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Finding Optimal Targets for Change Agents: A Computer Simulation of Innovation Diffusion*

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Abstract

We introduce a diffusion of innovation model based on a network threshold approach. Realistic network and threshold data were gathered regarding the diffusion of new software tools within part of a large organization. Novel model features are a second threshold for innovation rejection and a memory that allows actors to take trends into account. Computer simulations produce expected outcomes, such as the S-shaped diffusion curve, but also diffusion breakdown and oscillations. We define and compute the quality of change agent targets in terms of the impact targeted actors have on the diffusion process. Our simulations reveal considerable variance in the quality of actors as change agent targets. Certain actors can be singled out as especially important to the diffusion process. Small changes in the distribution of thresholds and changes in some parameters, such as the sensitivity for trends, lead to significant changes in the target quality measure. To illustrate these interdependencies we outline how the impact of an actor targeted by a change agent spreads through the network. We thus can explain why a good change agent target does not necessarily need to be an opinion leader. Simulations comparing the effectiveness of randomly selected targets versus a group of good change agent targets indicate that the selection of good targets can accelerate innovation diffusion.

Keywords: diffusion, innovation, simulation, change agent, oscillation, construct, viscosity, network

1. Introduction

Change agents promote concrete change in groups or organizations. For instance, they foster the diffusion of innovations by influencing chosen group members towards innovation adoption. The success of a change agent may depend on the choice of targets. In order to be efficient change agents have to pick the right targets for their efforts. Who are those right targets? Are they the most central actors in the organizational network, as sometimes suggested in the diffusion of innovation literature (see e.g., Rogers, 1995; Valente and Davis, 1999)? To address this question we developed a diffusion of innovation model and

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performed computer simulations.[1] Our model advances the network threshold approach (see Valente, 1996) by providing actors with a memory and the capacity to reverse their decision to adopt the innovation. We incorporated realistic data about the network structure and the distribution of thresholds by using survey data regarding the diffusion of software tools within part of a large organization. In the first part of this paper we describe our diffusion model. We then present the results of our computer simulations. Special consideration is given to the task of finding optimal targets for change agents. After that, we compare our model with two similar models—the viscosity model and Construct. Finally we discuss our results and the model's empirical adequacy.

2. Model

The main component of our model is a set of actors who differ in the social ties they have among each other and in the way they make decisions to adopt or reject an innovation. At each time step every actor has to decide whether to adopt the innovation, or if already adopted, whether to disadopt it. Each actor's decision is based on (a) her attitude towards the innovation and (b) the adoption behavior of her social network. Two thresholds are assigned to each actor. The first threshold governs adoption; the second threshold is always a fixed fraction of the first and governs the disadoption of the innovation. We also provide the actors with a memory. In this way our actors can base their decision to adopt an innovation on their perception of how well this innovation has been established in the past. This seems to be a realistic assumption, especially for late adopters. It is intuitively plausible that actors count increases (or decreases) in innovation use in their personal network in favor of (or against) adoption.[2] To take the observed trend in innovation use into account we define an actor a's "personal network trend" as the weighed sum of

- the average number of adopters in a's personal network and
- the average gain/loss of adopters within a's network over a period of ten time steps.

If a's personal network trend exceeds a's threshold for adoption, a will adopt; if this degree falls below a's threshold for disadoption, a will disadopt the innovation. The memory that allows actors to take trends into consideration and the disadoption threshold distinguish our model from other threshold models.[3] These components, as we shall see, enable our actors to disadopt an innovation. Allowing for innovation disadoption is a necessary model feature in our setting since new software tools often get disadopted after initial adoption.

Realistic data about our actors' social network were extracted from a survey we administered to a group of employees within a large organization.[4] Thresholds for the actors were determined from self-reports. We described a software innovation that was to be released shortly thereafter and asked the actors directly how likely they would be to adopt the innovation.[5] Individual adoption thresholds were assigned in a manner inversely proportional to this self-reported likelihood estimate. Possible adoption thresholds ranged from 0 (innovator) to the free parameter l ("worst laggard"). The higher l the more adopters are needed on average to influence actors to adopt. Table 1 formalizes the model dynamic.

Table 1. Main parameters and decision mechanism of the model.

Parameter	Meaning
l	Threshold maximum (general aversion against the innovation)
i	Number of innovators (adopters at time $t = 0$)
r	Threshold ratio (disadoption threshold = $r\cdot$ adoption threshold)
w_1	Weight for the average number of adopters in a personal network
w_2	Weight for average gain/loss of adopters in personal net (observed trend)

Determination of the adopter status of actor j at time $t > 0$

$$\text{status}_j(t) := \begin{cases} 1 & \text{if } e_j \geq \text{threshold}_j \wedge \text{status}_j(t-1) = 0 \\ 0 & \text{if } e_j < \text{threshold}_j \wedge \text{status}_j(t-1) = 0 \\ 1 & \text{if } e_j \geq r^* \text{ threshold}_j \wedge \text{status}_j(t-1) = 1 \\ 0 & \text{if } e_j < r^* \text{ threshold}_j \wedge \text{status}_j(t-1) = 1 \end{cases}$$

$e_j = w_1 * \Sigma d_{ji}/10 + w_2 * \Sigma(d_{ji+1} - d_{ji})/9$ (personal network trend)

d_{ji} = number of $j's$ contacts who are adopters (status = 1) at time $t - 10 + i$ ($0 \leq i < 10$)

if $t - 10 + i < 0$, d_{ji} = number of $j's$ contacts who are adopters at time $t = 0$

Length of every actor's memory = 10

Number of actors = 106

To define the initial condition we identify the i actors with the lowest adoption threshold and define these as the initial adopters. This stipulation is justified because thresholds have been derived from self-reported inclinations to adopt the innovation. In real situations of innovation diffusion the number of initial adopters should depend on more factors than the intrinsic appeal of the innovation. For instance, management could increase the initial appeal of the innovation by offering a financial incentive for early adoption. The number of innovators is a free parameter in our model for greater generality and because we do not have access to the factors beyond the self-reported appeal that determine the initial appeal of the innovation.

3. Simulation Results

3.1. General Results

Most simulations reached a fixed point after a few hundred time steps, at the latest, with no further change occurring. We classified such outcomes either as diffusion success or diffusion failure depending on the final numbers of adopters. "Diffusion success" refers to simulations that end in a fixed point with more than half of the actors being adopters. Diffusion success occurred, by and large, in form of the usual S-shaped curve (see figure 1 and Rogers, 1995; Mahajan and Peterson, 1985). We speak of diffusion failure if a fixed point is reached with only 50% or less of the actors adopting the innovation (see figure 2). As a notable exception we also found oscillations in adopter numbers occurring at certain parameter combinations. Oscillatory patterns by definition do not reach a fixed point and are discussed later in this section.

