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Strategies for new product diffusion: Whom and how to target?☆

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A R T I C L E I N F O

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A B S T R A C T

This paper examines the promotional strategies for new product diffusion by leveraging peer effects among consumers. Previous studies have offered conflicting recommendations on whom to target (e.g., influentials, susceptibles, or unsusceptibles) with respect to new product promotions. Utilizing agent-based modeling and simulation (ABMS), we show that each of the proposed consumer groups can be a promising target, depending on how they are targeted, according to target size and promotion intensity. The authors further recommend the optimal combination of *whom* and *how to target* under budget constraints. Specifically, where a budget is limited, the best approach is to target as many susceptibles as possible with a weak promotion. Targeting unsusceptibles with free products should be the first choice, where the budget is large. In other cases, the best approach is to target as many influentials as possible with a moderate promotion.

1. Introduction

New products are essential to a firm's continued growth in revenues and profits. In order to ensure the success of new products, firms frequently develop and implement targeting programs. Firms offer promotions (e.g., discounts or freebies) to one or more special groups of consumers to foster product diffusion through peer effects among consumers (Ho, Li, Park, & Shen, 2012; Iyengar, Van den Bulte, & Valente, 2011). Recent technological advances, such as customer relationship management systems, consumer behavior scanners, online brand communities, and social media, offer firms unprecedented opportunities to leverage peer effects (Gruner, Homburg, & Lukas, 2014; Hinz, Skiera, Barrot, & Becker, 2011). As a consequence, the last decade has witnessed an increasing number of studies on targeting strategies (Haenlein & Libai, 2013; Hinz et al., 2011; Libai, Muller, & Peres, 2013; Nejad, Amini, & Babakus, 2015).

Despite this, two questions still need to be answered. The first is "whom to target," since previous studies provide conflicting recommendations: some propose to target influentials, that is, who have a wide-ranging influence in society (Hinz et al., 2011; Iyengar et al., 2011; Nejad et al., 2015); some others propose to target susceptibles, who are especially susceptible to peer effects (Jain, Mahajan, & Muller, 1995; Mahajan & Muller, 1998); and others point to unsusceptibles, who are the opposite of susceptibles and less prone to peer effects (H. Hu, Lin, & Cui, 2015a; Janssen, 2011). The second question is "how to target." This involves two issues, namely, target size (i.e., how many target consumers should be selected) and promotion intensity (i.e., how intensively they should be incentivized) (Aral, 2011). Related studies have examined the optimal number of free giveaways to offer (Libai et al., 2013; Nejad et al., 2015). However, those results do not apply to other commonly-practiced promotions that are less attractive than free products, e.g., 10% price discount and "buy two get one free" offers. With reference to the above-mentioned research gaps, this study aims to identify the most promising targets in various size-intensity settings.

In addition, we consider targeting strategies that are constrained by marketing budgets. For example, a limited budget may only allow a firm to offer free products to 0.1% consumers, or reach far more consumers with a 10% discount in price. In the former, the program may not be able to reach a sufficient number of key consumers, and thus fail to support product diffusion. By contrast, a 10% discount may be unattractive to induce adoptions. Hence, which one would be the better choice? Moreover, does it vary across consumer groups (influentials, susceptibles, and unsusceptibles)? It is the goal of every firm to make the best of their marketing investment. Thus, this study also investigates the optimal combination of *whom* and *how to target* under budget constraints.

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Table 1
Comparison of studies related to targeting programs.

Study	Methodology	Whom to target[a]				How to target		Budget constraints
		I	S	U	R	Intensity	Size	
Jain et al. (1995)	Mathematical		√		√	Free giveaway	Variable	No
Mahajan and Muller (1998)	Mathematical		√		√	Free giveaway	Variable	No
Lehmann and Esteban-Bravo (2006)	Mathematical		√		√	Free giveaway	Variable	No
Iyengar et al. (2011)	Empirical	√				Free giveaway	Not considered	No
Hinz et al. (2011)[b]	Empirical	√			√	Free giveaway	Variable	No
Watts and Dodds (2007)	ABMS	√			√	Free giveaway	Only one seed	No
Kiss and Bichler (2008)	ABMS	√			√	Free giveaway	Variable	No
Delre, Jager, Bijmolt, and Janssen (2010)	ABMS	√			√	Free giveaway	Not considered	No
Janssen (2011)[b]	ABMS	√	√	√	√	Modest promotion	Fixed	No
Libai et al. (2013)	ABMS	√			√	Free giveaway	Variable	No
Nejad et al. (2015)	ABMS	√	√		√	Free giveaway	Variable	No
H. Hu et al. (2015a)[b]	ABMS	√	√	√	√	Modest promotion	Fixed	No
This study	ABMS	√	√	√	√	Variable	Variable	Yes

[a] I = influentials, S = susceptibles, U = unsusceptibles, and R = random targets.
[b] The study also identifies targets based on other indicators of network centrality, such as betweenness and closeness.

We address our research objectives by using agent-based modeling and simulation (ABMS), a relatively new computational modeling approach that has been used to explore diffusion-related research questions (Rand & Rust, 2011). This approach allows us to examine various scenarios that occur in the real world but are difficult to capture by other methods.

The remainder of this paper is structured as follows. The following section elaborates on the theoretical background of targeting programs. The third section develops the hypotheses. The fourth section introduces the ABMS model, and the fifth section presents the outcomes. The paper concludes with a discussion of the theoretical contributions and managerial implications, as well as directions for further research.

