Physica A 492 (2018) 418–430

Contents lists available at ScienceDirect

Physica A

journal homepage: www.elsevier.com/locate/physa

Word-of-mouth dynamics with information seeking: Information is not (only) epidemics

Samuel Thiriot

EDF Lab Paris-Saclay, 7 Boulevard Gaspard Monge, 91120 Palaiseau, France

HIGHLIGHTS

- A model of word-of-mouth with information seeking.
- Two levels of knowledge represented: awareness and expertise.
- Highlights awareness cascades, expertise cascades and chains of information retrieval.
- Communication strategies depend on the initial expertise knowledge.
- Information seeking is mandatory to bootstrap the diffusion of knowledge.

ARTICLE INFO

Article history:
Received 7 August 2017
Available online 31 October 2017

Keywords:
Information dynamics
Word-of-mouth
Diffusion of innovations
Viral marketing
Complex systems
Multi-agent modelling
Complex networks

ABSTRACT

Word-of-mouth is known to determine the success or failure of innovations (Rogers, 2003) and facilitate the diffusion of products (Katz and Lazarsfeld, 1955). Word-of-mouth is made of both individuals seeking out information and/or pro-actively spreading information (Gilly et al., 1998; Rogers, 2003). Information seeking is considered as a step mandatory for individuals to retrieve the expert knowledge necessary for them to understand the benefits of an innovation or decide to buy a product (Arndt, 1967; Rogers, 2003). Yet the role of information seeking in the word-of-mouth dynamics was not investigated in computational models. Here we study in which conditions word-of-mouth enables the population to retrieve the initial expertise scattered in the population. We design a computational model in which awareness and expert knowledge are both represented, and study the joint dynamics of information seeking and proactive transmission of information. Simulation experiments highlight the apparition of cascades of awareness, cascades of expertise and chains of information retrieval. We find that different strategies should be used depending on the initial proportion of expertise (disruptive innovations, incremental innovations or products belonging to well-known categories). Surprisingly, when there is too much expertise in the population prior the advertisement campaign, word-of-mouth is less efficient in the retrieval of this expertise than when less expertise is initially present. Our results suggest that information seeking plays a key role in the dynamics of word-of-mouth, which can therefore not be reduced solely to the epidemic aspect.

E-mail address: samuel.thiriot@res-ear.ch.

https://doi.org/10.1016/j.physa.2017.09.056
0378-4371/

1. Introduction

1.1. Evidence on word-of-mouth

When individuals discuss an innovation (a novel product, practice, idea) [1], they *spread the word* about its existence and qualities. More people become aware of a product through word-of-mouth (or "buzz" [2]) than traditional advertisement [3]. Most consumers attribute a higher importance to interpersonal influence than other sources [4]. This observation led to viral marketing methods [5]; in these approaches, word-of-mouth is reduced to an epidemic process in which individuals "contaminate" each other with information [6].

Yet interpersonal communication about innovations or products [7] does not only include the proactive emission of information, but also communications initiated by people who seek out information about an innovation [1,8]. At the individual level, information seeking constitutes one step of consumer behaviour [9], innovation-decision process [1] or word-of-mouth behaviour [10].

When an individual discovers the existence of the innovation, that is when he receives awareness knowledge from advertisement or another individual, he might engage (or not) in information seeking depending on his characteristics [1,8,11]. As information seeking ultimately aims at reducing uncertainty about the innovation, individuals holding expertise are less prone to seek out the expert knowledge [8,11,12]. Expert knowledge covers "how to" use the innovation (know-how knowledge) [1], "why" the innovation works (principles-knowledge) [1], product category [13] or product-class knowledge [12] or brand knowledge [14]. We list in Table 1 several examples of awareness and expertise identified in field studies. This expert knowledge[1] might be gathered from individuals who hold it prior to the diffusion of the innovation because of their education or training, because they read specialized press, had experience with another product of same brand, category or class, or because they received this information from another individual. These individuals are referred to as experts in diffusion research [1, p. 399] or mavens in marketing [17,18].

Once they hold the expert knowledge, people might engage into pro-actively passing the word around about the innovation, for instance because they are willing to help others [8] or because they are satisfied or dissatisfied after adoption [19].

Information seeking stands as a step required for most individuals to be able to decide to adopt or reject a product [4]. In the case of the diffusion of disruptive innovations such as vaccination or contraceptives [1], information seeking is even seen as a mandatory step for individuals to adopt the innovation, as it enables people to understand why it works and how to use it. For instance, parents do not accept the vaccination of their children without gathering more knowledge first [20]. Even if innovations might be adopted without expert knowledge, the misuse of the innovation may later cause its discontinuance [1]. Misunderstanding of the principles of sexually transmitted viruses would for instance reduce the benefits of awareness of protection solutions [21]. As a consequence, *a company or organization promoting an innovation attempts to maximize the proportion of the population which is not only aware, but also holds expertise on the innovation* [1].

Understanding the joint dynamics of awareness propagation, expertise retrieval and expertise communication thus stands as a cornerstone of the adoption of innovations. We here investigate the following questions: How efficient is word-of-mouth to retrieve the expert knowledge scattered throughout the population? What are the respective roles of information seeking and proactive communication in word-of-mouth? Is it better to raise the curiosity of people or to make them pass the word once they understood it? Overall, what are the conditions for word-of-mouth to end with a population which is both aware and knowledgeable about an innovation?

2. Limits of existing models

Numerous computational or mathematical models [27–29] were designed to understand the diffusion of information and innovations [30–32], assess the potential diffusion of products [33], and recommend strategies to accelerate or maximize this diffusion [34]. The three main types of models related to information diffusion are based on information cascades, social influence and social learning [32,35].

Marketing models based on *information cascades* [6,34,36,37] rely on an analogy with epidemic models [6,38] such as the SIR model [39,40]: every individual is either in state Susceptible (no information), Infective (informed and pro-actively passing the information to others) or Recovered (informed but passive). A Susceptible individual becomes Infective ($S \rightarrow I$) when he meets an Infective individual. After a given time, Infective agents become Recovered ($I \rightarrow R$). When enough individuals are passing the word around, information cascades appear in the simulations, as observed in reality [32]. In this case, the cumulated curve of the proportion of people informed in time follows the traditional S-shaped curve. Unfortunately, because they only include the information passing behaviour without any information seeking, these models only capture part of the dynamics of word-of-mouth.

Most models rooted in sociology are centred on social influence using *threshold models* [30,41–44]. In these models, individuals do not spread information nor seek out it, but rather change their state depending on the state of their neighbours. Because communication is implicit, threshold models do not "open the box" of word-of-mouth: they describe the flow of influence without describing the underlying flows of information.

[1] Expert knowledge is also named background knowledge [1,14,15], prior knowledge [14] or expertise [1,13,16].

Table 1
Examples of the "awareness" and "expertise" knowledge for innovative products, services or consumption goods.