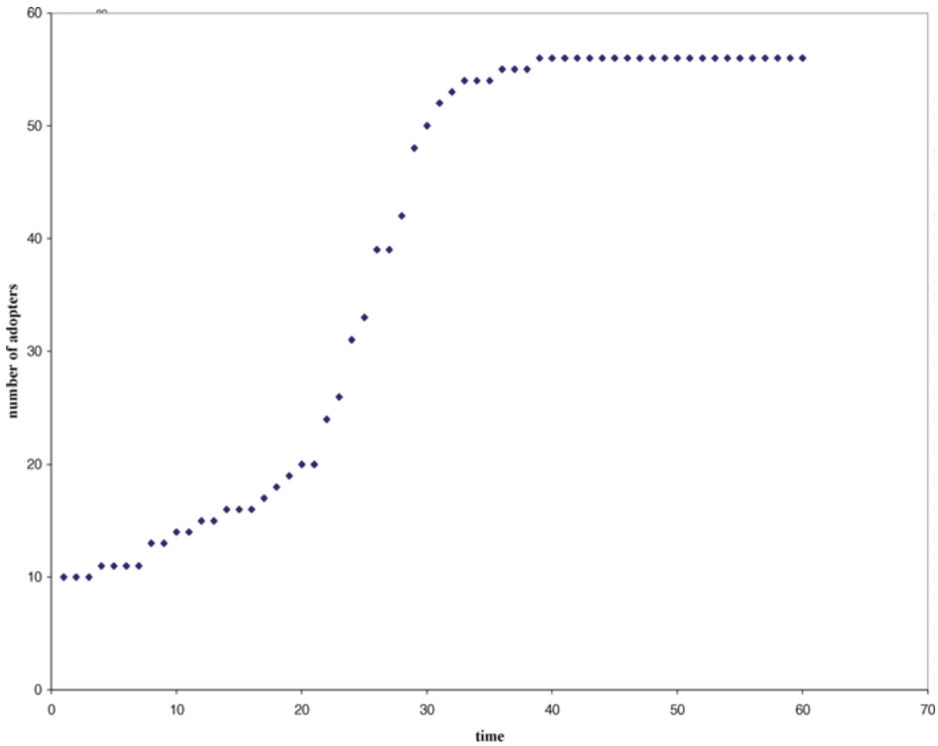

Figure 1. Sample of a diffusion success.

As expected, diffusion success depends strongly on the value chosen for l; the lower the general aversion against the innovation (l) the more actors adopt the innovation at the end of the simulation (figure 3). We generally observe three stages when decreasing thresholds while all other parameters stay relatively small (e.g., $i = 10$, $w_2 = \frac{1}{2}w_1$, $r = 0.25$). As the value for l decreases we observe:

1. No diffusion success: the end result of the simulation by and large reflects the initial stage.
2. Sudden improvements: if l falls below a certain threshold the final number of adopters increases significantly.[6] Several such jumps can occur as l continues to decrease.
3. Continued diffusion success: further decrease of l only renders the diffusion curve steeper once the maximal number of final adopters is reached.

How far l has to be decreased in order to observe a diffusion success depends, of course, on the number of initial adopters i. The more actors adopt the innovation initially the less appealing the innovation can be while still achieving diffusion success. This observation has its analogy in fire propagation: the more fireproof an apartment complex is built the more locations have to be set on fire to burn down the building (i.e., achieving diffusion success). However, choosing a high number of innovators does not guarantee diffusion success since

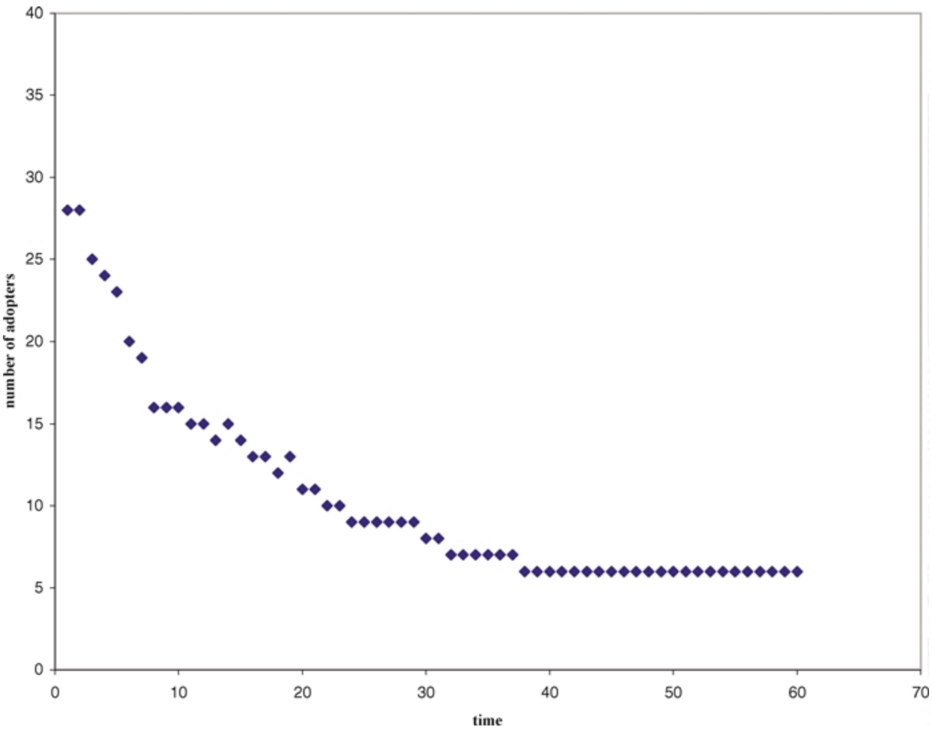

Figure 2. Sample of a diffusion failure.

our model allows for innovation disadoption. A high number of innovators in combination with an unappealing innovation and whimsical actors can result in diffusion failure in the form of a declining diffusion curve (see figure 2). To continue with the fire propagation analogy, setting many places on fire in a very fireproof building sometimes only leads to many fires going extinct.

The influence of the parameters w_1 and w_2 can be described as follows. If we set $w_2 = 0$ the actors have no sensitivity for trends and they decide solely on the basis of the average number of adopters in their personal networks during the last ten time steps. In this case, increasing w_1 basically amounts to decreasing l. Under conditions of diffusion success the following changes can be observed when we hold w_1 fixed, for instance to 1/10 of l, and we then increase w_2:

(a) The number of adopters increases.
(b) The diffusion curve gets steeper.
(c) Diffusion success appears at higher values of l (less appealing innovations).

