DiffuNET: The impact of network structure on diffusion of innovation

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Abstract

Purpose – To provide an explicit model to address the relationships between the structural characteristics of a network and the diffusion of innovations through it. Further, based on the above relationships, this research tries to provide a way to infer diffusion curve parameters (innovation coefficient and imitation coefficient) from network structure (e.g. centralization).

Design/methodology/approach – Based on the network and innovation literatures, we develop a model explicitly relating the structural properties of the network to its innovation and imitation potential, and in turn to the observed diffusion parameters (innovation and imitation coefficients). We first employ current theoretical and empirical results to develop postulates linking six key network properties to innovation and imitation outcomes, and then seek to model their effects in an integrative manner. We argue that the innovation and imitation potentials of a network may be increased by strategically re-designing the underlying network structure. We validated the model by searching the published empirical literature for available published data on network properties and innovation and imitation coefficients.

Findings – We validated the model by searching the published empirical literature for available published data on network properties and innovation and imitation coefficients. The results reported from various relevant research papers support our model.

Practical implications – This research shows that the innovation and imitation potentials of a network may be increased by strategically re-designing the underlying network structure; hence, provide guidelines for new product managers to enhance the performance of innovative products by re-design the underlying network structure.

Originality/value – The model developed in this paper is a breaking through result of synthesizing various traditions of diffusion research, ranging from anthropology and economics to marketing which were developed independently. The research explicitly modeled the diffusion process in terms of the underlying network structure of the relevant population allowing managers and researchers to directly link the diffusion parameters to the structural properties of the network. By doing so, it added value by making it possible to infer diffusion potential from directly measurable network properties. Vis-à-vis the network diffusion literature in particular, we added value by “unpacking” the diffusion process.

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process into innovation and imitation processes that form the building blocks of contagion. Moreover, we developed a holistic structural model of network diffusion which integrates the several network properties that have hitherto been studied separately.

**Keywords** Product management, Modelling, Innovation, Forecasting, Marketing

**Paper type** Research paper

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**Introduction**

As remarked by Rogers (2004a), there is an understandably natural interest by marketing researchers and professionals in the diffusion of product innovation because diffusion is essentially the marketing of new products. The interest by the marketing field in new product diffusion began around 1960 and peaked in the 1980s followed by gradual level off after then. Spurred by the current global context of rapid technological change and continuous innovation, researchers in several marketing-related fields have shown renewed interest in modeling the diffusion of innovations – e.g. Ganesh *et al.* (1997) and Mahajan *et al.* (1990) in new product marketing; Rogers (2003) and Valente and Rogers (1995) in communications research; Singhal and Rogers (2003) and Wolfeiler (1998) in health management; and Kelley and Brooks (1991) and Bretschneider and Bozeman (1986) in technology management. Such a trend is especially obvious when networking of the society is greatly influenced by the use of internet (Rogers, 2004a; Fenech and O’Cass, 2001). Within the various traditions of diffusion research, ranging from anthropology and economics to marketing, the main focus has been on tracing the spread of an innovation through a system in time and/or space (Rogers, 2003). It is acknowledged in the literature that diffusion is the process by which an innovation is communicated through certain channels over time among members of a social system (Rogers, 2004a), diffusion of innovation within a social group is fundamentally a process of social communication (Mahajan *et al.*, 1990), the patterns of which are inextricably linked to the social structure of the group (Burt, 1987). However, the link between social structure and diffusion parameters remains largely unexplored, in the sense that most current diffusion models simply have an unexpanded “parameter” that acknowledges the impact of word-of-mouth communication (Iacobucci, 1996; Midgley *et al.*, 1992). Against this background, we propose that explicitly modeling the diffusion process in terms of the underlying network structure of the relevant population will allow us to directly link the diffusion parameters to the structural properties of the network.

Drawing on the rich diffusion literature in structural sociology and related disciplines (Rogers, 2004b; Burt, 1987; Rogers and Kincaid, 1981), we address the following research question: What are the relationships between the structural characteristics of a network and the diffusion of innovations through it? Further, given the above relationships, how can we infer diffusion curve parameters (innovation coefficient and imitation coefficient) from network structure (e.g. centralization)?

There are three key areas in which we seek to contribute to the marketing literature on diffusion and networks. Vis-a-vis the diffusion literature in general, we seek to add value by making it possible to infer diffusion potential from directly measurable network properties. Vis-a-vis the network diffusion literature in particular, we first seek to add value by “unpacking” the diffusion process into innovation and imitation processes that form the building blocks of contagion. Next, we seek to develop a holistic structural model of network diffusion which integrates the several network
properties that have hitherto been studied separately. Consistent with these three goals, we make the following arguments:

- We posit that individual actors in a social network are each associated with an innovation potential and an imitation potential (i.e. each individual has a potential for innovative and imitative behaviors, which needs to be realized through marketing action), and that these constructs are fundamentally related to the network structure. We also argue that the innovation and imitation potentials of the individuals belonging to a network regulate the diffusion of an innovation through it.

- We posit that each network has associated with it an innovation potential as well as an imitation potential.

- Since the network is composed of individuals who are connected to one another, the network-level innovation and imitation potentials reflect an aggregation of individual potentials.

- Drawing on existing network literature to motivate the postulates, we model the respective relationships between innovation and imitation potentials and the relevant network properties.

- We derive the relationship between the innovation and imitation potentials of the network and the innovation and imitation coefficients of the standard diffusion model (Bass, 1969), respectively.

