Using system dynamics to analyze innovation diffusion processes within intra-organizational networks

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Abstract

The purpose of this study is to introduce system dynamics as a methodology to analyze intra-organizational innovation diffusion processes. Therefore, a purely algebraic model is replicated and analyzed in a system dynamics environment before it is extended by relaxing the restrictive assumption that intra-group diffusion and inter-group diffusion take place consecutively. The findings of this study suggest that the parallel occurrence of intra-group and inter-group diffusion can change the outcome of the diffusion process significantly. In addition, system dynamics is used to illustrate and analyze the complex dynamics of the diffusion process. The interplay between the self-reinforcing dynamics of intra-group diffusion and the balancing dynamics of inter-group diffusion is heavily influenced by the structure of the network. The simulations suggest that adopter-dominated groups should be connected to each other while non-adopter-dominated groups should be isolated from each other in order to increase the probability and speed of successful innovation diffusions. Major limitations of the study are that only one network structure between groups was examined and that all groups are considered to be homogeneous.

Keywords: system dynamics, algebraic models, innovation diffusion, communication networks, network structure, migration, conversion

1. Introduction

In innovation research, diffusion models have been used to examine the spread of innovations. Such models are employed to identify structure-related characteristics which ensure a quick and sustainable spread of innovations. However, models based purely on conventional mathematical algebra quickly reach degrees of complexity which inhibit their comprehension and make it necessary to further restrict the boundaries of the relevant system. By transforming such algebraic models into system dynamics models, certain restrictive assumptions can be relaxed. Besides, system dynamics has the advantage that the structure of a system and its dynamics can be easily visualized which, in turn, facilitates the comprehension of the system. Therefore, this paper applies system dynamics to analyze innovation diffusion processes at the level of organizations.

In most diffusion studies, the underlying models make the restrictive assumption that only adopters of an innovation can convert non-adopters and *not* vice versa (Abrahamson and Rosenkopf, 1997; Gibbons, 2004; Bohlmann et al., 2010). Thus, the percentage of adopters can only grow but never shrink. Mahajan et al. (1984, p. 1401) point out that this assumption is tenuous since communicators do not only promote an innovation but may also transfer neutral as well as negative information about it through interaction via inter-personal links, the so-called word-of-mouth communication. In opposition to the sole inclusion of positive word-of-mouth information, the additional consideration of negative word-of-mouth information also takes into account the arguments of non-adopters. Krackhardt (1997) explicitly models the discussion process between adopters and non-adopters of an innovation within and across five organizational groups each consisting of an adopter and a non-adopter camp. Due to the explicit consideration of non-adopter arguments, the communication between the two parties can also result in a conversion of adopters by non-adopters. Consequently, the converted adopters discard the innovation and become non-adopters by using the status quo instead. Thus, in Krackhardt's (1997) model, the percentage of adopters cannot only increase but also decrease.

Within Krackhardt's (1997, p. 186) model, the communication process between adopters and non-adopters is taking place in two steps. First, there is *between*-group migration: A certain fraction of adopters as well as non-adopters of a group migrate to the respective camp of all connected groups, e.g. adopters from group 1 migrate into the adopter camp of group 2. Second, the adopter and the non-adopter camp *within* each group interact with each other, resulting in the conversion of a fraction of non-adopters to the adopter camp of that group and vice versa. Krackhardt (1997) examines under which structural conditions four groups—which in the beginning consist only of non-adopters—can be converted by one initial adopter group. In particular, the influence of the migration rate, the network structure between groups, and the position of the adopter group are analyzed. However, Krackhardt (1997, p. 186) constructed the underlying model based on the assumption that conversion between the adopter and the non-adopter camp of a group and migration between groups are taking place in an iterative but sequential order.

The purpose of this paper is to relax the restrictive assumption of consecutively alternating migration and conversion. This is done by converting Krackhardt's (1997) algebraic model into a system dynamics model which allows for the concurrent and continuous occurrence of migration and conversion. The system dynamics model, which is analyzed in this paper, is part of a more extensive research which examines structural as well as actor-related influence factors of organizational innovation implementation processes.

This wider research is based on several studies which have shown that an organization's failure to benefit from an adopted innovation can often be attributed to a deficient implementation process rather than to the innovation itself (Klein and Sorra, 1996; Aiman-Smith and Green 2002; Gary, 2005; Karimi et al., 2007). It addresses the issue that literature is lacking multidimensional models which take into account multiple and to some extent interrelated drivers of implementation success (Dean Jr. and Bowen, 1994; Klein and Sorra, 1996; Klein et al., 2001; Repenning, 2002). In addition, Choi and Chan (2009, p. 245) point out that existing implementation studies tend to focus either on employee-related aspects, mostly at the individual level, or on organizational aspects such as management support, structure, and resources of the implementing organization. Therefore, our general research aims to contribute to existing implementation literature by examining the combined and interrelated influence of two organizational aspects (*communication structure* and *management support*) on implementation success, which is characterized by the employee-related aspect *innovation acceptance* and *usage*.

Within the scope of this paper, we focus on the communication structure by converting Krackhardt's (1997) model into a system dynamics model which allows for the parallel and continuous occurrence of migration and conversion. The structure of the paper is as follows. In the subsequent section, it is demonstrated that Krackhardt's (1997) model can be replicated using system dynamics which offers a clear visualization of the system's structure. In the third section, the model is extended by using the temporal dimension of system dynamics in order to dismiss the restrictive assumption of consecutive migration and conversion. The results of the extended model are compared to the results of the original model. Thereby, in contrast to Krackhardt (1997), the focus is not only on the outcome of the diffusion process but also on the process itself and on its underlying dynamics. The paper closes by summarizing and discussing the derived insights and by outlining possible further research.

2. Krackhardt's diffusion model in system dynamics

Krackhardt's (1997, pp. 183–184) model distinguishes between adopters and non-adopters of an innovation within each of five homogeneous and equally large groups of an organization. Those groups can represent for example worldwide branch offices of an enterprise or homogeneous departments of an organization which are connected to each other through communication, thereby, forming a social communication network. As Figure 1 illustrates, this paper focuses on Krackhardt's (1997) analysis of the groups being connected to each other in a chain structure. Within this network, an innovation diffuses in two steps. First, an exchange of opinions and experiences takes place *between* groups (Krackhardt, 1997, pp. 186–187). This so-called *migration* is modeled by exchanging a certain fraction of adopters as well as non-adopters with all connected groups. Thus, group 2, for example, sends a certain fraction of their adopters to the adopter camps of the connected groups 1 and 3. In return, certain fractions of adopters of the connected groups 1 and 3 migrate into the adopter camp of group 2. This migration also takes place between the non-adopter camps of connected groups. In the second step, an exchange of opinions and experiences takes place between the adopter and the non-adopter camp *within* a group, so-called *conversion* (Krackhardt, 1997, p. 187). In the course of conversion, a fraction of adopters as well as non-adopters is converted by the respective opponent party. The degree of diffusion within a group is measured by the proportion of adopters A_i of a group i after conversion took place and before migration happens again. Consequently, the term $(1-A_i)$ represents the proportion of non-adopters because the proportion of adopters and non-adopters within a group i always adds up to one.