As mentioned above, a high number of innovators in combination with an unappealing innovation can produce a declining diffusion curve. In this case, increasing the "trend-sensitivity" w_2 contributes to the diffusion failure and renders the declining diffusion curve

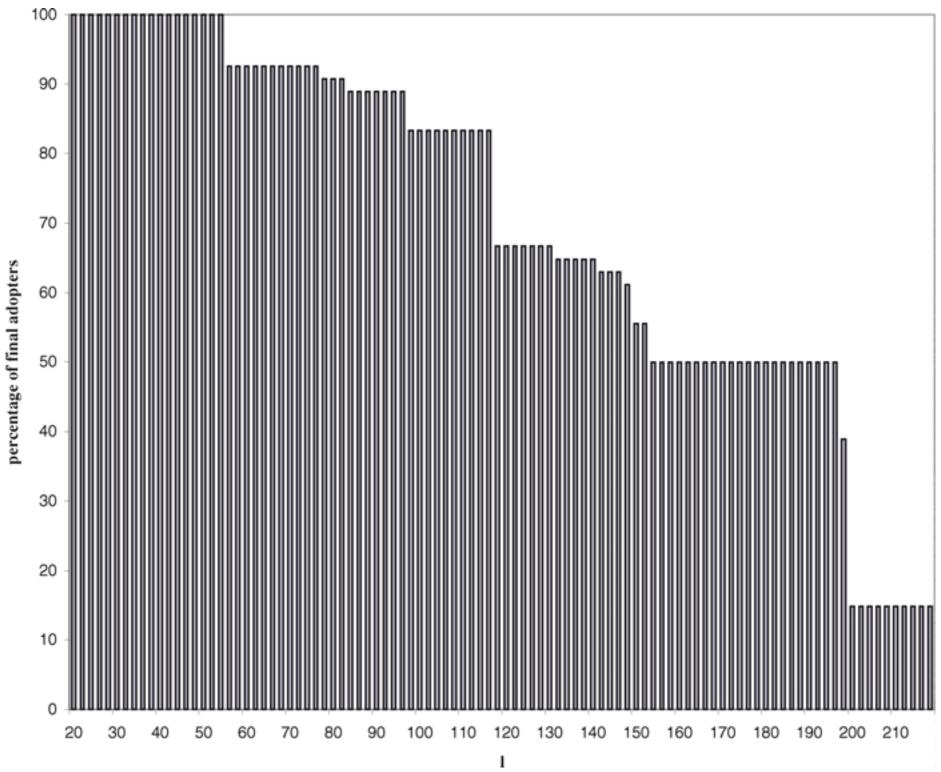

Figure 3. Sample of a relationship between parameter l and the diffusion outcome under conditions that lead either to diffusion success or diffusion failure.

steeper. These results are not surprising given that the observed trend in innovation use and the observed innovation use together determine the personal network trend.

Decreasing the distance between the disadoption and adoption thresholds by increasing r basically renders actors more "whimsical" with regard to innovation use.[7] The higher r the more inclined actors are to stop using the innovation when perceiving a decline in their personal network trend. Increasing "whimsicalness" often has no impact at all on the diffusion process since personal network trends only decline under certain conditions. However, increasing r may lead to a diffusion failure if a high number of innovators initially adopt an unappealing innovation. A further increase of r under these conditions can reduce the remaining number of final adopters in a stepwise manner.

Under conditions of high "trend-sensitivity" together with high "whimsicalness" we observe oscillations in the number of adopters (figure 4) or a diffusion breakdown after an initial period of growth (figure 5). Under these conditions too we generally observe three stages when decreasing l: diffusion failure is followed by a period of oscillatory patterns and finally diffusion success occurs. Figure 6 depicts schematically under which conditions oscillations occur. Oscillatory patterns can be explained as follows. If w_2 (trend-sensitivity) is high even actors with a high adoption threshold can become adopters when they experience

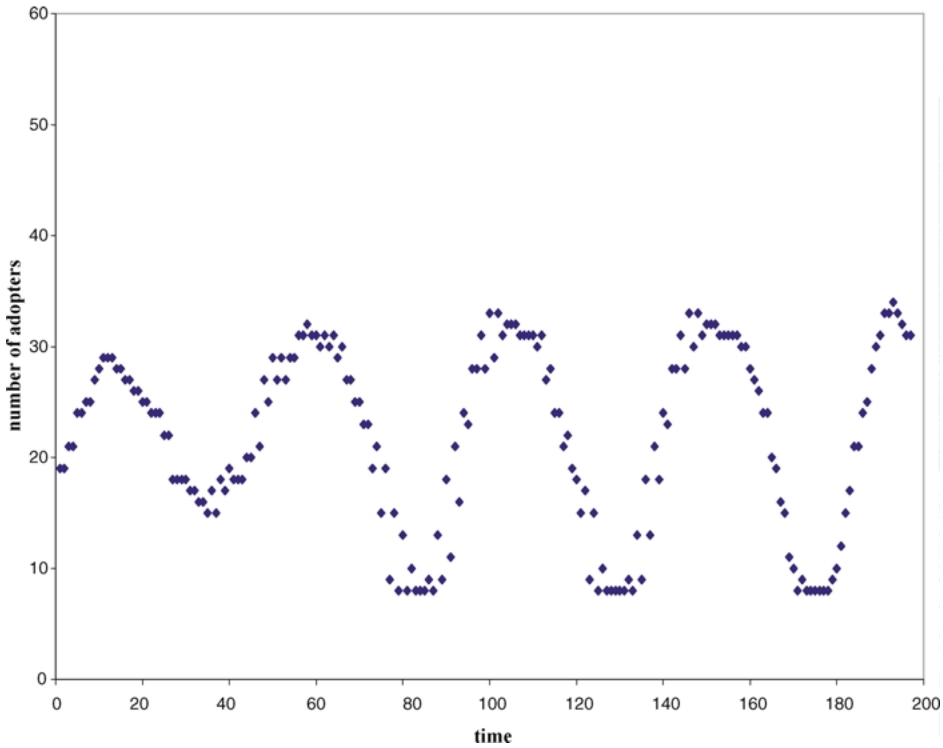

Figure 4. Oscillations of adopter numbers.

an increase in adopter numbers in their network. As diffusion progresses towards saturation such an increase is doomed to vanish. "Whimsical" actors then disadopt the innovation because their adoption depends on their experience of a positive trend. This forces even more actors to disadopt the innovation. After a while the decrease in adopter numbers fades out since the number of adopters cannot fall below zero. This can cause the diffusion process to bounce back: actors that disadopted the innovation because of the negative trend they observed become adopters again and contribute to other actors experiencing positive trends again. Since the point at which some actors become adopters again is not identical with the initial condition, the diffusion process could end in a fixed point without adopter numbers bouncing back. In this case we simply observe an initial period of growth followed by a diffusion breakdown that ends in diffusion failure. The collapse of an initially successful diffusion process is a common phenomenon that diffusion models without an disadoption mechanism cannot reproduce.

