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Ignition of New Product Diffusion in Entrepreneurship: An Agent-Based Approach

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Abstract

New product diffusion is critical to entrepreneurship. Without successful diffusion, the emergence of a new business is incomplete. Although we have several well-established models of the diffusion phenomenon, these models mainly describe the macro-level diffusion patterns *after* their ignition, thereby ignoring the ignition mechanism. This study conceptualizes an entrepreneur's introduction of a new product and its diffusion as a generative emergence from a complexity science perspective and employs agent-based modeling and simulation (ABMS) to explain the full ignition-diffusion process, as well as ignition failures. In this study's model, the ignition process is made of individual consumers' heterogeneous thresholds and their relative levels of activities. These micro-level characteristics and behaviors influence the speed and scope of the diffusion at the macro-level. Our simulations reveal the minimum number of initial adopters required to ignite the diffusion process and show how an entrepreneur's advertising campaign may accelerate the ignition and diffusion speed. The simulations also reveal how consumers' negative word-of-mouth may reduce the diffusion scope.

Keywords: ignition of new product diffusion, generative emergence, complexity science, agent-based modeling and simulation, word-of-mouth

1. Introduction

New product diffusion is critical to entrepreneurship. It is hard for most entrepreneurs to have successful businesses without diffusion of their products, even if the entrepreneurs have developed flawless new products. For the entrepreneur's venture to thrive, it is more important that their product is bought and used by consumers than it is that their product is perfect. Despite the importance of the new product diffusion, gaps in our knowledge remain regarding the critical conditions that *ignite* the diffusion process. Hence, the main purpose of this study is to identify the conditions that trigger this diffusion process, with particular emphasis on revealing the relative impact of entrepreneur's advertising efforts and consumers' word-of-mouth. In order to elaborate on this phenomenon and reveal how micro-level activities affect macro-level diffusion patterns, this study regards the ignition-diffusion process as an emergence process from a complexity science perspective.

At the macro-level, decades of diffusion research have successfully described how new products spread through society (Bass, 1969; Garcia and Jager, 2011; Laciana, Rovere, and Podestá, 2013; Rogers, 2003). In particular, the S-curve innovation diffusion process originated by Bass is widely used and thoroughly researched as a representative aggregated-level model (see Kiesling, Günther, and Stummer, 2012 for a comprehensive review). The S-curve shape of the diffusion process after the ignition is so prevalent across a wide range of conditions that it is deemed a 'stylized fact' of marketing and entrepreneurship (see Arroyo and Khalifa, 2015). The term stylized fact is used to identify something that is a generally known macroscopic pattern or observation widely accepted to be an empirical truth. The term is derived from economics, but commonly used in diverse areas of business studies including marketing (Garcia, Rummel, and Hauser, 2007; Rand and Rust, 2011).

In spite of their prevalence, the aggregated-level models of diffusion are often limited in similar ways. In particular, these models generally take ignition of the diffusion for granted or assume the ignition of diffusion as natural. However, this assumption may not be realistic, as many entrepreneurs fail to spread their products, contributing to the high death rate of new ventures. Without understanding of the diffusion ignition, it remains hard to predict diffusion speed or scope. This predictive challenge is a result of the complexity of the diffusion process including the complexity of the social interactions between consumers. Moreover, these aggregated-level models lack explanatory power for the micro-level mechanisms. While they can retrospectively describe the macro-level pattern by reproducing the stylized fact, it remains debatable whether they truly reflect the micro-level behaviors of heterogeneous individuals (Kiesling et al., 2012).

Complexity science provides an effective theoretical perspective with which to explain the micro- *and* macro-level of several entrepreneurial processes (Crawford and Kreiser, 2015; Ireland and Gorod, 2016; McMullen and Dimov, 2013; McKelvey, 2004). Within the complexity science perspective, Lichtenstein (2016) suggests 'generative emergence' as a central concept, which is the emergence of a larger pattern as a consequence of intentional behavior by individual agents, and presents five sequential phases for the generative emergence. In his sequential model, the cycle is initiated by the entrepreneur's pursuit of value creation (phase 1), followed by cycles of tensions and experiments (phase 2) as the entrepreneur figures out how to gain market share, thereby increasing the size and complexity of the system. At some point, positive (and negative) feedback from others in the system reach a tipping point (phase 3), and a 'new order' emerges (phase 4) and stabilizes (phase 5). This study uses Lichtenstein's sequential phases as a guide when modeling the new product diffusion process.

To make the complexity science perspective more concrete, this study employs agent-based modeling and simulation (ABMS). ABMS has been proposed as an effective way to elaborate on theories in complexity sciences (Davis, Eisenhardt, and Bingham, 2007; Garcia, 2005; Kiesling et al., 2012). It has a high degree of realism when applied to new product diffusion, because the behavioral models and attributes in the ABMS can account for the empirically observed heterogeneity of agents, their preferences and their activities at the micro-level, while reproducing the stylized fact at the macro-level (Dooley, 2002). This study simulates individuals' preferences and behaviors and how they aggregate to the S-curve new product diffusion process. The diffusion is situated in the online context for two reasons: (i) the Internet has become an essential platform for entrepreneurs to announce the launch of their new products and ventures and (ii) a substantial empirical literature on the structure of online social networks is now available.

While providing a relatively easy to follow demonstration of ABMS, this study addresses three significant issues. First, unlike prior studies, no initial adoption is assumed. Instead, initial adoption is a consequence of the entrepreneur's advertising activities, compounded by word-of-mouth. Second, the ABMS includes heterogeneous characteristics related to the potential consumers' likelihood to try a new product. Finally, social network structures are generated that are consistent with empirical data on online social networks as they simultaneously have power-law and small-world features (Crawford et al., 2015; Watts and Strogatz, 1998).

This study contributes to entrepreneurship research and practice in three ways. First, it reinforces the validity of adopting a complexity science perspective to understand entrepreneurship, including the new product diffusion process. This perspective enables understanding the diffusion process as a multi-level generative emergence. Second, it goes beyond providing only theoretical arguments for employing ABMS. It does this by demonstrating the mechanics of AMBS by linking empirically observed micro-level attributes and activities to macro-level observations. The ABMS used here also include network structures with power-law and small-world properties that are empirically more accurate than prior ABMS studies. Lastly, the simulation results help quantify the relative impact of the entrepreneur's and consumers' activities on igniting and spreading the diffusion. These findings provide a foundation upon which to elaborate on theories of new product diffusion processes, and pursue practical insights into entrepreneurs' attempts to ignite the diffusion of new products.

2. Theoretical and Methodological Frameworks

2.1. Complexity science

The complexity science perspective regards 'emergence' as its conceptual anchor, where emergence is a process in which a new order is created at a higher level through agents' activities at a lower level. In the entrepreneurship context, the emergence is manifested in several macro-level stylized facts, like the relative distribution of high growth firms, job creation and economic growth within or across regions (Brown, Mawson & Mason, 2017), all of which are outcomes of how entrepreneurs and other stakeholders act and interact within their ecosystem at the micro-level (Brown & Mason, 2017). This emergence sometimes referred to as generative emergence because it is based on individuals' intentional activities.

