Agent-Based Model to Viral Marketing: Influence of Mass Media, Positive and Negative Word-of-Mouth to Product Adoption

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Resumo
With the rise of social networks, viral marketing strategies offers many advantages to the firm. Word-of-mouth (WOM) communication strategies are appealing because they combine the prospect of overcoming consumer resistance with significantly lower costs and fast delivery. WOM has a stronger impact on new customer acquisition than traditional forms of marketing. Since the innovation diffusion process often involves thousands of potential adopters, researchers often use hypothetical network structures that have characteristics similar to real-world networks, as Agent-Based Model's (ABM). Based on diffusion processes of new products and viral marketing, this study investigates the effects of mass media, positive and negative WOM in the information dissemination of a typical product. Through the adaptation of information diffusion model (Bass, 1969), the role of negative WOM (resistors) was incorporated with influencers and imitators. As result, it confirms the role of network structure and network density in speed diffusion. The model shows that mass media has little influence compared with power of WOM in decision to adopt a new product on the market.

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Abstract: With the rise of social networks, viral marketing strategies offers many advantages to the firm. Word-of-mouth (WOM) communication strategies are appealing because they combine the prospect of overcoming consumer resistance with significantly lower costs and fast delivery. WOM has a stronger impact on new customer acquisition than traditional forms of marketing. Since the innovation diffusion process often involves thousands of potential adopters, researchers often use hypothetical network structures that have characteristics similar to real-world networks, as Agent-Based Model's (ABM). Based on diffusion processes of new products and viral marketing, this study investigates the effects of mass media, positive and negative WOM in the information dissemination of a typical product. Through the adaptation of information diffusion model (Bass, 1969), the role of negative WOM (resistors) was incorporated with influencers and imitators. As result, it confirms the role of network structure and network density in speed diffusion. The model shows that mass media has little influence compared with power of WOM in decision to adopt a new product on the market.
Keywords: Viral Marketing. Word-of-Mouth. Information dissemination. New products. Agent-Based Modeling.

1 Introduction

The growth of YouTube, Twitter, Facebook, Instagram and other digital social media capabilities has given marketing managers new platforms by which to advertise and market their products to consumers (Stonedahl, Rand & Wilensky, 2010). The viral marketing concept suggest that marketers can leverage the power of interpersonal networks to promote a product or service, that assumes that electronic, peer-to-peer communications are an effective means to transform communication networks into influence networks, capturing recipients' attention, triggering interest, and eventually leading to adoption or sales (De Bruyn, & Lilien, 2008). Also offers a way for companies by quickly and virally penetrates through markets, generating mass awareness and converting large numbers of consumers (Wang, 2008) and thus maximize the success of viral marketing campaigns (Hinz, Skiera, Barrot & Becker, 2011).

The premise of viral marketing is that by initially targeting a few influential members of the network, it can trigger a cascade of influence by which friends will recommend the product to other friends, and many individuals will ultimately try it (Kempe, Kleinberg & Tardos, 2003). This social network setting offers an appealing context to study word-of-mouth (Trusov, Bucklin & Pauwels, 2009). The significant role of word-of-mouth (WOM) in the dissemination of market information is supported by broad agreement among practitioners and academics (Goldenberg, Libai & Muller, 2001). While the primary dissemination mechanism of viral is by no means new, the concept that consumers can also be salespeople of the product within their social networks by sharing a video, post or website is and become strong nowadays (Wang, 2008).

And not just for positive WOM, unlike the positive interactions of consumers that lead to adoption and growth of sales, negative WOM is an invisible force, that do not have reliable measures about how shrinks the market by transforming potential adopters into non-adopters (Goldenberg, Libai, Moldovan & Muller, 2007), marketers can underestimate the presence of negative WOM in the marketplace and its potential impact on new product diffusion, since the most common sources of negative WOM are known to be dissatisfied adopters or product rejecters (Amini, Wakolbinger, Racer & Nejad, 2012).

However, researchers who have addressed WOM communications have usually been limited in their ability to collect complete, detailed, and accurate information. Largely because of the lack of such data, the mechanisms by which WOM communications influence behaviors are not well understood (De Bruyn, & Lilien, 2008). Then, while designing and executing a real-life experiment to study viral marketing is costly and time-consuming, a computational modeling method called agent-based modeling (ABM) offers a convenient method with which to study viral marketing. ABM focuses on a bottom-up approach to modeling society; it codes observable micro-motives in the model to predict societal macro-trends (Wang, 2008). This method is likely to assume a larger role in our understanding of the world (Rand & Rust, 2011).

ABM allows for the possibility of repeated simulations to find the mean behavior of stochastic, indeterminate processes, as well as the variation around the mean behavior. Such research goals are nearly impossible to obtain from empirical data because a data set that includes the same network with different characteristics yet the same diffusing process usually does not exist (Goldenberg et al., 2007). The key features of the ABM simulation includes that consumers' new product adoption decisions are influenced by marketing activities as well as positive and negative WOM between consumers and the interactions among them taking place in the context of their social network are captured at the individual level (Amini et al., 2012).

Agent-based modeling investigates aggregate phenomena by simulating the behavior of individual "agents", such as consumers or organizations, and observes the aggregate results, which can possibility substantial benefits for marketing (Rand & Rust, 2011), as diffusion models affects firms ability to successfully market innovations, a reason to determines whether they can create competitive advantage and secure long-term success. Since act as a tool that help them to pre-estimate the market response to new products, provide model-based decision-support, and allow to assess new product introduction strategies (Kiesling, Günther, Stummer, & Wakolbinger, 2012).