3.2. Change Agent Targets

3.2.1. Measuring the Quality of Change Agent Targets. The influence of a change agent can easily be incorporated in our model. This flexibility is a general advantage of discrete

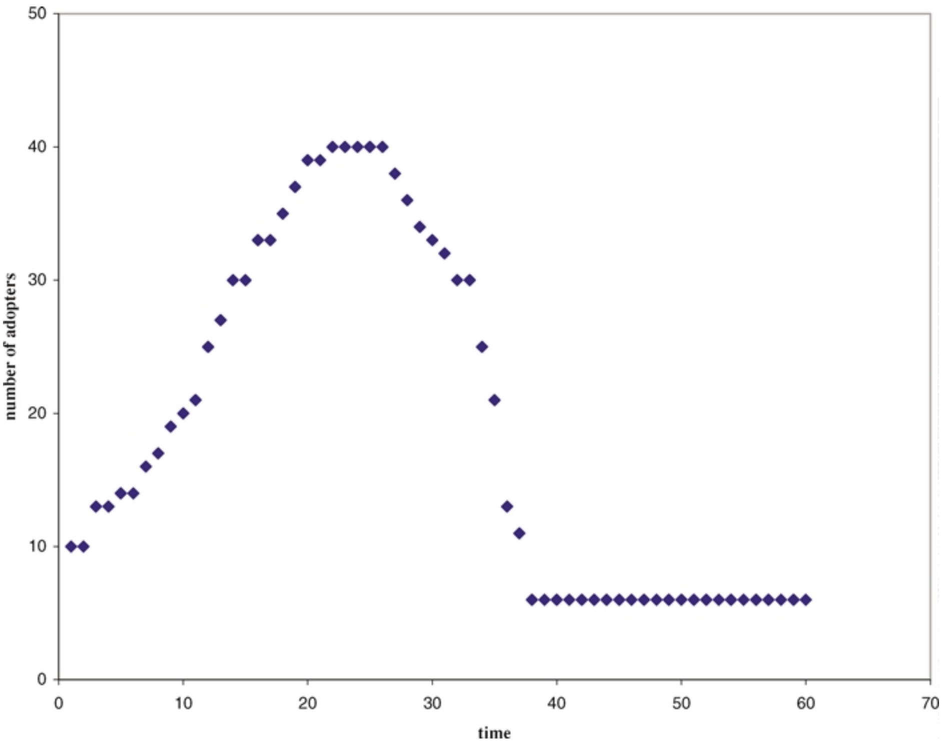

Figure 5. Diffusion failure after an initial period of growth followed by a diffusion breakdown.

models over continuous models using differential equations (see e.g., Mahajan and Peterson, 1985, p. 51). Exposure to a change agent in our model irreversibly renders the targeted actor an innovator by decreasing the actor's adoption threshold to 0. By modeling the change agent as maximally successful on the individual level we keep our results free of influences resulting from any variance in change agent success on that level. Real change agents, however, are often less successful (see also discussion section below).

We define the quality of a change agent target S as the extent to which targeting S increases the range of parameter l in which the simulation results in a diffusion success.[8] For example: at a particular parameter combination diffusion success only occurs with l ranging from 0 to 100 (see also figure 3). Targeting S makes it possible to increase l to 130, at which point diffusion failure occurs. Selecting a different target S' (all other parameters being equal) makes diffusion success possible until l reaches even the value 150. In this case we consider the target quality of S (under this parameter combination) to be 30% and the target quality of S' as 50%. S' clearly constitutes a better target under these conditions because by targeting S' the change agent can bring about diffusion success for a wider range of unappealing innovations. The better the change agent target the less appealing the innovation can be while still achieving a successful diffusion and hence the bigger the impact of the change agent's efforts. In terms of fire propagation it is reasonable to assume

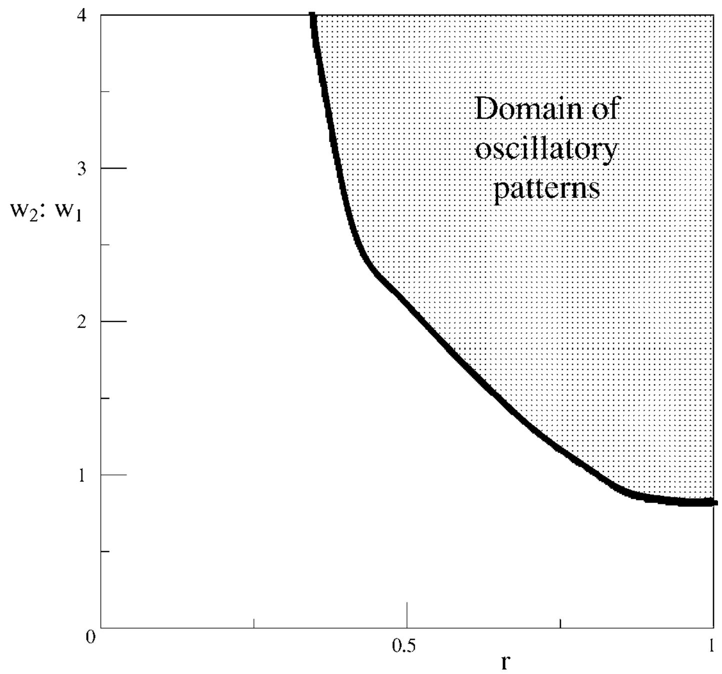

Figure 6. Occurrence of oscillatory patterns (at $i = 0$)—schematic figure.

that "fueling" a fire with a fixed amount of gasoline can be more or less efficient, depending on the distribution of the fuel.

3.2.2. Differences in the Quality of Change Agent Targets. We computed the quality of all single[9] change agent targets and found a significant variance (see figure 7). Targeting some actors has no impact whereas other actors foster the diffusion process considerably as change agent targets. Surprisingly, some actors even have a negative target quality under specific parameter combinations, which means that targeting them decreases the likelihood of diffusion success.[10] The target quality measure remains stable under certain variations in the parameter space, which allows us to speak more generally of good or bad change agent targets across a range of parameters. However, certain parameter variations change the qualities of actors as change agent targets. We calculated the target quality of every actor under systematic variations of the parameters i, r and w_1, w_2.[11] The following observations were made under non-oscillatory conditions (see figure 6) with the initial condition $i = 0$:

- Variations of r have virtually no impact on the ranking of actors according to their quality as change agent targets. This holds for every (fixed) degree of trend-sensitivity we tested (w_2 ranging from 0 to $2 \cdot w_1$). The average target quality slightly decreases as r approaches the value that marks the onset of oscillatory patterns.
- The quality ranking largely remains stable with w_2 ranging from 0 to w_1. The average target quality, however, rises with w_2: e.g., at $w_2 = \frac{1}{4}w_1$ the best target has a quality of

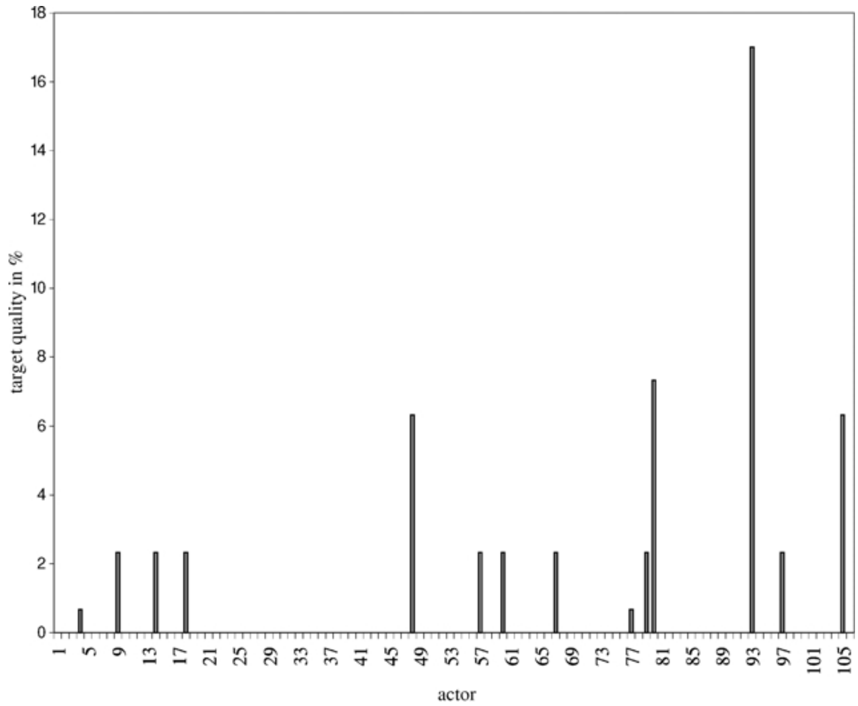

Figure 7. Variations in the quality of single change agent targets under non-oscillatory conditions at $i = 0$.