In the following, the mathematical formalization of migration and conversion is outlined by replicating Krackhardt's (1997) model, and thereby also the exact same results, in a system dynamics environment. As in Krackhardt's (1997) model, migration and conversion are not processes which happen over time. Instead, migration only takes place when the simulation time is even (t = 0, 2, 4, …). Conversion, on the other hand, only happens when the simulation time is uneven (t = 1, 3, 5, …). Thus, a single iteration in Krackhardt’s (1997) model, consisting of migration and conversion, equals two time periods in the system dynamics model. Since system dynamics simulates the respective model along a temporal dimension consisting of equally large time steps, it is assumed that one time period consists of eight time steps and that the unit of time is days. Thus, one time steps equals 0.125 time periods and thereby 0.125 days. In section 3, the assumption that migration and conversion only take place at certain points in time will be relaxed by using the temporal dimension of system dynamics to enable migration and conversion to take place continuously and simultaneously.

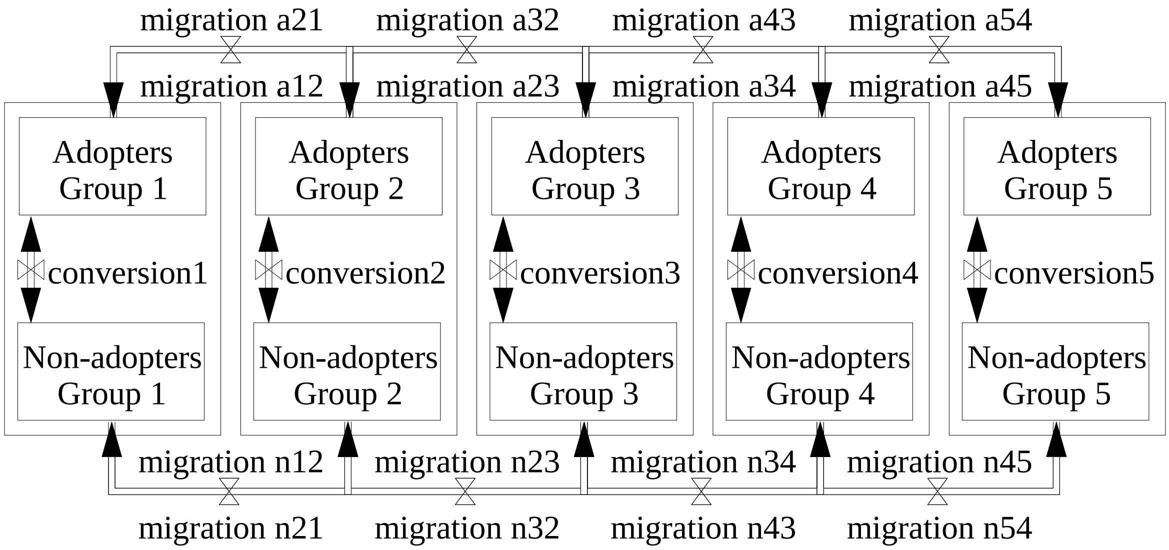


Figure 1: Organizational innovation diffusion process within a five-membered chain structure

Whenever migration takes place, a certain fraction of adopters as well as non-adopters migrates into the respective camp of each connected group. The fraction of adopters as well as non-adopters that leaves a group *i* to emigrate into a connected group *j* depends on the size of the adopter or non-adopter camp within group *i* and on the migration rate between group *i* and group *j* (= m_{ij}). Equation (1) specifies the total fraction of adopters who emigrate out of group *i* into all connected groups. Equation (2) illustrates this emigration loss with respect to the non-adopter camp of group *i*:

$$\frac{dA_{i\ emigr}}{dt} = \frac{\sum_j A_i \cdot m_{ij}}{Time\ Step}; \tag{1}$$

$$\frac{d(1-A_i)_{emigr}}{dt} = \frac{\sum_j (1-A_i)\cdot m_{ij}}{Time\ Step}. \tag{2}$$

However, besides adopters and non-adopters emigrating out of a group *i*, there are at the same time also adopters and non-adopters from the connected groups *j* who immigrate into group *i*. Equation (3) specifies the total amount of immigrating adopters, while equation (4) depicts the total amount of non-adopters who immigrate into group *i*:

$$\frac{dA_{i\ immigr}}{dt} = \frac{\sum_j A_j \cdot m_{ji}}{Time\ Step}; \tag{3}$$

$$\frac{d(1-A_i)_{immigr}}{dt} = \frac{\sum_j (1-A_j)\cdot m_{ji}}{Time\ Step}. \tag{4}$$

With regard to conversion, Krackhardt (1997, p. 183) states that group-internal communication is fuelled by the active search of organizational members for innovation-related information and opinions of other organizational members. According to the concept of *satisficing*, organizational members do not strive to obtain all information available (Simon, 1956). Instead, they randomly search for like-minded organizational members only within a limited fraction of their group. Based on Asch's (1963) work, it is assumed that only if no like-minded organizational member can be found within this fraction, the searching organizational member converts to the other camp with probability P_{AN}, in case it is an adopter, or with probability P_{NA}, in case it is a non-adopter (Krackhardt, 1997, p. 184). Asch (1963, p. 186) found that the presence of only one other like-minded individual within a group is "sufficient to deplete the power of the majority, and in some cases to destroy it". Krackhardt (1997, p. 184) assumes that adopters are more likely to convert the status-quo oriented non-adopters than the converse. This assumption is supported by East et al. (2008, p. 221) who find that positive word-of-mouth has a bigger impact on brand purchase probability than negative word-of-mouth. Regarding the model, the greater influence of the innovation-affirming adopters translates into a higher search intensity of adopters. This means that the fraction of the group which is searched by adopters for like-minded organizational members is greater than the fraction which is searched by non-adopters. Thus, the search intensity of adopters (S_A) is higher than the search intensity of non-adopters (S_N).