Example of awareness knowledge	Example of corresponding expert knowledge	Typical expert profile
Condoms can protect from sexually transmitted infections such as HIV [21].	What is HIV? How are infections sexually transmitted? How to use condoms? Can another method be used?	People who have been exposed to a prevention campaign on sexually transmitted infections.
Long Acting Reversible Contraception hysterectomy [22]	Can reversible contraception really be reversed? How do contraceptive implants prevent pregnancy? Are these methods painful?	Clinicians, nurses, general practitioners
Quadrivalent HPV vaccine is recommended for children [20].	What is Human papillomavirus? What are the virus risks? General understanding of vaccination. Connection between HPV and Cervical Cancer.	Physicians, or Parents who already gathered information on other vaccines.
Innovation: Plugin Hybrid Electric Vehicles (PHEV) are vehicles which batteries can be reloaded by plugging them [23].	How to charge the car? Are there enough loading stations? Is a specific plug required? What is the actual autonomy of the car? What are the acceleration capabilities of such a car?	Someone who monitors the market of electric cars; someone holding expertise on batteries and their loading characteristics.
A novel service is proposed by a brand: car diagnostic centre [24]	Is the quality of service provided by this brand ok?	Someone who reads specialized press on cars, or who knows many fans of cars.
News: the Canadian parliament has passed with a motion that recognizes Quebec as a nation within a United Canada [15]	History of the independence relationship between Quebec and Canada; difference between nation and country concepts.	Someone interested in geopolitics or history; a resident in Canada.
Incremental innovation on consumption goods: stainless steel blades for razors [3]	What are the benefits of stainless steel?	Someone who heard about stainless steel.
Medical innovation: pharmaceutics [25]	Background knowledge in medicine: use, limit of effects	Has identified limits in medicine thus has explored literature; has attended medical tests
Food innovation: a functional food enriched in selenium and xylitol [26]	What are selenium and xylitol? Why is functional food of importance?	Someone already aware of functional food. Someone who attended health education activities.

Models of social learning developed in economy [35,45,46] study what happens if people can decide to adopt a product based on the information gathered from previous adopters instead of relying on their private information. During simulations, information cascades likely develop in which people adopt based on prior adopters' choices [47]. These models do not explicitly study information seeking.

Models related to information dynamics such as computational models of culture [48] or opinion dynamics [44] also do not distinguish between information seeking or transmission. The rare models which include an explicit description of information seeking (such as [49]) are too complicated to be used to investigate the questions identified before.

As a consequence, *the role of information seeking in the dynamics of knowledge diffusion – and of actual word-of-mouth, made of both seeking and spreading – remains essentially unknown*.

3. Approach & outline

In order to investigate the role and impact of information seeking in word-of-mouth dynamics, we develop a computational model following an agent-oriented modelling approach. In such a model, the behaviour of each individual and the interactions between individuals are defined based on hypothesis rooted in field studies. Individuals in an agent-based model might be heterogeneous in their characteristics, behaviours and their position over a topology. Agent-based models are studied using simulation experiments to explore the consequences of these local hypothesis at the scale of the population.

We thus define a model (Section 4) based on the literature mentioned before, including the explicit representation of two levels of knowledge (awareness and expertise) or the heterogeneity in the characteristics of individuals (such as being prone to seek out information or not). When existing theories do not provide any reliable basis to define a hypothesis (for instance, do people have the same tendency to engage proactive transmission if they discover expertise before or after awareness) we encode the possible options as parameters of the simulation experiments. We then investigate what happens during a simulation (Section 5) and highlight the existence of cascades of awareness, cascades of expertise and chains of expertise retrieval. We drive a systematic exploration (Section 6) of the space of parameters, which reveals different regimes for different proportions of initial knowledge and individuals' characteristics. In each different case, we propose interpretations of results for institutions which attempt to maximize the proportion of individuals being both aware and expert at the end of the process. These experiments strongly suggest (Section 7) that word-of-mouth cannot be reduced to its sole epidemic component.

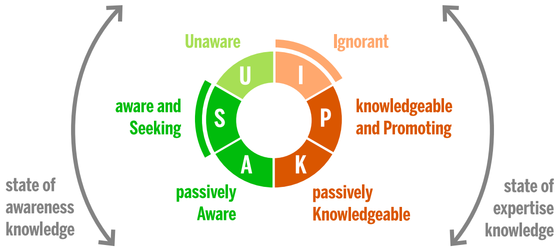


Fig. 1. Graphical representation of the state of knowledge of an agent. This agent is in state Seeking, Ignorant denoted (S, I).

4. Method: A simple model with awareness and expertise

4.1. Overview of the model

We here design a simple model to investigate the dynamics of word-of-mouth with information seeking. In this disaggregate model, each individual is represented by a simplification denoted "agent" [50]. Each agent holds a state of beliefs evolving in time, and constant characteristics which reflect heterogeneity in the population [33]. Agents interact over a social network which describes the structure of interactions. Based on the interactions between agents and the rules for the evolution of their states of knowledge (microscopic scale), we then explore by simulation the diffusion of awareness and expertise at the population scale (macroscopic scale).

4.2. Representation of knowledge

Each agent in the model holds a state of knowledge (Fig. 1) which evolves during the simulation. In order to study information seeking, we do not only represent one dimension of knowledge (S, I, R) as in epidemic models, but two: a state of knowledge on *awareness* (U, S, A) and another on *expertise* (I, P, K). Here *awareness knowledge* is understood as the element of knowledge directly related to the innovation that is either transmitted by advertisement or passed around by individuals. *Expertise knowledge* can be held independently of the innovation, can be known prior to the diffusion of the innovation it is related to, can be sent pro-actively or retrieved by information seeking.

On the *awareness* dimension, the individual might be **U**naware (did not hear about the innovation), **S**eeking (knows the innovation exists and actively searches for more information) or **A**ware (knows the innovation exists, but does not try to find information about it). On the *expertise* dimension, each agent is first **I**gnorant of the expert knowledge, might begin actively **P**romoting this expert knowledge, or be passively **K**nowledgeable. The state of knowledge of each individual is defined as a tuple: for instance (U, I) denotes an agent which is **U**naware of the innovation and **I**gnorant of the expert knowledge.

Awareness and expert knowledge can be considered as essentially independent dimensions. People can be expert without being aware of a specific innovation (for instance, knowing the category of product but not the last product in this category). Individuals can be aware of the innovation without holding the expert knowledge required to assess it. Awareness can be passed by word-of-mouth on the innovation (for instance: "Did you heard about HPV vaccines for children?" [20]). Expertise might also be transmitted independently of the innovation, for instance because another innovation of the same category is diffusing at the same time [1], or because some experts promote a category of innovation (e.g. "I recently heard about the vaccines recommended for children...") or the expert knowledge (e.g. "It seems like the secondary effects of vaccinations are marginal compared to the virus itself.").

Yet awareness and expert knowledge are related in the behaviour of individuals. Individuals can only be Seeking as long as they are not Knowledgeable of the expertise. When two individuals discuss, they will exchange at the same time awareness and expertise which are linked in the conversation: if an individual knows awareness and the other one expertise, an interaction ends with both owning awareness and expertise.

