Network Diffusion of Two Competing Ideas: An Application of Agent-Based Modeling

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Researchers interested in the diffusion of innovations have investigated various factors that determine an individual's adoption decision. The factors range widely, from characteristics of the innovation—such as compatibility, relative advantage, complexity, and trialability—to characteristics of the adopters—such as socio-demographic factors, and psychological and personality characteristics—to external or environmental conditions—such as marketing, governmental regulation, and cultural climate (Rogers, 1995; Wejnert, 2002). Interpersonal communication, in particular, is one of the most widely discussed mechanisms of adoption and is found in a variety of classical diffusion models such as a Bass' (1969/2004) imitation model, Granovetter's threshold model, the two-step flow hypothesis (Katz, 1957; Weimann, 1982), and social network models (Valente & Davis, 1999; Valente, 2005).

The importance of interpersonal influence in the diffusion of innovations leads one naturally to social network theory and analysis. The social network perspective highlights the interdependent nature of social relationships, the impact of interpersonal ties on agent behaviors, and the over-time changes in a community, organization, or society. Networks are primarily communication patterns, formed from informal talks and advice from friends, families, and neighbors, and technical, professional, or formal communication among members of a community or organization. Social networks have been understood as channels through which individuals influence the spread of innovation (DeBresson & Amme, 1991).

The current study aligns with those models that pay special attention to interpersonal influence on diffusion processes. We borrow Valente's (2005) notion of *Personal Network Exposure*, or PNE, which is the degree to which an individual witnesses others' adoption behaviors within his or her personal network. While the likelihood of an individual's adoption is determined by the level of PNE, computation of PNE can be varied depending on which particular property is understood as a major source of influence. We consider three different factors—opinion leadership, structural equivalence, and time since latest adoption—that may be exposed to potential adopters through their personal network.

Although the network model of diffusion is a useful approach to understanding social influences of adoption behaviors, it nonetheless has practical drawbacks. Network models require data not only about the longitudinal change of innovation penetration within a system but also on all pairs of individuals in the network. For example, if a system has 100 members, there are 4,950 pairs of individuals that either are or are not connected, and the researcher also has to keep track of who has adopted the innovation and when the adoption occurred. The amount of empirical data collected can be quite large.

An alternative to empirical data is simulated data. In this chapter, we use agent-based modeling (ABM) as an alternative means of exploring network effects on the diffusion process. ABM is a simulation technique that highlights the complex nature of social systems. As a web of interconnected actors, the social system changes over time, not by a fixed set of causal variables but by (possibly nonlinear) interactions among actors within the system. Although actors may follow a simple set of specified rules, the consequential change on the macro-level can be quite complex. Using ABM, a researcher can simulate agents' behaviors under these simple rules and observe how the system undergoes changes as a whole, driven by the members' micro-behaviors. Because it is not always easy to keep track of empirical micro-interactions among actors, an agent-based simulation is a complementary approach to the data-driven causal model of diffusion (Garcia, 2005).

Accordingly, the current chapter makes several contributions: First, we compare PNE measures based on different sources of social influence. Second, we examine the diffusion of not just one innovation, but two, a situation more realistic than the classic case of a single innovation. Finally, this chapter shows how the application of ABM to the network models of diffusion studies can produce fruitful avenues of inquiry.

The structure of the chapter is as follows: First, we review previous network models of diffusion and introduce the key adoption mechanism, namely personal network exposure. Then we give a brief description and review of agent-based modeling. Next we examine three different means of social influence and show how they can be incorporated into the measurement of personal network exposure. Finally, we present the details of an agent-based simulation, report the results of the simulation, and offer some concluding thoughts.

Network Models of Diffusion

Basic Network Concepts

A *network* consists of a set of *nodes*, numbered 1 through *N*, and a set of *ties* that link nodes together. Because we are looking at the diffusion of innovations among individuals—inidividuals who are represented by the nodes of a network, but are simulated by agents in an agent-based model—we will use the terms *individual*, *node*, and *agent* interchangeably. The ties are the basic connections between pairs of individuals, and these ties may or may not be directional. In an *undirected* network, a tie between nodes *i* and *j* is reciprocated by a tie from *j* to *i*. In a *directed* network, ties are not always reciprocated. In either event, the *density* of the network is the number of ties that it has divided by the number of possible ties.

If there is a tie from *i* to *j*, then *i* and *j* are said to be *adjacent* and *j* is a *neighbor* of *i*. We define the $N \times N$ *adjacency matrix* $\mathbf{A} = [a_{ij}]$ by setting a_{ij}, the matrix entry in the *i*th row and *j*th column of **A**, to be equal to 1 if there is a tie from *i* to *j*, and 0 otherwise. A node's *personal network* consists of the node's neighbors along with the ties amongst them. The number of neighbors a node has is the node's *degree,* which is given by the appropriate row sum of the adjacency matrix. In other words, the degree of node *i* is given by $\sum a_{ij}$, where the sum is to be taken across all *j*.

One of the most important nodal properties is how central the node is to the network. There are a variety of extant centrality measures. In this article, we use four: *degree centrality*, which is simply the node's degree; *closeness centrality*, which is based on the distance between the focal node and all other nodes in the network—the closer the node is to other nodes, the more central it is; *betweenness centrality*, which indicates how often a focal node is between other nodes in the sense of being able to shut off communication from one node to another; and *eigenvector centrality*, which measures a node's centrality on the basis of whether or not the node is connected to other nodes of high centrality. A review of all of these centrality measures can be found in Wasserman and Faust (1994).