- In essence, we conceive of the estimated innovation and imitation coefficients of a standard diffusion model as realized innovation and imitation potentials. The argument is that traditional marketing action (e.g. pricing, advertising, etc.) plays a critical role in realizing the innovation and imitation potential. Such traditional marketing action determines how much of the potential is actually “converted”; however, the potential itself may be increased by modifying the network structure. Thus, our formulation focuses attention on a different set of marketing objectives that are aimed at “re-engineering” the network in order to increase innovation and imitation potentials.

The rest of the paper begins with a brief review of the relevant literature, and then goes on to develop the model as outlined above. (Figure 1 provides an overview of the conceptual model.) We conclude with some directional analyses of the model and a discussion of implications for research and practice (Figure 1).

Network models of the diffusion of innovation

Networks have always been implied, often without elaboration, in the diffusion literature: the diffusion of innovations through a social system has usually been studied as a process of communication flow between connected partners (Rogers, 2003; Iacobucci, 1996). Diffusion researchers employing the network perspective have sought to explicate the actual structure of relationships that shape and constrain the communication, thus throwing further light on the diffusion process. The core idea in the network tradition is that social structure influences the spread of new ideas and practices by shaping patterns of interaction within the network – e.g. who talks to whom (Burt, 1987). Since adopting an innovation is risky – in terms of deviating from conventional norms of behavior – actors (individuals, firms, or other units of analysis)
tend to “model” their behavior on that of other actors. The fundamental intuition of the network theory of diffusion is that structural patterns determine whom a given actor will choose as a “model”.

While networks are composed of relationships between a set of actors, there are two broad approaches to the study of how relationships influence diffusion: relational and structural models of diffusion (Valente, 1995). Relational models consider the focal actor’s adoption or non-adoption in light of the behavior of those to whom the former is directly connected. Thus, for a given actor, direct contact with an influential “opinion leader” might be seen as impelling adoption. Structural models, in contrast, consider all relations in the network, rather than only the direct ties that a given actor may have. Founded on the key assumptions of structural sociology and network analysis (Wellman, 1988), structural network models acknowledge that the overall structure of the network, as well as a given actor’s position in it, influence that actor’s behavior and subsequent performance. For example, a given actor may adopt an innovation because of its prior adoption by a highly central and visible actor, even though the two actors may have no direct contact with each other. In modeling the effect of the overall network structure on diffusion, we adhere to the structural model.

The history of network models of diffusion may be traced (Valente, 1995) from opinion leadership formulations (Coleman et al., 1966), to the strength of weak ties formulation (Granovetter, 1973), to the communication network formulation (Rogers and Kincaid, 1981) and finally to the structural equivalence formulation (Burt, 1987). Network analysts refer to the specific process of innovation diffusion as contagion; thus, the chief concern of network models of diffusion is the variety of network mechanisms through which contagion operates (Burt, 1987). In developing our
postulates and mathematical model, we draw upon and expand the core ideas in this literature. The following key conclusions of the existing network research on the diffusion of innovations serve as background to our model development. These nine conclusions have been clustered into actor-level and network-level groups, depending on the relevant unit of analysis.

Actor-level (with primary reference to the position of individual actor in the network).

- Innovativeness is positively associated with the actor’s prominence in the network (a crude measure of which is the number of an actor’s contacts), which may be viewed as indicative of opinion leadership (Rogers, 2003) or, in a related manner, as a measure of how well integrated the actor is (Coleman et al., 1966).
- Highly central players are more likely to be early adopters of advantageous innovations, while peripheral players are more likely to adopt riskier innovations (Rogers, 2003; Becker, 1970; Burkhardt and Brass, 1990; Madhavan et al., 1998). Potential adopters who are highly central tend to have higher reputations that they are less willing to risk by adopting unproven or contra-normative innovations; peripheral players have less at stake and may be more willing to take such risks (Rogers, 2003; Abrahamson and Rosenkopf, 1997).
- Isolates, i.e. actors who are not connected to anybody else, tend to show considerably later adoption times (Rogers and Kincaid, 1981).
- Weak ties, i.e. actors that serve as bridges between unconnected groups, are important links in the diffusion process (Granovetter, 1973; Burt, 1992).
- Innovativeness is positively associated with structural centrality, i.e. how significant a position the actor has in the network. For example, betweenness centrality measures the degree to which an actor lies between other actors (corresponding to potential control), while closeness centrality measures the degree to which an actor is close to others (corresponding to potential access). Actors who are highly central in these respects are more likely to receive innovation-related information and influence early, and hence more likely to adopt early (Burkhardt and Brass, 1990).

Network-level (with primary reference to overall patterns of relationships).

- Highly centralized networks (with a small number of highly central actors) should demonstrate a higher rate of diffusion; once adopted by the central actors, the innovation will spread rapidly through the network (Valente, 1995).
- Diffusion will be more rapid in networks that are densely interconnected (Black, 1966).
- Contagion operates through cohesive ties, i.e. through strong connections with close contacts (Coleman et al., 1966).
- An alternative hypothesis to contagion through cohesion is that it operates through structural equivalence, i.e. actors may take their cues from others that they consider to be similar to themselves, even in the absence of direct ties between them (Burt, 1987).
Against the background provided by the current network literature on the diffusion of innovation, we develop postulates and a mathematical model relating structural properties and the innovation and imitation coefficients.