2. Background

2.1. Mechanisms underlying diffusion: peer effects

Peer effects, which are characterized as the dependence of one's adoption decision on interactions with others, are essential to the adoption of a wide range of products. Specifically, peer effects refer to an increase in the probability of a consumer's adoption of a product with respect to the number (or proportion) of peers who have already adopted the product (Bollinger & Gillingham, 2012; Iyengar et al., 2011; Moretti, 2011).

DiMaggio and Garip (2012) highlight three principal mechanisms underlying peer effects, namely, local network externality, social learning, and normative influence. Local network externality arises when the value of a product is dependent on the number of peers adopting it. Classic examples include telephone and online social networking, where a greater number of users increase the value to each. Social learning occurs when prior adopters share product information with their friends, which reduces the cost or risk of buying a new product or increases its utility. For example, association with friends who have already used a new type of laptop can reduce quality uncertainty. Friends may also share the experience of the additional features of the equipment, thereby raising the reservation price.

The third mechanism, normative influence, functions as social rewards bestowed on adopters and sanctions exacted on non-adopters by their peers. For example, the tendency to use biodegradable garbage bags can be reinforced by the positive response of friends and neighbors who appreciate the use of environment-friendly products. Normative influence may also arise because of status competition (Iyengar et al., 2011). For example, high-status physicians might be driven to adopt a medical innovation quickly once they observe the adoption of lower-status peers, out of fear that their own status advantage will be eroded (Burt, 1987).

Consumers are heterogeneous in terms of susceptibility to peer effects; thus, they tend to adopt a new product at different times (Rogers, 1995). A small number of risk-taking consumers, often referred to as innovators, will try an unproven product as soon as it becomes available. Some consumers, who are known as early adopters, are especially susceptible to peer effects and adopt quickly. Next in the adoption line is the early majority, which refers to consumers who are relatively more cautious in trying new products and who only adopt after early adopters have validated the product. The late majority, consisting of skeptical consumers, adopt only after the product has become popular in the population. Consumers who avoid change and are unsusceptible to peer effects do not adopt the product until traditional alternatives become unavailable; they are also known as laggards.

2.2. Targeting strategies

When developing promotional campaigns, marketers need to determine who the targets are (Aral, 2011). Several options are available. Undifferentiated targeting is a common strategy, whereby marketers ignore market segment differences and appeal to prospective customers randomly through mass distribution. A typical example is when Microsoft distributed 450,000 free copies of Windows 95® to consumers across the US (Rosen, 2009). Alternatively, marketers may focus on a specific group of consumers. For example, US pharmaceutical firms often spend fairly sizeable budgets on marketing products to opinion leaders (Nair, Manchanda, & Bhatia, 2010). Another example is cell phone makers like Apple and Samsung, when launching an upgraded handset, offer a trade-in plan to customers who have demonstrated a willingness to buy their products (Apple, 2017; Samsung, 2017).

Studies commonly suggest that specialized targeting is superior to undifferentiated targeting. However, these studies can be divided into two categories in terms of the criteria used to identify promising targets, as summarized in Table 1. One category focuses on consumers who are at the center of a social network. In this line of research, influentials connected with a high number of peers are often recommended. The other category of studies pinpoints targets based on consumers' susceptibility to peer effect (also known as the propensity to adopt) and recommends susceptibles, who constitute the basis for a successful diffusion, and unsusceptibles, who resist change and disrupt the process of diffusion. These conflicting recommendations necessitate evidence-based comparisons (Hinz et al., 2011; Nejad et al., 2015).

In addition to deciding whom to target, marketers must consider *how to target*, including target size and promotion intensity, to make the best use of marketing efforts. Prior studies have placed primary focus on seeding programs, i.e., free giveaways, as Table 1 illustrates. These studies show that the optimal size for seeding programs ranges from 3% to 7% of the market (Hinz et al., 2011; Jain et al., 1995; Nejad et al., 2015). Nevertheless, seeding programs appear to be applicable only if the product has a low marginal cost (e.g., software) or if the firm has a huge marketing budget. Numerous less expensive promotional options (e.g., price discounts, coupons, branded gifts, or free trials) have long been used in practice as effective promotion policies. In these cases, the optimal target size may change considerably, because the cost and effects of modest incentives are both lower than those of free products.

More importantly, literature analysis suggests that *whom to target* may be a function of *how to target*. Watts and Dodds (2007) seed only one consumer to initialize diffusion and find that the effect of seeding influentials is not greater than that of seeding average consumers. When seeding size is increased (e.g., 0.25%–20% of the potential market), seeding influentials becomes the most beneficial tactic (Libai et al., 2013; Nejad et al., 2015). However, tapping influentials is unlikely to be promising once modest promotions are considered (Hu et al., 2015a; Janssen, 2011). In conclusion, the varying settings of *how to target* are likely the culprits for inconsistent recommendations on *whom to target*. In the following section, we will expound on when, i.e., under which conditions, influentials, susceptibles, and unsusceptibles are the promising targets. Moreover, the constraints of marketing budget on the selection of *whom* and *how to target* are clarified for practical purposes.

3. Hypotheses

3.1. Influentials vs. random targets

Influentials have several advantages over ordinary consumers in terms of promotional targets. First, influentials are linked to many others. Targeting them exposes the product to a large number of consumers who are directly or indirectly connected to them. Second, influentials have a strong influence on the attitudes and behaviors of other consumers. Evidence shows that the number of peers is positively related to opinion leadership (Y. Hu & Van den Bulte, 2014). Influentials are more likely to be heavy users and well-informed about others' experience of a product (Iyengar et al., 2011) and hence, are usually persuasive experts in their networks (Goldenberg, Han, Lehmann, & Hong, 2009). Moreover, influentials have a strong normative influence on others, and thus, their adoption may exert greater pressure on others to follow (Burt, 1987).