Networks and Diffusion

Since the pioneering studies of communication networks by Coleman, Katz, and Menzel (1957) and Rogers and Beal (1958), decades of diffusion research have shown that diffusion is a social process susceptible to interpersonal influence. That interpersonal influence is an essential component in the diffusion process is supported by many well-known diffusion models. For example, Bass (1969/2004) proposed that the probability of adoption depends on the number previous adopters, modified by two parameters: an innovation parameter governing the number of innovators (adopters at time 0), and an imitation parameter governing the extent to which individuals imitate others in the system. Another widely applied model, Granovetter's threshold model (1978), also assumes that individuals choose to adopt a behavior when they perceive a certain rate of adoption among other members of a community.

Both of these models highlight the importance of interpersonal influence, but, strictly speaking, neither is a network model. Both Granovetter and Bass assume that adoption decisions are made based on what is happening in the population as a whole. A more realistic assumption is that interpersonal influence operates by means of those to whom one is close in a social, physical, or structural sense.

Valente and Davis (1999) embraced this more realistic assumption by explicitly using social networks. Their network model highlights the importance of our immediate social surroundings, so called personal networks. According to Valente and Davis, rather than the adoption rate in the entire population, what is most important is the adoption rate in one's personal network; an individual adopts the innovation only if the proportion of adopters in his or her personal network exceeds some threshold. Hence it is the adoption decisions of one's immediate interpersonal contacts that are important rather than those of more socially distant individuals.

Valente (2005) generalized this concept, calling it *Personal Network Exposure*. The underlying assumption is that individuals make decisions based, not on perfect knowledge about the whole community, but on partial knowledge formed through interactions within a personal network. If the level of personal network exposure is greater than a specified threshold, then the individual adopts the innovation. Different members in an agent's personal network may have differing levels of interpersonal influence on the agent, and these levels of influence are captured in a weighting matrix, $\mathbf{W} = [w_{ij}]$, where w_{ij} is the influence that agent j has on agent i. The particular source of influence might be structural, such as an agent's centrality in the network, or it might be a non-network feature, such as the whether an agent is an early or late adopter. A given agent's influence on others might be constant, such as the previously mentioned example of centrality, in which case w_{ij} would be the same across all agents i, or it might be a feature like structural equivalence that varies across agents, in which case the w_{ij} are not constant across i. To compute agent i's PNE, one adds the weights of those neighbors of i who have adopted the innovation, and then divide by the total possible. In particular, agent i's personal network exposure, E_i, can be computed as

$$E_i = \frac{\sum_j w_{ij} y_j}{\sum_j w_{ij}}, \qquad (1)$$

where y_j is equal to 1 if agent j has adopted the innovation and is equal to 0 otherwise, and where the sums are to be taken across all nodes j in i's personal network. The numerator of the above expression sums the weights of those neighbors of i who have adopted the innovation; the denominator, which is merely the sum of the weights of all individuals in agent i's personal network, serves to put the measure on a 0-1 scale. In the case where the weights are 1 or 0 depending on whether or not i and j are adjacent (i.e., where the weighting matrix is equal to the adjacency matrix), then E_i is simply the proportion of i's neighbors that have adopted the innovation, as in Valente and Davis (1999).

Competing Innovations

Although much diffusion literature highlights the diffusion processes of a single innovation, in reality it is common to observe situations in which two or more innovations compete with each other to attract adopters within the same market. For example, Häagen-Dazs and Ben & Jerry's compete within the same ice cream market. As another example, consider that two contrasting ideas are often spread simultaneously about a particular innovation. For example, when a new movie is released, positive and negative comments are spread and our decision to watch is often affected by the level of exposure to each type of comment. Our simulation model considers the situation where two competing innovations or ideas are introduced, rather than just a single innovation as in the classic case.

The model is exemplified by the following scenario: Consider a group of agents who have not yet purchased a mobile phone. They make up a social network in which each agent is connected to at least one agent, thus nobody is isolated. There are two mobile carriers offering the latest high-tech phone options—let's suppose Verizon and AT&T—and agents will choose one over the other when they perceive higher popularity: If an individual perceives higher popularity of Verizon, the individual will adopt Verizon over AT&T and vice versa. If a person does not perceive predominance of either carrier, the person delays the adoption decision. In other words, agents follow the majority choice of previous adopters in the personal network.

Of course, the majority choice does not have to be a strict count of adopters for each innovation. This "majority" is modified by the influence that each of the agents has on others, that is by the weights in the weighting matrix **W**. Morover, one's observation cannot be perfect because an individual does not have a bird's eye view of the whole community. Accordingly, agents in our model decide whether to adopt, and if so which of two innovations to adopt, based on their immediate environment which determines the level of PNE. Rather than having an overall threshold, as in Valente and Davis (1999) and Valente (2005), we will let the innovations compete against each other, computing a PNE for each innovation. An agent will then adopt the innovation that has the higher PNE value. Stated in terms of our example, an agent will adopt Verizon if and only if the agent's PNE for Verizon is larger than the agent's PNE for AT&T. Similarly, an agent adopts AT&T if and only if the AT&T PNE is larger than that for Verizon.