Equation (5) describes the proportion of non-adopters of a group *i* that converts to the adopter camp of that group because those non-adopters could not find any like-minded people within their searched fraction of the group:

$$\frac{dA_{i\,conv}}{dt} = \frac{P_{NA} \cdot (1 - A_i) \cdot A_i^{S_N}}{Time\ Step}. \qquad (5)$$

The term $A_i^{S_N}$ represents the probability that a non-adopter only meets adopters in his or her searched fraction of the group (Krackhardt, 1997, p. 187). The group-internal proportion of non-adopters that does not find any like-minded organizational members corresponds to the term $(1 - A_i) \cdot A_i^{S_N}$. Those isolated non-adopters convert to the adopter camp with the probability P_{NA} whenever simulation time is uneven. Similarly, equation (6) describes the increase of the non-adopter fraction within a group i due to the conversion of adopters:

$$\frac{d(1 - A_i)_{conv}}{dt} = \frac{P_{AN} \cdot A_i \cdot (1 - A_i)^{S_A}}{Time\ Step}. \qquad (6)$$

By means of the introduced diffusion model, Krackhardt (1997, p. 188) examines under which conditions a minority of adopters can convince a majority of non-adopters within a five-membered chain structure (see Figure 1). For the following simulation, it is assumed that group 1 initially constitutes the adopter minority within the organization. Thus, group 1 is the mother group (MGr_1) which is only composed of adopters, while the other four groups consist to 100 percent of non-adopters. The other parameters take the following values: $S_A = 6$, $S_N = 4$; $P_{AN} = P_{NA} = 1$; $Time\ Step = 0.125$.

Figure 2 shows the results of five simulations which differ with regard to the underlying migration rate that is assumed to be equal for all connections between groups. It portrays the average adopter fraction among the five groups. It can be seen that the average adopter fraction within the organization reacts to an increasing migration rate in a non-linear way. In case the migration rate is only 7.5 percent (graph 5 in Figure 2), the average adopter fraction is about 22 percent, thus, only slightly higher than at the beginning of the simulation, when one out of the five groups was dominated by adopters (MGr_1) resulting in an average adopter fraction of 20 percent. However, if the migration rate increases to 10 percent (graph 4 in Figure 2), the fraction of adopters migrating from group 1 into group 2 is big enough to dominate group 2 by converting its non-adopters. This causes a domino effect in group 3, 4, and 5, resulting in the complete diffusion of the innovation throughout the organization. A further increase of the migration rate to 12.5 and 15 percent (graph 3 and graph 2 in Figure 2) accelerates this diffusion process. However, if the migration rate is 17.5 percent (graph 1 in Figure 2) its positive influence on the organizational adopter fraction reverses into a negative one, leading to a complete rejection of the innovation throughout the organization. In this case, the fraction of adopters leaving group 1 and being replaced by immigrating non-adopters from group 2 is too high. The non-adopter camp within group 1 becomes too strong, converting adopters quicker than the emigrating adopters of group 1 can compensate for by converting non-adopters in group 2. Therefore, only a migration rate between 7.6 and 16.4 percent results in a total diffusion of the innovation. A lower migration rate leads to an average adopter fraction of around 20 percent while a higher rate causes the complete rejection of the innovation by converting all adopters of the mother group 1. Krackhardt (1997, pp. 190–192) refers to this narrow window of opportunity (8.8 percent) in which a minority of adopters wins over a non-adopter majority as the *Principle of Optimal Viscosity*.

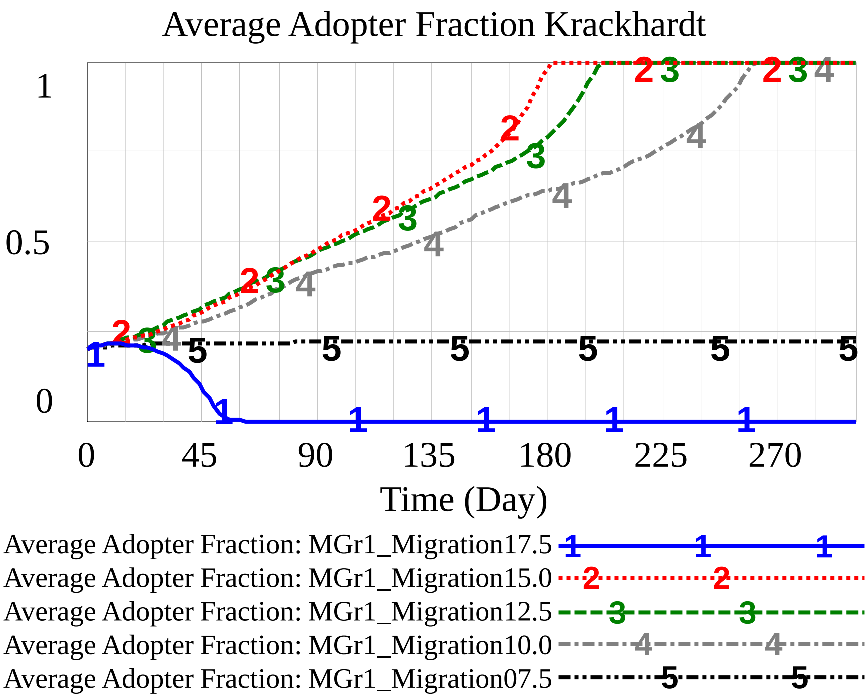


Figure 2: Activity spectrum of the migration rate with the adopters situated in group 1

Krackhardt (2001, p. 256) finds that this principle is surprisingly insensitive to different conversion probabilities, "as long as they do not differ markedly from each other", and to changes of the search intensities, provided that they take values between 2 and 20 and that $S_A > S_N$. The system dynamics model replicates these findings. However, the outcome of the model is not only sensitive to the migration rate but also to the position of the mother group within the chain structure (Krackhardt, 1997, p. 194). Figure 3 illustrates the average adopter fraction as a function of the migration rate when the only difference to the previous simulations is that now group 3 is the mother group (MGr_3) which is only composed of adopters. The simulations depicted in Figure 3 show that the window of opportunity for an adopter minority now completely disappears. In contrast to the mother group being the peripheral group 1 (graph 5 in Figure 2), the centrally located mother group 3 cannot maintain its adopter majority when the migration rate is 7.5 percent (graph 3 in Figure 3). Due to the fact that group 3 is connected to two groups instead of to just one, the fraction of emigrating adopters as well as immigrating non-adopters is twice as big. Lowering the migration fraction to 5 percent (graph 2 in Figure 3) only delays the extinction of adopters in group 3 but cannot prevent it. In case the migration rate is only 2.5 percent (graph 1 in Figure 3), the conversion of the immigrating non-adopters can compensate for the emigration loss of adopters within group 3. Therefore, the adopter fraction of group 3 stays close to 100 percent. However, in contrast to the previous simulations, the emigrating adopter fraction is not big enough to survive within the non-adopter dominated groups 2 and 4, let alone to prevail over the non-adopters there. This results in an average adopter fraction of 20 percent. Krackhardt (1997, pp. 194–196) refers to the superiority of a rather isolated position of the mother group within a network as the *Principle of Peripheral Dominance*.