5% which grows to 50% at $w_2 = w_1$. Increasing w_2 beyond w_1 introduces new good targets that gradually surpass some of the formerly top ranking targets. At $w_2 = 2 \cdot w_1$ the number of good targets has roughly doubled and includes all actors that are good targets at lower values of w_2.

Samples taken in the region of the parameter space that produces oscillations indicate a substantial difference between the target quality measure under oscillatory and non-oscillatory conditions.[12] For instance in one sample only three out of eleven good targets under oscillatory conditions are actors that are also good targets under non-oscillatory conditions. Under oscillatory conditions variations of r and w_2 have a more complex influence on the target quality measure. For example, with two relatively close parameter combinations in the oscillatory domain we observed the following differences: at $i = 0, r = 0.8, w_1 = 20, w_2 = 30$ seven good targets exist, whereas at $i = 0, r = 0.9, w_1 = 20, w_2 = 40$ eleven good targets exist; only 4 actors are good targets in both conditions. Furthermore, under oscillatory conditions an increase of w_2 does not necessarily lead to an increase of the average quality of targets and variations of r can lead to changes in the target ranking.

Increasing the number of innovators can also lead to significant changes in the target quality distribution. For instance, half of the good targets at $i = 0$ in a typical non-oscillatory condition are bad targets at at $i = 10$ and are replaced by new good targets. Adding even more

Table 2. Correlations between target qualities for different innovations.

	Target quality (A)	Target quality (B)	Target quality (C)	Target quality (D)
Target quality (A)	1	0.01	0.52*	0.48*
Target quality (B)	0.01	1	0.07	−0.05
Target quality (C)	0.52*	0.07	1	0.36*
Target quality (D)	0.48*	−0.05	0.36*	1

Note: All correlations marked * are significant at the $p < 0.01$ level. Target quality (x) refers to the qualities of change agent targets in simulations of the diffusion of innovation x.

innovators can change the target quality distribution further. However, under conditions of high whimsicalness and trend-sensitivity that can produce declining diffusion curves the target quality measure remains relatively stable.[13] This stability may be due to the fact that many innovators disadopt the innovation soon if i, r and w_2 are high. Variations of the initial condition affect the target quality measure for obvious reasons: e.g., a potentially good change agent target can become a bad target simply by being rendered an innovator. Section 3.2.4 discusses those reasons in more detail.

Our simulation also revealed instability in the form of significant changes in the quality ranking of targets under small variations in the distribution of thresholds. In our survey we asked the subjects about their inclination to adopt four different innovations. All innovations were software products that broadly aimed at enhancing group communication. This provided us with four realistic and not too different threshold distributions. Correlation coefficients between these different threshold distributions ranged from 0.67 (inclinations to adopt innovations A and B) to 0.85 (innovations C and D). Subjects who liked one innovation also tended to like the other innovations. Subsequently the individual thresholds for each innovation were significantly correlated. However, the resulting qualities of actors as change agent targets were significantly less correlated (see Table 2). Note that target quality (B) is not well correlated with the other target qualities. One possible reason for this might be that threshold distribution B correlates significantly less with the other threshold distributions.[14]

Our findings show a considerable variance in the quality of change agent targets in most areas of the parameter space. Under non-oscillatory conditions the magnitude of these variations depends on the degree of trend-sensitivity. Small variations of the threshold distribution can have a large impact on the target quality distribution among actors. Furthermore, variations in the initial condition, whimsicalness and trend-sensitivity can influence who would be a good change agent and who would not. The best facilitators of an innovation diffusion that starts with a few innovators are not necessarily the same actors that most efficiently prevent the decline of an initially widely accepted innovation, or the same actors who most efficiently prevent oscillations.

3.2.3. The Importance of Finding the Right Targets for Change Agents. Does it pay off for a change agent to invest time in investigating the social network in order to find good targets? Or would it be more efficient to rely on quantity instead and use this time to approach more targets picked at random? The diffusion of innovation literature favors the

Table 3. Average percentage of final adopters in simulations with randomly selected target groups of different sizes compared with a reference group of size 3.

	Size = 3	Size = 4	Size = 5	Size = 6	Size = 9	Size = 18	Reference
Final adopters (Ø)	6.9%	7.9%	8.2%	8.5%	12.6%	37.5%	53%

former strategy and emphasizes the importance of targeting so-called opinion leaders.[15] For instance, Rogers (1995, p. 354) writes: "*Diffusion campaigns are more likely to be successful if change agents identify and mobilize opinion leaders*." In order to determine how important the selection of good targets is in our model setting, we ran trials with randomly selected target groups of different sizes and compared them to a reference group of size three. The reference group contained the three actors with the highest target quality. For each group-size we ran 10,000 simulations and determined the average number of final adopters. We set the parameters so that the reference group had a small diffusion success and no oscillations occurred. We found that randomly selected target groups have to be considerably bigger than the reference group in order to achieve a similar level of effectiveness (see Table 3).

These results are in line with the diffusion of innovation literature and especially with the simulation results in Valente and Davis (1999). These authors compared the strategies of targeting opinion leaders, targeting at random and targeting marginals in a network threshold diffusion model. Opinion leaders are here defined as the actors with the highest numbers of incoming ties (i.e., actors with the highest *indegrees*). They found that the popular opinion leaders fostered the diffusion process considerably more than did less popular actors. Our model also strengthens the claim that change agents are well advised to find the right targets. If we think in terms of fire propagation our model indicates that it pays off to distribute the gasoline wisely rather than just use more gasoline. However, the next section shows that good change agent targets are not necessarily opinion leaders and vice versa.

3.2.4. What Specifies A Good Change Agent Target? It seems fair to say that selecting the right targets matters for change agents. Who are the good change agent targets? Can we characterize them as opinion leaders in the sense of Valente et al. (i.e., as those actors who received the most nominations as important contacts)? Indeed, with regards to all four threshold distributions we found the network centrality measure "indegree" significantly correlated to our measure of target quality. Actors whom many others regard as important contacts tend to be good change agent targets. However, even in the best case the correlation was only of moderate extent, leaving ample variance in need of explanation (see Table 4).