4.3. Evolution of knowledge

At the beginning of the simulation, a proportion $k \in [0 : 1]$ of the N simulated agents are initialized in state (U, K): they represent individuals who are Unaware of the innovation, but are already Knowledgeable of the brand, category of product, or the know-how required to understand this innovation. The remaining agents are initialized in state (U, I): they neither know the existence of the innovation nor hold the expertise to understand it. This initial population of agents reflects the situation of an actual social system prior to the communication campaign promoting an innovation or product: a given proportion of individuals holds the expertise required to understand it, but no one knows yet the innovation or product.

Awareness is introduced into the population by an exogenous advertisement campaign which arbitrarily lasts for the ten first simulation steps. At each step, 10% of the agents randomly picked up from the population receive awareness.

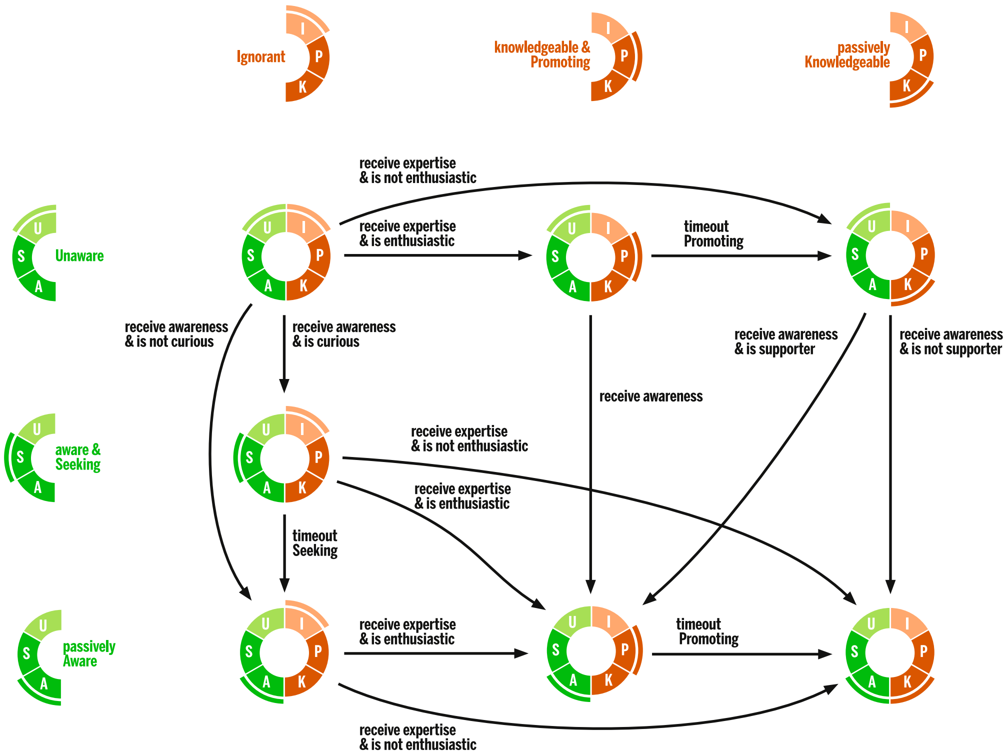


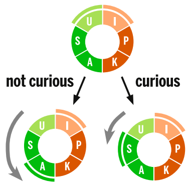
Fig. 2. State diagram representing the evolution of the state of agents on the dimensions of awareness and expertise depending on the characteristics of the agent (curious, enthusiastic, promoter) when the agent receives awareness or expertise. The vertical dimension contains the states related to awareness: Unaware, Seeking, Aware; the horizontal dimension contains the expertise states: Ignorant, Promoting, Knowledgeable. The combined state is read as: (U, I) "the agent is Unaware and Ignorant". Arrows depict the conditions for an agent to switch from one state to another one. For instance $(U, I) \rightarrow (S, I)$ is read as: "an agent starts Seeking out information after receiving awareness if it is curious, but does not change its level expertise which remains Ignorant". An agent holds complete knowledge when he is Aware and Promoting or Aware and Knowledgeable. An agent instigates conversations either when it is Seeking out information (S, I) or because it is Promoting the expert knowledge (U, K) or (A, K).

Each agent is positioned over an undirected graph which describes the structure of interactions within the population (i.e. a social network). At each step of the simulation, each pair of agents X, Y in the graph (iterated in random order) has the opportunity to interact. If at least one of the agents X and Y is in state Seeking or Promoting (that is, if at least one of the two persons meeting is willing to discuss something related to the innovation of interest in the study), the agents exchange their knowledge: if X holds awareness (resp. expertise) and Y does not, then Y receives awareness (resp. expertise). Because communication in a discussion is bidirectional, the same process takes place for Y and X. As a consequence, in this model, if X comes with the question "did you heard about HPV vaccines for children?", agent Y becomes aware of these vaccines if he was not already. If agent Y knows expert knowledge, then it will share it (even if it was not Proactive, meaning he would not have raised the topic himself), like "I read that even risky vaccines are still less dangerous that the sickness itself". In this case, agents X and Y will end with a complete knowledge of both awareness and expertise: "There are HPV vaccines for children, and even risky vaccines are positive to individuals".

As soon as it receives awareness or expertise, each agent changes its knowledge state according to the rules defined in Fig. 3. The corresponding state diagram for agents is provided in Fig. 2. These rules rely on three Boolean characteristics associated with each agent at the beginning of the simulation and constant throughout it[2]. These three characteristics represent the individual factors susceptible to influence the reaction of individuals when they receive awareness or expertise. Because there is no proof in the literature that people react the same when they discover awareness prior to expertise, or expertise prior to awareness, these different cases are split with different independent characteristics which will be further investigated by simulation.

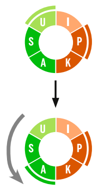
Agents with characteristic "curious" being True will start Seeking out information when they receive awareness if they are not Knowledgeable of the expert knowledge already.

2 The characteristics of agents in the model (curious, enthusiastic, supporter) represent personality traits of individuals which impact their communication behaviour. We here assume their evolution is slow enough compared to the speed of the word-of-mouth dynamics to be considered constant.



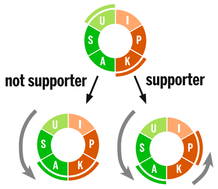
$$(U, I) \xrightarrow{\text{awareness}} \begin{cases} \text{if curious:}(S, I) \\ \text{else:}(A, I) \end{cases}$$

An agent Unaware of the innovation and Ignorant of the expertise receives awareness. If it is curious, it starts Seeking out information, or becomes passively Aware of it.



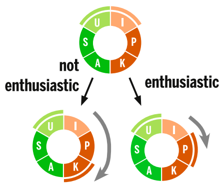
$$(U, P) \xrightarrow{\text{awareness}} (A, P)$$

An agent is Pro-actively speaking about the expert knowledge but is Unaware of the innovation. When it receives awareness, it does not seek out the expertise it already has, thus becomes passively Aware (and remains Promoting the expert knowledge).