Based on the diffusion processes theory and viral marketing, specifically using ABM, this study goal to investigate the effects of mass media, positive and negative WOM in the dissemination of product information. The study aims to answer this research questions: Which of the effects - mass media, positive WOM or negative WOM - has more influence on the aggregate growth of information dissemination? How does the network density in which individuals are linked affect adoption of an innovation? Which of the two WOM paths will have more impact on product adoption?

The article discusses the theoretical studies on viral marketing, specifying for agent-based models of social diffusion; in the sequence, addresses the positive and negative peer effects (WOM). In the methodology is presented the model properties of ABM viral marketing, the experimental design and parameter settings. Following the analysis of results and discussion with the contributions of the study.

2 Background

2.1 Viral marketing

Viral marketing utilizes advertisements or types of content communication that encourage or incentivize agents to spread the advertisement within their social network, thus creating the potential for exponential growth in the message's exposure and influence (Bampo et al., 2008). In essence, the target audience members serve as the distributor of the advertisement (Wang, 2008), without involvement of the original source (Woerndl, Papagiannidis, Bourlakis & Li, 2008), based on the idea that customers and consumers discussions about a product are more powerful than traditional advertising (Stonedahl, Rand & Wilensky, 2010). Once consumers often make buying decisions based on their friends' advice or their social network, which affects product diffusion and influences the dominance of a brand in a market (Rand & Rust, 2011), and will generate to the company awareness and conversion (Wang, 2008).

The spread of information in a given social system may be described as "an adaptive complex system", i.e., a system that consists of a large number of individual entities which interact with each other, ultimately generating large-scale, collective visible behavior (Goldenberg, Libai & Muller, 2001). The most common intentional viral marketing is word-of-mouth marketing, that occurs when consumers willingly become promoters of a product or service and spread the message to their friends; they are driven to do so either through an explicit incentive (e.g., financial incentives, need to create network externalities) or simply out of a desire to share the product benefits with friends (De Bruyn & Lilien, 2008).

In this way, marketers are actively using it to encourage product adoption and word-of-mouth (WOM) referral, because viral marketing offers three main advantages: first, it incurs little expense since the individual carries the cost of forwarding the brand message; second, the act of forwarding electronic messages is voluntary rather than a paid testimonial or a mass ad campaign and thus may be viewed more favorably by the recipient; third, those forwarding the messages will be more likely to know which of their friends, family members, and work colleagues have similar interests and thus more likely to read the message, hence, more effective targeting (Dobele, Toleman & Beverland, 2005).

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 (Hu, Lin, Qian & Sun, 2018). WOM communications have received extensive attention from both academics and practitioners for decades (De Bruyn & Lilien, 2008). WOM communication strategies are appealing because they combine the prospect of overcoming consumer resistance with significantly lower costs and fast delivery. Since that beyond a relatively early stage of the process, the effect of external marketing efforts (e.g., advertising) quickly diminishes and strong and weak ties become the main forces propelling the process (Goldenberg et al., 2001). Unfortunately, empirical evidence is currently scarce regarding the relative effectiveness of WOM marketing in increasing firm performance over time (Trusov et al., 2009).

Besides, Trusov et al. (2009) find that a change in WOM activity continues to significantly affect the firm's new signups for 21 days. WOM also has a much stronger impact on new customer acquisition than traditional forms of marketing. In particular, long-run WOM elasticity is about 20 times higher than the elasticity for marketing events, significant for only five days. The study of Wang (2008) found that viral advertisement effectively overcome the lack of awareness in the beginning by taking advantage of the ability to quickly generate awareness through WOM. However, in the end, viral marketing is only marginally more effective than traditional marketing, but that advantage is significant. De Bruyn and Lilien (2008) work suggests to online marketers that not all social networks are equally effective for harnessing the potential of peer-to-peer referrals, it seems that networks of friends (as opposed to networks of professionals or colleagues) are more suited to the rapid and effective diffusion of peer-to-peer online referrals.

Previous studies have examined the crucial contribution of opinion leaders and positive WOM on new product adoption, under the assumption that advertising is vital when launching the innovation but less essential to its diffusion. Moldovan and Goldenberg (2004) attempted to understand the dynamics underlying the innovation adoption process by adding resistance leaders and negative WOM to a model of market growth. It has demonstrated that not only do resistance leaders significantly reduce the ultimate market size, their very existence may completely negate the positive effect of the opinion leaders. The work of Goldenberg et al. (2007) found that, the optimal level of advertising is highly affected by the process of WOM and too much advertising might indeed negatively affect profitability.

Hinz et al. (2011) undertake an empirical comparison of the success of different seeding strategies for viral marketing campaigns and identify that marketers can achieve the highest number of referrals if they seed the message to hubs (high-degree seeding) or bridges (high-betweenness seeding). These two strategies clearly outperform both the random strategy (+52%) and are up to 8 times more successful than seeding to fringes (low-degree seeding).

Given the importance of viralization of brand messages, studies show controversial results and understanding how the presence of dissatisfied customers interacts with the social structure and the ways messages are passed from consumer to consumer is of practical importance. Despite these studies, researchers who have addressed WOM communications have usually been limited in their ability to collect complete, detailed, and accurate information (De Bruyn, & Lilien, 2008). In this way, is highlighted studies about the diffusion process with an agent-based modeling (ABM) approach including heterogeneity effects and the influence of different types of social network structures (Bohlmann, Calantone, & Zhao, 2010).

2.2 Agent-based models of social diffusion

The diffusion process consists of four key elements: innovation, communication channels, time, and the social system. By definition, diffusion models are concerned with representing the growth of a product category (Mahajan, Muller & Bass, 1990). Diffusion theory’s focus is on the means by which information about an innovation is communicated within or transmitted to a social system. members of a social system have different propensities for relying on mass media or interpersonal channels when making decisions about adopting an innovation (Mahajan et al., 1990; Bohlmann et al., 2010). Then, the diffusion pattern that results from the interaction of many consumers may be much more complex than the adoption rules of the individuals (Rand & Rust, 2011).