Using Lichtenstein's (2016) five phase model as a guide, phase 1 captures the intentions of the entrepreneur: "the cycle is initiated when an entrepreneur starts to pursue an idea for value creation, which enacts or takes advantage of an opportunity" (p. 47). For the emergence to be ignited and proceed, the entrepreneur must interact with other stakeholders (especially consumers). These interactions include validating the consumer's needs (phase 2) and accumulating positive feedback (phase 3) until a tipping point, at which point the system reorganizes itself (phase 4) and stabilizes (phase 5). At a finer-grained level of detail, these 5 phases may be mapped onto the 21 different complexity 'ingredients' (McKelvey, 2016), including tension, emergent phase transitions, heterogeneous agents, tiny initiating event, connections, bottom-up emergence, multi-level, and power-law phenomena (Crawford et al., 2015; Shim, 2016).

Adapted to the new product diffusion process, this sequential model reads as follows: The diffusion process is initiated by the entrepreneur's introduction of a new product they believe that consumers will value (phase 1). Potential consumers to whom the new product is introduced or advertised are then placed in a state of tension between perceived utility and disutility of the new product before making a decision to try the product (phase 2). At some point, the entrepreneur's advertising efforts are overshadowed by the (net) positive word-of-mouth among consumers, which then drives (or stalls) further diffusion (phase 3). Finally, the market reorganizes in favor or against the entrepreneur's product (phase 4) and stabilizes at some level of market penetration (phase 5).

2.2. Agent-based modeling and Simulation (ABMS)

Analysis of complex systems may be separated into two streams (McKelvey, 2004; Edmonds and Moss, 2004): (i) descriptive analyses for inductive theory development, and (ii) simulations and modeling for predictive theory testing and refinement. Descriptive complex systems analyses produce 'thick' descriptions of "causal plot lines" regarding how elements influence each other (McKelvey, 2004, p. 330). Such descriptions, including diagrams, help visualize how actors in socio-economic systems interact to create value (e.g., Garnsey and McGlade, 2006; Maine and Garnsey, 2006), and may form the basis of subsequent simulations studies. Simulation and modeling based analysis is focused on identifying the simplest possible system that can quantitatively predict nonlinear relations, emergence, phase-transitions and dynamics of systems over many time steps (Anderson, 1999; McKelvey, 2004; Crawford, 2009). Simulations are virtual environments implemented by computer programs, in which researchers reproduce actual systems, processes, and events. The benefit of simulations (versus field research) is that they provide researchers with the ability to control all the input variables and efficiently perform large numbers of repetitive tests (Anderson, 1999; Davis, Eisenhardt, and Bingham, 2007; Dooley and Van de Ven, 1999). Through such tests or what-if analyses, researchers can simulate plausible or even extreme scenarios by examining how variables change and what effect their change has on the overall system (Harrison et al., 2007).

There are multiple modeling methods for simulations to consider, including discrete event modeling, system dynamics modeling, and agent-based modeling. Discrete event modeling regards a process as a sequence of discrete events. This modeling approach may account for the internal entities' behaviors, but the entities only passively react to external events (Siebers et al., 2010). Thus, discrete event approach is less suitable for modeling complex autonomous systems where many stakeholders act independently and interact with each other like new product diffusion process. System dynamics modeling is very useful for analyzing the response of complex systems, as modeled by aggregated sub-components in the system. However, system dynamics modeling does not explicitly model the behaviors and preferences of individuals in the system or their heterogeneity, and is therefore not well suited to studying the ignition of diffusion processes. ABMS is well suited to explain the micro-macro link between individuals and macro-level stylized facts because it can explicitly express heterogeneous activities and attributes of individuals and their interaction (Dooley, 2002). ABMS are particularly useful when the underpinning activities and attributes are based on empirical data (Corley, Jourdan, and Ingram, 2013).

For agent-based simulation, the first step is to build an agent-based model (ABM) that imitates the actual behaviors of individuals on the basis of their complex and high-level cognitive information-processing capabilities and intrinsic temperament (North and Macal, 2007). This imitation requires explicitly defining attributes and behavioral rules for each agent in the ABM, including statistical variation of their attributes (i.e., heterogeneous agents) and thus also variation of when any given behavioral rule is activated.

2.3. Bass model of innovation diffusion

We benchmark the emergent pattern against the Bass model of innovation diffusion (Bass, 1969) as a macro-level model for new product diffusion. This model has been widely used, thoroughly researched, and verified in empirical settings (see also Kiesling et al., 2012). The S-curve pattern, governed by the Bass model has been observed across of a wide spectrum of products (Bass, 1969; Firth, Lawrence, and Clouse, 2006; Lim, Choi, and Park, 2003; Naseri and Elliott, 2013; Sultan, Farley, and Lehmann, 1990; Wong et al., 2011). Therefore, the S-curve pattern has been regarded as a stylized fact of new product diffusion. The Bass model describes the diffusion phenomenon as a combination of two adoption processes by consumers. On the one hand, adoption originates from consumers' intrinsic tendency to try new things. On the other hand, adoption is influenced by other consumers' adoptions as a contagious process. An empirical limitation of the Bass model is an assumption of the existence of a small proportion of the population, called 'innovators', who "decide to adopt an innovation independently of the decisions of other individuals in a social system" (Bass, 1969, p. 216) who then provide the cue for others to imitate their adoption.

These two processes are represented in the Bass model by parameters *p* and *q*. The parameter *p* reflects people's intrinsic tendency to try a new product, independent of the influence of other people in their network. The parameter *q* reflects imitation or social contagion, wherein the decision to adopt the new product is related to interactions with extant consumers or cumulative adopters in their network (e.g. word-of-mouth). At the aggregate level, the Bass model can be represented by the following equation that expresses the rate of adoption within a system at a given point in time as a function of *p*, *q*, and the proportion of cumulative adopters in the system, n^+ (the + denotes adoption by n^+ out of n people).

$$\frac{dn^+}{dt} = (p + qn^+)(1 - n^+) \qquad \text{(Equation 1)}$$

In other words, for the remaining proportion of people who have not yet adopted the product (1 - n^+), the rate at which people will adopt a new product (dn^+/dt) is a function of the degree to which these people are intrinsically inclined to try the product (p) and the degree to which they are influenced by peers who have already adopted the product (qn^+). As such, this model relies on average values of p and q, and remains relatively silent about what exactly happens at t = 0, when $n^+ = 0$. Nonetheless, the equation accurately reproduces the stylized S-curve of cumulative adopters as a function of time as shown in Figure 1.