**The relationship between diffusion parameters and network structure variables**

Consistent with the diffusion literature, we model the diffusion process in terms of the innovation and imitation potential of the individual and the network. The structural properties proposed to influence innovation potential are centrality, constraint, and range. The structural properties proposed to influence imitation potential are centralization, density, and embeddedness. Based on the extensive theoretical and empirical support available in the research literature, we take as axiomatic the individual effects of these network properties on innovation and imitation potential[1]. In other words, our goal in this paper is not to develop further theoretical or empirical arguments in support of each causal link, but rather to develop a parsimonious mathematical model that integrates their effects holistically.

**Network structure and innovation potential**

Centrality is a key property of the individual actor within a network, and is a structural measure of the importance of a given player in its network (Freeman, 1979). In general, an actor is highly central in its network if it has a large number of connections with other actors, or if it occupies a position of strategic significance in the overall structure of the network (Scott, 1991). Centrality derives from being the object of relations from other actors, implying that the central actor is “in demand” as a relationship partner (Burt, 1991). Drawing on the logic of resource dependency (Pfeffer and Salancik, 1978), i.e. that organizational interaction arises because organizations seek access to critical resources, it may be argued that centrality indicates the extent of potential resources available to an actor. Thus, an actor who is “in demand” as a partner has access to a large stock of resources through its various contacts.

Extensive theoretical and empirical support is available for the argument that the highly central actor is in a good position to innovate. There are three causal mechanisms underlying this argument. First, there is a resource-based argument: if centrality is taken as a proxy for the quantity of critical resources available to an actor (Galaskiewicz, 1979), it may be argued that highly central actors are more likely to have “slack” resources which foster experimentation (Nohria and Gulati, 1996) and facilitates innovation (Rogers, 2003). Second, there is an information-based argument: Innovation is more likely to take place in a rich and complex information environment, as individuals and firms are exposed to a wide variety of cues that stimulate innovation – e.g. lead users (von Hippel, 1988) or sophisticated suppliers (Porter, 1990). A highly central actor is at the confluence of a large number of information sources (each contact can be viewed as one), and is thus well positioned to innovate. Further, the highly central actor is more likely to receive innovation-related information and influence earlier than less central actors in the same network (Rogers, 2003). Third, there is a status-based argument: the highly central player is unlikely to imitate widespread practices that are already in use by the “followers”. Rather, the former will either innovate or imitate other highly central peers. (Imitating a small number of high-visibility elites should be tantamount to innovation.) Especially where the
innovation has social prestige attached to its adoption, late adoption may reduce the social value of the innovation (Rogers, 2003). This might work in the opposite direction as well, in the sense that an imitator may not be sought out by others as much as an innovator would be. This argument is consistent with the postulate that early adopters must continue to make judicious innovation decisions in order to maintain a central position in the communication structure (Rogers, 2003). Extensive empirical support is available for the argument that centrality is positively related to innovation potential. Rogers and Kincaid (1981, p. 228) report on several early studies which show that connectedness – a concept “very similar, if not identical” to centrality (Rogers and Kincaid, 1981, p. 178n) – is positively related to innovativeness. Valente’s (1995, p. 54) re-analysis of three separate data sets showed that structural centrality is associated with innovativeness. Ibarra (1993, p. 492) found that network centrality is a strong determinant of individual involvement in administrative innovation. Based on evidence illustrated by the above-mentioned studies, and combining the resource-based, information-based and status-based arguments, thus, the first postulate is that

**P1.** The network centrality of an individual node will be positively related to its innovation potential.

Constraint, drawn from Burt (1983b) recent work on structural holes, is another key structural property of the individual actor. The constraint image may be summarized as follows (Krackhardt, 1995): Assume that A has a relationship with B and C. A is in a better position to profit from the relationships if B and C are not connected to each other. When B and C are connected only through A, a structural hole exists between them, which can be exploited by A. A’s advantage is built upon three factors. First, A obtains information separately and with minimum redundancy from both B and C. Second, A has the opportunity to control B and C by “playing them off against each other”. Finally, A can simply arbitrage resources between B and C – e.g. buying from B and selling to C at a premium. All of this is possible only if A has exclusive relations with B and C, and the latter have no substitute for A – i.e. there is a structural hole between B and C. On the other hand, if B and C are connected to each other in some other way as well – either directly or through another actor – A’s advantage begins to disappear. The absence of a structural hole between B and C poses a constraint on A. It has been empirically demonstrated that constraint is negatively related to performance in a variety of contexts, such as industry returns and managerial career progress (Burt, 1992).

Building on the above, we argue that constraint will have a negative influence on an actor’s propensity to innovate. If an actor has a network rich in structural holes, its contacts are unconnected with each other. This makes the network both efficient and effective in information terms, as it ensures that redundancy in information sources is eliminated (Burt, 1992). Thus, for the same level of network activity, the actor whose network is rich in structural holes will gain more varied information. In contrast, the actor whose network is poor in structural holes is at a disadvantage, since its partners – being connected to each other – will “recycle” redundant information to it. Since innovation and new knowledge arises at the interfaces of existing knowledge domains (Simon, 1985; Granovetter, 1973) and are accentuated in a rich and complex information environment, it may be argued that a network rich in structural holes will
spur innovation. In contrast, the absence of structural holes, termed constraint, should be a negative influence on the actor’s propensity to innovate. From an empirical standpoint, the constraint argument — although a recent theoretical development — has garnered extensive support. Burt (1998) has demonstrated constraint effects across five study populations. The beneficial effects of structural holes have been found to influence outcomes ranging from industry profits (Burt, 1992), career progress (Podolny and Baron, 1997), annual bonus (Burt, 1997), and finding better jobs (Granovetter, 1974). Ahuja (1998, p. 27) has specifically demonstrated that networks rich in structural holes are associated with higher innovative output. Thus, the second postulate is that

\[P2.\] The network constraint of an individual node will be negatively related to its innovation potential.