Agent-Based Modeling (ABM)

Agent-based modeling is a simulation technique whereby rules of local interaction among agents give rise to global patterns. In other words, it is a methodology for studying "how complex outcomes flow from simple schemata and depend on the way in which agents are interconnected" (Anderson, 1999, p.220). Macy and Willer (2002) argued that ABM is different from other types of simulation. According to Macy and Willer, two types of social simulation pre-dated ABM: macrosimulation and microsimulation. Macrosimulation uses computers to simulate the impact of systemic factors on a population distribution. Typically, a model is composed of a set of differential equations. Microsimulation, on the other hand, like ABM, is a bottom-up approach that uses individuals as units of analysis. Given that the focus is on individuals, microsimulation and ABM are similar. However, two important aspects distinguish ABM from the preexisting simulation methods. First, while the primary goal of macrosimulation and microsimulation is "empirically based macro-level forecasting," ABM is a kind of "thought experiment" which pursues theoretical development rather than prediction (Macy & Willer, 2002, p.145-147). Second, unlike microsimulation in which actors are socially isolated, ABM highlights local interactions among agents who are assumed to be autonomous, adaptive, and interdependent.

A classic use of ABM is Reynolds' (1987) modeling of flocks of birds. In his model, birds follow basic rules that define their behaviors in relation to other birds. Despite the simplicity of rules that determine the movement of individual birds, the flock as a whole is an extremely complex system that cannot be easily explained by a top-down account of global behavior. As in the Reynolds' model, the main goal of ABM is to observe how micro-behaviors result in complex macro-phenomena. Local interactions among individual actors are performed based on simple shared rules. However, the outcome of the local interactions as a whole is often nonlinear, which is hard to capture with standard causal analyses of a set of factors. The advantage of ABM is realized when the researcher is interested in a system's emergent properties such as cultural convergence, segregation, social influence, or imitation (e.g. Axelrod, 1997; Carley, 1991). The diffusion of innovations is a fruitful area for ABM, particularly when one is interested in the spread of information or social influence through social networks (e.g. Bonabeau, 2002; Delre, Jager, & Janssen, 2007; Guardiola, Díaz-Guilera, Pérez, Arenas, & Llas, 2002; Valente, 1995; Young, 1999).

As Garcia (2005) has noted, ABM is particularly useful when "both macro- and microlevels of analyses are of interest," and when "social systems can easily be described by 'what-if' scenarios but not by differential equations" (p.383). In this chapter, we use ABM for three separate reasons: First, although diffusion is a macro-level phenomenon, the dynamics of diffusion are not effectively captured without observing micro-level adoptions. Second, we want to delineate different patterns of diffusion according to different "what-if" scenarios that capture different ways that personal network exposure affects the individual's decision to adopt. These variations in decision rules cannot be measured or operationalized as an analytic attribute. Finally, we conceive of diffusion in social networks as a competitive market of innovations. The competition between innovations implies that the two different innovations are coevolving within the same environment.

Three Approaches to Personal Network Exposure

Assume that we have two competing innovations, A and B. We consider three different weighting factors for PNE: opinion leadership, structural equivalence, and time since latest adoption. Because we have two competing innovations, we will calculate two separate PNE measures for each weighting possibility: A_i, agent *i*'s PNE for innovation A, and B_i, the equivalent PNE for innovation B. Because we are not using an absolute threshold, but, rather, are comparing the PNEs to each other, there is no reason to normalize to a 0-1 scale, and hence we can simplify the equations by not dividing by an agent's sum of weights. In other words, our PNEs will be given by

$$A_i = \sum_j w_{ij} x_j \tag{2}$$

and

$$B_i = \sum_j w_{ij} y_j \, , \tag{3}$$

where x_j is equal to 1 if *j* is one of *i*'s neighbors who has adopted innovation A, and is equal to 0 otherwise (y_j is defined similarly for innovation B), where w_{ij} is the weight (influence) that *j* has on *i*, and where the sums are to be taken across all individuals in *i*'s personal network These weights will be different depending on whether we are considering opinion leadership, structural equivalence, or time since latest adoption, and their computation is discussed next.

Opinion Leadership

In network diffusion studies, opinion leadership has generally been based on sociometric position. For example, a name nomination approach has been used to identify those who are contacted frequently for advice or information within a community. These highly nominated individuals are considered highly influential (Becker, 1970; Coleman et al., 1957; Valente & Davis, 1999). Weiman (1991) found further support for the positional measure of opinion leadership by showing a high correlation between centralities in communication networks and a personality-based assessment of influence ability. Accordingly, we assume that the social network may be composed of peer nominations, and we use degree centrality as the indicator of opinion leadership. Then, the weights in the PNE measures are simply the degrees of the nodes:

$$w_{ij} = \sum_{k} a_{jk}. \tag{4}$$

Structural Equivalence

Valente (1995, 2005) suggested structural equivalence as one means for interpersonal influence. Structural equivalence is the degree to which “two individuals occupy the same position in a social system” (Valente, 1995, p. 56). The idea is that the greater the structural similarity between a current adopter and the potential adopter, the more likely the potential adopter is to actually adopt the innovation. Burt (1987) showed that weighting the network effects by structural equivalence scores predicted an individual’s time of adoption better than considering simply direct ties.