With these advantages, influentials have 30% to 10 times more impact than average consumers on a market-wide diffusion process (Hinz et al., 2011; Kiss & Bichler, 2008; Libai et al., 2013; Nejad et al., 2015). Therefore, we argue that targeting influentials can have a greater return of investment than random targeting and test the following hypothesis:

H1. As promotional targets, influentials outperform random consumers given any context of how to target.

3.2. Susceptibles vs. influentials

Our second hypothesis concerns the effect of targeting susceptibles. According to innovation diffusion theory (Rogers, 1995), a diffusion proceeds from a small segment of the market (i.e., innovators) to early adopters (generally susceptibles), and then to the early majority and late majority of the market. Watts and Dodds (2007) show that successful diffusion is driven by a critical mass of susceptibles because the early adoption of susceptibles can expand the installed base quickly (Jain et al., 1995). If susceptibles are not triggered sufficiently, the diffusion process is disrupted in the early stages. Thus, marketing campaigns can be beneficial when both influentials and susceptibles are identified (Christakis & Fowler, 2011).

We argue that the role of susceptibles versus influentials in targeting programs is relevant to promotion intensity. Loyal customers who have demonstrated a high commitment toward a firm, a typical group of susceptibles, are inclined to adopt the firm's new products and thus require only a small marketing inducement. By contrast, inducing influentials is not an easy task (Nejad et al., 2015). That is, targeting susceptibles should be more effective than targeting influentials when offering a low-intensity promotion. When the promotion is strong enough to stimulate influentials, however, targeting influentials should become more promising because of their extensive connections and strong influence. Thus, we propose the following hypothesis:

H2. As promotional targets, susceptibles outperform influentials when promotion intensity is low.

3.3. Unsusceptibles vs. influentials

The third hypothesis focuses on unsusceptibles. Unsusceptibles are highly resistant to new products, since they focus more on the risks of new products (Mahajan, Muller, & Srivastava, 1990; Rogers, 1995). For practical purposes, marketers usually consider unsusceptibles to be a lost market (Goldenberg & Oreg, 2007). However, unsusceptibles in fact play a critical role in the process of diffusion and often disrupt the chain of adoption. Put another way, they effectively offset the positive influence of influentials and susceptibles.

Stimulating the adoption of unsusceptibles benefits firms directly and indirectly (Cavusoglu, Hu, Li, & Ma, 2010). The direct benefit comes from purchases that would not take place otherwise. Although one additional adoption may be insignificant, its indirect benefit is substantial, because it repairs the chain of adoption and increases peer confidence in new products. We thus believe that under certain conditions, unsusceptibles are a promising alternative as promotional targets. A strong incentive is essential for unsusceptibles' adoption because they strongly resist change. Moreover, a small target size may not be sufficient to ensure that targeting unsusceptibles is better than targeting influentials, as suggested by scholars who focus on the intervention of collective behavior (H. Hu et al., 2015a; Janssen, 2011). Based on these views, we propose the following hypothesis:

H3. As promotional targets, unsusceptibles outperform influentials when promotion intensity is high and target size is large.

3.4. Strategies under budget constraint

Here, we aim to identify the optimal choice of *whom* and *how to target*, while maximizing the expected profit under budget constraints. We classify budget constraints into three areas. The first area is where the budget is low. With a low budget, a firm would choose to either reach sizable targets with a weak promotion or offer a strong promotion to a few targets. As susceptibles can be induced by low-intensity promotions, targeting a considerable number of susceptibles should be the optimal choice in this area (corresponding to H2).

The second area is where the budget is medium. According to H2 and H3, we expect influentials to be the best targets under a medium budget and a moderate promotion is preferable for influentials as a whole. The third area is where the budget is large. In this area, firms can balance target size and promotion intensity at will, and the most promising targets should be unsusceptibles, according to H3. As unsusceptibles are strongly insensitive to inducement, the promotion should be highly intensive (e.g., free giveaways). Based on the above arguments, we propose the following hypotheses:

H4a. When the budget is low, targeting as many susceptibles as possible with a weak promotion is the optimal configuration.

H4b. When the budget is medium, targeting as many influentials as possible with a moderate promotion is the optimal configuration.

H4c. When the budget is large, targeting unsusceptibles with free giveaways is the optimal configuration.

4. Method

4.1. Introduction of ABMS

A reliable approach for testing our hypotheses is to build experiments based on real data. However, the introduction of new products in the real market and identification of different target groups in real settings are complex and expensive (Libai et al., 2013; Rand & Rust, 2011). An alternative analytical tool is offered by ABMS. ABMS is an individual-centric modeling approach used to understand and analyze how often-surprising collective phenomena (e.g., innovation diffusion) arise from the behavior and interaction of agents (e.g., consumers). It allows for the exploration of complex systems that display irreducible heterogeneity, randomness, and non-independence of individuals (Rand & Rust, 2011). More importantly, it is not limited to observed data and can be used to model experiments that may be impossible to conduct in the real world. ABMS has been seen in extensive applications to marketing problems, as described in sophisticated reviews by Kiesling, Gunther, Stummer, and Wakolbinger (2012), Nejad (2016), and Rand and Rust (2011).

The ABMS model we adopt has two main components. One defines consumer agents with the rule of adopting a new product, while the other specifies the network of consumer agents. Both components are derived on a strictly specified set of assumptions about the real world. Therefore, the model can be viewed as an in silico mock-up of real systems. Relying on it, a series of experiments were built in which the characteristics of the market and consumers are kept constant. First we ran computer simulations to generate "histories" to reveal how large-scale diffusion patterns arise from micro-processes of interactions among consumers (e.g., peer effects) and next, we compared the effects of different targeting strategies.