Network range is the third structural property of the individual actor that is proposed to influence innovation. Network range is defined as the extent to which an actor’s ties link it with diverse others (Burt, 1983a). For example, if an individual’s friendship network is limited to others that belong only to one ethnic or social group, that individual has low network range. On the other hand, a friendship network comprising others of a wide variety of ethnic and social groups has high network range. Network range implies that the actor is connected to partners that are dissimilar from itself and each other. The actor with a higher network range will therefore have access to more diverse resources. In addition, this will mean that the actor has an efficient-effective network, in that the resources it has access to are not duplicated or redundant (Burt, 1992). Rogers and Kincaid (1981, p. 244) develop Epstein’s (1961) finding that networks characterized by greater heterophily and diversity are informationally rich. Burt (1983b, p. 169) found that large firms, with the highest network range, also tended to have multiplex directorate ties and access to the influence of diverse economic sectors on their boards. Madhavan’ (1996) data from the steel industry showed that range was positively associated with flexibility. Building on these empirical findings and on the insights of the psychological literature on creativity referred to above, it may then be argued that the higher the network range, the higher ought to be the innovation potential. Thus, the third postulate is that

\[P3.\] The network range of an individual node will be positively related to its innovation potential.

**Network structure and imitation potential**

Imitation is a social phenomenon that takes place within the context of a social network to which both imitators and the “imitatee” belong. Thus, consistent with the basic argument of this research, it may be proposed that network structure influences imitation patterns.

Network density is the first network property of interest, and refers to the proportion of links present relative to those possible (Marsden, 1990). A dense network is characterized by a large number of links being present among the actors. For example, a network in which actors have direct relations with most other actors is a high-density network. In contrast, if actors have a limited number of direct relations, we have a low-density network.
Our model suggests that network density will be positively related to the imitation potential. There are three main arguments for the proposed effect of network density on imitation. First, there is a communication argument: high network density indicates high levels of communication in the network, increasing the likelihood that actors will be exposed to news and influence about the innovation sooner rather than later. Second, there is the information argument: since densely connected actors are likely to have access to the same information (Granovetter, 1973), the scope for “information variation” and subsequent innovation will be limited. Thus, imitation, rather than innovation, will become the dominant mode. Third, there is the socialization argument: high density networks function as “cliques” creating strong behavioral pressures to conform – leading to imitation – rather than to adopt new practices – which would lead to innovation (Kraatz, 1998).

Research from several different fields supports the above reasoning. In the field of epidemiology, studies have shown that, for diseases with same infectiousness, high density networks are more likely to experience epidemics than lower density networks (Bailey, 1975). Similarly, Krassa (1988) argued that dominant opinions become more widespread quickly in more integrated communities. Valente's (1995, p. 42) re-analysis of three classic data sets showed that network density is indeed associated with faster diffusion. Based on computer simulations, Abrahamson and Rosenkopf (1997, p. 298) argued that “the greater the network density, the greater the number of adopters”. Similar conclusions may be inferred from Morris (1981) and Mizruchi (1992), Strang and Soule (1998, p. 273). Combining the communication, information and socialization arguments, then, it may be proposed that

\[ P4. \] Network density will be positively related to the imitation potential of the network.

Centralization is the next network property proposed to influence imitation, and refers to the variability in centrality scores among actors (Marsden, 1990). A network with a few highly central actors and many actors with low centrality is a highly centralized network; a less centralized network will have a more equitable distribution of centrality scores. Reiterating the resource-based, information-based, and status-based logic behind Postulate 1, highly central actors should be innovators in general, and less central actors should be imitators. If this is the case, a highly centralized network – with relatively few highly central actors – should demonstrate a high imitation potential. Moreover, once the innovation is adopted by the central actors in a centralized network, it diffuses rapidly to the rest of the less central actors, facilitating imitation on their part (Valente, 1995). This postulate builds on the empirical support already reported for centrality. Moreover, Valente’s (1995, p. 54) re-analysis showed that advantageous innovations diffuse more rapidly in highly centralized networks. Thus:

\[ P5. \] Centralization will be positively related to the imitation potential of the network.

Embeddedness is the final structural property of the individual actor proposed to influence imitation. According to Granovetter (1985), embeddedness refers to the fact that economic action and outcomes are affected by actors’ pairwise relations (relational embeddedness) and by the structure of the overall network of relations.
An actor’s level of embeddedness refers to the extent to which its behavior is affected by its relationships with its partner(s). Generally speaking, the stronger the relationship with a partner, the higher is the actor’s commitment to the relationship, and the more likely is the relationship to be a factor in its decisions. Based on finely-detailed ethnographic and quantitative data, Uzzi (1997) has argued that embeddedness increases each party’s commitment to exceed the letter of the contract, and to contribute to the relationship. For example, an individual may be willing to pay a higher “price” – emotionally or otherwise – to sustain a strong friendship than she would to sustain a casual acquaintance. By the same token, embeddedness also facilitated fine-grained information transfer and complex adaptation to environmental changes (Uzzi, 1997). Uzzi’s (1997) data suggest that the width of information search decreases with the number of embedded ties, while the depth of information search increases with the strength of the embedded ties – a claim that has significant implications for the tendency to imitate.