The structural equivalence between agents *i* and *j* can be computed with a Euclidean distance formula utilizing the entries of the adjaceny matrix:

$$SE_{ij} = SE_{ji} = \sqrt{\sum_k [(a_{ik} - a_{jk})^2 + (a_{ki} - a_{kj})^2]}\ . \tag{5}$$

Note that in the above formula, if agent *i* and agent *j* have ties to exactly the same other agents, then inside each of the above sets of parentheses the two terms will either be both equal to 1 or both equal to 0, hence the sum will also be 0. Consequently, the lower SE_{ij}, the more structurally equivalent the two agents are. We wish to have our PNEs so that larger weights (not smaller) correspond to greater influence. Structural equivalence, as defined above, is in the "wrong direction," with larger scores representing less structural similarity and, therefore, less influence. We can make the scores run in the correct direction by subtracting from the maximum. In other words, for structural equivalence we set the weights as follows:

$$w_{ij} = M - SE_{ij}, \tag{6}$$

where $M = \max\{SE_{ij}\}$ is the maximum structural equivalence score amongst all pairs of nodes in the network. The resulting weights are thus similarities; the greater the similarity, the greater the weight, and thus the more influence *j* exerts upon *i*.

Time Since Latest Adoption

One important variable that should be considered is the time since adoption. An agent is more likely to be influenced by an individual who adopted the innovation quite some time ago as opposed to an individual who only recently adopted the innovation. For example, Watts and Dodds (2007) simulated the degree of influence in diffusion of public opinions. Although they used the term *opinion leaders*, their consideration of the influential individuals was not based on a sociometric definition of opinion leaders (as ours is, above). Instead, they examined the impact of initiators or early adopters as opposed to late adopters. Accordingly, another possible weighting factor in measuring PNE is the length of time the innovation has been adopted by an individual.

As will be seen in the Method section, we consider two separate cases regarding adoption time. First, we consider the classic case that distinguishes between adopters and nonadopters. Individuals who become adopters, stay adopters for all time. Because we are dealing with two innovations, however, it makes sense allow individuals to switch between innovations—in other words we allow them to change their minds. We will therefore take as our weights the time since latest adoption (rather than the time since initial adoption).

Our simulations proceed in discrete steps. In other words, we start at time 0 and continue thence to time 1, time 2, etc. Each time step is called an *iteration*. Let t be the current iteration in the simulation, and suppose that at iteration t agent j is a current adopter of innovation A. Let $t(j)$ be the most recent iteration in which agent j was *not* an adopter of innovation A. Then the appropriate weighting score to use in the computation of A_i is:

$$w_{ij} = \frac{t - t(j)}{t}. \tag{7}$$

The above expression is the proportion of time that agent j's most recent adoption has been innovation A. Of course, the weights can be defined similarly for those agents that are current adopters of innovation B.

With Equation 7 we have come to the end of our theoretical exposition. Using these various weights for the computation of PNE, we conducted a simulation using three empirical networks. In brief, for each network we chose a pair of innovators (one for A, one for B), and we allowed the innovations to propagate throughout the network according to the three different weighting rules above. Details of the simulation can be found in the next section.

Method

Empirical Networks

The simulation used three types of real life social networks: a Facebook friendship network, an advice network, and a network of jazz bands. The Facebook network consists of a user's 112 friends. This network comes from a larger data set from one of the author's (Kwon) dissertation project. Although the average size of personal networks in Facebook tends to be larger, often reaching over 300 individuals, we intentionally chose a smaller size to lessen the computational burden in the simulation. The ties are binary, with a tie being placed between *i* and *j* if *i* and *j* are friends. In Facebook, two individuals become friends only when there is mutual agreement. Accordingly, this network is undirected. It has 1,481 ties and a density of .12.

The advice network consists of 77 individuals in a research team for a manufacturing company. This network comes from the research of Cross and Parker (2004) and is available at http://toreopsahl.com/datasets/. In its original form, this was a directed network with a tie from *i* to *j* indicating that *i* sought *j*'s advice. In our simulation, we used a symmetrized version by adding reciprocal ties wherever an unreciprocated tie was found. Although there is nothing in our theoretical analysis that requires symmetric networks, we felt it best not to introduce this particular confounding condition, keeping all of our networks undirected. This way, any difference between the advice network and other networks will not be due to its status as a directed network. In the symmetrized version of the network, there are 2,682 reciprocated ties for a density of .46.

Finally, the jazz network consists of 198 bands that performed between 1912 and 1940, with a tie placed between two bands if they shared a common musician. There are 5,484 such ties, giving the network a density of .15. The jazz network was first discussed by Gleisser and Dannon (2003), and the data set can be found at http://deim.urv.cat/~aarenas/data/welcome.htm.

Design

Our simulation consists of a large number of *runs*. We used a 3 × 3 × 2 design (Network × PNE × Decision Type) to set the parameters of each run. In other words, each run appears in exactly one cell of the 3 × 3 × 2 design. The three different networks were the Facebook, advice, and jazz networks discussed above. The three different PNEs were those where the weights were based on our three influence factors: opinion leadership, structural equivalence, or time since latest adoption. The two decision types were fixed and floating. In the fixed-decision condition, once an agent adopted an innovation, whether A or B, that agent stayed with that innovation until the end of the run. In the floating-decision condition, we allowed the agents to change their minds. For example, an agent adopting innovation A will change to innovation B if the agent's PNE for B becomes greater than the PNE for A, a result that might happen as the other agents in the first agent's personal network make their own decisions about which innovation, if either, to adopt.