4.2. Consumers and the rule of adoption

We use the classical threshold model (Granovetter, 1978) to define consumers, and consider the transition from non-adopters to adopters in a deterministic manner. Each consumer has a unique threshold, a point at which the consumer's perceived benefits of adopting a new product exceeds his/her perceived costs; this reflects the consumer's personal characteristics and preferences. As described in Section 2.1, peer effects can increase a consumer's perceived benefits or decrease the perceived costs of a new product. Thus, a consumer will adopt the new product only if peer effect exceeds the threshold, which is given by the following formula:

$$Adoption_i = \begin{cases} 1, & if \;\; peer effect_i > threshold_i \\ 0, & otherwise \end{cases}, \tag{1}$$

where $peer\_effect_i$ is measured by the proportion of adopted peers in the local network of consumer i. Following the conventions in literature (Granovetter, 1978; Libai et al., 2013; Nejad et al., 2015; Watts & Dodds, 2007), we assume that the thresholds are time-independent and consumers cannot "unadopt" the product once it has been adopted. Note that the threshold is inversely proportional to one's susceptibility to peer effects.

There is another dominant approach to modeling the adoption of new products –in which a consumer adopts a new product with a certain probability in response to marketing efforts (e.g., advertising) and peer effects (Goldenberg et al., 2009; Goldenberg, Libai, & Muller, 2001; Haenlein & Libai, 2013; Libai et al., 2013). We use the threshold model for two reasons. First, it is suitable for modeling complex contagion, a phenomenon where a change of behavior requires social reinforcement from multiple resources (Centola & Macy, 2007). New products are associated with high risk and cost and often lack market reputation (Mick & Fournier, 1998); thus, consumers generally hesitate to adopt new products unless many peers have adopted the products (Centola & Macy, 2007; Rogers, 1995). Under the stochastic approach, adoption spreads as a simple contagion, like a disease or computer virus, requiring only one contact for transmission. Second, the threshold model allows for the failure of diffusion, i.e., only a small number of consumers use the product. Under the stochastic approach, all consumers will eventually adopt the product unless the diffusion process is disrupted externally.

4.3. Consumer network

Consumers interact with each other through their social ties, which are the source of peer effects. Thus, the topology of the consumer network should be defined carefully to model the micro-level process of diffusion. This study uses a generative algorithm (Hu, Lin, & Cui, 2015b) to create consumer networks. We first create a two-dimensional social space where consumers are located randomly. The position of a consumer in this space represents his/her attributes, such as geographical location, age, social status, political belief, or religious faith. Consumers find persons to form social ties in two ways: some are found at random (called random peers), whereas others are found locally based on their location in the social space (called local peers). Since people show a strong preference for local peers (McPherson, Smith-Lovin, & Cook, 2001; Watts & Strogatz, 1998), local peers account for a large proportion of the network.

The hypothetical network reflects reality as much as possible. It exhibits the small-world property of real-world networks (Watts & Strogatz, 1998), i.e., people in the world are located a few steps away from each other, although they tend to cluster together. Moreover, it reproduces the unequal number of social ties people have. That is, some people have more social contacts than others, thereby acting as "hubs" in a network (Goldenberg et al., 2009; Watts & Dodds, 2007). Under this setting, a pair of peers may have an asymmetric influence on each other: Amy's influence on Bob is higher than Bob's influence on Amy when Amy has more peers. This condition is consistent with the fact that influentials have a greater influence on peers than ordinary consumers (Iyengar et al., 2011).

4.4. Targeting programs and performance measure

We use a targeting program in which a selected group of consumers receives a special promotion. As discussed earlier, we focus on three groups of consumers (i.e., influentials, susceptibles, and unsusceptibles) and a control group (i.e., randomly selected consumers). Consistent with prior research (Haenlein & Libai, 2013; Libai et al., 2013; Watts & Dodds, 2007), we consider influentials the top 10% of consumers with the largest number of peers. In a similar manner, we consider susceptibles and unsusceptibles the top 10% of consumers with the lowest (positive) and highest thresholds, respectively. For each targeting program, target members are selected from the target pool randomly. For selected consumers, the adoption threshold is reduced according to promotion intensity.

We use the increase in market share (IMS) to capture the benefit of targeting programs. It is based on a comparison of the market share between two diffusion processes: the diffusion process in which a firm implements the targeting program ($MS_{targeting}$) and the diffusion process without intervention ($MS_{baseline}$). IMS is calculated as follows:

$$IMS = MS_{targeting} - MS_{baseline} \tag{2}$$

Note that in our case, maximizing market share is equivalent to maximizing profits, because the size-intensity setting, or marketing budget, is fixed.

Table 2
Parameters of consumer market.

Parameter	Default value or range	Robustness check	Source(s) for selected parameter
No. of general consumers	10,000	–	None
No. of innovators	250	–	Rogers (1995)
Average number of peers	10	6, 20	Libai et al. (2013); Nejad et al. (2015); Trusov et al. (2010)
Proportion of local peers	0.9	0.1, 0.5	Libai et al. (2013); Nejad et al. (2015); Watts and Strogatz (1998)
Threshold distribution of general consumers	U (0, 1)	U (0.1, 1), U (0, 0.9)	Delre et al. (2007); van Eck et al. (2011); van Eck et al. (2011)

4.5. Experiment design and parameter settings

All experiments proceed as four stages. In Stage 1, we create a virtual market consisting of 10,250 consumers. Each consumer has an average of 10 peers, of which 90% are local peers. These values replicate the main structural characteristics of real-world networks (Libai et al., 2013; Nejad et al., 2015; Watts & Strogatz, 1998). Note that the value of the 10 peers can also apply to online contexts, since the average person in online networks are influenced by a few others although they have hundreds of connections (Trusov, Bodapati, & Bucklin, 2010).