The link between embeddedness and imitation also stems from the fact that strong relationships will be associated with strong behavioral pressures to conform – because of the desire to keep the relationship going by living up to expectations, as well as to avoid jeopardizing it through non-conforming behavior. Embeddedness, as a measure of the actors’ commitment to the network, may thus influence how high the behavioral pressures to conform are. As argued earlier, behavioral pressures to conform should lead to imitation rather than to innovation. Thus, the sixth postulate is that

P6. Embeddedness will be positively related to the imitation potential of the network.

As indicated earlier, the above six postulates are also graphically presented in Figure 1.

Model formulation

Based on the postulates described above, we can now formulate the relationship between the six network structure variables and the two network potential parameters. The two diffusion curve coefficients are then, respectively, derived in terms of the network innovation and imitation potential parameters, INP and IMP.

Individual and network parameters

As indicated earlier, innovation potential and imitation potential may be conceptualized at the level of the individual as well as of the network. While we acknowledge that innovative and imitative actions originate at the individual level, innovation potential and imitation potential at the network level are the key inputs to marketing strategy formulation – e.g. the overall strategy may be different for networks with high innovation potential than for networks with low innovation potential. Thus, the following model employs individual-level innovation and imitation potentials as the basis on which to estimate network-level innovation and imitation potentials (Iacobucci and Hopkins, 1992). Equations (1)-(5b) represent the analytical process by which we

(1) aggregate individual-level innovation and imitation potentials into network-level potentials, and then

(2) relate the network-level potentials to the innovation and imitation coefficients familiar in the innovation literature.
Based on postulates 1 to 3, the innovation potential of an individual \( i \) (\( \text{INP}_i \)) may be expressed as:

\[
\text{INP}_i = \beta_{p0} + \beta_{p1}x_{1i} + \beta_{p2}x_{2i} + \beta_{p3}x_{3i} + \varepsilon_i
\]

(1)

where \( x_{1i} \) is centrality of individual \( i \) in the network, \( x_{2i} \) is constraint of individual \( i \) in the network, \( x_{3i} \) is range of individual \( i \) in the network, \( \beta_{pk} \) is regression coefficients to be estimated, \( \varepsilon_i \) is random error.

Defining the innovation potential of a network as the innovation potential of an individual chosen at random, the innovation potential of the network (\( \text{INP} \)) will be:

\[
\text{INP} = E(\text{INP}_i)
\]

where

\[
E(\text{INP}_i) = \beta_{p0} + \beta_{p1}x_1 + \beta_{p2}x_2 + \beta_{p3}x_3
\]

(2)

While individuals are associated with a potential to innovate due to their structural position, whether or not this potential is actually realized depends on the marketing effort (product, price, promotion, place) applied. The realized innovativeness is indicated in the diffusion of innovation literature by the time at which an individual adopts. We term the realized innovativeness of individuals as their innovation propensities. (In this view, innovators will have higher innovation propensities than those who belong to the early majority. Early majority members will have higher innovation propensities than late majority members, and laggards will have the lowest innovation propensities.) Thus, the time at which individuals adopt an innovation is dependent on their respective innovation propensities. Innovation propensities, by definition, can at most be the respective individual innovation potential. The difference between innovation propensity and innovation potential both at the individual and network levels is accounted for by the marketing effect. Thus, marketing effort combined with the individual network characteristics of centrality, constraint, and range characteristics leads to the realization of a specific innovation propensity by an individual member of a network. The bounded nature of this relationship is consistent with common empirical observation in the marketing literature (Lilien et al., 1992, p. 475). Formally, in general, \( P_i \) is modeled as

\[
P_i = \phi(\text{INP}_i, \text{MKT})
\]

(3a)

where \( P_i \) is individual \( i \)'s innovation propensity, \( \text{INP}_i \) is individual \( i \)'s innovation potential (as previously defined), \( \text{MKT} \) is a summary measure of the marketing effort used.

Following Lilien et al. (1992), we specify the more specific, yet generally applicable model between \( P_i \) and MKT as

\[
P_i = a_i(1 - e^{-b_i \text{MKT}}) + c_i
\]

(3b)
with \( a_i + c_i = \text{INP}_i \) as a constraint \( \text{INP}_i \) is the maximum value that \( P_i \) can attain at maximal marketing effort. 

Earlier, we defined the innovation potential of the network as the innovation potential of an individual chosen at random. We also assumed that under normal conditions, the innovation potential of a network could be estimated as the expected value of the innovation potentials of its members. Therefore, the innovation coefficient of a network may be written as 

\[
\hat{p} = E(P_i) = a(1 - e^{-\nu \text{MKT}}) + c
\]  

(3d)

where

\[
b = E(b_i) \quad \text{and} \quad a + c = E(a_i + c_i) = E(\text{INP}_i) = \text{INP}
\]  

(3e)

From equation (3d), \( b \) may be interpreted as the innovation response elasticity of the network to marketing effort.

Similarly, the relationship between the imitation potential of the network (IMP) and the other three network structural variables (density, centralization, and embeddedness) can be modeled based on postulates 4, 5, and 6. Since these three network structural variables are aggregate network properties, IMP can only be measured/identified at the aggregate level; therefore, the imitation potential of the network is modeled directly at the network level as follows:

\[
\text{IMP} = \beta_{q0} + \beta_{q4}x_4 + \beta_{q5}x_5 + \beta_{q6}x_6 + \sigma
\]  

(4)

where IMP is imitation potential of the network, \( x_4 \) is the density of the network, \( x_5 \) is the centralization of the network, \( x_6 \) is the embeddedness of the network, \( \beta_{qk} \) is the regression coefficients to be estimated, \( \sigma \) is random error.

