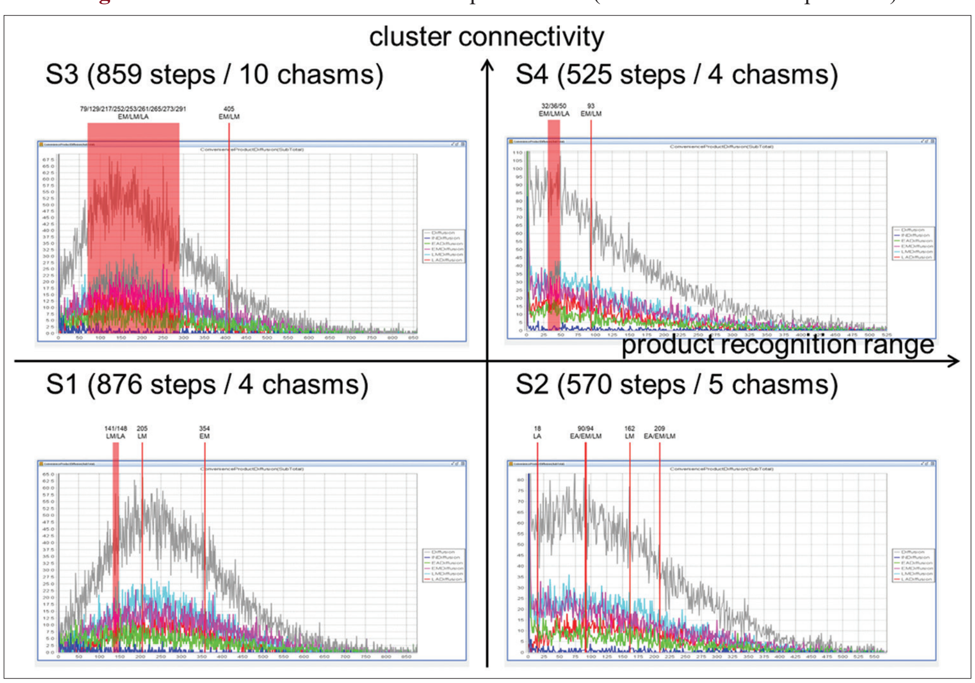
From the above results, it is clear that vw_t and flw_t are the factors that cause the occurrence of chasms and cracks in this model. Further, the results show that the level of cluster connectivity (high or low) and the width of the product recognition range (wide or narrow) affect the word-of-mouth and advertising effects in the market. This verifies the proposition that opinion leaders who either cause widespread word-of-mouth effects or are responsible for the introduction of advertising into the market affect the speed of product diffusion.

The analysis shows that when vw_t and flw_t are at values that cause chasms or cracks, the market will experience a period of stagnant sales and decline for a long period of time. Since vw_t and flw_t are parameters that refer to communications within each cluster, it follows that companies should make efforts to increase their word-of-mouth effect. Previously, it was pointed out that the manipulability of companies to word-of-mouth is low (Golder and Tellis, 2004). Word-of-mouth refers to contact with people who are using a new product without going through a medium such as the Internet, such as meeting people directly and asking them about the comfort of using the product or estimating the convenience of a product by directly witnessing others using it. In the past, companies were unable to significantly manipulate word-of-mouth because users were unlikely to come into contact with them without going through such a medium. However, with the spread of the Internet and the accompanying development of Social Networking Services (SNS) and product word-of-mouth sites, the opportunities for users to contact each other are thought to be increasing. In fact, there is data showing that some people use word-of-mouth information on the Internet before purchasing a convenience product, such as food (Vuzz Inc., 2015), and that this habit has come to have a significant impact on purchasing behavior. Therefore, it is more feasible than ever before for

Table 7: Condition 3 of the experiment

	Innovator	*Early Adopter*	*Early Majority*	*Late Majority*	*Laggard*	Total
Field of view (vw_t)	1	1	1	1	1	
Number of observed Users (flw_t)	10	10	10	10	10	
Average innovator scores	32,906	27,421	20,503	13,902	6,605	
Ratio (%)	2.0	15.4	31.7	33.9	17.0	100.0
Number of users	345	2,685	5,534	5,912	2,974	17,450

Figure 9: Number of subtotal diffusions per scenario (Condition 3 of the experiment)



companies to operate websites about their products to generate word-of-mouth.

By contrast, cluster connectivity is a concept that refers to the cross-market communication effect of opinion leaders. In vw_t and flw_t of this model, it is assumed that users in each cluster only communicate to other users in the same cluster. However, in practice, one cluster may communicate to another cluster. Therefore, in practice, opinion leaders such as innovators and early adopters must be identified, and extensive word-of-mouth must be allowed to spread a new product in a short period of time. Since innovators and early adopters account for a small number of users in the market, it may be difficult to immediately initiate cross-market communication even if they are identified using this method. However, since these identifications are a prerequisite for the rapid diffusion of a new product in the market, it is believed that efforts should be made to approach innovators and early adopters before other companies in the same industry do.

Further, product recognition range is a concept that implies advertising effectiveness. Advertising is a prerequisite for controlling the number of times a chasm occurs and to disseminate a new product to the market in a short period of time. However, it is a measure with high marketing costs. Hence, its implementation should be considered after considering cost-effectiveness.

6. CONCLUSION

In this study, we have developed a model that reproduces the product diffusion process and chasms by using innovator scores and agent-based modeling. This model is then used to discuss how to overcome chasms and cracks.

The results of the sensitivity analysis show that both parameters vw_t and flw_t must have desirable values in order to suppress the occurrence of either chasms or cracks. As pointed out in Chapter 5, these parameters are manipulable by companies, although being subject to uncertainty. Therefore, for companies looking to spread new products in the market, the key to their new product diffusion strategy would be to approach opinion leaders ahead of their competitors and promote the dissemination of product information through website management.

In the phenomenon analyzed here, the product recognition range has a significant impact on the curve of diffusion and changes its shape pattern. In this sense, market penetration with a wide product recognition range tends to result in a large number of purchases in the initial stage. Conversely, in a market with a narrow product recognition range, the curve forms as shown by a simple diffusion model. It is also shown that high or low cluster connectivity affects the rate of diffusion, but not the shape of the curve.

The limitations of this study are that (1) the modeling is conducted for a limited set of consumer behaviors, and (2) the analysis focuses on the number of times chasm occurs. With respect to (1), consumer purchasing behavior cannot be simply divided into pre-purchase and post-purchase, but can be divided into several stages, such as AIDMA and AISAS. These can be considered to reproduce a market closer to reality. Especially in O2O, user behavior can be divided into ARASL (Matsuura, 2012) stages. In terms of (2), this model does not allow us to grasp the specific factors of chasms and cracks and it is difficult to examine marketing measures to counteract them.

However, this does not mean that there are no measures to counteract chasms and cracks. Rather, with such data validation, it is necessary to consider measures to counteract them through other data analyses. Therefore, based on the simulation results in this study, future studies may consider incorporating the structure of users' purchasing behavior into the model and reflecting elements such as the influence of consumer behavior and consciousness, analyzed from the structure in marketing measures. Further, we would like to deepen our discussion on whether it can be rationally used as a framework for marketing policies in the uncertain market of convenience products.

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