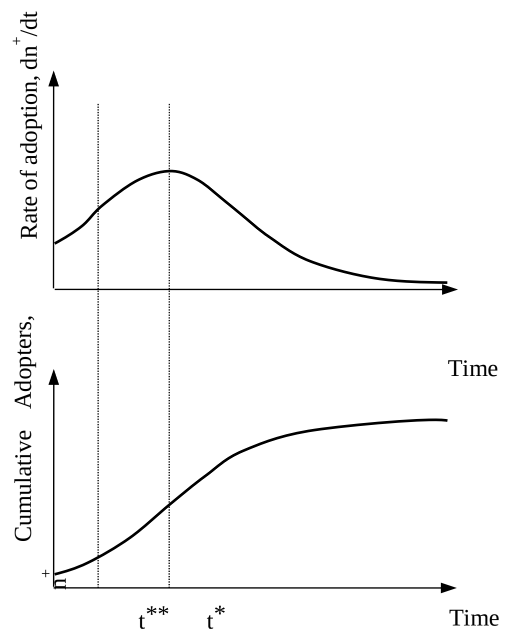


Figure 1. Bass (1969) rate of adoption and cumulative adoption over time

Key measures of diffusion are the time at which the rate of adoption is maximal (*t**), and the time at which the increase of adoption rate is maximal (*t***). The latter is also referred to as the 'take-off time' at which the product is starting to spread and there is the greatest acceleration of adoption. Conceptually, 'take-off time' is analogous to the tipping point between phase 3 and phase 4 in Lichtenstein's model (2016).

3. Micro-Foundations and Assumptions

This section reviews the micro-level empirical findings upon which this study’s ABM is based, and specifies model assumptions.

3.1. Online advertising

One key finding of studies on online advertising is regarding the exposure frequency of online advertising and its effectiveness. Frequent exposure of online advertising to a given individual increases the effectiveness of the advertising on that person, in terms of advertising recall, brand recognition, and brand awareness (Dreze and Hussherr, 2003). For example, a given individual’s cumulative click rate of a banner ad increases with the number of banner ad exposures, but then diminishes beyond a critical point at which the consumer is already familiar with the product (Broussard, 2000). Likewise, online purchasing increases with the number of online advertising exposures, again with diminishing returns (Manchanda et al., 2006). Importantly, these same studies also found considerable heterogeneity across consumers, with some people adopting sooner, and others later (or not at all), consistent with Rogers (2003) and Bass (1969). Based on these empirical observations, the ABM includes two modeling assumptions.

- Assumption 1a. Each ad impression increases a potential consumer’s probability of new product adoption.
- Assumption 1b. The additional impact of ads has an inverted-U shape. Each person has a threshold number of ad impressions at which a new ad impression has maximum impact, and this threshold is heterogeneous across consumers.

3.2. Word-of-mouth

After a consumer tries a new product, they may provide positive or negative word-of-mouth to their friends. Negative word-of-mouth significantly reduces the perceived credibility of advertising and purchasing intentions (Smith and Vogt, 1995). Empirical research showed that positive and negative word-of-mouth were similar forms of advice-giving behavior, and that the impact of positive word-of-mouth was generally greater than the impact of negative word-of-mouth, with the caveat that the relative impact depends on the product category (East, Hammond, and Lomax, 2008; East, Hammond, and Wright, 2007). Subtracting the negative word-of-mouth from the positive word-of-mouth creates a measure of net positive word-of-mouth. More recent research indicates that, when word-of-mouth mechanisms are present, a product’s quality is the most significant factor affecting the new product diffusion (Karakaya, Badur, and Aytekin, 2011). Based on these empirical observations, the ABM includes two assumptions regarding word-of-mouth.

- Assumption 2a. Net positive word-of-mouth increases a given person’s probability of adopting a new product, and the relative impact of positive versus negative word-of-mouth varies by product category.
- Assumption 2b. As with ads, the additional impact of word-of-mouth has an inverted-U shape. Each person has a threshold number of word-of-mouth impressions at which a new positive word-of-mouth has maximum impact, and this threshold is heterogeneous across people.

3.3. Network structure

Given the importance of interactions between potential consumers and consumers (e.g. word-of-mouth) in this process, the extent to which each individual is connected in their network plays a significant role. Prior research demonstrates that a network’s structural characteristics can have a significant effect on the breadth and speed of the diffusion process (Choi, Kim, and Lee, 2010; Opuszko and Ruhland, 2013). When modeling new product diffusion, it is therefore important that the simulated network structure closely resembles the empirical phenomenon.

The structure of online social networks is relatively well documented as having highly skewed power-law (aka scale-free) degree distributions – a minority of people has many links to others while the majority of people have minimal links. This power-law network structure can be approximated using preferential attachment algorithms (e.g. Kunegis, Blattner, and Moser, 2013). However, purely power-law structures are only a crude approximation of reality. Observations from Facebook (Ugander et al.,

2011) and Twitter (Kwak et al., 2010) reveal that online social network structures also have small-worlds features, such as short path lengths and high clustering coefficients.[1] Interestingly, among the 29 ABMS studies recently reviewed by Kiesling et al. (2012), none were specifically tailored to accurately reflect these clustering coefficients. Instead, most ABMs assumed lattice or simple small-world network structures, which have lower validity (Barabasi, 2002; Kunegis, Blattner, and Moser, 2013). The ABM used in this study addresses this gap by generating network structures that match the degree distributions and clustering coefficients observed by Ugander et al. (2011) or Kwak et al. (2010). More specifically to the influence of a given person's network on their propensity to try a new product, this study makes one assumption.

- Assumption 3. People are differentially sensitive to word-of-mouth (versus advertising) according to their network centrality. More central people are more sensitive to word-of-mouth, while peripheral people, by necessity, make more independent decisions, but the impact of word-of-mouth is at least the same as the impact of advertising (following Choi, Kim, and Lee, 2010; Opuszko and Ruhland, 2013; Vilpponen, Winter, and Sundqvist, 2006).

4. Agent-Based Model

This subsection follows the principles of the Overview-Design-Details (or ODD) protocol to describe the ABM employed (Grimm et al., 2006; Grimm et al., 2010), as also reflected in Rand and Rust (2011). The ODD protocol was proposed for a rigorous representation of ABMs and consists of seven subsections of three general categories.

4.1. Model description

4.1.1. Purpose of the ABM

[1] See also http://konect.uni-koblenz.de/plots/ for visual summaries of degree distributions and clustering coefficients across a wide range of social media websites.

The purpose of the ABM is to explore the critical conditions for the ignition of new product diffusion and the relative impact of each agent's micro-level behaviors, i.e. advertising versus word-of-mouth on the online diffusion process.

4.1.2. *Entities, state variables, and scales*

This ABM explicitly has only one type of entity (agent), i.e. consumers. The existence of the entrepreneur and the new product they are introducing are implicit to the ABM. Each consumer has six state variables (aka attributes), as also summarized in Table 1.

Table 1. Entity and its state variables

Entity	State variable and meaning
Consumer 	*my-adoption-status* "Potential" – The consumer has not yet tried the product. "Positive" | "Negative" – The consumer formed a positive [negative] opinion after adopting it.
	my-threshold A minimum utility value that the consumer must perceive before deciding to try the product, heterogeneously distributed across the consumers (ranging 0.2 - 0.8).
	my-marketing 1 – If the consumer is being targeted by the entrepreneur's ad campaign. 0 – Otherwise.
	my-current-ads The running total of periods for which the consumer is exposed to an ad.
	my-current-wom The running total of periods for which the weighted net word-of-mouth is positive.
	my-alpha The proportion to which a consumer's decision is based on word-of-mouth, calculated by ranking each consumer's centrality (spread from 0.5 at periphery - 1 at centre).