In a social 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 (Hu et al., 2018). Since the innovation diffusion process often involves thousands or even millions of potential adopters, researchers often use hypothetical network structures that are believed to have characteristics similar to real-world networks (Bohlmann et al., 2010). While this makes external validation difficult, simulated models do allow a comprehensive look into how certain characteristics of the network influence the diffusion process (Bohlmann et al., 2010). Then to overcome the limitations and open up new research opportunities, agent-based modeling and simulation (ABMS), as a computational modeling tool, has increasingly been adopted in diffusion research in recent years (Kiesling, Günther, Stummer & Wakolbinger, 2012).

ABMS allows to capture: (a) consumers as agents with three essential attributes: autonomy, interactivity, and bounded rationality, i.e., agents that are neither fully informed nor fully rational (Wang, 2008); (b) dynamic social network interactions among consumers; (c) the effect of marketing activities on consumers; (d) positive and negative WOM between consumers; and (e) adoption status of individual consumers as well as aggregate diffusion at the market level throughout the new product diffusion process (Amini et al, 2012).

To Rand and Rust (2011), the strongest benefit of using an ABM approach within marketing is that the actions of firms and consumers within the model can be constructed based upon strong theories of behavior, but at the same time, the results can be validated against empirical data and the model can then be used to make predictions. In this way, one purpose of ABM’s is to identify improved business practices that can then be implemented in the company. If the model is expressed and modified directly in terms of behaviors, implementation of its recommendations is a matter of transcribing the modified behaviors of the agents into task descriptions for the entities in the real world (Jiang, Bass & Bass, 2006).

A pivotal element of agent-based diffusion models is the explicit representation of consumers' decision making processes, consider the interactions between individuals on the micro-level, most importantly those related to the decision to adopt an innovation (or to reject it) (Kiesling et al., 2012). Then, ABMs produced novel insights into the role of social influence, and WOM is arguably the most relevant form of micro-level social influence, boost by the fact that social networks tend to be highly clustered (Kiesling et al., 2012). So ABM studies allow one to pinpoint the key communicators within a network and the extent to which they must be influenced to affect adoption decisions of others in the network (Bohlmann et al., 2010).

2.2.1 Positive and negative peer effects (WOM): a way underlying diffusion

Accordingly Moldovan and Goldenberg (2004), when an idea is perceived as new, individuals will seek information to evaluate its expected utility and consequences. WOM and other interpersonal communications occur among individuals who have already adopted the idea, on one hand, and other individuals in the market, on the other. To Stonedahl et al. (2010), assuming that product is beneficial and that seeded consumers are inclined to speak positively about it, sowing more consumers will increase the speed of product adoption. However, seeded consumers are removed from the pool of potential customers, which can decrease total product revenue. Thus, it is important to choose the right target consumers to seed and correct the propagation budget to maximize adoption.

Literature analysis suggests that whom to target may be a function of how to target, the role of susceptibles *versus* influentials in targeting programs is relevant to promotion intensity (Hu et al., 2018). Besides, it is distinguishes the role of leaders who can influence positively or negatively (resistors) the brand message. Influentials have several advantages over ordinary consumers in terms of promotional targets: first, they are linked to many others directly or indirectly, targeting them exposes the product to a large number of consumers; second, influential have a strong influence on the attitudes and behaviors of other consumers. In opposition, unsusceptibles or resistors, in fact, plays a critical role in the process of diffusion and often disrupt the chain of adoption, they effectively offset the positive influence of influentials and susceptibles (Hu et al, 2018).

As example, the study of Moldovan and Goldenberg (2004) adopted consumers in one of three states: uninformed (not spreading WOM), adopter (spreading positive WOM), or resistor (spreading negative WOM). The population is exogenously divided into three groups: (1) opinion leaders, who may only adopt the innovation, (2) resistance leaders, who may only reject the innovation, and (3) regular consumers subject to both positive and negative WOM. The results indicate that resistance leaders will reduce sales significantly, as a function of both their relative number and the strength of their social influence. Then, firms may benefit if they are able to identify and activate opinion leaders at an early stage of the launch, to encourage positive WOM, and to discourage negative WOM.

Hu et al. (2018) study findings' are: (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 (influential, susceptible, and unsusceptible) 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 allocated to the promotional program. In this way, targeting influential is the best choice when offering a moderate promotion, while susceptible and unsusceptible are the optimal targets when offering weak and strong promotions, respectively.

Generally, the marketing literature suggests that negative WOM has a greater impact on potential consumers' adoption decisions than positive WOM. Because the behavior and views of individuals tends to be weighted more heavily by negative WOM than positive communication. These consumers will communicate their dissatisfaction to at least nine other people and 13% of these dissatisfied consumers will communicate their negative view to more than thirty people (Solomon, 2004). Despite, marketing literature pays little attention to the negative form of WOM. Roots of negative WOM may range from dissatisfaction with a specific product to a generalized opposition to change. Dissatisfaction with a new product usually arises from inadequate performance relative to expectations (Moldovan, & Goldenberg, 2004). Furthermore, each additional percentage point of dissatisfied customers increases by 1.8% the harm caused by negative WOM in Net Present Value (NPV) (Goldenberg et al., 2007).