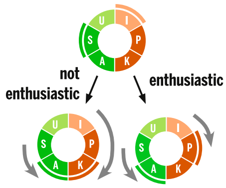
$$(U, K) \xrightarrow{\text{awareness}} \begin{cases} \text{if supporter:}(A, P) \\ \text{else:}(A, K) \end{cases}$$

An agent Unaware of the innovation but Knowledgeable of the expertise discovers awareness. This agent becomes Aware. If it is supporter, the agent might also start Promoting the innovation.



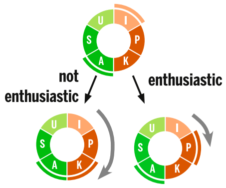
$$(U, I) \xrightarrow{\text{expertise}} \begin{cases} \text{if enthusiastic:}(U, P) \\ \text{else:}(U, K) \end{cases}$$

An agent Unaware of the innovation and Ignorant of expert knowledge receives expertise. If it is enthusiastic, the agent starts Promoting the expert knowledge, else becomes passively Knowledgeable.



$$(S, I) \xrightarrow{\text{expertise}} \begin{cases} \text{if enthusiastic:}(A, P) \\ \text{else:}(A, K) \end{cases}$$

An agent Seeking out information about the innovation receives the expert knowledge. It stops Seeking and becomes Aware. If it is enthusiastic, it might also start Promoting it.



$$(A, I) \xrightarrow{\text{expertise}} \begin{cases} \text{if enthusiastic:}(A, P) \\ \text{else:}(A, K) \end{cases}$$

An agent Aware of the innovation receives the expertise it was Ignorant of. If remains Aware, and might start Promoting if it is enthusiastic.

Fig. 3. Rules of evolution of knowledge states when an agent receives awareness or expertise, depending on the agent's characteristics curious (interested by the innovation when it becomes aware of it), enthusiastic (promotes the innovation or expert knowledge when it understands it) and supporter (when initially knowledgeable, decides to promote the innovation when it discovers it). The first line depicts the initial state at time step t, the second line the future state $t + 1$.

"Enthusiast" agents represent people who, when they discover expertise, are so enthusiastic about the principles they discover that they start Promoting it. This reflects how, in the case of cross-brand or cross-category innovations [28,51] or even for standalone expert knowledge [17,18], individuals might spread the expert knowledge even if they are not aware of the innovation under study when they discuss other categories and products.

"Supporter" agents are people who, when they already hold expert Knowledge and receive awareness, find this innovation interesting enough based on their prior knowledge to start Promoting it.

The parameters for the proportions of curious, enthusiastic and supporter agents will be explored below to understand their impact of word-of-mouth dynamics.

In reality, most people do not keep Seeking out information nor Promoting expert knowledge forever. In the model, agents in state Seeking shift to passively Aware after a given number of steps defined by the model parameter timeout^S:

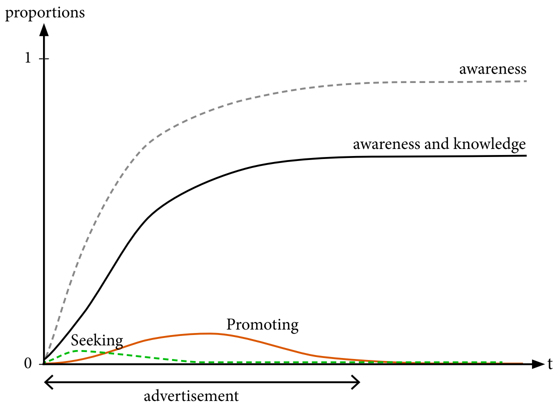


Fig. 4. Typical successful diffusion of awareness (all the agents in state $(A, *)$) and complete information ((A, K)). Dashed curves depict the propagation of awareness, and the underlying proportion of agents Seeking out information during the simulation.

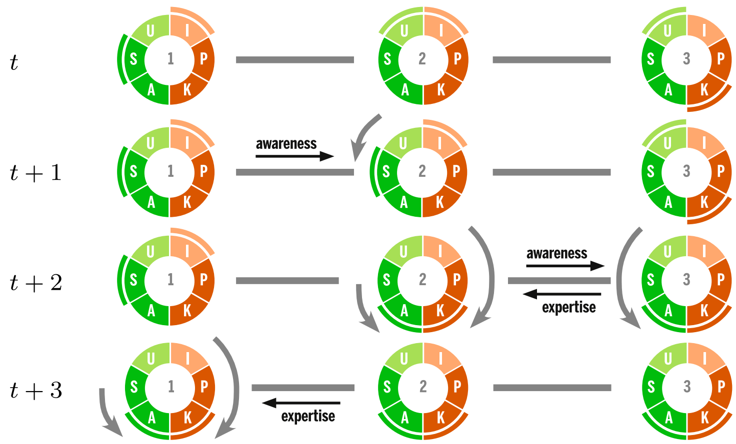


Fig. 5. Example of a *cascade of awareness* and of a *chain of information retrieval*. At time t, agent (1) is Seeking out expert knowledge; this expertise is only available from agent (3) to which (1) is not directly connected with in the social network. When it seeks for information, agent (1) makes agent (2) aware as well. If agent (2) has property curious, it also enters Seeking. Then at time $t+2$, this agent sends awareness to agent (3). There was a cascade of awareness between (1), (2) and (3). Agent (2) also retrieves expertise from (3), which can later be retrieved by (1). There was a chain of information retrieval from (3) to (1). These chains enable the population to retrieve expertise even if it is rare in the population.

$(S, I) \xrightarrow{\text{timeout}^S} (A, I)$. In the same way, agents also leave state Promoting for state Knowledgeable after a number of steps defined by parameter timeout^P: $(*, P) \xrightarrow{\text{timeout}^P} (*, K)$.

5. Results: Simulation experiments

5.1. Experimental conditions

For these simulation experiments, we generate for each simulation a different Watts–Strogatz small-world network [52] with $N = 1000$, $p^{\text{rewiring}} = 0.01$ and $nei = 4$. The resulting networks have an average degree of 4.0 and an average path length of 4.35. The time-out for states Seeking and Promoting is defined to 5; this parameter has no impact as long as it is greater than the average path length. The simulation is stopped when the advertisement campaign is finished, and when there is no Promoting nor Seeking agent any more.

5.2. Diffusion dynamics

We show on Fig. 4 a typical example of the diffusion of awareness and knowledge.