- The *'my-adoption-status'* variable indicates whether a consumer has not yet tried the product (their status is "potential"), or whether the consumer has bought the product and formed a positive or negative opinion about it (their status is then changed to "positive" or "negative", respectively).
- Each consumer is assigned a random value (ranging from 0.2-0.8) of '*my-threshold*', a minimum utility value that a consumer must perceive before deciding to try the product. The threshold is heterogeneously distributed across the consumers and reflects the tendency for some consumers to adopt earlier than others (Rogers, 2003). As explained in 4.1.5, this

threshold is compared against the cumulative impact of ads and word-of-mouth for a decision to be made.

- Only some consumers are exposed to ads. If a consumer is being targeted by the entrepreneur's ad campaign, then their '*my-marketing*' attribute is set to 1, 0 if otherwise.
- The running total of time periods for which a given consumer is exposed to an ad is recorded into their '*my-current-ads*' variable (aka their total ad impressions).
- Likewise, the running total of periods for which the weighted net word-of-mouth is positive for a given consumer are recorded into the consumer's '*my-current-wom*' variable. To calculate a weighted net word-of-mouth, the relative weight of negative (vs positive) word-of-mouth was considered prior to being totaled among immediate peers in a potential consumer's network (Karakaya, Badur, and Aytekin, 2011).
- The proportion to which a consumer's decision to try the product based on social contagion (i.e., word-of-mouth) is a factor of how central they are. Peripheral people, by necessity, make decisions more independently. This proportion is described by a fixed '*my-alpha*' parameter, which is calculated by measuring each consumer's centrality, then ranking consumers by centrality, and normalizing the rank to a distribution of 0.5 to 1, with 0.5 being the most peripheral and 1 being the most central. Thus the influence of word-of-mouth is always greater than ads, with the most central people being influenced almost completely by their network, while those on the periphery make decisions based on nearly 50:50 relative influence of word-of-mouth to ads.

4.1.3. *Initialization*

Before running each simulation, three general parameters are initialized – '*ad-penetration*' ('*Ads*' for short), '*chance-of-negative-wom*' ('*Nwom*' for short), and '*relative-weight-of-nwom*' ('*Weight*' for short). The '*Ads'* parameter defines what proportion of consumers in the network are exposed to the ads. This is analogous to the scope of the target market for the entrepreneur's marketing campaign. The '*Nwom*' parameter defines the probability by which consumers form a negative opinion upon adopting the product, thus reflecting the quality of the product. The '*Weight*' parameter is a fixed value for each simulation with which we explore the relative impact of negative versus positive word-of-mouth (effectively modeling different product categories).

Each simulation initializes the state variables specific to each consumer. All consumers' '*my-adoption-status*' was set to "potential", and their counters for '*my-current-ads*' and '*my-current-wom*' were set to zero. For a random selection of consumers, representing the proportion being marketed to according to '*Ads*,' their '*my-marketing*' variable was set to 1. For every complete run of simulation, the network structure is generated as per below.

4.1.4 *Network structure generation*

Each simulation consists of 1,000 agents who are connected in a single network. The link distribution of the agents has power-law and small-world properties that are representative of actual online social networks. To generate such a power-law and small-world network, the preferential attachment algorithm (Barabási and Albert, 1999; Kunegis, Blattner, and Moser, 2013) that is built into NetLogo's NW Extension[2] was modified. The unmodified preferential attachment generates a power-law network by adding one new agent at a time, and connecting them to only one other agent, with preference for connections to (central) agents who already have many connections.

The algorithm was modified by specifying that, when a new agent was added and connected to an existing (more central) agent, the new agent was then also connected to a random subset of 50% of that existing agent's connections (i.e., friends-of-friends). This modification created more clique-like structures and brought the average clustering coefficient closer to what was observed empirically (0.4-0.6) while maintaining a degree distribution of a power-law network. This network was then modified further to increase the small-world properties (measured by the mean path length in the network) without significantly compromising the (power-law) degree distribution or (clique-like) clustering coefficient. This modification was done by adding 10% more connections between agents who were

[2] Available for NetLogo version 5.0.5-RC1 at https://github.com/NetLogo/NW-Extension

not already connected. These additional connections are analogous to weak ties in real networks. The resulting network generated usually had around 4,400 connections between the 1,000 agents, with realistic degree distributions, clustering coefficients and mean path lengths (as per Ugander et al., 2011; Kwak et al., 2010). Figure 2 illustrates the difference between a structure generated using only preferential attachment and a structure using the modified preferential attachment process.

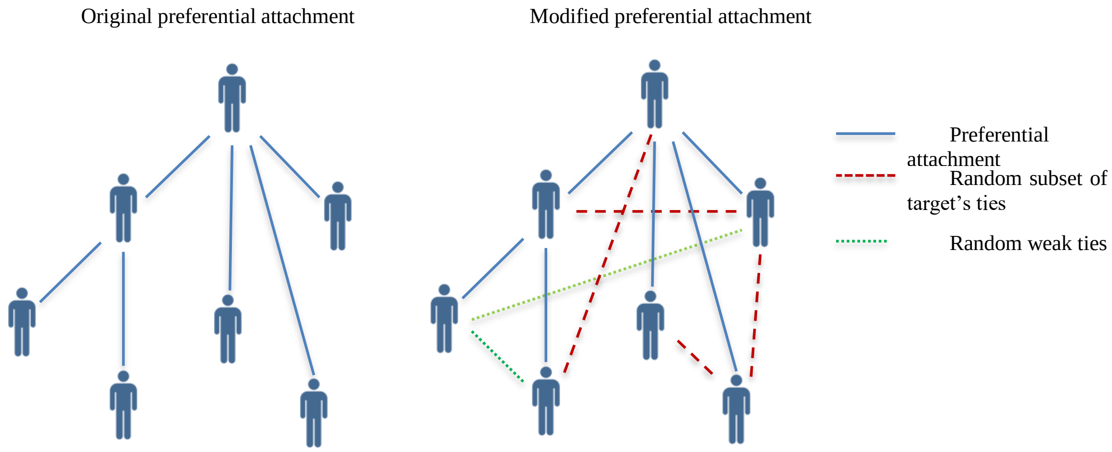


Figure 2. Network structure generation (Original preferential attachment vs. Modified preferential attachment)

4.1.5. Process overview and scheduling

At each time period, the simulation makes three types of calculations for each potential consumer. First it recalculates the running total of times a potential consumer has been exposed to an ad and (net weighted) positive word-of-mouth. These totals are then used to evaluate whether the potential consumer decides to adopt the new product. Lastly, upon adoption, the consumer generates a positive or negative opinion about the product. The simulation ends after 200 time steps or if all agents have adopted the innovation, whichever is first. These calculations are explained in greater detail below and visualized in Figure 3.