Therefore, even a small percentage of dissatisfied consumers can cause considerable damage to long-term profits, since they create an invisible diffusion of product rejection which may not be noticed immediately (Amini et al., 2012; Goldenberg et al., 2007; Hu et al, 2018; Kiesling et al., 2012). The studies of Amini et al. (2012) and Kiesling et al. (2012) unequivocally suggest that managers planning the market introduction of an innovation should heed to warns of the destructive power of negative WOM. Neglecting this effect can lead to poor policy recommendations, incorrect conclusions concerning the impact of operational parameters on the policy choice, and suboptimal choice of build-up periods (Amini et al., 2012).

2.3 Model properties of ABM viral marketing

The model developed by Bass (1969), which characterizes the diffusion of an innovation as a contagious process that is initiated by mass communication and propelled by WOM is widely cited (Amini et al., 2012). The most important model assumptions is based on: agents live in a closed world; are independent but can be swayed by peer pressure and WOM; there is only one market segmentation and all agents are target consumers; agents can only consume one product at a time, and all have the same influence (Wang, 2008).

The Bass model is an aggregate model of diffusion, do not explicitly consider consumers' heterogeneity and the complex dynamics of social processes that shape the diffusion and can therefore tackle only a limited set of theoretical issues. However, even in this aggregate model, two (p and q) of the three parameters (p, q, and m) are related to individual-level characteristics. The rates of adoption are based on mass media (coefficient of innovation, p) and word-of-mouth (coefficient of imitation, q) (Rand & Rust, 2011) in a market (m).

The adopters of an innovation comprise two groups: one group is influenced by the mass-media communication "p" (external influence) and the other group is influenced by the WOM "q" (internal influence) (Lee, Trimi & Kim, 2013; Mahajan et al., 1990). Bass (1969) termed the first group Innovators and the second group Imitators. The imitation effect comes from social interactions, and is closely related to subjective norm and WOM, for this reason there were temporal changes of innovation and imitation effects: the innovation effect was more influential for innovators and opinion leaders than it was for the entire adopter population; however, the innovation effect diminished as time passed. Conversely, the imitation effect became a powerful factor for all adopters (Lee et al., 2013).

The Bass model derives from a hazard function (the probability that an adoption will occur at time t given that it has not yet occurred). This premise states that the conditional probability of adoption at time t (the fraction of the population that will adopt at time t) is increasing in the fraction of the population that has already adopted. Therefore, the basic premise states that part of the adoption influence depends on imitation or "learning" and part of it does not (Mahajan et al., 1990). To Bohlmann et al. (2010), adoption involves a deliberate choice by an individual based upon specific social interactions, especially in the case of high involvement products (e.g., consumer durables). Therefore, there are systematic differences in adoption times across individuals based upon when and with whom they interact; it is not just who you are but also where you are located and with whom you are associated that make a difference in diffusion networks.

In addition to properties and behaviors of model agents, another important decision is with the environment (Rand & Rust, 2011). The environment refers the agents' interaction topology. Diffusion can be very difficult to predict, and network structure can impact diffusion in terms of peak adoption and the likelihood of saturated diffusion (Bohlmann et al., 2010), and have a significant impact on campaign performance (Bampo et al., 2008). Then, network topology refers to the shape or structure of a network, which determines how different nodes (individual agents) in a network are connected to each other and how they communicate, what may lead to fundamentally different diffusion patterns (Bohlmann et al., 2010).

A network is specified by a set of *nodes* and a set of *edges* linking pairs of nodes. The nodes represent members of the population, or audience, and the edges represent communication links between them that may be used to spread the viral message (Bampo et al., 2008). There is no consensus on what might be a typical network size for weak and strong ties. Classic cellular automata research uses a strong-tie network of eight individuals around each agent; however, the range covered 8-28 still reflects a reasonable range for a product-related personal network (Goldenberg et al., 2007). A recent experiment found that the average number of consumers' social ties is 25 (Goldenberg, et al., 2007).

Random networks, as opposed to more regular or more clustered ones, tend to favor the spread of information and they are therefore frequently associated with faster diffusion and an increased share of adopters at the end of the diffusion process (Kiesling et al., 2012). The random network can be defined as: N vertices are connected by edges, such that each pair of vertices (i,j) has a connecting edge with independent probability *p*. In a random network, if the average number of edges per vertex is z, a vertex will have z neighbors, z^2 second neighbors, z^3 third neighbors, and so on (Bohlmann et al., 2010).

3 Research Methodology

3.1 Viral Marketing ABM

This study used a mathematical diffusion model to verified time-series data of the number of adopters. In ABM, the social system is modeled as a collection of autonomous decision-making units, or agents. Individual agents have local networks that define the set of other agents connected to them, based on the overall topology of the network. For the innovation diffusion problem, agents make an adoption decision based upon inter-actions with other agents within their local network (Bohlmann et al., 2010).

The properties of the agents in this model are initially based on the original macro-level model (Bass, 1969). The rules that define transitions of potential adopters from state to state are: mass media factors, such as advertising, where a probability *p* exists that an individual will be influenced by these factors to adopt the innovative product; and local factors, where a probability *q* exists that during a given time period, an individual will be influenced by an interaction with another individual (Goldenberg et al., 2007). In the network version, each agent will also have a set of neighboring agents. The output measure is the number of adopters and non-adopters per time step. The model is run on NetLogo, a platform designed to create ABM.

The formula for an agent's decision to adopt a product follows the Rand and Rust model (2011), which is an adaptation of the classic model of Bass (1969). Any agent i who has not yet adopted the innovation (i.e., $adopted_i$=false) decides whether to adopt the innovation. This is done by generating two random variables each time step and comparing them to the p and q values, after which the $adopted_i$ state variable is updated appropriately. Specifically, $adopted_i$=true if:

$$x_{1,i} < p \; or \; x_{2,i} < q * \frac{n_{a,i}}{n_i} \qquad (1)$$

where n_i is the number of neighbors of agent i and $n_{a,I}$ is the number of neighbors of agent i who are in the adopted=true state. Rand and Rust (2011) model considers two different agents in a product innovation diffusion process: influencers and imitators; each agent determines whether to adopt separately from other agents and then updates its status at the end of an iteration after all other agents have had a chance.