Table 4. Typical correlations between indegree and target quality of actors with regards to four different innovations.

	Target quality$_A$	Target quality$_B$	Target quality$_C$	Target quality$_D$
Indegree	0.28	0.26	0.43	0.33
	($p < 00.1$)	($p < 0.05$)	($p < 00.1$)	($p < 0.01$)

All other samples taken with different parameter combinations confirm this picture. The indegree measure, hence, may not be a very good predictor of target quality. Some actors have a high indegree but they have virtually no impact as change agent targets whereas other actors have a low indegree but are highly effective change agent targets. In our model, popularity alone cannot explain why some actors are good change agent targets. This gap between having a high indegree and being a good change agent target does not contradict the findings of Valente & Davis for two reasons. First, Valente & Davis do not look at all possible change agent targets and secondly**,** their model assigns the same threshold to every actor. In our model we have to look at the distribution of thresholds in the network in order to understand what accounts for the quality of a change agent target. The contribution of the threshold distribution to an actor's impact on the diffusion process can be clarified as follows.

Assume actor x adopts at time $t = 1$ as the result of a change agent effort. At time $t = 2$ this adoption has maximally influenced n other actors towards adoption, whereby n denotes the indegree of x. Not all of the n actors who consider x an important contact have necessarily been rendered adopters by x's adoption at that time. For some of these actors x's adoption was not sufficient to lift their personal network trend over their adoption threshold. For others it was not necessary to observe x's adoption in order to become an adopter. The remaining say n-k actors have been *directly* pushed towards adoption by x's adoption.[16] At time $t = 3$ the same story can be told about the impact of each of these n-k actors on those actors who regard *them* as important contacts. They will have pushed some but possibly not all of those actors towards adoption, thereby increasing the number of actors *indirectly* influenced by x's adoption. In this way an actor's impact can spread step by step through the network. If the simulation reaches a fixed point the overall impact of the change agent's effort to target x can be characterized by the number of actors that adopted at the end of the simulation but would not have done so if x had not been targeted by the change agent.

In its unfolding the simulation specifies "*the impact of the social structure and individual preferences on the collective outcome*" (Granovetter, 1978). The simulation thereby provides the fullest explanation we can give for an actor's impact as a change agent target. To understand an actor's quality as a change agent target we have to look at all components: the network, the threshold distribution, the parameters that determine the decision mechanism and the initial condition.

Referring, however, to the whole simulation in explaining an actor's impact on the diffusion process is sometimes not necessary. We can sometimes give a satisfactory explanation of an actor's quality as change agent target by just considering the immediate network neighborhood of that actor. For instance, actor 94 provides us with a good example in which promotional efforts fail despite targeting a very popular actor. Actor 94 has a very high indegree and turned out to be an excellent change agent target for innovation C. However, for the diffusion of innovation B actor 94 turned out to be a very inefficient change agent target. A closer look at the simulation details reveals that in the case of innovation C actor 94 has 5 contacts that would adopt if and only if actor 94 is targeted by a change agent (all other things being equal). In the case of innovation B the number of such "sensitive contacts" is 0. The five contacts of actor 94 that are "sensitive" with regards to innovation C are either innovators with regards to innovation B or they adopt this innovation without the help of actor 94 early in the unfolding of the simulation. The adoption threshold of actor 94 for innovation B is also much lower than for innovation C. This contributes to the fact that actor 94 adopts innovation B (but not innovation C) without change agent influence early in the simulation. More generally, we can explain actor x's target quality in reference to the immediate network neighborhood:

1. X's threshold is neither too high nor too low so that change agents are needed to create adoption.[17]
2. The thresholds of x's contacts are neither too high nor too low so that x's adoption contributes to adoptions by her contacts.

Despite their seemingly narrow focus these explanations do implicitly refer to the whole network. For x's contact y to have the "right" threshold does not depend solely on the adoption status of y's important contacts. After n time steps the impact of x's adoption on y can principally depend on every actor that is connected to y with less than n degrees of separation. Even if x is an innovator we cannot infer without further information that x is a bad change agent target since our model allows innovators, but not change agent targets, to disadopt an innovation. It hence seems justified to say that being a good change agent target is a systemic property—a property that generally[18] cannot be determined by looking at an actor's personal network and the distribution of adoption attitudes therein.

4. Comparison with Similar Models

Computer simulations of group behavior have become increasingly popular in recent years. In this chapter, we compare our model with two widely known multi-agent network models. Special consideration is given to the main differences in the underlying assumptions. Such differences can shed light on important issues not addressed by the individual models.

4.1. Viscosity Model

Krackhardt's (1997) "viscosity" model focuses on the structural conditions under which smaller groups of adopters can bring about diffusion success for innovations that are not obviously inferior or superior. Like our model, the viscosity model postulates discrete time steps in which actors consider their social surroundings in deciding whether to be an adopter or a non-adopter. Actors are assumed to encounter a fixed number of other actors randomly at each time step. Those who encounter at least one other like-minded actor retain their status, while those who find themselves isolated will convert with a given probability. A pro-adoption bias is introduced through the assumption that adopters have a "proselytizing edge"; they obtain more contacts per time step than non-adopters do. Within our framework, these actors can be interpreted as "uniformly stubborn" (i.e., they all share the same high threshold and score low in whimsicalness.) Under these conditions and if the organization contains only a small number of innovators, diffusion failure is almost certain. Krackhardt then introduces a social structure through the following assumptions:

The organization is partitioned into a network of same-sized groups within which all interaction takes place;

- At each time step a certain fraction v (“viscosity”) of each group is exchanged with members of all adjacent groups;
- In the beginning, one of the groups—the “Mother site”—contains only adopters, whereas all other groups contain no adopters.

At this point, a small minority of innovators in the Mother site can overcome the majority under certain parameter combinations. The system is surprisingly insensitive to many parameter variations but very sensitive to changes in viscosity. For diffusion success to occur the viscosity parameter has to be in a narrow range. If viscosity is too low, only the Mother site remains dominated by adopters; if the migration rate is too high, non-adopters will dominate the whole organization.

The main difference between our model and the viscosity model are the computational units: i.e., groups of actors in the viscosity model vs. actors in our model. At every time step the fraction of adopters in each group is calculated recursively by taking into account the rates of migration[19] and conversion.[20] The concepts of migration and viscosity do not apply in our framework due to the social network structure that lies at the foundation of our model. This difference leads to an interesting question: when is it appropriate to use a group level approach to modeling and when is it better to stay at the level of individual actors? The available network data dictated an individualistic approach in our setting; a group approach might be more appropriate for settings in which interaction occurs within relatively stable groups such as different departments of a business organization, different strata of a society or different societies.

4.2. Construct

The construct model (Carley, 1990) is another widely known multi-agent network model of group behavior in which actors use information about others in choosing an action. Construct has been used to examine the factors underlying group stability (Carley, 1991) and the evolution of networks (Carley, 1999). Actors choose one communication partner and one piece of information at a time to communicate. The probability of communication between actors increases with the extent of their common knowledge (homophilly assumption). Under these assumptions, groups evolve into a state of full connectedness in which everyone knows everything that everyone else knows. Several modification have been developed to enrich Construct’s sparse characterization of actors. For instance, Rode (1997) incorporates errors in information transmission and Mark (1996) allows actors to forget facts.