Every agent reached by the advertisement campaign receives awareness; if the agent is curious, it might start Seeking out information. Then, when Seeking, the agent transmits awareness knowledge and might create one or more Seeking agents. As a consequence multiple *awareness cascades*, as illustrated in Fig. 5, appear in the population. When the proportion of

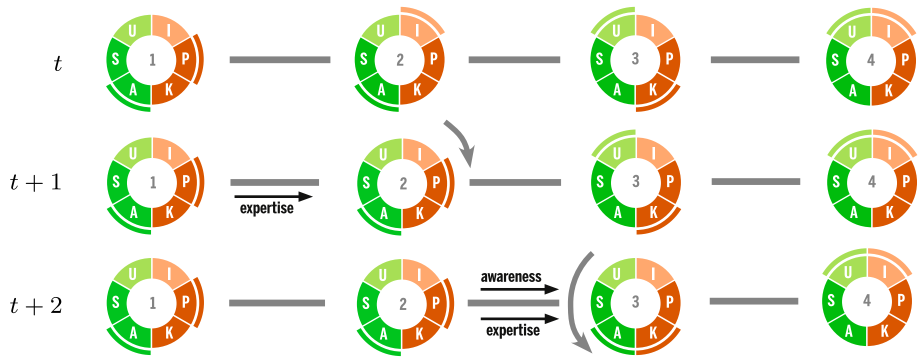


Fig. 6. Example of a *cascade of expertise*, and its *blockage because of a Knowledgeable agent*. Agent (1) is promoting and might thus transmit expert knowledge to the Ignorant agent (4) through agents (2) and (3). Agent (1) is promoting, thus sends awareness and expert knowledge to agent (2). Then if agent (2) is enthusiastic, it might pass expertise to agent (3), thus contributing to the cascade of expertise between (1), (2) and (3). Yet because (3) is already Knowledgeable, it will only start Promoting information if it has the "supporter" characteristic. If it is not the case, the presence of knowledge will stop the cascade of expertise. Agent (4) will not discover the expert knowledge. Because of this phenomenon, populations having more expertise are less efficient in its retrieval, except if there are enough supporters.

curious agents is high enough compared to the degree of the network, cumulated awareness in the population exhibits a S-shape curve, or even a log-curve when advertisement is seeding enough awareness within the population, as depicted in Fig. 4.

When an awareness cascade reaches an agent Knowledgeable of the expertise, the last Seeking agent in the chain retrieves this expertise and becomes Knowledgeable of expertise; it might thus transmit it to Seeking agents the next time they ask him a question. As the previous agents of the awareness cascade are probably still Seeking[3], each of them will eventually retrieve this expertise. As a consequence, most awareness cascades might turn into *chains of information retrieval* as shown in Fig. 5.

Simultaneously, every Ignorant agent who receives expertise might, if it is enthusiastic, start Promoting it. In this case, *cascades of expertise* also appear which diffuse expertise within the population (Fig. 6). Cascades of expertise or awareness continue to occur even after the end of the advertisement campaign, as observed in actual word-of-mouth [53].

Awareness cascades, expertise cascades and chains of information retrieval occur simultaneously in different parts of the population as shown in Fig. 7. These flows of information hardly extend the entire population — only high values of proportions of curious, enthusiasts, supporters on networks having a high average degree of connectivity enable massive information diffusion in the network. This is compliant with field studies identifying rather short cascades of information [32] or the cascades of recommendations which remain split in distinct clusters of the network [54]. The simultaneous process of cascades of awareness, chains of information retrieval and expertise cascades lead to an exponential diffusion and retrieval of this joint awareness and knowledge, thus leading to a cumulated S-shape curve of diffusion as shown in Fig. 4. Note that the proportion of joint awareness and knowledge always remains lower than the sole awareness (by definition). Incidentally, a survey measuring the awareness in the population might suggest a high success rate in the advertisement campaign, even if the population fails to retrieve the expertise and is actually unable to assess the innovation or product because of a lack of expertise.

6. Results: Exploration of the space of parameters

In order to uncover the efficiency of word-of-mouth in the diffusion of awareness and the retrieval of the scattered expertise, we explore the space of parameters of initial knowledge k and various proportions of curious, enthusiastic and supporters. Using the same experimental setting as described before, we measure the amount of the population ending with both awareness and knowledge. For each combination of parameters, results are the mean result over 100 simulations or more.

The model highlights three different types of dynamics depending on the initial expertise k.

6.1. Efficiency of word-of-mouth for disruptive innovations

Fig. 8 depicts the amount of the population ending with both awareness and knowledge when 1% of the population initially holds the expert knowledge ($k = 0.01$). 1% stands as a case of a disruptive innovation or product that only rare people in the population are able to understand [1].

[3] Chains of information retrieval depend on the parameter timeout^S: if it is bigger than the path length of interest, the chain will be laddered back.

Fig. 7. Excerpt of a simulation of 1000 agents over a small-world network. Awareness cascades are represented in green; expertise cascades in orange; chains of information retrieval in purple. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

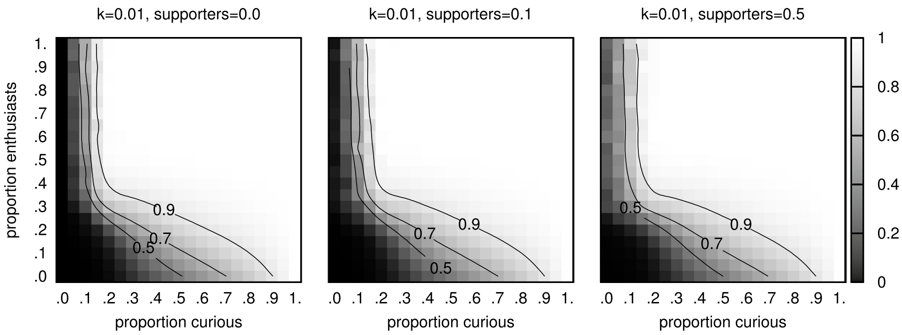


Fig. 8. For a low proportion of initial knowledge of $k = 1\%$, depicts the final proportion of the population holding both awareness and expertise. In such a case of a disruptive innovation, there is a minimal proportion of curious people mandatory to bootstrap the diffusion of expertise; once this proportion is reached, it is better to have as many enthusiastic people as possible.

Each graph of Fig. 8 exhibits a *threshold effect* on both the proportions of curious and enthusiasts. With 20% of seekers, 20% enthusiasts and no supporter, only 50% of the population ends up with both awareness and expertise. With 30% of seekers, 30% of enthusiasts and no supporter, up to 90% of the population ends with the complete knowledge. Such as threshold effect is similar to epidemic thresholds identified in epidemics [55].

The proportion of supporters has a marginal impact here, as it only concerns the few agents k Knowledgeable prior to receiving awareness.

Experiments also highlight an *asymmetry between the impact of enthusiasts and curious*. If there are only enthusiasts and no curious, diffusion fails; yet if there are enough curious with no enthusiast, diffusion can happen. However, as soon as curiosity is high enough in the population (20% in our experimental conditions), increasing curiosity becomes less efficient than increasing the proportion of enthusiasts.

In fact, the proportion of enthusiasts defines how many people would pass the word around when they found the expertise; yet they first have to gather this expertise from some source. If supporters are rare, cascades of expertise are too rare for their impact to be noticeable. That explains why a minimal proportion of curious agents is required for the proportion of enthusiasts to have any impact.