3.1.1 Model adaptation: WOM by agent type

In this study, a third agent is incorporated, resistors, which negatively affect the product information broadcast (negative WOM). The agent decision to adopt a product depends on mass media effect, the number of resistors in neighborhood who has a negative network impact in such decision and the number of influential neighbors who has a positive effect.

The mass media is regulated by parameter p which affects only the agents whose has neither adopted an innovation or decide not adopt, following the resistors. In this case an agent i at time t, will decide to adopt a new product (A = T) by mass media influence if p is greater than a uniform probability functions:

$$A_{i,t} = \begin{cases} True & if \; p \geq Unif[0,1] \\ False & otherwise \end{cases} \qquad (2)$$

On the other hands, the WOM effect for each agent (ωi) is regulated by parameter qi and depends on the number of neighbors (links) and is computed to random network, as follow:

$$\omega_1 = 2q_1 \frac{l_i^{infl}}{l_i^{neigh}} \qquad \text{for influentials} \qquad (3)$$

$$\omega_{2a} = q_2 \frac{l_{i,adopt=T}^{Imit}}{l_i^{neigh}} \qquad \text{for imitators who adopted} \qquad (4)$$

$$\omega_{2b} = q_2 \frac{l_{i,adopt=F}^{imit}}{l_i^{neigh}} \qquad \text{for imitators who not adopted} \qquad (5)$$

$$\omega_3 = 3q_3 \frac{l_{i,resist=T}^{Imit}}{l_i^{neigh}} \qquad \text{for resistor} \qquad (6)$$

Where qi is a parameter, $l^i_{adopt=T,F}$ is the number of linked agents who has adopted or non-adopted innovation by imitation and A_{imit} is the total number agents that imitate. How agents decide to adopt or not? The agents will consider adopting an innovation by imitation if:

$$A_{i,t} = \begin{cases} True & if \; p \geq Unif[0,1] \\ False & otherwise \end{cases} \qquad (7)$$

Based on this model, this study model performs as in the Amini et al. (2012) and Goldenberg et al. (2007), influenced by positive and negative WOM and marketing efforts, potential consumers decide to adopt the product or reject it. While positive WOM communicated with the undecided consumer through his/her social ties and marketing effort encourage undecided consumers to adopt the new product, negative WOM discourages potential adopters from adopting.

In accordance with Goldenberg et al. (2007) and the above-mentioned literature, we can assume that negative WOM effect is stronger than positive. Hence, the effect of negative WOM may be x times as strong as that of positive WOM. The parameter that describes the relative power of negative word-of-mouth is fixed at a reasonable level of three. Similarly, it is assumed that an influencer is stronger than the imitating agents of model, thus, a multiplier (2) has been inserted for the role of the influencers. Thus, we created a hierarchical level in this model as follows: the resistors (negative WOM) has a value 3, influencers (positive WOM) has value 2 and the imitating agents are regarded as value 1, they will be affected by mass media, resistors and influencers and decide whether to adopt the product.

3.2 Experiment design and parameter settings

The network topology is another model input. The random network was chosen because are frequently associated with faster diffusion and an increased share of adopters at diffusion process (Kiesling et al., 2012). Erdös and Rényi (1959) define a random graph as N labeled nodes connected by n edges, which are chosen randomly from the N(N-1)/2 possible edges. A random network can be generated by starting with a set of isolated nodes and allowing each of the *N* nodes to have a probability θ of being connected by an edge to each other node (Bampo et al., 2008). To calculate the random network it was simulated a network-density fraction from 10% to 100% of connections that can exist between individuals (Rand & Rust, 2011).

The structure model developed in NetLogo is shown in Figure 1. In the virtual market created there are proposed three types of agents (m=300): influential are represented by yellow triangles, resistors by blue squares, imitators are represented by white circles. The parameter representing the mass media (p) is the green target set at the center of the virtual market. It is important to remember that mass media does not depend on links between agents. The mass media parameter can be activated or not in the simulation. In Figure 01 are hidden links that interconnect agents according to the random network structure to facilitate visualization.

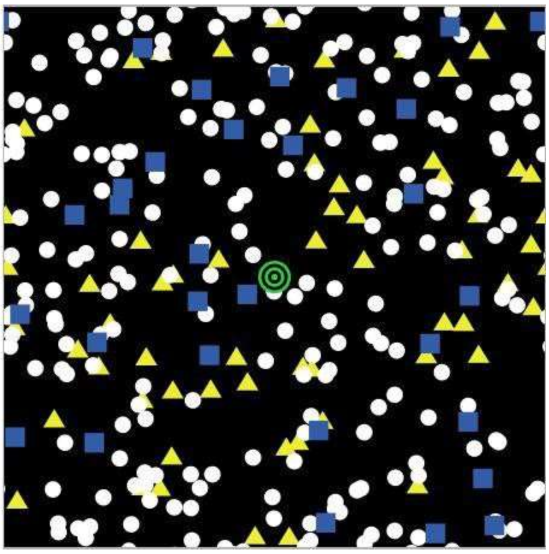

Figure 1. Virtual market model interface.
Note. Source - Authors, 2018 from NetLogo interface.