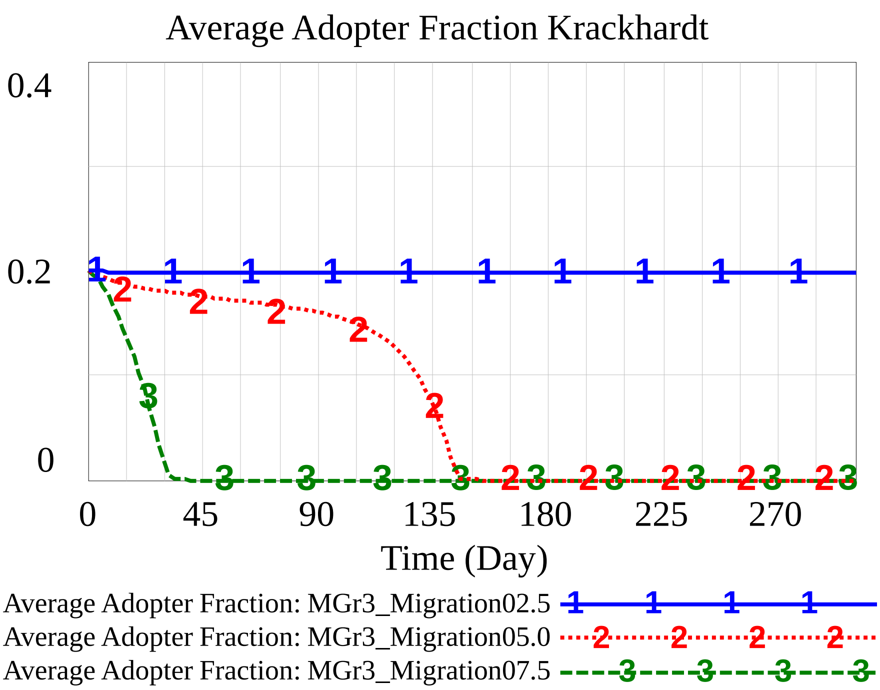


Figure 3: Activity spectrum of the migration rate with the adopters situated in group 3

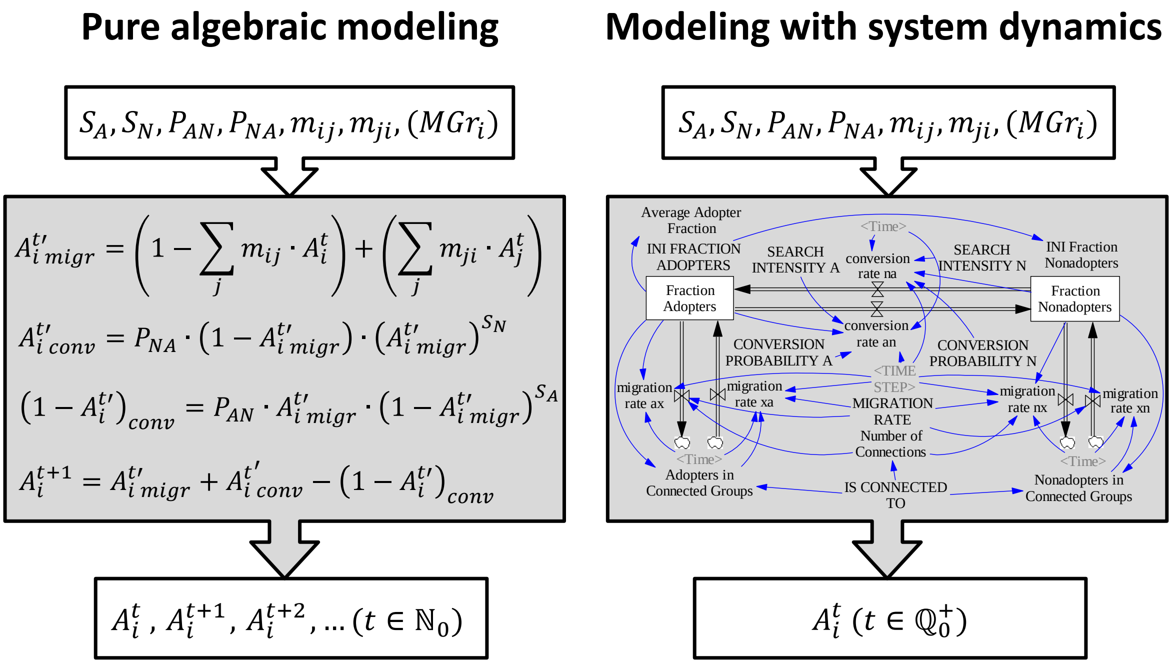
Besides the *Principle of Optimal Viscosity* and the *Principle of Peripheral Dominance*, Krackhardt (1997, p. 196) also finds that it is “almost impossible for the non-adopters to retake control of the organization once adopters have dominated it”. This so-called *Principle of Irreversibility* is the result of the assumption that the search intensity of adopters is higher than the search intensity of non-adopters.

After replicating and analyzing Krackhardt's (1997) diffusion model in a system dynamics environment, the following section uses the temporal dimension of system dynamics to relax the restrictive assumption that migration and conversion take place successively. The results of the new model are then compared to the results of the model described above. In addition, the dynamics of the extended model causing those results are analyzed.

3. Extended system dynamics model allowing for migration and conversion to take place continuously and simultaneously

Figure 4 contrasts pure algebraic modeling with system dynamics modeling in an illustrative way. The left part of Figure 4 depicts the algebraic equations Krackhardt (1997) uses to calculate the adopter fraction of one iteration. Even though those equations are similar to the system dynamics equations described in section 2, a key difference between purely algebraic models and system dynamics models is the underlying software of a system dynamics environment. This software not only facilitates the modeling of feedback processes by automating the algebraic calculation of variables across several time steps, it also supports the structuring and visualization of the model by distinguishing between different kinds of variables (e.g. stocks and flows) and by offering a graphical user interface that also permits meaningful variable names (Forrester, 1961, pp. 14–16; Forrester, 1968, pp. 4-1–4-17). The right part of Figure 4 sketches the structure of the model described in section 2 within the system dynamics environment *Vensim*. The two stocks *Fraction Adopters* and *Fraction Nonadopters* can be identified as boxes in the Stock/Flow Diagram. The conversion and migration rates that change them are flow variables which are represented by black arrows with a valve in the middle (also see Figure 1). The causal relations leading to a change of flow variables or information variables are depicted by blue arrows.