Procedure

At each iteration, each agent is in one of three states, A, B, or N, depending on whether the agent is currently an adopter of innovation A, innovation B, or neither and thus is Neutral. At the beginning of each run, we choose a pair of agents to act as *seeds*. One of the two seeds is placed in state A and one in state B. All of the other agents begin the run in state N. Then, in each iteration, we use Equations 4, 6, or 7, depending on PNE condition, to compute weights for each agent, and we use Equations 2 and 3 to compute the PNEs A_i and B_i for each agent (in the floating-decision condition) or for each agent currently in state N (for the fixed-decision condition). Then, for every agent that is eligible to change states (i.e. all agents in the floating-decision condition, but only those agents in state N for the fixed-decision condition) we use the following updating rule: In the next iteration, place agent i in state A if $A_i > B_i$, in state B if $A_i < B_i$, and in state N if $A_i = B_i$. The iterations continue in this fashion until the agents converge to a steady state, in which no agent ever changes states again, or until the maximum number of iterations (100) is reached.

At the end of a run, we record the number of iterations in the run and the saturation level of each innovation (i.e., the proportion of agents in state A at the end of the run, and similarly for innovation B), and we choose a new pair of seeds for the next run. We conduct a separate run for each possible pair of seeds, thus the number of runs in each network condition varies on the basis of network size. In particular, there were 6,216 runs in each of the Facebook cells of the design, 2,926 in the advice cells, and 19,503 in the jazz musician cells. In all, across the 18 cells of the design, we conducted 171,870 runs.

Independent and Dependent Variables

We are interested the structural properties of seed agents in terms of how their innovations spread through the network. Consequently, we chose as our independent variables degree centrality, closeness centrality, betweenness centrality, and eigenvector centrality. To compute the centralities, we used UCINET 6 (Borgatti, Everett, & Freeman, 2002).

Regarding dependent variables, we gave a seed credit for a *win* if the innovation that the seed began with at the outset of the run was adopted by a plurality of the agents in the network at the end of the run. In a network of size N, in each cell of the design each agent is used as a seed

N – 1 times (once with each of the other N – 1 agents), thus the number of wins for an agent in a given cell of the design can vary from 0 to N – 1. If we look at the saturation level of a seed's innovation in each of the seed's wins, we can compute the mean saturation level in runs where the agent won. We can also compute a similar mean for time to convergence, or what we call *saturation time*. These three variables—win count, mean saturation level, and mean saturation time—serve as our main dependent variables.

Results

Centrality

As mentioned previously, we used various centrality measures to assess each seed's positional properties. Within each of the three networks, the four measures of centrality were significantly correlated, a result to be expected based on previous research (Valente, Coronge, Lacon, & Costenbader, 2008). We obtained large correlations amongst degree, closeness, and eigenvector centrality, ranging from a low of .78 to a high of .98. The correlations between each of these three measures and betweenness centrality were smaller, ranging from a low of .26 to a high of .96.

After computing centralities, we correlated the scores with the diffusion outcome variables: mean saturation percentage (SP), mean saturation time (ST), and win count (WC). Tables 1 - 3 summarize the results. The most outstanding finding is that win counts show remarkably high correlations with most of the centrality scores; the more central the seed, the more wins obtained by that seed, regardless of network, PNE, or decision type. The only exceptions to this result were the two nonsignificant correlations with betweenness in the Facebook network: the structural equivalence version of PNE with fixed decisions and the adoption time version of PNE with floating decisions. In all other cells of the design, an innovation diffused by a central seed was very likely to dominate the market share. In general, the betweenness scores were moderately correlated with the win counts (ranging from r = .21 to r = .58), while the correlations between win counts and the rest of centralities scores were very strong (ranging from r = .76 to r = .97).

The results regarding saturation percentage varied depending on which PNE model was of interest and which network was examined. With the Facebook network, eigenvector centrality was negatively associated, and closeness centrality was positively associated, with saturation percentage when using the structural equivalence PNE in the fixed and floating decision-types, respectively. On the other hand, betweennness centrality was positively associated with saturation percentage in all of the other Facebook cells. In the advice networks, all of the centrality measures were associated with saturation percentage for two of the fixed-decision models, namely when using an adoption time PNE or when using an opinion leadership PNE. None of the centrality measures predicted saturation percentage in the other advice network cells. In the jazz network, the results are mixed, with different centralities predicting saturation percentage to different extents in the various decision-type and PNE conditions.

Likewise, the effect of a seed's network position on saturation time seems to vary from model to model. The most consistent results are for the advice networks where all correlations save one (fixed/adoption time) were significant. In the other networks, the results were more varied. In all cases, significant coefficients were negative, indicating that the more central the seed, the less time it took to reach convergence.