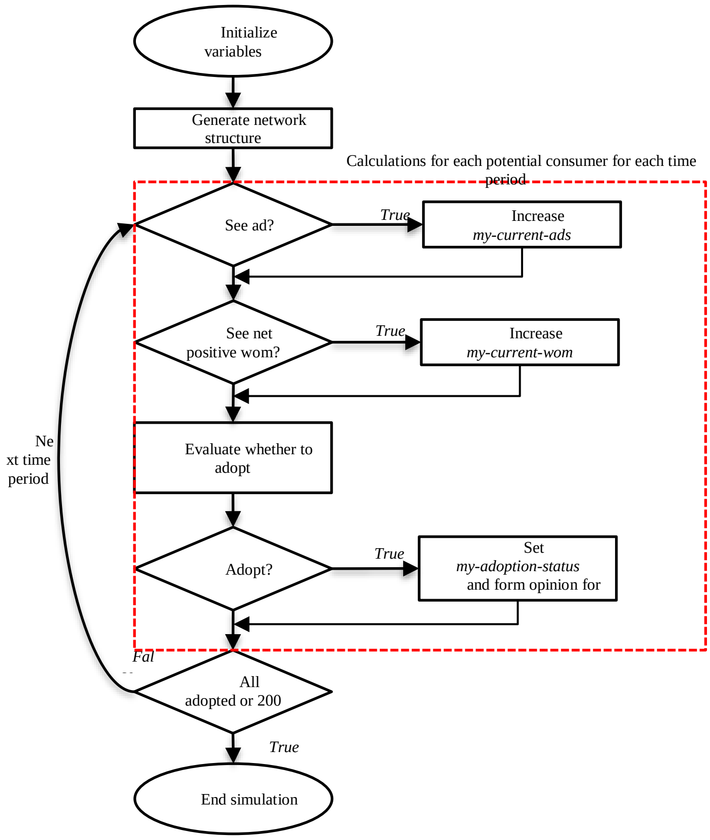


Figure 3. Process overview

At each time period, each potential consumer who has '*my-marketing*' set to 1, sees one more ad impression and increases their '*my-current-ads*' counter by one. A potential consumer's '*my-current-wom*' counter only increases by one if the number of '*positive-opinions-nearby*' is greater than '*Weight * negative-opinions-nearby*', where the counts of nearby (positive or negative) opinions are limited to each consumer's direct contacts, and '*Weight*' reflects the relative impact of negative versus positive impact (within range of observations by Karakaya, Badur, and Aytekin, 2011). Based on these variables, each consumer evaluates the perceived utility of the product to make a decision whether or not to adopt the product. Following the logic of the Bass model, but at the level of each potential consumer, the product is adopted if the overall perceived utility, U, is greater than their 'my-threshold' value, where U is the sum of the cumulative word-of-mouth (v) and the cumulative advertising (u). U is calculated as:

$$U = \alpha \cdot v + (1 - \alpha) \cdot u \qquad \text{(Equation 2)}$$

The α represents the individual's relative impact of word-of-mouth versus advertising, and ranges between 0.5 to 1.0. The α represents each consumer's '*my-alpha*' variable according to the consumer's centrality in the social network; as above, more peripheral consumers are less influenced by others around them. The variables *v* and *u* are logistic functions, where:

$$v = \frac{1}{1 + \exp(my\_effective\_wom - my\_current\_wom)} \qquad \text{(Equation 3)}$$

$$u = \frac{1}{1 + \exp(my\_effective\_ads - my\_current\_ads)} \qquad \text{(Equation 4)}$$

As per assumptions 1b and 2b, the '*my-effective-wom*' and '*my-effective-ads*' are the points at which the incremental influence of an additional word-of-mouth or ad impressions are maximum, respectively. Before or after this point, each impression will only have a smaller marginal impact (e.g. early impressions are overlooked, and later ones are ignored). For simplicity, we assume all potential consumers have the same overall threshold number of exposures to the new product at which each additional exposure is most effective ('*average-criterion*' is set to 20 for all consumers). To account for peripheral consumers having to make decisions more independently, and central consumers being more susceptible to social contagion (consistent with assumption 3), this overall threshold is separated into a threshold for ads and for word-of-mouth according to each agent's level of centrality in the network:

*my-effective-wom = average-criterion * my-alpha* (Equation 5)

*my-effective-ads = average-criterion * (1 - my-alpha)* (Equation 6)

Using the above equations (2-6), a decision is made whether or not to adopt the new product. Consumers who adopt the new product then form an opinion about the actual utility of the product. The '*my-adoption-status*' variable of a consumer then becomes "negative" with the probability specified by the parameter '*Nwom*', otherwise the variable becomes "positive".

4.1.6. *Design concepts*

Our ABM includes individual decisions to adopt a new product that are based on the combined effects of ads and word-of-mouth in relation to each individual's attributes and position in the network. The model implicitly assumes that consumers notice every ad and every nearby word-of-mouth review.

There are various ways in which we introduce heterogeneity and stochasticity in the ABM. First, for each complete simulation run, the network structure is generated using three separate stochastic steps. Each consumer's position in the network then moderates the relative impact of word-of-mouth versus ad impressions. Second, each consumer is assigned a randomly distributed threshold of adoption ('*my-threshold*'), making some more likely to be early adopters, and some more likely to be laggards. Third, a random subset of consumers are exposed to the ads as specified by the '*Ads*' parameter. Lastly, after a decision to adopt the product is made, a consumer's negative opinion is formed with a probability according to the '*Nwom*' parameter (else a positive opinion is formed).

4.2. Experimentation with input parameters

The present analysis involved 1,200 simulations, each lasting 200 time periods, generated by experimenting with 60 combinations of values for three input parameters, and repeating each of these combinations for 20 simulations. Each simulation included a freshly generated structure of 1,000 agents (and thus also '*my-alpha*'),[3] a randomly generated '*my-threshold*', and a new random subset of consumers who would see the ads according to the '*Ads*' parameter. The simulations were run using the program NetLogo, which has a built-in option to vary the input parameters across simulations. The values of the parameters were chosen based on observations in the literature and practice, with the aim for the parameters to be within a plausible range; these simulations were not used to explore extreme scenarios that are highly unlikely to occur in reality. The three input parameters and their respective values were:

- '*Ads*' was set to {1%, 5%, 10%, and 20%}. When running social media campaigns, it is common for entrepreneurs to experiment with smaller campaigns to fine-tune messaging before aiming for a mass market. Targeting these percentages of a relatively small market of 1,000

[3] As a separate test, we regenerated the structure multiple times, and confirmed that the aggregate topology (degree distributions and clustering coefficients) were practically the same across each structure.

potential consumers plausibly represents these common practices for entrepreneurs (Carson et al., 1995).

- '*Nwom*' was set to {0%, 5%, 10%, 20%, and 30%}. This variable was varied to address a gap in our knowledge relating to the impact of negative word-of-mouth. Higher probabilities may be analogous to premature launches of faulty prototypes that are not yet ready for the mass market.
- '*Weight*' was set to {0.5, 1, and 2}. This parameter varied to explore the relative impact of negative versus positive word-of-mouth, and may also represent different product categories for which one outweighs the other (within range of observations by Karakaya, Badur, and Aytekin, 2011). The range was selected to represent equal and opposite ratios of negative to positive word-of-mouth impact (1:2, 1:1, and 2:1, respectively). These values correspond approximately to the range of relative impact of positive and negative word-of-mouth (East, Hammond, and Wright, 2007; East, Hammond, and Lomax, 2008).