On the other hand, a curious agent will propagate awareness around him. Because most agents are initially not Knowledgeable, that might create cascades of awareness and maybe chains of information retrieval. Also, each agent discovering expertise might start a cascade of expertise, with a likelihood directly dependent on the proportion of enthusiasts. Therefore, information seeking (driven by curiosity) plays the role of a bootstrap: a minimal amount of curiosity will create more

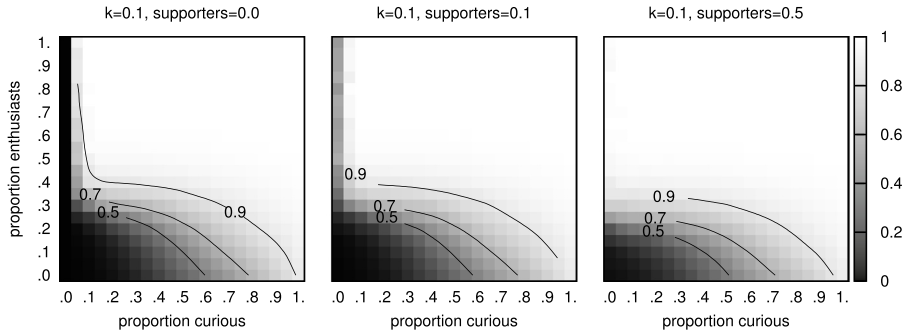


Fig. 9. For $k = 10\%$ of people initially able to understand the innovation, final proportion of the population holding both awareness and expertise for different proportions of curious, enthusiasts and supporters. For such an incremental innovation, one can either have supporters or enthusiasts to bootstrap the diffusion of knowledge; then success mainly depends on the proportion of enthusiasts.

awareness, information retrieval chains, thus bringing expert knowledge to agents which start Promoting the expert knowledge (depending on the proportion of enthusiasts in the population).

This suggests for policies that *when little expert knowledge is initially available in the population, as for disruptive innovations, raising curiosity of individuals is mandatory*. Once this threshold on curiosity is reached, the success of diffusion is directly correlated to the proportion of enthusiasts. If both these conditions are met, in our simplistic model, the entire population can retrieve the rare expertise scattered within the population: with 20% of curious and 20% of enthusiasts, 50% of the population achieves to retrieve the rare 1% of initial expertise.

6.2. Efficiency of word-of-mouth for incremental innovations

We now investigate a case with more initial expertise ($k = 10\%$) available in the population, as for an incremental innovations [1] or novel products belonging to a novel product category.

Simulation results displayed in Fig. 9 also highlight a *strong asymmetry* between the impact of enthusiasts and curious: when a threshold of curious is passed (here, over 10%), increasing the proportion of enthusiasts is twice more efficient than increasing the proportion of curious. This suggests it is more important to have enthusiastic people passing the word once they understood the innovation (as they pass at the same time both awareness and knowledge) than having curious people Seeking out information and relaying the sole awareness message.

Proportions of curious and supporters play the same role: as soon as a given level is reached (10% in this experimental setting), the diffusion can happen, with success depending on the proportion of enthusiasts. This happens because of the higher proportion of Knowledgeable people present in the population. If the advertisement campaign reaches a Knowledgeable agent, it will start Promoting only if it is a supporter, and might then create cascades of expertise. If the campaign reaches an Ignorant agent instead, this agent will only start Seeking if it is curious — and might in this case create a chain of information retrieval. In both cases, once the expertise is obtained by agents, enthusiasts might start Promoting of their own accord and create more cascades of expertise.

The fact curious and supporters play the same role suggests that *an incremental innovation which successfully raises curiosity does not require the support of knowledgeable people for it to be known and understood* — or reciprocally that the support of market mavens might balance the absence of people made curious by the awareness message.

6.3. Efficiency of word-of-mouth for well-known categories

We show in Fig. 10 the diffusion of expertise when $k = 50\%$ of the population is initially able to understand the innovation. These experiments investigate what happens for an incremental innovation [1] or a product of a popular category, that is an innovation that can already be understood or evaluated by half the population.

One might expect that having more expertise available in the population should make it easier for the remaining Ignorant agents to retrieve it. Surprisingly, when there are few supporters, *the more initial knowledge prior to the diffusion, the lower the efficiency rate of word-of-mouth* (comparison between Figs. 8–10 for proportions of supporters 0 or 0.1). Prior knowledge, indeed, plays a role similar to vaccination in epidemics: Knowledgeable agents never engage in Seeking out the expert knowledge they already hold. Enthusiastic agents also only promote when they discover expertise — yet many agents are already Knowledgeable in this experiment. As illustrated in Fig. 6, *if they are not supporters, Knowledgeable agents block the flow of information*, as Recovered agents do in epidemic SIR models, thus limiting the effect of cascades of awareness and expertise.

Even if many agents are curious, only those not being Knowledgeable already might start Seeking out information; they will quickly discover a Knowledgeable agent around them, and will immediately quit Seeking without propagating their

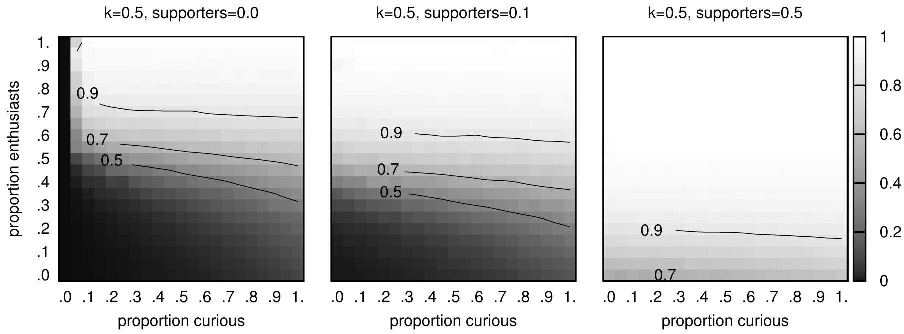


Fig. 10. When 50% of the population already holds expertise on the innovation, depicts the final proportion of the population holding both awareness and expertise. Diffusion success here mainly depend on the proportion of supporters, that is Knowledgeable agents who start Promoting the innovation when they discover its existence.

awareness any more; thus they only start a few cascades of awareness. These cascades of awareness are quickly stopped by the Knowledgeable agents they meet. The impact of curiosity is thus low.

In the same way, the few enthusiastic agents which were not initially Knowledgeable might start promoting the expert knowledge when they discover it. This might reach all the connections of the agent, leading to a strong impact of the proportion of enthusiasts parameter (notice how, even for such a well-known category of product, word-of-mouth still contributes the propagation of knowledge as observed for actual consumption goods [3]). Yet these chains of expertise are blocked if they meet an agent which is already Knowledgeable and is not supporter.