In Stage 2, a new product is introduced into the virtual market created in the first stage. In response, each consumer evaluates the product and forms an adoption threshold. New products are associated with high risk, and consumers generally are risk-averse (Mick & Fournier, 1998). Thus, we specify 10,000 consumers to a positive threshold, distributed uniformly over the 0–1 interval (Delre, Jager, Bijmolt, & Janssen, 2007; van Eck, Jager, & Leeflang, 2011). The remaining 250 consumers (approximately 2.5% of the market) are innovators (with a negative threshold), responsible for initiating a naturally occurring process of diffusion (Rogers, 1995).

In Stage 3, the targeting program is executed. The effect of two input parameters of interest, namely, target size and promotion intensity, is examined. To be consistent with the previous settings, the maximum values of target size and promotion intensity are set to 10% and 1, respectively. A promotion intensity value of 1 indicates that a new product is free and the target consumers will adopt it immediately. Both parameters take 50 values with constant intervals (see Table 3).

In Stage 4, the diffusion process starts. In the agent-based environment, time is discrete ($t = 1, 2\ldots, T$). During period $t = 1$, innovators and some (or all) targeted consumers adopt the product and trigger the diffusion process. At each period $t > 1$, each consumer who has not adopted makes a decision based on the threshold and the peer effect perceived during the last period, $t - 1$. The diffusion process continues until all consumers have adopted the product or until the number of adopters no longer increases.

Each combination of target type, target size, and promotion intensity constitutes a single experiment. Once an experiment is completed, we store the simulation parameters and diffusion outcome – market share – in a data file to be analyzed later. The results of the two experiments may differ completely even if they use the same configuration parameters, because of the randomness of the threshold assignment and network construction. Therefore, we repeat each experiment 1000 times and use the average of the 1000 runs in the analysis.

4.6. Validation of the model

In a recent article, Rand and Rust (2011) presented a structured guide to rigorously validate ABMS research. According to this guide, four main steps are needed: micro-face validation (validating the mechanisms and properties of the model), macro-face validation (validating the aggregate pattern of the model), empirical input validation (checking parameter settings), and empirical output validation. The threshold model is simple; however, it is well-established in both empirical and theoretical research (Centola & Macy, 2007; Granovetter, 1978; Granovetter & Soong, 1986; Watts & Dodds, 2007). Moreover, the model can produce S-shaped diffusion processes, as documented in many studies (Hauser, Tellis, & Griffin, 2006). Thus, both micro-face and macro-face validation are achieved.

To achieve empirical input validation, real data regarding consumer network and threshold distribution (or, alternately, similar distributions) should be used as the input of the model. This would substantially improve the quality of the model and, in turn, the reliability of the results. In this study, the parameter sets are generated according to circumstantial evidence from previous research. To address this deficiency, we consider the alternative values of main parameters, including the average number of peers, the proportion of local peers, and the threshold distribution (see Table 2). The results show that our main conclusions do not depend on the specific choice of these parameter values.

Empirical output validation is difficult to achieve, because testing the research questions posed in the real world is too difficult. However, many of our findings are consistent with those of prior research. Our results support a number of studies that focus on influentials rather than random targets (Libai et al., 2013; Nejad et al., 2015) and support a few studies that recommend susceptibles and unsusceptibles (Goldenberg & Oreg, 2007; Jain et al., 1995).

5. Results

5.1. Preliminary analysis

Preliminary analysis shows that without intervention, the product will take 12.06% of the virtual market. Determining the success of the product can be difficult because the criteria for success differ across markets. However, promotion appears to be necessary. Fig. 1 illustrates the performance of targeting programs under different target schemes. The results are consistent with our intuition such that: (1) for influentials and random targets, *how to target* exhibits a similar effect on IMS, because the threshold distribution of the two groups is the same; (2) for susceptibles, increasing promotion intensity does not influence IMS once the intensity value surpasses the ceiling of the susceptibles' threshold (in this case, 0.1); and (3) for unsusceptibles, a strong enough stimulus is necessary to affect the IMS.

Table 3
Parameters of targeting program.

Parameter	No. of levels	Values or range	Source(s) for selected parameter
Target types	4	Influentials, susceptibles, unsusceptibles, and random targets	See in Table 1
Target size	50	0.2%–10% of the market	
Promotion intensity	50	0.02–1	

Table 4
Regression analysis results (dependent variable = IMS).

	H1: Influentials vs. random targets (N = 5000)	H2: Susceptibles vs. influentials (N = 1778)	H3: Unsusceptibles vs. influentials (N = 172)
Target size	0.698	0.777	0.989
Promotion intensity	0.608	0.404	0.223
Target type[a]	0.164	− 0.331	− 0.338
Adjusted R^2	0.883	0.838	0.935

Note: All reported coefficients are standardized, and are significant at $p < 0.001$.
[a] The dummy value for target type: 1 for influentials, 0 for others.