5. Simulation Results

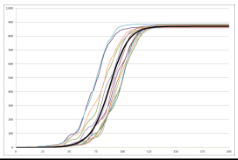
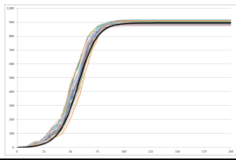
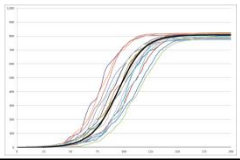
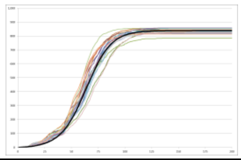
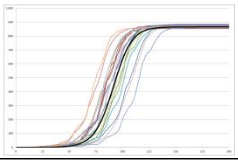
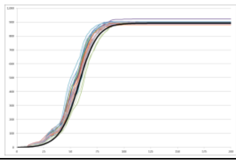
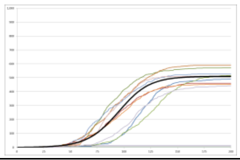
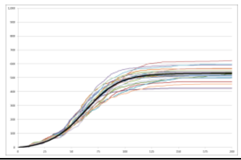
5.1. ABM validation

ABM validation is essential to confirm the simulated behaviors correspond to the empirical phenomenon. This can be classified into macroscopic and microscopic validation. Macroscopic validation deals with whether the aggregated simulation results correspond to the reality as a whole. The most common macroscopic validation is to compare the simulated results with the stylized facts observed in the field (Gilbert and Terna, 2000; Jansen and Ostrom, 2006; Takadama, Kawai, and Koyama, 2008).

For this study, there are two stylized facts against which to validate the ABM: the S-curve of diffusion and the occurrence of failure to ignite diffusion. While the exploration of ignition failures is the main contribution of this study, we first establish the ABM 'works' and does not generate spurious results by validating the S-curve. To confirm the S-shaped diffusion pattern with respect to the Bass model, the values of *p*, *q*, and nonlinear model fit are calculated using Wolfram Mathematica 9's NonLinearModelFit function, which produced high R^2 values. Of the 1,200 main simulations, there were 1,112 successful diffusion patterns and 88 diffusion failures, where failure has fewer than 12 adopters out of 1000 consumers. For each of the successful diffusion processes, R^2 ranged from 95.443% to 99.997%, demonstrating high degrees of fit with the stylized S-curve. The *p*, *q* values for the fit curves ranged from 0.00000 to 0.00275, and from 0.02435 to 0.13727, respectively. These values are within the ranges observed in actual diffusion patterns reported throughout the literature (Bass, 1969; Bass, Krishnan, and Jain, 1994; Gatignon, Eliashberg, and Robertson, 1989; Laciana, Rovere, and Podestá, 2013). These results show that the ABM consistently and realistically reproduced the stylized S-curve of the new product diffusion phenomenon, contingent on successful ignition.

Instead of visualizing all 1,112 successful diffusion curves, Table 2 summarizes the curves for the eight most extreme combinations of input parameters. Each major cell in the table includes a summary of the parameters for that sub-model, and a graph of the 20 simulations with those input parameters (marked A through H). The top row is based on the minimum *Weight* (0.5) and the bottom row is based on the maximum *Weight* (2.0). The first and third columns are based on the minimum *Ads* (1%), and the other columns are based on the maximum *Ads* (20%). Similarly, the first and second columns are based on the minimum *Nwom* (0%) and the other columns are based on the maximum *Nwom* (30%). In the graphs in each major cell, the X-axes denote time (up to 200 simulation periods across all graphs) and Y-axes denote the number of adopters (up to 1,000 consumers across all graphs). Form the fitted *p* and *q* values of the curves of each sub-model, a median value is calculated with which to create a median curve (drawn in a bold black line) that is then a representative curve of that sub-model. In addition to the statistical validation in the previous paragraph, the S-curvature in the simulation results and representative sub-model's curves validate the first stylized fact. The graphs also visualize the variance within each sub-model, indicating moderate levels of sensitivity to the heterogeneity and stochasticity in the ABM summarized in the Design concepts section above.

Table 2. Diffusion patterns by input parameters

Input Parameters	*Ads*	*Nwom*	*Weight*	*Ads*	*Nwom*	*Weight*	*Ads*	*Nwom*	*Weight*	*Ads*	*Nwom*	*Weight*
	1%	*0%*	*0.5*	*20%*	*0%*	*0.5*	*1%*	*30%*	*0.5*	*20%*	*30%*	*0.5*
Diffusion Patterns	*A.* 			*B.* 			*C.* 			*D.* 		
Input Parameters	*Ads*	*Nwom*	*Weight*	*Ads*	*Nwom*	*Weight*	*Ads*	*Nwom*	*Weight*	*Ads*	*Nwom*	*Weight*
	1%	*0%*	*2.0*	*20%*	*0%*	*2.0*	*1%*	*30%*	*2.0*	*20%*	*30%*	*2.0*
Diffusion Patterns	*E.* 			*F.* 			*G.* 			*H.* 		

The second stylized fact under consideration is the existence of ignition failures, as reported throughout practice, while remaining under-researched. As stated by Mahajan, Muller and Wind (2000, p. vii), "new-product failure rates have variously been reported in the range of 40 to 90 percent." This study is less interested in the percentage of failures, and more interested in why they may occur, as explained by the factors in the ABM. Among 1,200 simulations, 88 simulations resulted in a diffusion failure, as illustrated in Figure 4. This figure shows the diffusion results of 20 simulations when 'Ads' is minimum (1%), 'Nwom' is maximum (30%), and 'Weight' is maximum (2.0), of which 11 cases were ignition failures. The X axis denotes time (up to 200 simulation periods) and Y axis denotes the number of adopters (capped at 600 consumers). The right portion of the figure magnifies the range up to 100 adopters. The presence of these failures confirms that the otherwise reliable ABM can produce diffusion failures, consistent with the second stylized fact.

At the microscopic level, the behavioral rules and ranges of variables are based on the observations in the corresponding empirical literature as referenced above across multiple studies. We acknowledge a limitation that all variables are not simultaneously validated within the same study, noting that such a study may be outside the scope of journal length manuscripts or even most books. We therefore assume that the micro-validity of the ABM is sufficiently (but not absolutely) attained based on the aforementioned empirical studies.

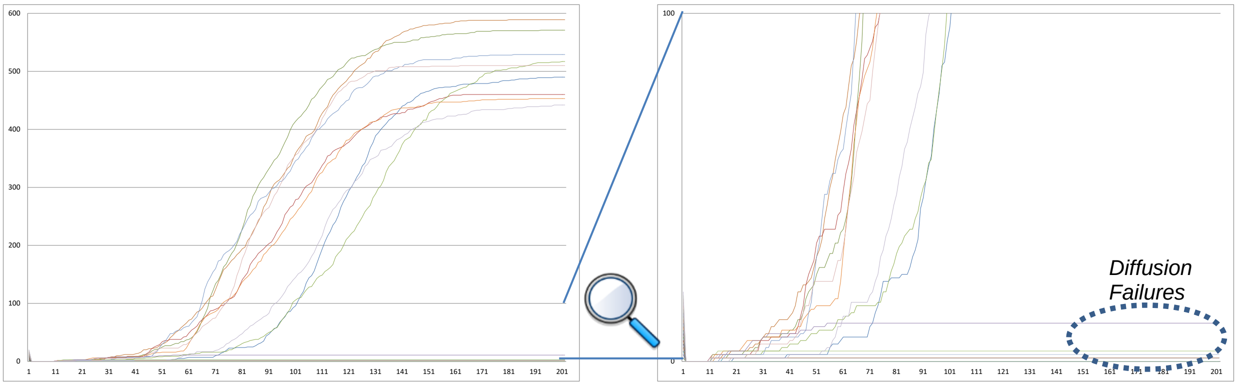


Figure 4. Diffusion patterns including diffusion failures

5.2. Diffusion speed and scope

Regression analysis of the 1,112 successful diffusion simulations reveals that the level of ads ('*Ads*') was the single most important factor influencing the speed of diffusion (compare also the graphs in Table 2 above, noting the left-shift in graph B versus graph A). As shown in the regression analysis results in Table 3, '*Ads*' was the most significant factor for take-off time (t^{**}) (β = -.8025), more than 5 times higher than the impact of *Nwom* (β = .1577).