When the proportion of prior expertise is high in the population, the proportion of supporters is thus the key for the efficiency of word-of-mouth. As a consequence, if a product belongs to a category which is well-known by the population (as for consumption goods like razors), raising curiosity is possible for so few people that it does not constitute a relevant strategy any more. In this case, *it is more important to have mavens to support this product, which would probably happen only if this product has a strong comparative advantage over other products* (or a strong disadvantage, provided the model is not including valence for expert knowledge). Despite being counter-intuitive, these simulation results appear coherent with observed dynamics of word-of-mouth; buzz is rarely observed for standard consumption goods which are well understood in the population. Our findings suggest the explanation is not the lack of interest of the population (the proportion of curiosity might be high with no success) but rather that *prior expert knowledge plays a role similar to vaccination in epidemics, by blocking cascades of awareness and expertise in the population.*

7. Discussion

Our computational studies on the joint dynamics of information seeking and proactive emission of information reveal complex dynamics for word-of-mouth. The actual diffusion of awareness and expertise at the macroscopic scale is driven by the joint dynamics of awareness cascades, expertise cascades and chains of information retrieval occurring at the mesoscopic scale (Section 5).

There is no universal setting that would always guarantee the retrieval of expertise in the entire population (Section 6). Our simulation experiments exhibit three main regimes depending on the amount of initial knowledge k, suggesting different communication strategies should be used depending on the initial amount of expert knowledge. In any case, having people passing the word when they discover expertise after awareness ("enthusiasts" in the model) is positively correlated with the proportion of the population ending with both awareness and expertise. Yet this sole "epidemic" process does not start alone for disruptive or incremental innovations. For well-known categories of innovations or products, the diffusion only relies on enthusiasts (expert people promoting the innovation when they discover it). For incremental innovations, it can be bootstrapped either by curiosity (people seeking out information when they receive awareness) or by supporters (people who transmit their expert knowledge when they discover the existence of the innovation). For disruptive innovations, information seeking seems mandatory to start the diffusion of awareness and expertise in the population.

These results are based on a model which was purposively oversimplified (as were the previous computational models) to analyse the precise question of the impact of information seeking on word-of-mouth. Many aspects are not described in this model, including the complexity of human communication behaviour [1,32,54], network of interactions [36], or word-of-mouth content (including its valence or multi-dimensionality). Therefore, these simulation results should not be seen as an exact description of what happens in actual societies in their entire complexity.

Nevertheless, this model is rooted in evidence collected from past field studies, as for the existence of information search or the existence of at least two levels of knowledge (awareness and expertise). The description of individuals' states, characteristics and behaviours are based on field evidence. Unknown behaviours were defined as dependent to parameters of the simulation experiments, in order to change uncertainty into a domain which can be systematically investigated by experimentation (Section 6). Even the unexpected simulation results appeared to be compliant with literature on word-of-mouth, such as the limited size of cascades or the negative relationship between the amount of initial expertise and the efficiency of word-of-mouth.

These simulation experiments illustrate how word-of-mouth dynamics are more complex than a sole epidemic process. This study suggests that strategies of information dissemination should not rely on the pure epidemic paradigm which ignores the role of information seeking, which was acknowledged in both marketing studies and diffusion of innovations studies, and now appears to have a potentially significant impact on word-of-mouth dynamics.

8. Additional material

The source code of the model is freely available in the public repository https://www.openabm.org/model/5834/. It can be opened with the last version of the open-source, free NetLogo simulation engine: https://ccl.northwestern.edu/netlogo/download.shtml.

Acknowledgements

The author would like to thank Sarah Thiriot for the numerous improvements she suggested in the presentation of this research. This study is partly based on previous research discussed with Jean-Daniel Kant.

References

[1] E.M. Rogers, Diffusion of Innovations, fifth ed., Free Press, New York, 2003.
[2] W.J. Carl, What's all the buzz about? Everyday communication and the relational basis of word-of-mouth and buzz marketing practices, Manag. Commun. Q. 19 (4) (2006) 601–634.
[3] J.N. Sheth, Word of mouth in low risk innovations, J. Advert. Res. 11 (3) (1971) 15–18.
[4] E. Katz, P. Lazarsfeld, Personal Influence: The Part Played by People in the Flow of Mass Communication, Tech. Rep., Bureau of Applied Social Research, Columbia University, 1955.
[5] B. Lang, R. Lawson, N. Zealand, Dissecting word-of-mouth's effectiveness and how to use it as a proconsumer tool, J. Nonprofit Public Sector Mark. 25 (2013) 374–399. http://dx.doi.org/10.1080/10495142.2013.845419.
[6] W. Goffman, V.A. Newill, Generalization of epidemic theory: An application to the transmission of ideas, Nature 204 (1964) 225–228.
[7] J. Arndt, Role of product-related conversations in the diffusion of a new product, J. Mark. Res. 4 (1967) 291–295.
[8] M.C. Gilly, J.L. Graham, M.F. Wolfinbarger, L.J. Yale, A dyadic study of interpersonal information search, J. Acad. Mark. Sci. 26 (2) (1998) 83–100. http://dx.doi.org/10.1177/0092070398262001.
[9] J.R. Bettman, An Information Processing Theory of Consumer Choice, Addison-Wesley Pub. Co., Reading, Mass, 1979.
[10] A. De Bruyn, G.L. Lilien, A multi-stage model of word-of-mouth influence through viral marketing, Int. J. Res. Mark. 25 (3) (2008) 151–163. http://dx.doi.org/10.1016/j.ijresmar.2008.03.004.
[11] T. Mazzarol, J.C. Sweeney, G.N. Soutar, Conceptualizing word-of-mouth activity, triggers and conditions: An exploratory study, Eur. J. Mark. 41 (11/12) (2007) 1475–1494. http://dx.doi.org/10.1108/03090560710821260.
[12] M. Brucks, The effects of product class knowledge on information search behavior, Source J. Consum. Res. 12 (1) (1985) 1–16. http://dx.doi.org/10.1086/209031.
[13] P. Moreau, D. Lehmann, A. Markman, Entrenched knowledge structures and consumer response to new products, J. Mark. Res. 38 (2) (2001) 14–29. http://dx.doi.org/10.1509/jmkr.38.1.14.18836.
[14] J.R. Bettman, Effects of prior knowledge and experience and phase of the choice process on consumer decision processes: A protocol analysis, J. Consumer Res. 7 (3) (1986) 234.
[15] D. Mathieu, Cultural knowledge in news comprehension, J. Audience Recept. Stud. 6 (1) (2009) 77–117.
[16] D.H. Park, S. Kim, The effects of consumer knowledge on message processing of electronic word-of-mouth via online consumer reviews, Electron. Commer. Res. Appl. 7 (4) (2008) 399–410. http://dx.doi.org/10.1016/j.elerap.2007.12.001.
[17] L.F. Feick, L.L. Price, The market maven: A diffuser of marketplace information, J. Mark. (1987) 83–97.
[18] G. Walsh, R. Elsner, Improving referral management by quantifying market mavens' word of mouth value, Eur. Manag. J. 30 (1) (2012) 74–81. http://dx.doi.org/10.1016/j.emj.2011.04.002.
[19] E.W. Anderson, Customer satisfaction and word of mouth, J. Serv. Res. 1 (1) (1998) 5–17. http://dx.doi.org/10.1177/109467059800100102.
[20] K. Trim, N. Nagji, L. Elit, K. Roy, Parental knowledge, attitudes, and behaviours towards human papillomavirus vaccination for their children: A systematic review from 2001 to 2011, Obstet. Gynecol. Int. 2012 (2012) 921236. http://dx.doi.org/10.1155/2012/921236.
[21] S. Sood, C. Shefner-Rogers, The impact of a mass media campaign on HIV/AIDS knowledge and behavior change in North India: Results from a longitudinal study, Asian J. Commun. 16 (3) (2006) 231–250. http://dx.doi.org/10.1080/01292980600857740.
[22] E. Okpo, L. Allerton, S. Brechin, 'But you can't reverse a hysterectomy!' Perceptions of long acting reversible contraception (LARC) among young women aged 16-24 years: A qualitative study, Public Health 128 (10) (2014) 934–939. http://dx.doi.org/10.1016/j.puhe.2014.08.012.
[23] J. Axsen, K.S. Kurani, Interpersonal influence within car buyers' social networks: Applying five perspectives to plug-in hybrid vehicle drivers, Environ. Plan. 44 (5) (2012) 1047–1065.
[24] J.F. Engel, R.J. Kegerreis, R.D. Blackwell, Word-of-mouth communication by the innovator, J. Mark. 33 (3) (1969) 15–19.
[25] L. Fuks Nielsen, C. Moldrup, The diffusion of innovation: Factors influencing the uptake of pharmacogenetics, Community Genetics 10 (4) (2007) 231–241. http://dx.doi.org/10.1159/000106562.
[26] T. Bech-Larsen, J. Scholderer, Functional foods in Europe: Consumer research, Market experiences and regulatory aspects, Trends Food Sci. Technol. 18 (4) (2007) 231–234. http://dx.doi.org/10.1016/j.tifs.2006.12.006.
[27] N. Meade, T. Islam, Modelling and forecasting the diffusion of innovation–A 25-year review, Int. J. Forecast. 22 (3) (2006) 519–545.
[28] R. Peres, E. Muller, V. Mahajan, Innovation diffusion and new product growth models: A critical review and research directions, Int. J. Res. Mark. 27 (2) (2010) 91–106. http://dx.doi.org/10.1016/j.ijresmar.2009.12.012.
[29] E. Kiesling, M. Günther, C. Stummer, L.M. Wakolbinger, Agent-based simulation of innovation diffusion: A review, CEJOR Cent. Eur. J. Oper. Res. 20 (2) (2012) 183–230. http://dx.doi.org/10.1007/s10100-011-0210-y.
[30] M.S. Granovetter, Threshold models of collective behavior, Am. J. Sociol. 83 (6) (1978) 1420–1443.