In NetLogo, the initialization step model creates the agents and the network. In each iteration step (t, t+1, t+2, t+3… t+n), each agent determines if it will innovate or imitate by

WOM (positive or negative). Repeated simulation cycles represent the progression of time as would be observed in a real-world diffusion process. The model does not give the option to remain netro, ie, all agents must choose to adopt or not adopt. To Bohlmann et al. (2010) equilibrium model is defined as a situation where none of the non-adopters has enough adopters in their respective neighborhoods to exceed the adoption threshold. However, in this model by virtue of resistor performance, there will always be subjects who will not adopt the product, so the model stops when all players have made their choice.

To calculate the individual-level parameters, it was chose the value of aggregate-level parameters q = 0.4 and p = 0.03, this values selected represent average values considered for a typical product (Jiang et al., 2006). This p and q values are the overall average of the averages for five product categories (Home Appliances, housewares, consumer electronics, business & Consumer Products and subscription services) which considered 39 products estimates. The m value is the size of the market of potential adopters; it was choose a market of 300 consumers. The Table 1 shows the model parameters and the used values.

Table 1
Parameter Choices for ABM Computational Experiments

ABM Simulation Model Parameters	
Parameters	**Parameter Value or Range**
Market size (m)	300
Coefficient of innovation (p)	0.03
Coefficient of imitation (q)	0.40
Network topology	Random
Percentage of non-adopters (resistors)	10%
Percentage of influentials (adopters)	20%
Relative power of resistors (negative WOM) to imitators	3
Relative power of influential to imitators	2
Network-density	0.01 – 0.1
Coefficient of mass media	Set 1 at beginning

Note. At each step in time, the imitators are influenced by one of the parameters (p or q) and change color depending on the choice made.

4 Analysis

To generate data from the model we use the built-in BehaviorSpace software tool. BehaviorSpace is a platform that enables users to perform runs of NetLogo models with varying parameter settings and simulations were run. It follows the figure related to the number of adopters of a typical product in the market, considering 300 subjects interconnected by means of a random network. The following scenario should be considered: percentage of influences = 20% and percentage of resistors = 10%, knowing that the percentage of imitating agents in the model is the difference of the sum total of the percentage of the influencers and resistors.

The results were imported to R to adjust variables, make computations and graphs. The Figure 2 shows the results of 100 simulations with no fixed random-seed to identify some pattern of product adoption. It was used the network density of 30% and a market of 300. Notes a high consistency in the model with respect to product adoption rates. Confirming the robustness model, i.e., changes in pseudo-random seeds do not produce very different results. Congruent with the properties of the random network, this virtual scenario agents' respond by a high innovation dissemination of a product in the market, with the adoption by more than 250 agents until the period of 50 steps.

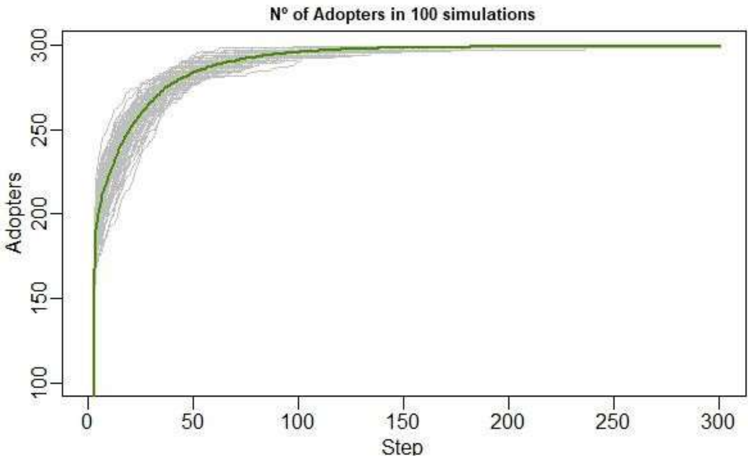

Figure 2. Number of product adopters over 100 run simulations.

The second simulation, explore how network density and topology affect the adoption of innovations. The network parameter was first set to the random topology, and the network density parameter was varied from 10% to 100% at 10% increments. For each increment, the model was executed 10 times using NetLogo's headless BehaviorSpace (Wilensky, 1999) mode, and the number of adopters at each time step was collected.

In Figure 3, each line represents a value for the density network, keeping others variables constant. Given the random distribution between agents, it is notice the rapid diffusion information, characteristic of random network (Bampo et al., 2008; Kiesling et al., 2012). Until step time 50, almost all the agents already have taken their decisions. Proving the higher the density of the network the faster the adoption of the product, therefore, the greater the diffusion process.

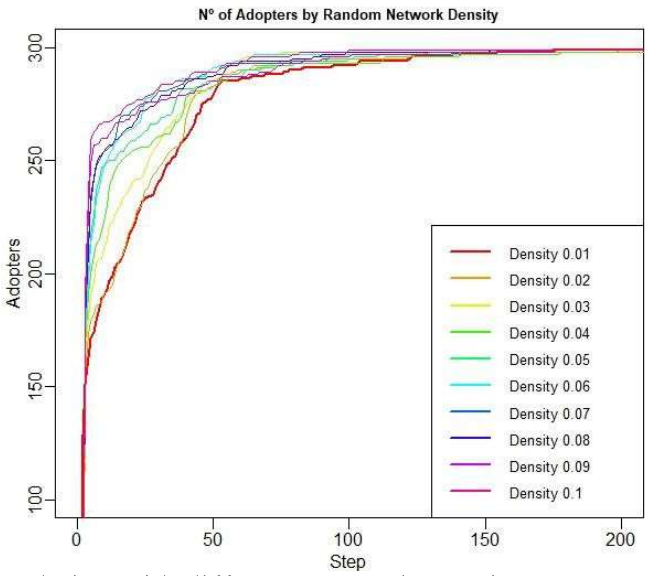

Figure 3. Import 10 simulation with different Network Density

To investigate the effects of mass media on positive and negative WOM in the dissemination of product information. A simulation switching on/off mass media was conducted, it was used the network density of 40%. Figure 4 shows the results of mass media effect.