Mean Comparisons

Table 4 shows the means and standard deviations of each of the dependent variables in each of the 18 cells of the design. Several consistent patterns can be observed. First of all, means for win counts were remarkably constant across different PNEs and decision types. There are big differences between networks, but this is an artifact of network size. In the smallest network—the advice network—each node is used as a seed 76 times, whereas in the largest network—the jazz network—each node is used as a seed 197 times. Naturally, there is more opportuity for a node to accumulate wins in the jazz nework than in the advice network, with the Facebook network being intermediate. Nonetheless, within each network, the win counts are very, very close to each other. Neither PNE nor decision-type seemed to affect the means.

Second, in general, the mean saturation percentage was high across all models, ranging from 70% to 99% with small standard deviations. This result indicates that regardless of which agent initiates the diffusion, one innovation is likely to win by a landslide against the competing one. The saturation percentages for fixed decisions seem to be somewhat smaller than for floating decisions. The means for floating decisions, in particular, suggest that we may be hitting a ceiling, and this ceiling effect probably attenuated the correlations we reported early, making patterns difficult to discern for mean saturation percentage.

With respect to saturation time, the fixed decisions once again are smaller than for the floating decisions, a situation that mirrors the results for saturation percentage. Naturally, if agents are not allowed to change their minds, then it is less likely that a single innovation totally takes over the network, and, moreover, it will take less time for the agents to come to a steady state. We can also see from Table 4 that opinion leadership results in quicker convergence for fixed decisions than does time since latest adoption.

Third, the mean scores among PNEs suggests that, in the fixed decision condition, leadership influence may be the most efficient both in terms of saturation percentage and time. Regarding the time spent to reach saturation, leadership and structural equivalence took equal time periods for saturation. However, the leadership based PNE shows the highest saturation level across all networks.

PNE Correlations

Finally, within each cell of the design, we correlated the mean saturation percentages with each other by considering in a pairwise fashion each of the three PNE weighting schemes. As Table 5 shows, the correlations are in general very high, suggesting that, with respect to saturation percentage at least, the three PNE weighting schemes are largely interchangeable.

Discussion

The current study applied agent-based modeling to simulate diffusion processes of two competing innovations. Our model was based on the simple rule that individuals will follow the (appropriately weighted) majority choice when facing competing innovations, one of which an individual might adopt. The specific form of the model was based on Valente's (2005) personal network exposure, PNE. We investigated three different "what-if" scenarios embodied by three differently weighted versions of PNE—opinion leadership, structural equivalence, and adoption time—along with two decision-making conditions and three different real social networks.

Our findings support the important role of an innovator's network position, particularly when it comes to the chances of winning the competition. The winning frequencies were highly correlated with the centralities of the seed of the particular innovation. In our study, a seed's centrality was especially important because in most of the cases the winner dominated the market, with a minimum saturation of 70%, and usually higher. This finding suggests that it should be a strategic matter of choice "where to begin" as well as "how to spread." Subsequently, understanding positional properties of the potential innovator is an important prerequisite for success in a competitive market of ideas or innovations.

One emergent question related to the seed centralities is the influence of the discrepancy between the competing seeds' centralities on diffusion outcomes. We looked at each seed's centrality in isolation, but despite the pattern of correlations we obtained, it may be that it is not the seed's absolute centrality that is important, but, rather the seed's centrality vis-à-vis the centrality of the seed beginning with the other innovation. For example, if innovation A's seed has a high centrality while innovation B's seed has a low centrality, the diffusion outcome might be different than when both seeds have equally high centralities. We leave answering this question to future research.

When mean saturation and saturation time are considered, our findings reveal inconsistencies across different models and different networks. The inconsistencies suggest that the saturation level and saturation time might be influenced more by both the specific network context where the competition occurs and the method by which the innovations diffuse than to seed centralities. One possibility is an interaction effect between network structures and the diffusion strategies. Network properties such as size, diameter, or centralization could interact with the different weights of PNE. Unfortunately, three networks are far to few to adequately explore this question, and thus we leave this issue to future research as well.

On the other hand, we observed that type of decision resulted in different mean saturation levels and different mean saturation times. Recall that we employed two decision types, one of which was fixed, in that once an agent adopts an innovation the agent never changes, and one of which was floating, in that agents could change from iteration to iteration as to which, if either, of the innovations they adopt. With floating decisions, saturation levels were higher and the saturation times were longer than with fixed decisions. Considering that it largely depends on the nature of innovation whether or not we could change our adoption decision easily, decision type can be understood as an indirect indicator of innovation characteristics. Within the same decision type, we found no drastic differences among different PNEs. High correlations among PNE models also reflect the interchangeability of the three weighting factors, which indicate that what mattered more in our simulation seemed to be the decision types, or the characteristics of innovation, than the factors that influenced the PNE level.

However, this result should not lead to the simple conclusion that network effects are trivial in the diffusion process. Rather, our results should lead to the pursuit of more advanced application of PNE weights. While our focus was to compare the different PNE weights, these weights could be at work simultaneously. It is probably unrealistic that all agents use the same weighting rules, or that agents keep a single rule for all time. Therefore, future study can consider extending the network influence model by combining the three PNE factors in one scenario. The simultaneous consideration could be performed in various ways, for example by adding the three weights together and applying the combined PNE to the whole agent population, by segregating populations into three subsets and applying different rules to the different subpopulations, or by taking into account certain agent attributes or times and accordingly applying different PNEs.