[31] J. Goldenberg, B. Libai, S. Solomon, N. Jan, D. Stauffer, Marketing percolation, Physica A 284 (1–4) (2000) 335–347.
[32] J. Leskovec, L.A. Adamic, B.A. Huberman, The dynamics of viral marketing, ACM Trans. Web 1 (1) (2007) 5. http://dx.doi.org/10.1145/1232722.1232727.
[33] R.A. Chatterjee, J. Eliashberg, The innovation diffusion process in a heterogeneous population: A micromodeling approach, Manage. Sci. 36 (9) (1990) 1057–1079. http://dx.doi.org/10.1287/mnsc.36.9.1057.
[34] D. Kempe, J. Kleinberg, É. Tardos, Maximizing the spread of influence through a social network, in: Proceedings of the Ninth ACM SIGKDD International Conference on Knowledge Discovery and Data Mining - KDD '03b, 2003, p. 137. http://dx.doi.org/10.1145/956755.956769. arXiv:0806.2034v2.
[35] H.P. Young, Innovation diffusion in heterogeneous populations: Contagion, social influence, and social learning, Am. Econ. Rev. 99 (5) (2009) 1899–1924. http://dx.doi.org/10.1257/aer.99.5.1899.
[36] J. Goldenberg, B. Libai, E. Muller, Talk of the network: A complex systems look at the underlying process of word-of-mouth, Mark. Lett. 12 (3) (2001) 211–223.
[37] D.J. Watts, J. Peretti, M. Frumin, Viral Marketing for the Real World, Tech. Rep., Collective Dynamics Group, Columbia University, 2007.
[38] D.J. Daley, D.G. Kendall, Epidemics and rumours, Nature 204 (4963) (1964) 1118.
[39] W. Kermack, A.G. McKendrick, A contribution to the mathematical theory of epidemics, in: Proc. R Soc. Lond. A, vol. 115, 1927, pp. 700–721.
[40] N.T.J. Bailey, The Mathematical Theory of Epidemics, first ed., Griffin, London, 1957.
[41] G. Ellison, D. Fudenberg, Word-of-mouth communication and social learning, Q. J. Econ. 110 (1) (1995) 93–125. http://dx.doi.org/10.2307/2118512.
[42] T.W. Valente, Social network thresholds in the diffusion of innovations, Social Networks 18 (1) (1996) 69–89.
[43] D.J. Watts, P.S. Dodds, Influentials, networks, and public opinion formation, J. Consumer Res.
[44] G. Deffuant, S. Huet, F. Amblard, An individual-based model of innovation diffusion mixing social value and individual benefit, Am. J. Sociol. 110 (2005) 1041–1069.
[45] K. Chatterjee, S.H. Xu, Technology Diffusion By Learning from Neighbours, Tech. Rep., Penn State University, 2001.
[46] A. Banerjee, D. Fudenberg, Word-of-mouth learning, Games Econom. Behav. 46 (2004) 1–22.
[47] S. Bikhchandani, D. Hirshleifer, I. Welch, Learning from the behavior of others: Conformity, fads, and informational cascades, J. Econ. Perspect. 12 (3) (1998) 151–170.
[48] R.M. Axelrod, The Complexity of Cooperation: Agent-Based Models of Competition and Collaboration, Princeton University Press, Princeton, New Jersey, 1997.
[49] S. Thiriot, J.-D. Kant, Using associative networks to represent adopters' beliefs in a multiagent model of innovation diffusion, Adv. Complex Syst. 11 (2) (2008) 261–272.
[50] J. Ferber, Multi-Agent Systems, Addison Wesley, 1999.
[51] B. Libai, E. Muller, R. Peres, The role of within-brand and cross-brand communications in competitive growth, J. Mark. 73 (2009) 19–34.
[52] D.J. Watts, S.H. Strogatz, Collective dynamics of 'small-world' networks, Nature 393 (1998) 440–442.
[53] L. Groeger, F. Buttle, Deciphering word-of-mouth marketing campaign reach everyday conversation versus institutionalized word of mouth, J. Acad. Bus. Econ. (2016) 368–384. http://dx.doi.org/10.2501/JAR-2016-000.
[54] J.L. Iribarren, E. Moro, Information Diffusion Epidemics in Social Networks, 2007. https://arxiv.org/abs/0706.0641.
[55] M.J. Keeling, P. Rohani, Modeling Infectious Diseases in Humans and Animals, Princeton University Press, 2008.