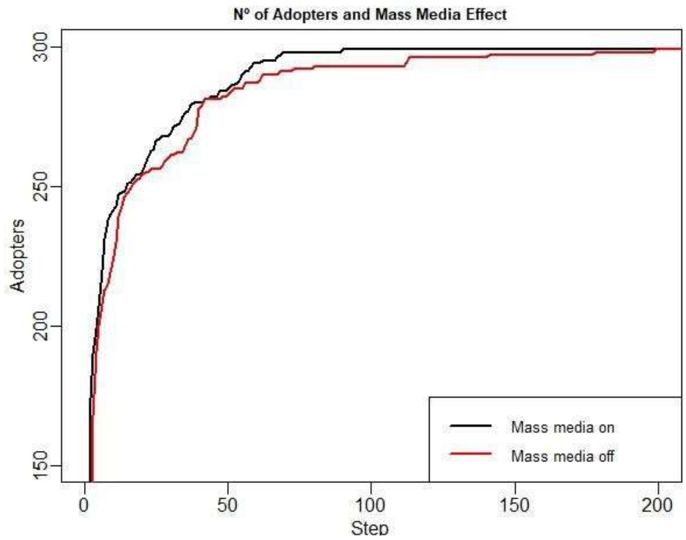

Figure 4. Simulation to compare the mass media effect on the number of adopters.

The presence of mass media accelerates product adoption, but by the current model, where the mass media effect is fixed, this impact is relatively small. However, it is stated that, even residual, this impact is positive, meaning that mass media increases the diffusion of product adoption.

Finally, to answer which of the two WOM paths will have more impact on product adoption, a new simulation was done relating the number of agents over time to type of influence adopted: mass media (p), product adoption (influencers - positive WOM) and non-adoption (resistors - negative WOM) (Figure 5).

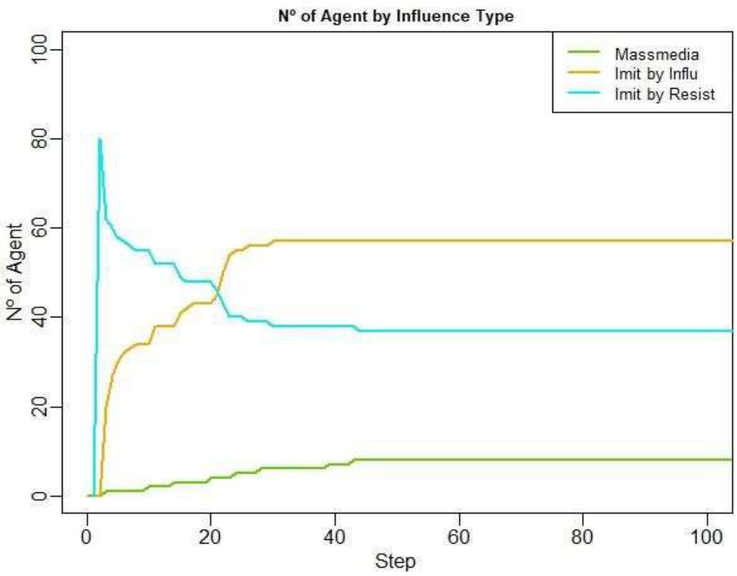

Figure 5. Total number of agents by type of influence.

It highlights the strength of the negative WOM at the beginning of product diffusion, being a threat to growth sales of the product in the market. Over time, positive WOM becomes more influential (step = 20), while mass media remains constant at low rates. This reinforces the power of WOM in adopting a new product on the market.

5 Results and Discussion

This paper uses mathematical modeling methodology to contribute to the theory of information diffusion (Bass, 1969) by adding the role of the resistor in the diffusion of negative information about a given product. And testing the aggregate effects of imitation parameter and innovation in a virtual market.

First, results confirm Lee et al. (2013) implications by identifying the social network effect in the acceleration of adoption speed through massive numbers of imitating consumers. Concurrent with the properties of random network, this virtual scenario agent responds to a high innovation dissemination of product in market (Bampo et al., 2008; Kiesling et al., 2012).

A second finding is that density network positively affects diffusion of product adoption, in the sense that the higher the density, the faster information diffusion, to random network structure. Compared the mass media power with the word-of-mouth (positive and negative), it was found that the mass media presence accelerates product adoption by information dissemination, but this impact is relatively small. Raising managerial questions for conduct and investments of product advertising campaigns. Marketers can improve their campaigns by using sociometric data to seed their viral marketing campaigns. Thus, it is essential for marketers to adopt an appropriate seeding strategy and use sociometric data to increase their profits (Hinz et al., 2011).

Third, the study reinforces the power of WOM in decision-making about a product. In particular, it demonstrates the role of negative WOM is high in initial diffusion process, which may harm the product/brand image in the market and its profitability. According Bampo et al. (2008), the impact of a viral marketing campaign is due to messages being received from friends and acquaintances and not from mass marketing.

This study has some limitations, which could provide opportunities/suggestions for future research. First, the parameters used represent the diffusion of innovation of a typical product of the market, future studies can simulate comparisons with utilitarian and hedonic products and services, to verify the impact of WOM and mass media in each one. The simulations made in this study considered only one type of network topology, future studies may use other types of networks such as preferential attachment and small words or not define any network structure to see how is the behavior of the agents. Third, the study makes only three simulations (1) the variation of the network density, (2) the presence or not of mass media and (3) number of agents by influence type. Future studies may explore the best variation of influencers' and resistors percentage in a market, if there is a balancing factor between these agents. What proportion is best for the diffusion innovation with different products and markets? Finally, as product adoption is affected by large ranging external and internal factors, such as investment in advertising, competitors, market share and brand value, it cannot be fully explained by the innovation and imitation effect. Therefore, it may be necessary to expand the model used in this study by including other relevant factors.