The main difference between Construct and our model lies in the information processing. Construct actors exchange information without any alteration and only use information to determine future interaction partners. Our actors exchange information about their adopter status simultaneously with their personal network and use the information they receive to determine their adopter status and subsequently the information they will communicate. Information processing in our setting hence creates the information being transmitted; an actor with a high adoption threshold surrounded by adopters might nevertheless continue to communicate his abstinence from adoption. It seems fair to say that Construct models the diffusion of information via communication whereas we model the diffusion of behavior informed by communication about this behavior. This difference elucidates an interesting general aspect of multi-agent models with information exchange: the way in which information is processed and used. From a biological standpoint, the transmission of information is an energy expenditure that has to be explained in terms of expected benefits for the organism's genes. Idealizing human actors as perfect transmitters of information might be more or less empirically sound depending on the specific setting. For instance, the diffusion of the information that Kennedy had been assassinated might have progressed relatively undistorted due to the absence of an incentive to lie. On the other hand, the diffusion of facts about global warming might be driven by entirely different forces. Receiving the results of a new study might cause an environmental activist to spread the information while causing a car manufacturer to disseminate opposing arguments. From a model builder's standpoint it seems advisable to consider that human beings process information in various ways for various purposes, some of them directly opposed to information diffusion.

4.3. Mutual Enrichment

Despite the differences mentioned above, both models present viewpoints that provide insightful suggestions for our model and vice versa:

- A threshold distribution at the group level can be introduced into the viscosity model by making the pro-adoption bias variable.[21] It seems natural to assume that groups vary in their reaction to an innovation depending on various factors. For instance, the usefulness of an innovation might vary for different divisions of a business organization, or, on the level of whole societies, an innovation might vary in its cultural aptness.
- Change agent influence can also be incorporated into the viscosity model by increasing the fraction of adopters in the group being targeted by a change agent. More interestingly, change agents could influence innovation diffusion by varying the migration rate between groups. Thus, change agents would then try to promote innovation diffusion by bringing the right people in an organization together.[22] On the other hand, this idea could be implemented in our model by allowing the change agent to create network ties. A change agent's task would then entail to find actors whose getting together would benefit innovation diffusion.
- The Construct viewpoint suggests that our model ignores any dynamic of interaction patterns by assuming a static network of communication flow. It is plausible to assume that similarity (in adoption behavior) between actors might influence the network structure, especially since the innovations we look at are communication tools. Actors who share a new communication tool might thus be more inclined to communicate with each other. After all, the purpose of a communication tool is to facilitate communication.
- Our model suggests that Construct ignores established patterns of communication as they are reflected in the self-reported communication frequencies of our real-life actors. In assuming that homophilly is the only driving force behind communication, Construct

excels in working out how homophilly affects the flow of information. It might, however, be less accurate in capturing settings in which communication patterns are more habitual or goal-oriented in kind. For instance, habits and organizational routines might affect the flow of communication, as do the informational needs of actors whose careers can depend on which information they base their decisions on. Considerations of similarity might be only one factor among others that determine the choice of communication partners. A future model could combine static considerations reflecting past communication behavior and dynamic considerations reflecting forces, such as homophilly, that drive interaction choices.

5. Discussion

Although our model deviates from other diffusion models by incorporating features that allow actors to disadopt an innovation, it is capable of reproducing patterns that have also been noted by other authors: e.g., typical patterns of diffusion success and diffusion failure, the sensitivity of diffusion outcomes with regards to small variations in the distribution of actor attitudes and a variance in the quality of change agent targets that makes it efficient for change agents to concentrate their efforts on good targets. The advanced features of our model also lead to two findings we want to discuss in more detail:

1. The model is able to produce declining numbers of adopters, oscillations and collapses of initially successful diffusions.
2. The model pinpoints actors who can have a significant impact on diffusion processes and are not easily discernable: good change agent targets with a low indegree.

(1) These patterns occur in reality but models that do not allow for innovation disadoption cannot account for these phenomena. Collapses of initially successful diffusions occur, for instance, when fashion items quickly fall out of fashion or initially successful software innovations suddenly become “shelf ware”. Constantly declining numbers of adopters occur when an innovation is initially forced upon many who do not want the innovation or when an innovation is widely adopted for a reason that quickly looses its motivating power (e.g., New Year’s resolutions). Oscillations are unrealistic outcomes in our setting, which is marked by oscillation inhibiting conditions: actors in our group have no reason for being especially trend-sensitive and whimsical and they would be expected to learn from the diffusion history. Oscillations might, however, occur under the absence of these conditions. Examples of settings where actors are trend-sensitive, whimsical and learning-inhibited can be found in the stock market and in the world of fashions and fads. Actors might not learn in these realms because learning is irrelevant for them.[23] In these domains actors also tend to be trend-sensitive and whimsical, at least if they are growth- instead of value oriented (both categories broadly construed). That the popularity of a certain stock or fashion item suddenly increases/decreases might be a bigger reason for some investors to buy/sell this item than the average popularity of the item.[24] The perception of change might be a major driving force behind developing trends in these domains.

For declining diffusion curves, diffusion breakdown or oscillations to occur some actors must disadopt innovations they once adopted. The examples above illustrate that it can be necessary to allow for decision reversal in order to adequately model the interaction of human decisions over time in a variety of settings. The reasons why actors disadopt an innovation can, of course, be more complex than our decision mechanism allows. For instance, the innovation might get competition through another innovation, or innovators get disappointed because they adopted the innovation on the basis of wrong expectations about the innovation or its diffusion. To model such effects we would have to modify our model (see below). The interesting point, however, is that these common patterns can be produced with our simple decision rule that only takes histories of local adoption patterns as input.

(2) The observed gap between change agent target quality and the centrality measure indegree raises doubt about the current recommendation for change agents to target opinion leaders. This gap might partly be due to the fact that our model assumes that the ability to influence is uniformly distributed among the actors. Opinion leadership is hence only characterized by a high indegree. Further differences in the ability to influence others could be taken into account by coloring the network graph.[25] The degree to which such a modification could bridge the gap between opinion leadership and target quality might be an interesting question for future research. Section 3.2.4 contains some applicable ideas about the circumstances under which targeting non-opinion leaders might pay off. For instance, an opinion leader surrounded by innovative followers might be a less efficient target than a non-opinion leader who has at least some influence on yet undecided potential adopters. Future research should investigate the conditions under which targeting opinion leaders is an optimal strategy. Our findings show that the following factors can play a role: network structures, decision mechanisms and the parameters that determine them, initial conditions and the distribution of attitudes towards the innovation.

By introducing a memory and the capacity to reverse a decision our model gains empirical aptness as a model of interacting human decision processes. We are, however, aware of the shortcomings our model has as a realistic model of human decision-making. In the remainder of this section we discuss the empirical aptness of our model and further possibilities for future research.