Again, at the network level, the realized imitativeness depends on the marketing effort deployed and is constrained by the innate imitation potential of the network. As will be recalled, the imitation potential of a network depends on its density, centralization, and embeddedness. Symmetric to the way innovation was modeled, the relationship between imitation propensity (\( q \)) and imitation potential (IMP) is modeled as 

\[
q = s(1 - e^{-\nu \text{MKT}}) + u
\]  

(5a)

where

\[
s + u = \text{IMP}
\]  

(5b)

That is, the imitation coefficient of a network varies exponentially with marketing effort (MKT) and has a maximum value of the innovation potential (INP) of the network. The coefficient \( \nu \) may be interpreted as the imitation response elasticity of the network to marketing effort.

Recall that the relationships between these two network potential variables (INP, IMP) and the six network structure variables \((x_1, x_2, x_3, x_4, x_5, x_6)\) are formulated in equations (2) and (3).
Model analysis

The relationships derived above are useful for both predictive and normative purposes. First, the diffusion curve for an innovation can be predicted given knowledge of the network structure variables. Given a set of current network structure variables, $x_{1o}$, $x_{2o}$, $x_{3o}$, $x_{4o}$, $x_{5o}$, and $x_{6o}$, the innovation potential and imitation potential of the current network, INP$_o$ and IMP$_o$, can be calculated via equations (2) and (4). In turn, the innovation coefficient and imitation coefficient, $p_o$ and $q_o$, can be calculated via equations (3d), (3e), (5a) and (5b) for any level of marketing effort.

On the other hand, if a marketer wants to achieve a certain pattern of diffusion for an innovative product, then the following analysis may be helpful. Two cases are detailed below. Case A deals with situations when the analyst sets targets for the diffusion coefficients directly. Case B deals with situations when the analyst sets targets directly for peak sales and the time to peak sales. The latter is more likely to be found in managerial practice.

**Case A**

Let the target diffusion curve parameters chosen be $p_t$ and $q_t$, respectively. Then the corresponding values of the target network potential variables, INP$_t$ and IMP$_t$, can be calculated using equation sets (3) and (5), respectively for a given planned marketing effort. Using equations (2) and (4), there are infinite sets $(x_1, x_2, \ldots, x_6)$ that lead to INP$_t$ and IMP$_t$ because the system of equations is under-identified. The system can be made to yield a unique solution by imposing additional constraints on it. Since changing a network structure would involve additional costs, cost minimization imposes additional constraints on the system. Let $w_{pk}$ and $w_{qk}$ be the cost of a unit change in the respective network structure variables ($x_k$), then the problem can now be defined as finding the values of the network structure variable that will lead to the target potential variable values with minimum cost of changing the network structure variables. Let $X_p$ be the column vector

$$
\begin{bmatrix}
    x_1 \\
    x_2 \\
    x_3
\end{bmatrix}
$$

and $X_q$ be the column vector

$$
\begin{bmatrix}
    x_4 \\
    x_5 \\
    x_6
\end{bmatrix}
$$

Therefore, the problem can be defined as one of finding $X_{pt}$ and $X_{qt}$ such that the distances between $X_{pt}$ and $X_{po}$, and between $X_{qt}$ and $X_{qo}$ are, respectively, minimized.

The solutions are:

$$
X_{phk} = X_{pho} + \left( (\text{INP}_t - \text{INP}_o)/\beta_p \beta_{ph} \right) \beta_{ph} / w_{pk}^2
$$

(6)
\[ X_{qtk} = X_{qok} + [(\text{IMP}_t - \text{IMP}_o)/\beta_q] \beta_{qk} y_{qk}/w_{qk} \]  \hspace{1cm} (7)

where “·” represents the dot product operation of vectors; “o” represents original/current status; “t” represents target status; “k” = 1, 2, 3, 4, 5, 6.

**Case B**

If target peak sales quantity \((Q_t^*)\) and target peak sales timing \((T_t^*)\) are known and the target innovation coefficient \((p_t)\) and target imitation coefficient \((q_t)\) are not known, then \(p_t\) and \(q_t\) can be obtained by solving the following set of equations (see Lilien *et al.*, 1992, p. 471):

\[ T_t^* = \frac{1}{p_t + q_t} \ln \frac{q_t}{p_t} \]  \hspace{1cm} (8)

\[ Q_t^* = Q_m \frac{(p_t + q_t)^2}{4q_t} \]  \hspace{1cm} (9)

where \(Q_m\) is the estimated market potential.

Then, the values of \(X_p\) and \(X_q\) can be arrived at as in Case A.

**Discussion**

Our goal in this paper has been to develop an analytical framework characterizing the diffusion of innovation through a network as a function of its structural properties. Drawing upon the rich literature on the diffusion of innovation and on networks (Rogers, 2003; Burt, 1987, 1992), we developed a model of the diffusion curve parameters as functions of the six structural properties, centrality, constraint, range, density, centralization, and embeddedness. In this final section, we discuss issues related to the validity of our approach, and sketch its contributions and implications.

**Validity issues**

Given that our goal in this paper was to develop a mathematical model of the relationship between network structure and innovation and imitation coefficients, a full-fledged empirical demonstration of the model is a task we leave to future research. However, in the hope of providing a test of “face validity”, we provide below a proxy-based argument that builds on the well-accepted dimensions of culture (Hofstede, 1980). The ideal way to establish the validity of the model would be to have data on network properties and on innovation and imitation coefficients for different networks, so that the proposed relationship between network properties and the innovation and imitation coefficients may be tested. In the absence of such data, however, our goal here is only to show that the model is conceptually sound, and that further data collection and testing are worthwhile – the actual collection of primary data and its testing are beyond the scope of this paper.