References

Amini, M., Wakolbinger, T., Racer, M. and Nejad, M. G. (2012). Alternative Supply Chain Production-Sales Policies for New Product Diffusion: An Agent-Based Modeling and Simulation Approach. *European Journal of Operational Research*, 216 (2), 301-311.

Bampo, M., Ewing, M. T., Mather, D. R., Stewart, D., & Wallace, M. (2008). The effects of the social structure of digital networks on viral marketing performance. *Information systems research*, *19*(3), 273-290.

Bass, F. M. (1969). A new product growth model for consumer durables. *Management Science*, 36(9), 1057–1079.

Barabási, A. -L., & Albert, R. (1999). Emergence of scaling in random networks. *Science*, 286, 509–512.

Bohlmann, J. D., Calantone, R. J., & Zhao, M. (2010). The effects of market network heterogeneity on innovation diffusion: An agent‐based modeling approach. *Journal of Product Innovation Management*, *27*(5), 741-760.

De Bruyn, A., & Lilien, G. L. (2008). A multi-stage model of word-of-mouth influence through viral marketing. *International Journal of Research in Marketing*, *25*(3), 151-163.

Dobele, A., Toleman, D., & Beverland, M. (2005). Controlled infection! Spreading the brand message through viral marketing. *Business Horizons*, *48*(2), 143-149.

Erdös, P., & Rényi, A. (1959). On random graphs, I. *Publicationes Mathematicae (Debrecen)*, *6*, 290-297.

Goldenberg, J., Libai, B., & Muller, E. (2001). Talk of the network: A complex systems look at the underlying process of word-of-mouth. *Marketing letters*, 12(3), 211-223.

Goldenberg, J., Libai, B., Moldovan, S., & Muller, E. (2007). The NPV of bad news. *International Journal of Research in Marketing*, 24, 186-200.

Hinz, O., Skiera, B., Barrot, C., & Becker, J. U. (2011). Seeding strategies for viral marketing: An empirical comparison. *Journal of Marketing*, *75*(6), 55-71.

Hu, H. H., Lin, J., Qian, Y., & Sun, J. (2018). Strategies for new product diffusion: Whom and how to target?. *Journal of Business Research*, *83*, 111-119.

Jiang, Z., Bass, F. M., & Bass, P. I. (2006). Virtual Bass Model and the left-hand data-truncation bias in diffusion of innovation studies. *International Journal of Research in Marketing*, 23, 93-106.

Kempe, D., Kleinberg, J., & Tardos, É. (2003). Maximizing the spread of influence through a social network. In *Proceedings of the ninth ACM SIGKDD international conference on Knowledge discovery and data mining*, p. 137-146.

Kiesling, E., Günther, M., Stummer, C., & Wakolbinger, L. M. (2012). Agent-based simulation of innovation diffusion: a review. *Central European Journal of Operations Research*, 20(2), 183-230.

Lee, S. G., Trimi, S., & Kim, C. (2013). Innovation and imitation effects' dynamics in technology adoption. *Industrial Management & Data Systems*, *113*(6), 772-799.

Mahajan, V., Muller, E., & Bass, F. M. (1990). New product diffusion models in marketing: A review and directions for research. *The Journal of Marketing*, 54(1), Jan., 1-26.

Moldovan, S., & Goldenberg, J. (2004). Cellular automata modeling of resistance to innovations: Effects and solutions. *Technological Forecasting and Social Change*, 71(5), 425-442.

Rand, W., & Rust, R. T. (2011). Agent-based modeling in marketing: Guidelines for rigor. *International Journal of Research in Marketing*, 28(3), 181-193.

Rand, W. & Wilensky, U. (2012). NetLogo Simple Viral Marketing model. http://ccl.northwestern.edu/netlogo/models/SimpleViralMarketing. *Center for Connected Learning and Computer-Based Modeling,* Northwestern University, Evanston, IL.

Solomon, M. (2004). *Consumer Behaviour*: Buying, Having and Being, Pearson, Upper Saddle River, New Jersey.

Stonedahl, F., Rand, W., & Wilensky, U. (2010). Evolving Viral Marketing Strategies, *Genetic and Evolutionary Computation Conference* (GECCO), July 7-11, Portland, OR, USA.

Trusov, M., Bucklin, R. E., & Pauwels, K. (2009). Effects of word-of-mouth versus traditional marketing: findings from an internet social networking site. *Journal of marketing, 73*(5), 90-102.

Wang, T. S. (2008). An Agent-Based Model of Viral Marketing: Comparing online-based viral and traditional marketing in a closed system for fashion trends in a competitive setting. CUREJ: *College Undergraduate Research Electronic Journal*, University of Pennsylvania.

Wilensky, U. (1999). NetLogo. http://ccl.northwestern.edu/netlogo/. Center for Connected Learning and Computer-Based Modeling, Northwestern University, Evanston, IL.

Wilensky, U. & Rand, W. (2015). *Introduction to Agent-Based Modeling*: Modeling Natural, Social and Engineered Complex Systems with NetLogo. Cambridge, MA. MIT Press.

Woerndl, M., Papagiannidis, S., Bourlakis, M., & Li, F. (2008). Internet-induced marketing techniques: Critical factors in viral marketing campaigns. *Int. Journal of Business Science and Applied Management*, Vol 3, Issue 1.