Table 3. Results of Regression Analysis for Take-off Time and Time to max adoption rate (n = 1,112)

	Take-off time (t**)			Time to max adoption rate (t*)		
Variable	Coef.	Std. Err.	Beta	Coef.	Std. Err.	Beta
Ads	-1.6805	.0364	$-.8025^{***}$	-1.6848	.0382	$-.7580^{***}$
Nwom	.2167	.0239	$.1577^{***}$	.4827	.0251	$.3309^{***}$
Weight2	.9968	.4847	$.0556^{*}$	.9398	.5081	.0494
Nwom×Weight2	-.0657	.0291	$-.0610^{*}$	.0485	.0305	.0424
Constant	71.4954	.5245		82.7826	.5498	
Adj R^2			.6646			.6729

'*Weight2*' is equal to 'log2(*Weight*)', and has values of {-1, 0, +1}
* p < .05
*** p < .001

Figure 5 visualizes the effects of ads ('*Ads*') and negative word-of-mouth ('*Nwom*') on the take-off time. This figure highlights that although the diffusion process is delayed slightly due to the likelihood of negative word-of-mouth, these effects are overshadowed by the impact of advertising (as a portion of the potential consumers).

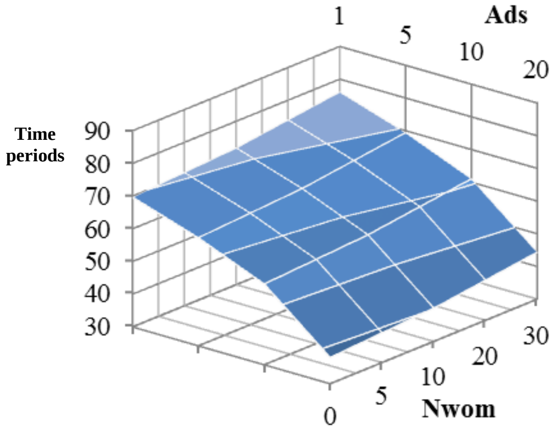


Figure 5. Take-off time as a function of ads and negative word-of-mouth

Regression analysis of the 1,112 successful diffusion simulations further reveals that the probability of negative word-of-mouth ('*Nwom*') significantly decreases the number of total adoption of a new product (compare also A and C in Table 2, above), and this effect was amplified by the product's relative weight of negative (versus positive) word-of-mouth ('*Weight*') (compare also C and G in Table 2, above). In contrast, the level of ads ('*Ads*') had relatively low coefficient. As shown in Table 4, for total adoption, the most significant factors were '*Nwom*' (β = -.7308) and the interaction term of '*Nwom * Weight2*' (β = -.6879).

Table 4. Results of Regression Analysis for Total Adoption (n = 1,112)

	Total Adoption		
Variable	Coef.	Std. Err.	Beta
Ads	1.5553	.1325	.1083***
Nwom	-6.8881	.0869	-.7308***
Weight2	9.7315	1.7633	.0791***
Nwom × Weight2	-5.0808	.1059	-.6879***
Constant	882.8361	1.9079	
Adj R^2			.9056

'*Weight2*' is equal to 'log2(*Weight*)', and has values of {-1, 0, +1}
*** p < .001

Figure 6 visualizes these results and shows the total adopters as a function of '*Nwom*' and '*Weight*'. While advertising is a major component in our ABM, its impact was overshadowed by factors relating to word-of-mouth after the 'seeding' process. Because of the negligible effect of '*Ads*' on the number of total adoption, we omit this variable when we visualize as a 3-dimensional surface.

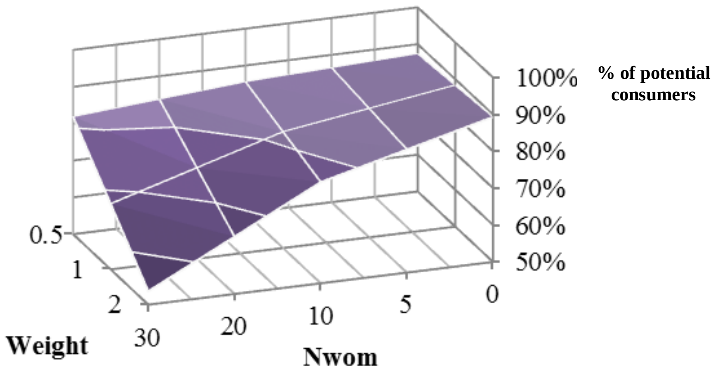


Figure 6. Total adopters as a function of negative word-of-mouth and weight

5.3. Ignition of diffusion

Of the 88 diffusion failures, 85 of them were for cases with 1% '*Ads*' (the lowest level of ads), and the remaining three occurring in cases with a 5% value thereof. To better understand these diffusion failures, 750 additional simulations were performed for '*Ads*' values from 0.1% to 5.0% in increments of 0.1%. Of these 750 simulations, 113 diffusion failures were reproduced, where the diffusion quickly and completely stalled with fewer than 12 adopters (applying the same 'failure' criterion as in the first 1,200 simulations), for which it becomes irrelevant to analyze whether the handful of adopters followed an S-curve. All other (successful) simulations reproduced the S-curve. These additional failures can be grouped into three failure types:

- *No adopters:* 68% of the failure cases.
- *Lone adopter*: 15% of the failure cases. 94% of these lone adopters were negative.
- *Less than 12 adopters*: 17% of the failure cases had 2-8 adopters. All but one case had 58-67% negative adopters.

Logistic regression analysis of these 750 simulations (Table 5) revealed that *ln('Ads')* is the most critical factor for ignition to occur. Greater *ln('Ads')* decrease the probability of a diffusion failure significantly (z = -11.54) while greater '*Nwom*' increases the probability significantly (z = 4.97) but less so.