We began the process by searching the published empirical literature for available published data on network properties and innovation and imitation coefficients. Given the amount of research in marketing on innovation diffusion, it was not difficult to find studies that have compared \(p\) and \(q\) across different societies. Two of the best examples of such studies were Takada and Jain (1991) and Helsen *et al.* (1993) – e.g. the latter reported \(p\) and \(q\) for Color TV sets across Europe, Japan, and the US. However, we were
unable to locate any usable study that compared all the network properties of interest across different national societies. While there were a number of studies that examine different network properties in different networks – e.g. the density of interpersonal networks in Japan or the US – we could find very few studies that compare the network properties of interest across the countries for which we had \( p \) and \( q \) data. The only usable study was the one by Money et al. (1998), which compared word-of-mouth networks in Japan and the United States.

According to data reported by Money et al. (1998), Japanese firms in Japan demonstrated an average tie strength of 7.1, while American firms in the United States demonstrated an average tie strength of 4.5. Viewing the strength of ties as an indicator of embeddedness, we interpret this to mean that Japanese firms are more embedded in their networks than American firms – an assertion that is at least tangentially supported by the extensive literature on Japanese business networks (Gerlach, 1992). Since this was the only suitable data available, we decided to focus the validation attempt on the embeddedness postulate.

To strengthen our argument, we decided to identify a suitable proxy that could be as an additional indicator of embeddedness. The best candidate for such a proxy, both conceptually and empirically, appeared to be Hofstede’s (1980) dimensions of cultural values. Based on data from over 116,000 employees of a single company – thus controlling for company culture – Hofstede’s four dimensions of cultural values are generally accepted as explaining differences among national cultures. As network structures are inextricably linked to the culture of the society, we propose that Hofstede’s dimensions of cultural values can be used as a proxy for network properties for the purposes of this analysis.

In his research, Hofstede (1980) proposed four dimensions of cultural values: individualism/collectivism, power distance, uncertainty avoidance, and masculinity/femininity. However, we focus on two of these dimensions as being directly relevant to network properties: individualism/collectivism, and uncertainty avoidance. In individualistic countries, the dominant concern of most people is for themselves and their families, rather than others. The individual and his/her rights are highly valued. Collectivist cultures, on the other hand, value the overall good of the group very highly. It is expected that individual interests will be subordinated to the needs of the group. In collectivist countries, people look after each other in exchange for loyalty, emphasize belonging, and often make group decisions (Francesco and Gold, 1998). We argue that collectivist nations will have high-density and high-embeddedness networks, and therefore high \( q \). For example, Chinese society is well known for emphasizing interpersonal relationships as a guiding structure for economic and social organization (Bian, 1997). In contrast, networks in more individualistic nations will be characterized by less dense networks and less social embeddedness.

Uncertainty avoidance is related to the preferred amount of structure. Countries with strong uncertainty avoidance will be characterized by greater structure, and explicit rules of behavior. There is usually a greater concern for doing things right, greater risk-aversion, and greater stability in employment relations. Weak uncertainty avoidance, in contrast, is associated with a preference for unstructured situations, greater flexibility of behavioral norms, and a higher incidence of entrepreneurship.
Strong uncertainty avoidance – greater dependence on behavioral modeling – stronger networks – higher density and embeddedness – high $q$.

Juxtaposing our postulates with the data from Money et al. (1998), as well as Hofstede’s (1980) data on cultural dimensions, we would expect to find the following pattern:

**US:** Low tie strength (mean: 4.5); High individualism (score: 91); Low uncertainty avoidance (score: 46) → Less dense and less embedded networks → Low $q$

**Japan:** High tie strength (mean: 7.1); Low individualism (score: 46), High uncertainty avoidance (score: 92) → Denser and more embedded networks → High $q$

Indeed, comparative data from Takada and Jain (1991) and Helsen et al. (1993) appear to support this expectation. According to Takada and Jain (1991), the US $q$ was lower than the Japanese $q$ for six out of seven products. Although Helsen et al. (1993) did not have country-level data, they reported imitation coefficients for two different “segments” with the US and Japan in separate segments. $q$ for the segment containing the US was lower than that of the segment with Japan for two out of two products reported.

The above comparison suggests that embeddedness (and perhaps density) may have a demonstrable impact on imitation coefficient. Given the absence of readily available data, our proxy-based approach addresses only part of our model. Despite these limitations, however, we believe that this analysis serves to strengthen the face validity of our argument.

**Contributions and implications**

The network approach to modeling diffusion espoused here seeks to make several contributions to the theoretical literature on diffusion. As pointed out in our introduction, previous treatments, while acknowledging the role of network communication in diffusion, have dealt with the issue largely by means of an unexpanded parameter (Iacobucci, 1996) that throws no further light on the process of diffusion through networks. By directly modeling the link between network structural properties and diffusion curve parameters, we explicitly incorporate the network process and “unpack” the parameters to demonstrate the effects of network structure on the diffusion of innovation. Further, by investigating the diffusion effects of relatively recent network constructs such as constraint and embeddedness, we add value to current network models of diffusion, represented by the work of authors such as Rogers and Kincaid (1981) and Valente (1995). Finally, this paper bridges the hitherto largely isolated traditions of diffusion networks (Coleman et al., 1966; Rogers and Kincaid, 1981) and the mathematical modeling of diffusion (Bass, 1969). While researchers in these two traditions have acknowledged each other (Iacobucci, 1996), we believe that our paper is an early attempt to directly and comprehensively model the diffusion of innovation in terms of network structure.