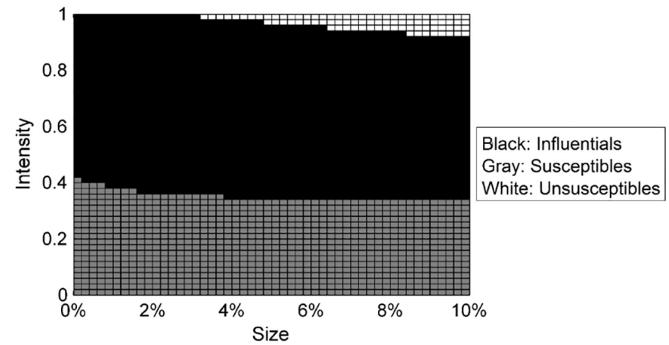

Fig. 2. Optimal targets in various size-intensity settings.

5.2. Testing hypotheses H1–H3

Hypothesis H1 predicts that in any case, targeting influentials is a better choice than random targeting. A simple comparison shows that targeting influentials produces a greater performance in all of the 2500 size-intensity combinations. We further conduct an OLS regression with IMS as dependent variable, and target size, promotion intensity, and a dummy for target type (1 for influentials, 0 for random targets) as covariates. Regression results provided in Table 4 show that the superiority of influentials versus random targets is statistically significant, supporting hypothesis H1.

Hypotheses H2 and H3 focus on the effectiveness of susceptibles and unsusceptibles compared to influentials. To illustrate this clearly, the results are organized into a cell plot (Fig. 2), where each cell is colored black, gray, or white representing influentials, susceptibles, and unsusceptibles, respectively, as optimal targets in a particular size-intensity setting.

From Fig. 2, the results are apparent. When promotion intensity is relatively low (< 0.34), susceptibles are superior to influentials (and to unsusceptibles, as well). If free products are offered to a sufficient number of consumers (above 3% of the market), unsusceptibles become the preferred option. When the promotion intensity is slightly lower than 1, firms need to increase the target size to ensure that unsusceptibles are the preferred targets. However, once promotion intensity drops to 0.92, influentials become more promising than unsusceptibles. Thus, influentials are the optimal targets in more than half of the various size-intensity settings.

The regression results corresponding to H2 and H3 can be found in Table 4. In these regression models, IMS is used as dependent variable, and independent variables include target size, promotion intensity, and a dummy for target type (1 for influentials, 0 for susceptibles and unsusceptibles). We sampled 889 size-intensity combinations (the gray segment in Fig. 2) for the case of susceptibles vs. influentials (H2), and 86 combinations (the white segment in Fig. 2) for the case of unsusceptibles vs. influentials (H3). The results demonstrate that the

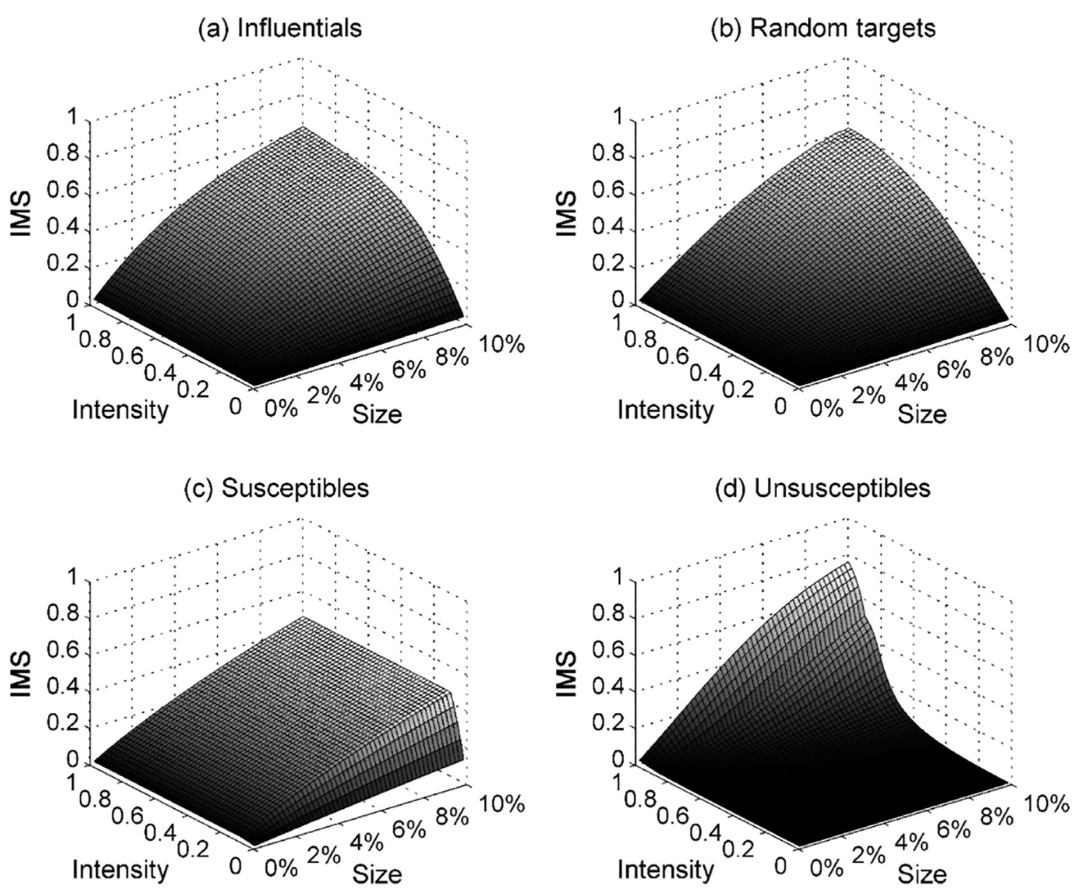

Fig. 1. Functions of *how to target* under different target types.