Table 5. Results of Logistic Regression Analysis for Diffusion Failure (n = 750)

	Diffusion Failure		
Variable	Odds Ratio (OR)	Std. Err.	Z
Ln(Ads)	0.1462	.0244	-11.54***
Nwom	1.0654	.0136	4.97***
Weight2	0.5570	.1637	-1.99*
Nwom × Weight2	1.0250	.0153	1.66
Constant	0.1172	.0287	-8.78***
Pseudo R^2			.3906

'*Weight2*' is equal to 'log2(*Weight*)', and has values of {-1, 0, +1}
* p < .05
*** p < .001

6. Discussion

The ABM consistently and accurately reproduces both stylized facts of new product diffusion process: diffusion is follows the S-curve, but can also fail to ignite. These results contribute to establishing links between the micro-level behaviors and the macro-level phenomenon. Analysis of the micro-level parameters identifies that ignition is not automatic and therefore not to be taken for granted. Advertising activities are essential to ignite and accelerate the diffusion process at the introductory stages (phases 1 and 2 in Lichtenstein, 2016). Table 5 shows that the likelihood of diffusion failure was mainly affected by insufficient levels of advertising (*'Ads'*) and compounded by negative word-of-mouth (*'Nwom'*).

For ignition to lead to diffusion occur, a critical mass of adopters is required. The likelihood of securing such a critical mass is a factor of advertising, and compounded by positive word-of-mouth. Upon attaining such a critical mass of initial adopters, the diffusion process always proceeds with an S-curve pattern. In the simulations in this study, the critical mass within a population of 1,000 customers appeared to be around 12. Further research is required to explore a relationship between the size of the population and this critical mass, and be beyond the scope of this study. The implication for igniting the diffusion process is that it may be more important to secure one real positive adopter than it is to identify and target many potential adopters. Because the critical mass of adopters is relatively low, these findings have implications for alternative approaches to advertising. For example, instead of advertising to strangers using conventional online advertising methods, entrepreneurs may activate their own personal network to attract the critical mass of initial adopters to ignite the diffusion process.[4] Therein resides another area for future research: modelling the entrepreneur as an agent within the network, including their connections. This could involve altering the likelihood of positive.

Our results have several implications for practice. There are clear incentives to advertise intensively in the early stages of a new product launch, because the advertising may be the largest contributing factor to igniting the diffusion process and reaching the take-off faster. However, once the word-of-mouth process kicks in, continuing the ads may be a waste of resources and better spent on improving the product. Although this study assumed that the online advertising was an entrepreneur's primary means to ignite the diffusion process, entrepreneurs may explore other means. For example, an entrepreneur may personally invite a small number of potential adopters from an intermediate stage of the new product development. By reflecting on the feedback received, the entrepreneur may have more chances to develop a new product that is more likely to receive more positive word-of-mouth.

Given ignition of the diffusion process, advertising can increase the rate of diffusion and negative word-of-mouth becomes a critical factor in determining the range of diffusion at the maturity stage (phases 3 through 5 in Lichtenstein, 2016). Analysis of simulation data more precisely quantifies the relative impact of each of these variables. These results clearly showed the sequential impact of advertising and word-of-mouth. Word-of-mouth cannot spread without some minimum level of adoption due to advertising. Once word-of-mouth kicks in, advertising has little effect. Further use of an AMBS approach may thus help deepen our understanding of the sequential impact of advertising and word-of-mouth, and may be essential in exploring the optimal timing or duration of the advertising in future research projects.

Network structure plays a significant role in the new product diffusion process, but remains an under-researched area (Choi, Kim, and Lee, 2010, Opuszko and Ruhland, 2013). As detailed in 3.3, this study employed a modified preferential attachment procedure in order to reproduce a plausible online network structure according to the simultaneous power-law and small-world features of actual online

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[4] Dropbox's story popularizes the notion that word-of-mouth and virality trumps advertising: http://venturebeat.com/2010/10/27/dropbox-drew-houston-adwords/ (retrieved 24 Jul 2014)

social networks. In small-world networks, word-of-mouth has more paths to follow and can bypass central consumers who may have formed a negative opinion about the product (Watts and Strogatz, 1998). As a result, potential consumers have a greater chance to be encouraged to try the new products than in power-law networks without small-world features. The existence of small-world features in our ABM might determine the relatively small proportion of diffusion failures (88/1,200 in the main simulations, 113/750 in the additional simulations). In a future study, it would be useful to investigate the relationship between the level of small-world features of entrepreneur's social networks (e.g. the number of weak ties) and the probability of the new product ignition and diffusion.

7. Conclusion

This study adopts a complexity science perspective using ABMS to increase our understanding of the micro-level factors and processes resulting in the ignition and diffusion of a new product. Unlike most other studies that start with an assumed proportion of initial adopters, the simulations assumed zero adoption as the initial conditions. An ABM was constructed based on attributes, behavioral rules and network structures from the empirical literature. This required introducing a new tactic to generate network structures that have power-law and small-world properties. Using this ABM, the results of 1,112 simulations consistently and accurately reproduced the stylized S-curve at the macro-level with R^2 values between 95.443% to 99.997%. Consistent with the reality of failed ignition of diffusion, the 1,200 base-line simulations included 88 cases of failed ignition, as well as 113 failures out of 750 additional simulations with more extreme values for the simulation's input parameters.

By using the ABMS, we were able to discern the conditions where the diffusion process ignited, and quantify the relative importance of advertising and word-of-mouth in different stages of the diffusion process. Analysis of the results reveals that the probability of diffusion failure decreases exponentially with every additional adopter. The impact of word-of-mouth is instantly significant as soon as even the first consumer adopts the innovation, albeit at a much lower magnitude. Nonetheless, for ad campaigns with minimal penetration, early negative word of mouth can instantly stop the diffusion process.

Provided that ignition of diffusion occurs, advertising rate (as a % of population) has between 3.5 and 7.6 times more impact than the likelihood of negative word-of-mouth on the speed of diffusion, as measured by time to maximum adoption and take-off time. Word-of-mouth becomes the main determining factor for total number of adoption in two ways: the likelihood of negative word-of-mouth (*Nwom*) and the relative impact of negative versus positive word-of-mouth (*Weight*). For lower ranges of either of these variables, both have relatively similar magnitude of impact on total adoption (coefficients of -6.89 for *Nwom* and 9.73 for *Weight*). The effects of more likely negative word-of-mouth and greater weighting of it compound each other with a coefficient of -5,08 for *Nwom*Weight*. In comparison, Ad penetration is statistically significant for total adoption, but with a coefficient of 1.55; much lower than the total effects related to word-of-mouth. Overall, adverting is crucial to igniting the process and plays an important role in achieving maximum adoption as quickly as possible. However, total adoption is almost completely dominated by word-of-mouth effects.

Limitations and future research opportunities also exist in empirically validating the micro-behavior within a single study. This may be done using field data, or by conducting experiments in controlled settings (e.g. Janssen and Ostrom, 2006). In order to discern essential mechanisms of new production diffusion processes including diffusion failure, this study assumed a closed system: the ABM used here only included one product by one entrepreneur and an isolated niche of 1,000 consumers. Although this model is complex enough to reflect the stylized facts, there is therefore an opportunity to explore competitive dynamics with the introduction of a competing product. With a more competition oriented ABM, it would be beneficial to explore the relative benefits of pouring the entrepreneur's limited resources into advertising to trigger adoption take-off earlier than the competitor, or into product development to develop a product that is more likely to spread further due to positive word-of-mouth. Regarding the advertising effects, this study assumed a non-linear cumulative effect of advertising and does not assume consumers' forgetting behaviors over time. In future studies, the forgetting behavior may be jointly modelled based on empirical findings.

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