Figure 4 indicates that both models use the same inputs and are basically capable to produce the same outputs. However, system dynamics models can generate output values at very short time intervals much more easily than purely algebraic models. To do so, one simply needs to decrease the time step of the respective system dynamics model. However, the model described in section 2 can only benefit from this increased accuracy if the temporal dimension of system dynamics is actually used. Up until now, the differential equations described in section 2 were only calculated during the time steps at even or uneven simulation times for reasons of congruency with Krackhardt's (1997) original model. Multiplying those differential equations with the time step yields the actual change of the adopter or non-adopter fraction which is caused by the respective flow variable during this time step. In doing so, the time steps in the denominator and numerator of the resulting equations cancel each other out showing that the output of the model in section 2 is totally independent from the size of the time step.



S_A = Search intensity of adopters, S_N = Search intensity of non-adopters,
P_{AN} = Probability of becoming a non-adopter, P_{NA} = Probability of becoming an adopter,
m_{ij} = Fraction of adopters or non-adopters of group i that migrates to group j,
m_{ji} = Fraction of adopters or non-adopters of group j that migrates to group i,
MGr_i = Mother group within the network that comprises the initial adopters,
A_i^t = Adopter fraction within group i at time t

Figure 4: Comparison of pure algebraic modeling with system dynamics modeling

In order to allow migration and conversion to take place simultaneously, the increased accuracy of a smaller time step is needed to ensure that the fraction of adopters or non-adopters leaving their respective camp does not exceed the fraction of adopters or non-adopters within this camp. Therefore, the temporal dimension of system dynamics is used by redefining the parameters P_{AN}, P_{NA}, m_{ij}, and m_{ji}. From now on the conversion probabilities P_{AN} and P_{NA} reflect the likelihood that an adopter or non-adopter converts to the other camp within one day. Similarly, the migration rates m_{ij} and m_{ji} represent the proportion of organizational members that migrate *from* or *to* a camp of group *i* within one day. The adjusted equations of section 2 for the adopter camp of a group *i* are as follows:

$$\frac{dA_{i\,emigr}}{dt} = \sum_j A_i \cdot m_{ij}; \tag{1'}$$

$$\frac{dA_{i\,immigr}}{dt} = \sum_j A_j \cdot m_{ji}; \tag{3'}$$

$$\frac{dA_{i\,conv}}{dt} = P_{NA} \cdot (1 - A_i) \cdot A_i^{S_N}. \tag{5'}$$

Even though not shown, equations (2), (4), and (6) —representing the non-adopter camp—are adjusted in the same manner. Now the temporal dimension of system dynamics has an effect on the output because it is distinct from the time step. It is included in the conversion probabilities and migrations rates whose unit is now *1/Day*.

In a next step, migration and conversion are transformed into processes by allowing both of them to take place not just at certain points of time but during the whole simulation period. This extended system dynamics model is then simulated using the same parameters as in the prior model: S_A = 6, S_N = 4; P_{AN} = P_{NA} = 1; *Time Step* = 0.125. The only difference to the prior system dynamics model is that migration and conversion now take place during the entire simulation period, thereby occurring simultaneously. In contrast to Krackhardt's (1997) work, the analysis of the extended system dynamics model does not only examine how variations of the input influence the output of the model. Over and above, the focus is on revealing and describing the inherent dynamics which actually define the output. The input of the model is altered and its effect on the output is analyzed in order to make those dynamics more transparent. Within this context, Figure 5 illustrates the influence of the migration rate on the average adopter fraction of the extended model assuming that group 1 constitutes the mother group and that the migration rate is equal for all connections between groups. In contrast to the previous system dynamics model (Figure 2), Figure 5 shows that the innovation does not diffuse through all groups when the migration rate is 10 percent in the extended model (graph 4 in Figure 5). Instead, it is largely confined to the mother group, as in the case of a 7.5 percent migration rate (graph 5). In fact, the average adopter fraction in the extended model is always between 20 and 23 percent, with group 1 and group 2 accounting together for over 95 percent of all adopters, if the migration rate is below 10.1 percent. Regarding migration rates of 12.5, 15, and 17.5 percent (graph 3, graph 2, and graph 1), the general behavior of Krackhardt's (1997) model (Figure 2) is similar to that of the extended model (Figure 5). However, the innovation diffuses (graph 2 and graph 3) or gets rejected (graph 1) much quicker in the extended model than in the previous model. Therefore, the continuous occurrence of migration and conversion has a positive as well as a negative effect on the average adopter fraction. On the one hand, the innovation diffuses generally within a much shorter period of time. On the other hand, only migration rates between 10.1 and 17.1 percent give a minority of adopters the opportunity to win over a non-adopter majority, thereby further narrowing this window of opportunity from an 8.8 percentage point range in Krackhardt's (1997) model to a 7 percentage point range in the extended model.