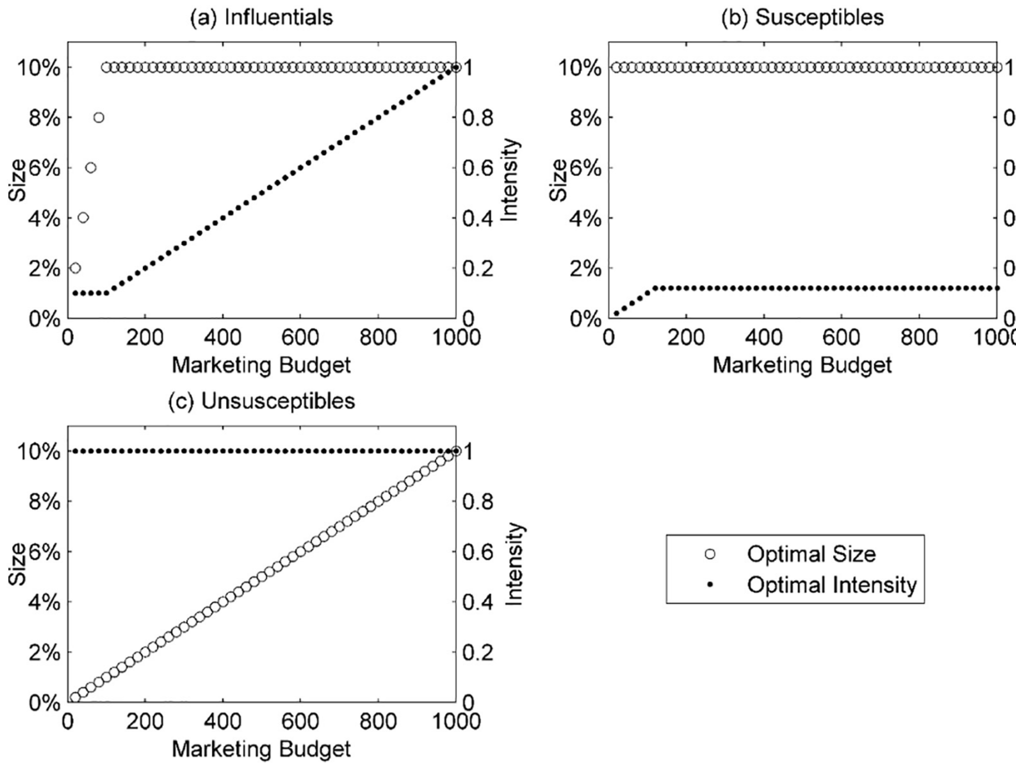

Fig. 3. Optimal settings of *how to target* under budget constraints given the target.

differences from susceptibles and unsusceptibles to influentials are statistically significant. These results, which are summarized in Fig. 2 and Table 4, support H2 and H3.

5.3. Testing hypotheses H4a–H4c

We allocate a budget from 20 to 1000 with steps of 20, and examine its constraints on the choice of *whom* and *how to target* (H4a–H4c). Fig. 3 shows the optimal size-intensity configuration for different target groups (excluding the random targets) under budget constraints. Note that each plot in Fig. 3 has two y-axes that correspond to target size (left) and promotion intensity (right), respectively.

Fig. 3(a) implies that while targeting influentials, a somewhat attractive promotion (with a promotion intensity larger than 0.1) should be provided, even if the available budget is limited. Once the budget increases, the firm should primarily increase its target size. The strategies toward susceptibles and unsusceptibles are quite straightforward, as shown in Fig. 3(b) and (c). For susceptibles, it is best to reach as many targets as possible while maintaining a low promotion intensity (0.1). For unsusceptibles, free products should be offered always.

Fig. 4 shows the optimal combination of target size, promotion intensity, and target types under budget constraints. When a budget is

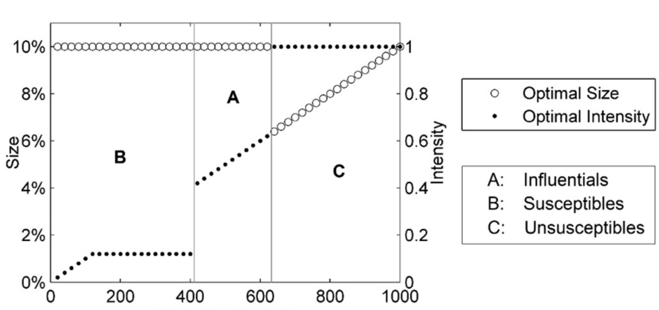

Fig. 4. Optimal combination of *whom* and *how to target* under budget constraints.

relatively low (< 400), susceptibles with low-intensity promotion are the best option. With a medium budget (400–620), influentials with moderate promotions are preferred. With a large budget (620–1000), unsusceptibles with free products are preferred. These results support the hypotheses H4a–H4c.

6. Discussion

6.1. Main findings

This study aims to improve our understanding of the effect of targeting strategies on new product diffusion. Two main findings are derived: (1) the choice of *whom to target* is highly dependent on the condition of *how to target*, and each of the three proposed consumer groups (influentials, susceptibles, and unsusceptibles) can be a promising target; and (2) the optimal configuration of *whom and how to target* is critically influenced by the size of the budget (low, medium, or large) allocated to the promotional program. The remainder of this section describes the theoretical contributions and management implications of this study, as well as limitations and directions for future research.