Our study has limitations that can be improved in future research. First of all, we applied a very simple behavioral rule, a weighted majority. But, ABM is a kind of thought experiment and it is up to a researcher’s insight as to how to define the rules. Our rule can be considered as a simple kind of bandwagon effect, driven by dynamic sub-mechanisms (Abrahamson & Rosenkopf, 1997), and it can be improved by considering more refined rules for agent behaviors such as requiring larger margins than simple majority, or by considering second order neighborhoods (the personal networks of those in one’s personal network). Second, we considered only binary, undirected social networks. Weighted networks or directed networks may present a quite different structural contexts and thus result in different diffusion patterns. Third, we did not consider the longitudinal pattern of diffusion processes. Observation of over-time processes is a common approach in diffusion studies and it may well be explored with ABM. We did not include this aspect in the current study because of computational difficulties: Running and computing the results of each of the 18 cells of the design, at each iteration, required an overwhelming amount of time. The same computational burden also prevented us from modeling diffusion processes with multiple seeds. It is more realistic, however, to consider more than a single seed to begin the diffusion of each innovation. A next step would be to consider multiple innovators in the model.

This chapter proposed the utility of ABM in exploring how interpersonal influence on the micro-level affects the diffusion pattern on the macro-level. Diffusion researchers can take advantage of ABM especially when it is hard to acquire empirical data. The network diffusion model of competing innovations, which we simulated in our study, is one good example for which data collection is so daunting that few empirical studies could have been conducted, even if such situations are commonly observed in our social life. ABM is a complementary and alternative methodology to the existing trend of diffusion research.

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Table 1. Correlations between Seed Centralities and Diffusion Variables: Leadership PNE Models

Networks		Facebook				Advice				Jazz		
		SP	ST	WC		SP	ST	WC		SP	ST	WC
	DG	n.s.	n.s.	$.97^{***}$	DG	n.s.	$-.31^{**}$	$.86^{***}$	DG	$.21^{**}$	$-.28^{**}$	$.85^{***}$
Floating	CL	$.24^{*}$	n.s.	$.91^{***}$	CL	n.s.	$-.29^{*}$	$.76^{***}$	CL	$.28^{**}$	$-.14^{*}$	$.86^{***}$
	BT	n.s.	$-.34^{**}$	$.22^{*}$	BT	n.s.	$-.24^{*}$	$.58^{***}$	BT	$.22^{*}$	$-.19^{*}$	$.32^{***}$
	EV	n.s.	n.s.	$.97^{***}$	EV	n.s.	$-.30^{**}$	$.93^{***}$	EV	n.s.	$-.34^{***}$	$.94^{***}$

Networks		Facebook				Advice				Jazz		
		SP	ST	WC		SP	ST	WC		SP	ST	WC
	DG	n.s.	n.s.	$.97^{***}$	DG	$.49^{***}$	$-.55^{***}$	$.86^{***}$	DG	$.28^{**}$	n.s.	$.86^{***}$
Fixed	CL	n.s.	$-.30^{**}$	$.92^{***}$	CL	$.47^{***}$	$-.61^{***}$	$.76^{***}$	CL	$.26^{**}$	n.s.	$.89^{***}$
	BT	$.19^{*}$	$-.23^{*}$	$.23^{*}$	BT	$.44^{***}$	$-.66^{***}$	$.58^{***}$	BT	$.26^{**}$	$-.15^{*}$	$.36^{***}$
	EV	n.s.	n.s.	$.96^{***}$	EV	$.45^{***}$	$-.46^{***}$	$.93^{***}$	EV	n.s.	$.21^{*}$	$.91^{***}$

Note. SP = mean saturation percentage, ST = mean saturation time, WC = win counts; Centralities: DG = degree, CL = closeness, BT = betweennes, EV = eigenvector; * p < .05, ** p < .01, *** p < .001, n.s. = not significant.

Table 2. Correlations between Seed Centralities and Diffusion Variables: Structural Equivalence PNE Models.

Networks		Facebook				Advice				Jazz		
		SP	ST	WC		SP	ST	WC		SP	ST	WC
Floating	DG	n.s.	$-.25^{*}$	$.92^{***}$	DG	n.s.	$-.28^{*}$	$.81^{***}$	DG	n.s.	$-.21^{**}$	$.77^{***}$
	CL	n.s.	$-.31^{***}$	$.84^{***}$	CL	n.s.	$-.28^{*}$	$.71^{***}$	CL	n.s.	$-.15^{*}$	$.86^{***}$
	BT	$.19^{*}$	$-.26^{*}$	n.s.	BT	n.s.	$-.29^{*}$	$.51^{***}$	BT	n.s.	n.s.	$.29^{***}$
	EV	n.s.	n.s.	$.96^{***}$	EV	n.s.	$-.24^{*}$	$.90^{***}$	EV	n.s.	$-.22^{**}$	$.85^{***}$

Networks		Facebook				Advice				Jazz		
		SP	ST	WC		SP	ST	WC		SP	ST	WC
Fixed	DG	n.s.	n.s.	$.94^{***}$	DG	n.s.	$-.47^{***}$	$.83^{***}$	DG	n.s.	n.s.	$.80^{***}$
	CL	n.s.	$-.30^{***}$	$.91^{***}$	CL	n.s.	$-.53^{***}$	$.72^{***}$	CL	n.s.	n.s.	$.88^{***}$
	BT	n.s.	$-.24^{*}$	n.s.	BT	n.s.	$-.56^{***}$	$.53^{***}$	BT	n.s.	$-.15^{*}$	$.32^{***}$
	EV	$-.28^{**}$	n.s.	$.96^{***}$	EV	n.s.	$-.40^{***}$	$.90^{***}$	EV	n.s.	$.19^{**}$	$.86^{***}$

Note. SP = mean saturation percentage, ST = mean saturation time, WC = win counts; Centralities: DG = degree, CL = closeness, BT = betweennes, EV = eigenvector; * $p < .05$, ** $p < .01$, *** $p < .001$, n.s. = not significant.