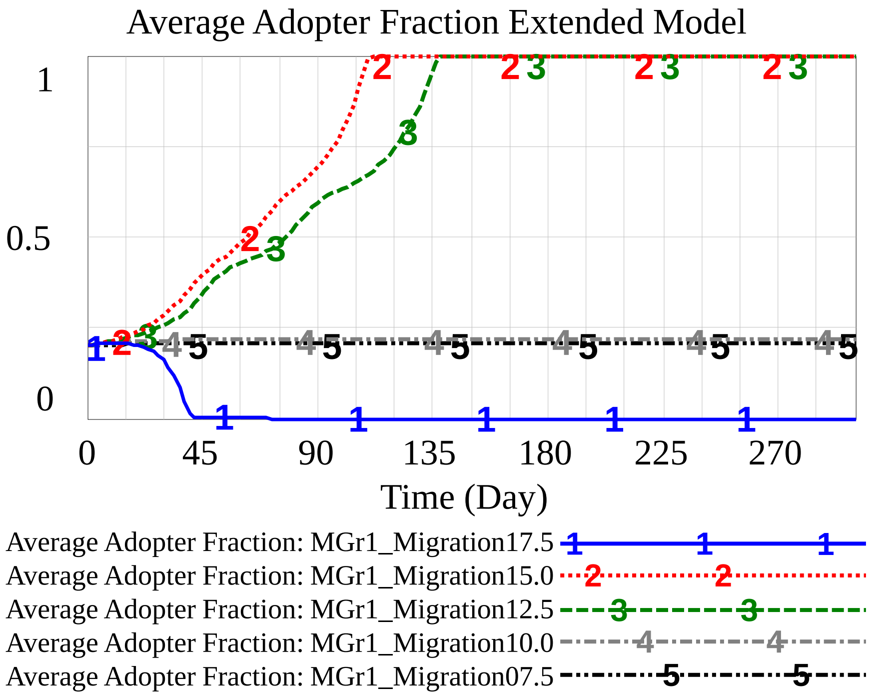


Figure 5: Activity spectrum of the migration rate in the extended model

Further simulation runs show that within the shared window of opportunity, comprising migration rates between 10.1 and 16.4 percent, innovations diffuse quicker in the extended model than in Krackhardt's (1997) model if the migration rate is higher than 10.5 percent. The minimal diffusion time in Krackhardt's (1997) model is about 180 days with a migration rate of 15.2 percent, while it is 110 days in the extended model with a migration rate of about 15.7 percent. Figure 6 contrasts the diffusion of an innovation through all five groups within Krackhardt's (1997) model (left part) and within the extended model (right part). The migration rate has been adjusted to 9.8 percent in the earlier and to 10.4 percent in the latter model so that the innovation diffuses completely in about 275 days within both models. Krackhardt's (1997) model shows the characteristic s-shaped growth of the adopter fraction within the initial non-adopter groups (graphs 2, 3, 4, and 5 in left part of Figure 6). The fraction of adopters migrating from group 1 into group 2 is big enough to gradually overcome the resistance within group 2 (graph 2) and small enough to ensure that adopters prevail within group 1 (graph 1). The increasing adopter fraction within group 2 induces an exponentially increasing adopter fraction within group 3 which only slows down after the lion's share of non-adopters within group 3 has been converted (graph 3). This chain reaction continues until group 4 and 5 are also dominated by adopters (graph 4 and 5).

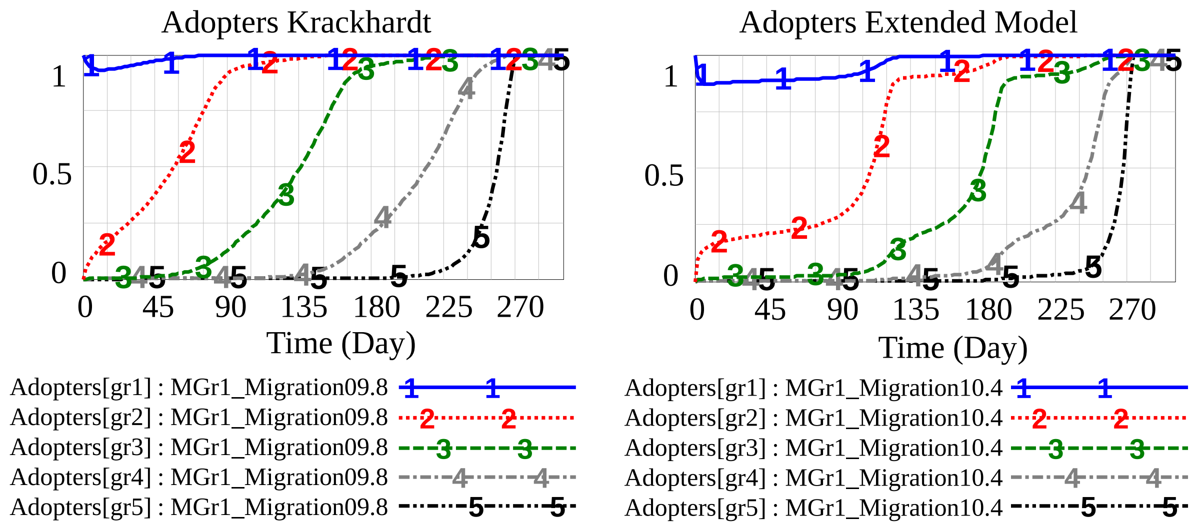


Figure 6: Group-internal diffusion within Krackhardt's and the extended model

The s-shaped growth of the adopter fraction within non-adopter groups, depicted in the left part of Figure 6, resembles the behavior of the Bass (1969) diffusion model. The underlying dynamics are however much more complex. These dynamics become more evident in the right part of Figure 6 because the underlying migration rate of 10.4 percent is very close to the left boundary of the window of opportunity. In this case, the diffusion within group 3, for example, resembles a triple s-shaped growth with points of inflection around day 120, day 180, and day 250 (graph 3 in right part of Figure 6). In order to identify the dynamics behind those graphs, the net migration rates and the net conversion rates are calculated within the system dynamics environment of the extended model. The net migration rate of a group *i* is defined as the difference between equation (3') and equation (1'). The net conversion rate of a group *i* is defined as the difference between equation (5') and equation (6'). Each rate, the net migration rate as well as the net conversion rate, is positive whenever it, by itself, increases the adopter fraction of the respective group. Since migration and conversion take place continuously and simultaneously, the sum of both rates constitutes the daily net change of the adopter fraction within a group *i*. In contrast to the net migration rate *of* a group *i*, the net migration rate *between* a group *i* and a group *j* describes only this part of the daily net change of the adopter fraction in group *i* which results from the migration relation with one specific group *j*. The left part of Figure 7 depicts the net migration rate *of* all five groups when the migration rate is 10.4 percent and when group 1 constitutes the mother group. The right part of Figure 7 illustrates the respective net conversion rate *of* all five groups.