How does our model compare with reality? Naturally a mathematical model abstracts from many features of the real systems of which it is a simplified representation. Ideally the features considered in the model are the only relevant features of the system with regard to the aspect of the system being explained with the model. However, in contrast to models of physical phenomena our model tries to depict a social system and the complexity of these systems makes it almost inevitable that some relevant features are neglected. Physical diffusion models, such as models of wave propagation in excitable media, can capture the essential features of those systems. The diffusion of an innovation might be more difficult to model adequately due to the fact that humans interact, learn, innovate and adapt, at times unpredictably, in a social world that has a historical dimension. Nevertheless, under certain circumstances simple models can capture the essence of human interaction. Examples can be found in the field of economics, some of which can directly relate to innovation diffusion.[26] However, laws of economics exploit the assumption that humans act rationally, which has come under severe criticism from psychological research[27] (see e.g., Barron, 2000; Stanovich, 1999). Introducing a memory that allows actors to take trends into consideration can be one way to increase the psychological aptness of models of innovation diffusion.

Table 5. Complicating factors—limitations of our model.

Complicating factor	Illustration
Some or all thresholds vary with time.	Management enforces use; alternative innovations appear.
Network structure varies with time.	Friendships or new work relations are formed.
Threshold ratio varies among actors.	"Whimsicalness" is not uniformly distributed.
Trend-sensitivity varies among actors.	Actors consider trends differently (value- vs. growth investor)
Actors vary with time.	Employees enter or leave the company.
Actors' social influence varies.	Some actors are stronger role models/opinion leaders.
Change agent influence varies.	Only some actors are malleable to change agent influence.
Memory length varies among actors.	Some actors act more spontaneously than others.

Table 5 lists further factors that might be relevant in various settings. These "complicating" factors also illustrate some limitations of our model and indicate potential avenues for future research.

Some of these complicating factors played a role during the diffusion of software tools that inspired our model. A follow-up survey administered 6 months later revealed that nearly half of the respondents did not match the former respondents. Furthermore, the remaining respondents on average kept only 5 of their ties (they reported on average of 13 ties in both surveys). We suggested that the diffusion of an innovation through a group shares some basic features with the spread of a fire through a building. It now appears more appropriate to envision that building as a collection of rooms that change their fire-relevant features, including even their positions—at least if the group is part of a modern business organization. The complexity of human interaction challenges researchers to choose wisely which forces to include and which to exclude in their models. Discrete models like ours (and the models discussed in the previous chapter) might be especially suitable due to their flexibility and aptness for computer simulations.

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Notes

1. The code was written in Borland C++ 5 for DOS. For access to the code please contact the author.
2. Consider, for example, the impact of hearing other audience members clapping when trying to decide if one should begin clapping or not. The same amount of clapping could have differential effects depending on wheter it occurs within an upswing or a downtrend in clapping.
3. See for example Granovetter (1978), Valente (1995, 1996), Valente et al. (1999) and Abrahamson et al. (1997).
4. See Rocco et al. (2001). The overall number of possible ties was limited to 20 and we only considered ties with a reported contact frequency of at least once a week.

5. E.g., we asked: "Please answer the following questions to the best of your ability using a 0 to 10 scale, with 10 being most likely and 0 being least likely. How likely would you be to adopt for regular use an application that enables you and your co-workers to share information about when you are at your desks?"
6. A particular point of interest, given our search for good change agent targets, is the onset of diffusion success. Where this point occurs will later on help determine the impact of change agent interventions.
7. Whimsicalness does not need to be interpreted as personality trait; it can be interpreted as adoption tendency based on the perceived ease of adoption and discontinuation of the innovation.
8. A change agent target can be any single actor or any group of actors.
9. Due to the increasing amount of calculations necessary we could only look at samples of larger target selections. These simulations revealed that combinations of good single targets also made good change agent target groups.
10. For instance, targeting actor 28 can make this actor merely adopt earlier and hence not contribute at a later moment to a trend that otherwise would trigger many trend-sensitive actors to adopt.
11. We do not have to look at parameter l in this regard since the target quality is defined in reference to the range of parameter l in which diffusion success occurs.
12. We did not investigate this domain thoroughly since we could only perform a visual inspection of the target qualities. No well-motivated definition of target quality was applicable for all cases.
13. Varying i maximally (between 0 and 106) under these conditions produces an average of 16 targets of salient quality. On average 7/8th of those actors are the same good targets seen in figure 7.
14. The average correlation between threshold distribution B and the threshold distributions of innovations A, C and D is 0.67 whereas the average correlation between the threshold distributions of innovations A, C and D is 0.82.
15. Opinion leadership is here defined as the degree to which an individual can influence other individuals' attitudes or behavior.
16. Who they are depends on *their* individual threshold, the number of further adopters in *their* network and parameters like w_1, w_2. It is also possible that x pushes a non-adopting contact to adoption at any time $t > 2$ because other actors in the network of that contact have adopted in the meantime (eventually even because of x's adoption).
17. The case that x's threshold is too high is not covered in our model in which change agents are always successful in inducing adoption.
18. Exceptions are cases in which an actor's threshold is so high (or so low) that adoption (or disadoption) can never occur, or cases in which an actor's personal network consists solely of actors with these kinds of thresholds. One can, however, estimate the target quality by considering "sensitive" nodes in the personal network.
19. The numbers of (non-) adopters migrating from and into a group depends on the adopter fractions in all adjacent groups and viscosity.
20. The rates of conversion for adopters and non-adopters are functions of the probabilities of not encountering a like-minded actor in all random encounters.
21. I.e., by assigning the numbers of encounters adopters and non-adopters individually for each group. An alternative method would be to assign the conversion probabilities for each group separately.
22. Krackhardt seems to have something like this in mind when he writes "... how much easier is the job of the purposive actor trying to diffuse the innovation if they could control the structure of organization and the viscosity of its mobile participants?"
23. E.g., disadopting a clothing style does not mean that it was initially wrong to adopt the style. Mutual fund managers might buy into an expanding "bubble" that is doomed to burst, because their salary is tied to short-term performance and their job turnover rate is high.
24. It might be more apt to think here in terms of investment *styles* (e.g., investing in growth stocks) and fashion *styles* (e.g., being underweight) adopted by constantly changing occupants of a social position (e.g., mutual fund manager, young adults) and not of individuals buying certain stock or fashion items.
25. I.e., weighting ties according to the degree and direction of advice seeking in the relationship.
26. Increasing return theories, for instance, suggest that the benefits of adopting an innovation (e.g., a new communication standard) increase with adopter numbers. This justifies assigning a threshold to potential adopters that reflects their estimate of the adoption costs (see e.g., Farell and Saloner, 1985).

27. Under certain conditions psychological realities can be safely ignored when predicting human behavior. We do not need to know how the brain works in order to predict the outcome of a normal person adding two numbers; we need to know the laws of arithmetic and that the person is in a position to perform the calculation. But this type of knowledge is exactly what is not available with regards to complex adoption decisions.

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