Table 3. Correlations between Seed Centralities and Diffusion Variables: Adoption-Time PNE Models.

Networks		Facebook				Advice				Jazz		
		SP	ST	WC		SP	ST	WC		SP	ST	WC
Floating	DG	n.s.	-.28**	.92***	DG	n.s.	-.52***	.85***	DG	.22**	-.36***	.79***
	CL	n.s.	-.34***	.84***	CL	n.s.	-.50***	.75***	CL	.20**	-.21**	.86***
	BT	.25**	-.29**	n.s.	BT	n.s.	-.45***	.58***	BT	.23**	-.15*	.30***
	EV	n.s.	-.19*	.96***	EV	n.s.	-.48***	.92***	EV	n.s.	-.33***	.87***

Networks		Facebook				Advice				Jazz		
		SP	ST	WC		SP	ST	WC		SP	ST	WC
Fixed	DG	n.s.	n.s.	.95***	DG	.70***	n.s.	.86***	DG	.18*	n.s.	.81***
	CL	n.s.	-.29**	.92***	CL	.69***	n.s.	.76***	CL	n.s.	n.s.	.88***
	BT	.19*	-.21*	n.s.	BT	.65***	n.s.	.58***	BT	.22**	-.15*	.33***
	EV	n.s.	n.s.	.96***	EV	.65***	n.s.	.92***	EV	n.s.	n.s.	.88***

Note. SP = mean saturation percentage, ST = mean saturation time, WC = win counts; Centralities: DG = degree, CL = closeness, BT = betweennes, EV = eigenvector; * $p < .05$, ** $p < .01$, *** $p < .001$, n.s. = not significant.

Table 4. Mean Comparisons among Diffusion Variables of 18 Models.

Network	PNE		Saturation Percentage		Saturation Time		Win Count	
			Float	Fix	Float	Fix	Float	Fix
Facebook	Leader	M (SD)	.99 (.09)	.83 (.12)	6.21 (1.89)	3.96 (.57)	55.47 (32.51)	55.34 (32.50)
	SE	M (SD)	.99 (.09)	.77 (.11)	6.21 (1.89)	3.96 (.57)	55.47 (32.51)	55.17 (32.31)
	Time	M (SD)	.85 (.11)	.80 (.11)	4.83 (.68)	4.06 (.11)	55.46 (32.53)	55.17 (32.33)
Advice	Leader	M (SD)	.99 (.11)	.83 (.11)	2.26 (.41)	1.95 (.37)	37.83 (22.17)	37.83 (22.17)
	SE	M (SD)	.99 (.11)	.70 (.09)	2.26 (.41)	1.95 (.33)	37.83 (22.17)	37.83 (21.85)
	Time	M (SD)	.97 (.12)	.73 (.12)	4.84 (1.37)	2.86 (.36)	37.83 (21.96)	37.82 (21.98)
Jazz	Leader	M (SD)	.89 (.10)	.78 (.09)	5.40 (.74)	4.36 (.42)	98.46 (56.98)	98.20 (56.76)
	SE	M (SD)	.89 (.10)	.72 (.08)	5.40 (.74)	4.36 (.43)	98.46 (56.98)	98.11 (56.17)
	Time	M (SD)	.84 (.10)	.76 (.09)	5.98 (.76)	4.50 (.41)	98.46 (56.89)	98.25 (56.90)
		Grand Mean	.93 (.10)	.77 (.10)	4.28 (.99)	3.55 (.39)	63.91 (37.20)	63.74 (37.00)

Table 5. Correlations among PNEs.

	Facebook			Advice			Jazz		
Saturation Percentage									
	L	SE	T	L	SE	T	L	SE	T
L	-	.70	.71	-	n.s.	n.s.	-	.85	.91
SE	.93	-	.98	.84	-	.76	.91	-	.96
T	.97	.96	-	.93	.68	-	.95	.97	-
Saturation Time									
	Facebook			Advice			Jazz		
	L	SE	T	L	SE	T	L	SE	T
L	-	.58	.65	-	.29	n.s.	-	.62	.65
SE	1.00	-	.94	.98	-	.51	.99	-	.75
T	.98	.98	-	.62	.68	-	.95	.95	-
Win Count									
	Facebook			Advice			Jazz		
	L	SE	T	L	SE	T	L	SE	T
L	-	.97	.99	-	.97	.98	-	.95	.97
SE	.98	-	.99	.99	-	.98	.97	-	.99
T	.99	.99	-	.99	.99	-	.98	.99	-

Note. Upper diagonal = floating model, lower diagonal = fixed model, n.s. = not significant.