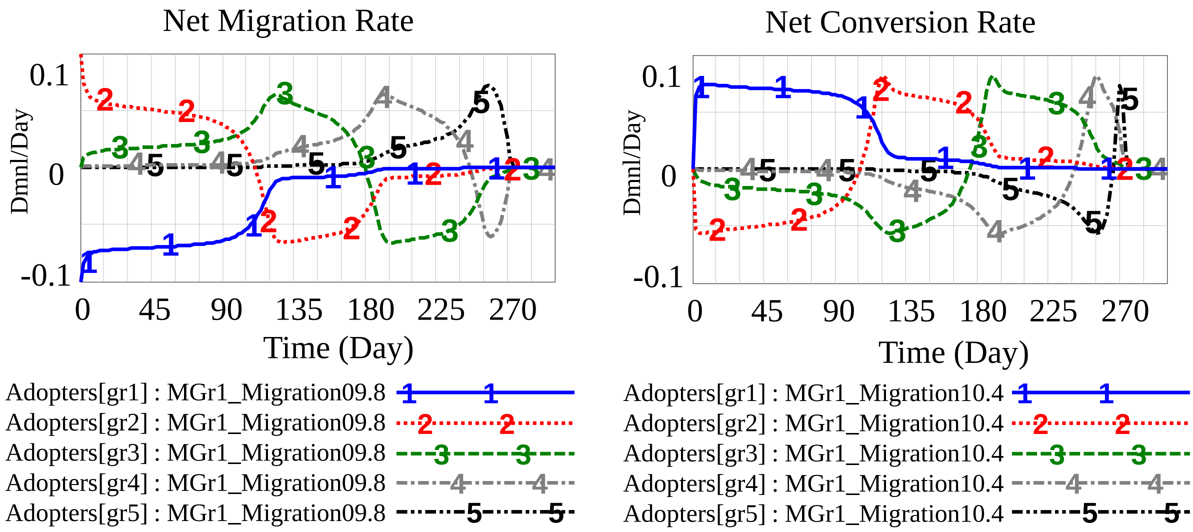


Figure 7: Net conversion and net migration rate within the extended model

In the beginning of the simulation, group 1 loses more adopters due to migration (graph 1 in left part of Figure 7) than it gains through conversion (graph 1 in right part of Figure 7) which explains the initial drop of the adopter fraction within group 1 (graph 1 in right part of Figure 6). From the perspective of group 1, the net migration rate between group 1 and group 2 is negative because the adopter fraction in group 1 is higher than in group 2. But when the adopter fraction in group 2 increases (graph 2 in right part of Figure 6), the proportion of adopters migrating from group 2 into group 1 also grows, thereby increasing the net migration rate of group 1 (graph 1 in left part of Figure 7). As a result, the adopter fraction of group 1 is steadily increasing after the initial drop, till it finally reaches 100 percent again.

Group 2, on the other hand, has a positive net migration rate, due to the immigrating adopters from group 1 (graph 2 in left part of Figure 7). Most of those adopters get converted by the dominating non-adopters resulting in a negative net conversion rate (graph 2 in right part of Figure 7). Since not all of the daily immigrating adopters get converted, the adopter fraction of group 2 still slowly increases (graph 2 in right part of Figure 6). This positive influence of the migration relation with group 1 slowly decreases the negative influence of the conversion process by increasing the net conversion rate of group 2 until it becomes positive around day 105. At this point, the adopter fraction in group 2 reaches a critical threshold of about 42 percent. From then on, the conversion process supports the positive influence of the migration relation with group 1 resulting in a sharp increase in the adopter fraction of group 2 until day 115. The threshold of about 42 percent depends on the relation of the two search intensities. For example, if the search intensity of adopters is assumed to equal to the search intensity of non-adopters, the threshold would be 50 percent.

This self-reinforcing feedback loop between the adopter fraction and the net conversion rate of group 2 is partially inhibited by the net migration rate between group 2 and group 3. From the perspective of group 2, the net migration rate between group 2 and group 3 is negative during that period because the adopter fraction in the connected group 3 is still smaller than in group 2. Despite the negative migration relation with group 3, the overall net migration rate of group 2 (graph 2 in left part of Figure 7) is still positive, due to the positive net migration rate between group 2 and group 1. However, this positive effect becomes much weaker when the gap between the adopter fractions of group 1 and group 2 decreases. The negative influence of the migration relation with group 3, on the other hand, grows stronger because the increasing adopter fraction in group 2 widens the gap between the adopter fraction in group 2 and the adopter fraction in group 3. From day 115 on, this negative effect dominates the self-reinforcing conversion process within group 2 and the positive effect of the migration relation with group 1. Consequently, the net migration rate of group 2 becomes negative (graph 2 in left part of Figure 7), thereby causing the daily net change of the adopter fraction in group 2 to decrease (decreasing slope of graph 2 in right part of Figure 6). The negative influence of the migration relation with group 3 leads to constant drain of adopters which keeps the adopter fraction of group 2 at a level of around 90 percent (graph 2 in right part of Figure 6). Only when the adopter fraction in group 3 closes the gap to group 2, does the net migration rate of group 2 increase (graph 2 in left part of Figure 7), leading to a complete diffusion of the innovation also within group 2.

From the perspective of group 3, the net migration rate between group 3 and group 2 is positive due to the higher adopter fraction in group 2 (graph 3 and graph 2 in right part of Figure 6). With an increasing adopter fraction in group 2, a growing proportion of adopters migrate from group 2 into group 3, day after day. Since the non-adopters still dominate group 3, the conversion process has a negative effect on those adopters converting almost all of them in the beginning of the simulation (graph 3 in right part of Figure 7). However, when the adopter fraction in group 2 grows exponentially, the net migration rate of group 3 also increases, thereby outweighing the decrease of the net conversion rate (graph 3 in left and right part of Figure 7). From day 120 on, the daily inflow of adopters from group 2 remains more or less constant because the adopter fraction of group 2 stalls at around 90 percent (graph 2 in right part of Figure 6). Nevertheless, the adopter fraction of group 3 keeps increasing, albeit with slower speed, because not all of the daily immigrating adopters are converted by the dominating non-adopters (graph 3 in right part of Figure 6). The increasing adopter fraction of group 3, in turn, has a positive effect on the net conversion rate which increases until it becomes positive around day 170 (graph 3 in right part of Figure 7). From then on, the conversion process supports the positive effect of the migration relation with group 2. However, from the perspective of group 3, the net migration rate between group 3 and group 4 is negative. The constant migration of adopters from group 3 to group 4 cannot be compensated by the conversion process and the positive migration relation with group 2. Hence, the adopter fraction of group 3 levels off at around 90 percent (graph 3 in right part of Figure 6). Only when the adopter fraction of group 4 increases and thereby decreases the negative influence of the migration relation with group 4, becomes the innovation fully adopted within group 3.

With regard to group 4 and group 5 (graph 4 and graph 5 in Figure 6 and Figure 7), basically the same dynamics as in group 3 are responsible for the complete diffusion of the innovation within these groups. However, they put up less resistance than previous groups because there are fewer non-adopter groups later in the chain which support them. This means that a fraction of the immigrating adopters can be passed on to fewer other non-adopter groups via migration. Thus, the immigrating adopters are split over fewer non-adopters groups which participate in converting them. Therefore, a smaller fraction of immigrating adopters is converted which makes it easier for adopters to gain a foothold in the non-adopter dominated groups and speed up the diffusion process.

4. Discussion and conclusions

This paper analyzes the diffusion of innovations within intra-organizational networks. Thereby, the focus is on system dynamics as the analytical method. In order to illustrate the benefits of system dynamics when analyzing the diffusion of innovations through networks, Krackhardt's (1997) purely algebraic diffusion model is replicated and analyzed in a system dynamics environment. Krackhardt's (1997) diffusion model is chosen because it does not solely focus on positive word-of-mouth effects but also considers negative word-of-mouth effects. However, it assumes that migration and conversion take place consecutively. Thus, after contrasting Krackhardt's (1997) purely algebraic model with its system dynamics replication, the latter is extended by relaxing the restrictive assumption that migration and conversion occur consecutively. Instead, the temporal dimension of system dynamics is used to transform migration and conversion into processes which take place continuously and simultaneously. In contrast to Krackhardt's (1997) work, the analysis of the extended system dynamics model does not only examine how variations of the input influence the output of the model. Over and above, the focus is on revealing and describing the inherent dynamics which actually define the output. The input of the model is altered and its effect on the output is analyzed in order to make those dynamics more transparent.