6.2. Theoretical contributions

First, we show how a firm should drive the diffusion of new products by various promotion options from offering a small discount to giving away a free product. Previous studies often recommend seeding the market through giving away free products. However, free giveaways are costly, especially for small businesses and manufacturing companies. Less expensive deals, such as price discounts, "buy one get one half off" deals, extra warranties, rebates, and banded promotional gifts, are more common in practice. Our results show that offering free products is uneconomical for targeting influentials and, especially, susceptibles, although both of them are the most recommended targets for seeding programs. The findings call for a comprehensive consideration of promotion intensity in exploring targeting strategies.

Second, this study explains the conflicting views on *whom to target*, which may be the most controversial issue in the related literature (Hinz et al., 2011; Libai et al., 2013; Nejad et al., 2015). Our results show that determining the most promising targets are closely related to promotion intensity and target size. Specifically, targeting influentials is the best choice when offering a moderate promotion, while susceptibles and unsusceptibles are the optimal targets when offering weak and strong promotions, respectively. These results support our conjecture that *whom to target* is a function of *how to target*.

Third, this study highlights the influence of marketing budget on the design of targeting strategies. Despite the importance of budgets in marketing practice, targeting strategies under budget constraints are not widely reported in the literature. A few studies have looked at how the cost of promotions affects optimal target size, but their focus have been on determining whether targeting programs are worth investing in (Lehmann & Esteban-Bravo, 2006; Nejad et al., 2015). This research shows that marketing budgets critically affect both *whom* and *how to target*. It suggests that future research should fully consider the role of marketing budgets in exploring targeting strategies.

6.3. Managerial implications

This study provides guidelines for selecting appropriate targeting strategies under various conditions. The results suggest that, to successfully launch a new product with a limited budget, a firm should focus exclusively on susceptibles and provide a weak promotion. This finding vindicates the marketing practices aiming at those who are most likely to purchase from the firm. Many businesses run loyalty programs, whereby a customer who makes frequent purchases gets discounts, coupons, or points toward merchandise. In these programs, the reward is often much lower than the price of a product, but it still effectively influences customers' purchase intentions. Popular examples include the Amazon Prime program that provides free, two-day shipping to subscribers (Amazon, 2017); Apple's offer to accept a trade-in of an old iPhone for $100–300 toward the purchase of iPhone 7 (Apple, 2017); and Samsung's trade-in program for launching the Galaxy S8 (Samsung, 2017). According to our results, we stress that targeting susceptibles with a low-intensity promotion is particularly suitable for firms whose products' marginal cost is high.

The results also show that targeting influentials is more promising than targeting susceptibles, if marketers are willing to spend more money on promotion. Marketing to influentials has resulted in the success of many products, such as 3M's Post-it® Notes and Pepsi's Sierra Mist Ruby Splash diet soda (Chief Marketer, 2009; Kirby & Marsden, 2005). This strategy becomes popular more than ever in the presence of social media. What is highlighted in this study is that the promotion offered to influentials should be intensive, such as a 50% discount, because motivating influentials to adopt a new product is not an easy task (Kozinets, Valck, Wojnicki, & Wilner, 2010). It is worth noting that only a small body of influentials has to be seeded by free giveaways. This is supported by the success of Ford's Fiesta car and HP's Dragon laptop; both of the firms only seeded a small group of prominent bloggers (Quinton, 2008; Tegler, 2009).

Our results suggest that, if a firm's budget for promotion is large, unsusceptibles are the most ideal targets. Targeting unsusceptibles with free products is often practiced to capture the customers of competitors, especially when the competitor has the monopoly in a market. For example, Google launched its Chrome operating system for free, a move to attract consumers habituated to Microsoft's Windows operating system (Reuters, 2009). Similarly, Microsoft released IE explorer for free to compete with Netscape's Navigator, which was the most widely used web browser at that time (Fontana, 2007). Consumers are persistent on their consumptive habits. A strong promotional campaign is a good way to educate consumers and change their consumptive habits. Hence, seeding unsusceptibles can also be applied when launching revolutionary products. It should be noted, however, that this strategy is better suited for firms whose products' marginal cost is low.

6.4. Limitations and directions for further research

This study is subject to some limitations and can be extended in several ways. The literature suggests that the susceptibility of a consumer to peer effects is also influenced by his or her social network position (Obstfeld, 2005). Therefore, an investigation of the correlation between degree and susceptibility may produce useful insights. The literature also points out that peer effects can be negative (Granovetter & Soong, 1986). Consider luxuries that are purchased to convey elevated status: the more people that purchase these products, the less these products allow them to convey elevated status. The dark side of peer effects may dramatically change the process of diffusion and in turn, influence the choice of targeting strategies. Therefore, it deserves further investigation in future research.

Future studies can also examine more complex targeting strategies. In this study, we only consider targeting programs implemented before the launch of a new product. However, the effect of targeting programs running at different stages in the product lifecycle may be interesting to marketers (Delre et al., 2007). In addition, we classify target groups only according to a consumer's number of peers or their susceptibility to peer effects. It would be interesting to explore whether using a hybrid metric (e.g., influentials with a high susceptibility) is important in the design of an effective targeting program.

Finally, running our ABMS experiments on hypothetical settings of consumer network and threshold distribution has its limitation. Although all parameter values in our model are derived from published studies, using the data provided by firms that operate with real targeting and WOM campaigns would generate more meaningful insights for developing targeting strategies. Some recent studies have fruitfully demonstrated how ABMS can heavily benefit from empirical support (Delre, Broekhuizen, & Bijmolt, 2016; Libai et al., 2013; Nejad et al., 2015; Toubia, Goldenberg, & Garcia, 2014; Trusov, Rand, & Joshi, 2013). Taking this one step further, it would be meaningful to test our hypotheses in a laboratory study and, if possible, an empirical field study.

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