Transforming Krackhardt's (1997) purely algebraic model into a system dynamics model is beneficial for several reasons. Firstly, Krackhardt (1997) models groups of organizational members that consist of adopters and non-adopters. Within the adopter or non-adopter camp of a group, organizational members are assumed to be homogeneous and well mixed. This coincides with system dynamics which also assumes that individuals are homogeneous and well mixed within each stock and which also operates on an aggregate level rather than on an individual level as for example agent-based modeling does (Rahmandad and Sterman, 2008, p 998). The aggregated character of system dynamics facilitates the linking of model behavior to its structure and even permits the extension of the model while keeping its complexity manageable (Rahmandad and Sterman, 2008, p. 999). Secondly, the communication between and within groups—in the form of migration and conversion—causes complex dynamics and numerous feedback processes. In contrast to purely algebraic models, system dynamics models promote the simulation of feedback processes by allowing a stock to be an output variable as well as an independent variable. This is possible because system dynamics operates along a temporal dimension consisting of equally large and definable time steps. Therefore, the calculation of the adopter fraction of a group *i* at several points in time is much less laborious than in a purely algebraic model. A third benefit of using system dynamics for analyzing intra-organizational diffusion processes is the graphical depiction of the model which contributes to a better understanding of the underlying network structure and the dynamics caused by it. This is achieved by distinguishing between stock variables, flow variables, information variables, and parameters, by giving them meaningful names, and by indicating the causal relations between them. Consequently, the dynamics between and within groups become more obvious, making it easier to grasp and comprehend the complex diffusion process.

Among others, those three points speak for the transformation of Krackhardt's (1997) algebraic diffusion model into a system dynamics model. The analysis in section 2 shows that the replication of Krackhardt's (1997) model in system dynamics is capable of producing the exact same results. In addition, the characteristics of system dynamics allow the model to be extended so that migration and conversion can take place continuously and simultaneously. In section 3, the analysis of the extended system dynamics model finds that the dynamics caused by the interplay between migration and conversion follow a certain pattern for all initial non-adopter groups. It is shown that the net migration rate of a non-adopter group *i* must be high enough so that not all immigrating adopters get converted immediately. If that is ensured, the adopter fraction of group *i* slowly increases until it reaches a threshold of about 42 percent, which depends on the relation of the two search intensities and is the same for all groups independent of their position in the network. At this point the negative influence of the conversion process becomes positive, supporting the adopter camp from then on. However, at one point the increasing adopter fraction negates the formerly positive influence of the migration process because the percentage of adopters leaving group *i* outweighs the fraction of immigrating adopters, resulting in a negative net migration rate. Only after the adopter fractions in the connected groups increase, the net migration rate of group *i* also increases, thereby elevating the adopter fraction of group *i* to 100 percent. Thus, the migration processes between groups are balancing feedback loops which would distribute the initial adopters evenly across all groups if conversion was turned off. On the other hand, the conversion process within each group is a self-reinforcing feedback loop. In case the adopter fraction of a group *i* is below the threshold of 42 percent, the conversion process would eliminate all adopters within that group if migration was not taking place. However, in case the adopter fraction exceeds this threshold, the conversion process would lead to an adopter fraction of 100 percent if migration was turned off.

Another finding of the extended system dynamics model is that the diffusion speed within a group *i* increases with the number of other groups being already dominated by adopters and decreases with the number of other groups still being dominated by non-adopters. Thus, the innovation diffuses much quicker in group 5 than in group 2 if group 1 is the mother group. This is the case because the balancing character of the migration process distributes the adopters of a group *i* over the neighboring groups and their neighbors. The more the neighboring groups and their neighbors are dominated by adopters, the higher the net migration rate of group *i* and the quicker the innovation diffuses within this group. On the other hand, the more neighboring groups and their neighbors are dominated by non-adopters, the lower the net migration rate of group *i* and the slower the innovation diffuses within it. This finding also suggests, that adopter-dominated groups should be connected to each other while non-adopter-dominated groups should be isolated from each other in order to increase the probability and speed of a successful diffusion process. Consequently, adopter groups support each other by having a higher net migration rate than if they were surrounded by non-adopter groups. This, in turn, increases the likelihood that the adopter fraction stays above the threshold of 42 percent, thereby ensuring that the self-reinforcing conversion process keeps working in favor of the adopter camp. Isolating non-adopter groups from each other, increases their net migration rate. This is the case because the ties with adopter groups become more influential. Thus, it is more likely that the negative influence of the conversion process of such a non-adopter group is inverted by increasing the adopter fraction above the threshold of 42 percent. When this happens, the conversion process starts working for the adopter camp.

The findings of this research have also been tested for very small time steps, finding no major changes in the dynamic behavior of the model. It could be argued that physical migration is not the only form of communication between groups. However, the concept of migration can be interpreted in a way which also includes other forms of group-spanning communication such as making a telephone call or using an instant messenger service. For this purpose, the migration rate between a group i and a group j ($=m_{ij}$) is interpreted as the fraction of adopters or non-adopters of group i which initiates interactions with group j during one day. Vice versa, the migration rate between group j and group i ($=m_{ji}$) represents the daily fraction of adopters or non-adopters of group j which initiates interactions with group i. Thus, even though members of a group i do not need to physically migrate to bridge the distance to a group j, they become part of group j as soon as they start communicating with it. An important aspect about this interpretation is that m_{ji} also contains members of group i that have only temporarily been part of group j—for example for the duration of a telephone call—but then terminate their interaction with group j and thereby become members of group i again. It is assumed that members who initiate the interaction are the ones who *migrate* to the contacted group while members who accept the communication request—for example by picking up the phone—stay in their group. Once members established a connection to another group, they engage in conversations which might change their attitude towards the innovation with probability $P_{NA} \cdot A_i^{S_N}$ in case they are non-adopters—see equation (5')—or with probability $P_{AN} \cdot (1 - A_i)^{S_A}$ in case they are adopters. Thus, members who have previously been adopters of group i, might *return* as non-adopters after communicating with group j. This interpretation of the migration process is possible because the continuous occurrence of migration and conversion processes allows organizational members to leave and return to group i within very short time intervals. Therefore, the proposed system dynamics model is applicable in a multitude of cases potentially providing insights into the dynamics of a variety of organizational communication networks.

In addition, it should be considered that this research focuses solely on a five-membered chain structure. Even though the presented findings might also hold for other network structures, additional research is required to examine to which extent this is the case. Thus, future research in this area could consider other network structures than the proposed one. In addition, further insights can be generated by relaxing the assumption that all groups are homogeneous and that the ties between groups are equally strong.

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