**Research directions.** The current conceptual and analytical investigation also points the way toward a promising line of future research. These research implications may be classified into three areas: empirical demonstration, assessment of explanatory potential, and theoretical elaboration. The first important task would be to subject the postulates outlined here and embodied in the model to rigorous empirical testing. Part of such an empirical testing program may be to compare and contrast the predictions and effectiveness of the network model as against models of diffusion. In this context,
it must be noted that the network properties themselves are well-founded in the empirical literature on networks – e.g. centrality (Burkhardt and Brass, 1990), constraint (Burt, 1992; Krackhardt, 1995), range (Burt, 1983a), density (Marsden, 1990), centralization (Madhavan et al. (1998)), and embeddedness (Uzzi, 1997) – and do not pose significant measurement challenges. Second, the explanatory potential of our approach may be assessed, in part, by its utility in explaining diffusion effects in multiple settings. As an example, our approach leads to the postulate that possible differences in diffusion curves among nations – as have been demonstrated by Takada and Jain (1991) – may be explained by differences in social network structure. For instance, it may be proposed that societies such as that of China, known for

(1) its emphasis on interpersonal relationships as a guiding structure in economic and social organization (Bian, 1997); and

(2) dense family and friendship relations, will display higher network densities and hence higher imitation potential.

Empirically validating the resultant set of postulates may pose a fruitful line of future inquiry.

Finally, future empirical and theoretical work could also be helpful in refining and further elaborating the model. For example, empirical investigation of the proposed effects in a variety of network and product settings (e.g. consumer products in a network of individuals and industrial products in a network of organizations) could potentially lead to a contingency model of diffusion in networks. Another key aspect of such elaboration would be to specify how the intrinsic qualities of the innovation interact with network properties in determining the diffusion pattern. Yet another promising avenue of research is to investigate the dynamics of network evolution and how they effect diffusion. For example, while structure clearly influences diffusion, the diffusion process in turn may influence structure, thus leading to a two-way causal relationship between structure and action as modeled in Giddens’ (1984) structuration theory.

**Implications for practice.** Significant managerial benefits stem from the model as well. Most importantly, it would allow the marketing manager to potentially use the network properties as “levers” so as to influence the diffusion process at a fundamental level. By implication (i.e. since they do not explicitly incorporate network structure), current diffusion models appear to assume network structure as given. Such a treatment is consistent with our formulation, in which marketing action moderates the relationship between the innovation and imitation potentials (INP and IMP) and the realized innovation and imitation coefficients (p and q). However, our model adds the insight that traditional marketing action, while determining the efficiency with which the potential is realized, cannot fundamentally increase the innovation and imitation potential – p and q will always be bounded by INP and IMP, respectively. The only way to increase INP and IMP is to change the network structure itself. Consider an example: Ciba-Geigy’s Agricultural Division had invested $12.5 million in the development of a new herbicide, Dual (HBS case #9-582-026, 1982). Faced with the problem of accelerating the product’s rate of adoption, Ciba-Geigy used a communications technology offered by TeleSession of New York City. TeleSession was a marketing service aimed at accelerating the adoption of new products by
bringing together opinion leaders, users, and potential users via teleconferences. What TeleSession effectively did was to help Ciba-Geigy reengineer the structure of the network of potential users so as to speed up the diffusion of Dual. A model explicitly relating network structure properties to diffusion curve parameters, as we propose, would enable managers to determine what modifications to the structure would be most beneficial.

Thus, the key managerial implication is that the network structure should be viewed as being potentially under managerial control. For example, a marketing manager may seek to increase the centrality of her clients by assisting them in forming strategic relationships within the network. Thus, managerial action aimed at changing the underlying network structure becomes a significant new tool to facilitate the diffusion process, as in the Ciba-Geigy example[2]. In this context, our model helps in two specific ways. First, it clearly identifies the network properties that influence the innovation and imitation coefficients, so that managerial action may be appropriately targeted. Second, our model points the way to estimating the cost and return associated with changing network properties. Thus, the marketing manager may take an informed decision as to where scarce resources can be most effectively employed. In a competitive context where many marketers may be trying to re-engineer customer networks, such an ability to fine-tune network re-engineering may be a significant strategic capability.

A further suggestion stemming from the model is a conception of “product-specific” augmented networks that may be different from the basic communication network (Midgley et al., 1992). Taking the basic communication network as a given, a manager may consider how to augment it with product-specific communication links so as to influence the diffusion of the innovation. In such a case, the diffusion model parameters would be determined not by the structural properties of the basic communication network, but by those of the augmented network. By highlighting the differential impact of the properties of basic and augmented networks, our model can help provide a more sophisticated understanding of the impact of network structure and ultimately of how the diffusion process works in a given market. Thus, the current model can be a potentially valuable addition to the market research toolkit.

Finally, our approach provides a basis for estimating the diffusion curve parameters in situations dealing with radically new products where prior experience with marketing mix variables may not be widely available. Thus, with radical innovations, knowledge of the underlying network structure may provide a better guide to diffusion than extrapolating from experience with more familiar, although less similar, products. A key point here is that traditional models of diffusion estimate $p$ and $q$ post hoc, based on experience with product performance (Mahajan et al., 1990). In contrast, the network model makes it possible to prospectively estimate the diffusion curve parameters, based on the structural properties of the network, which may be measured even before the product is launched. There may also be issues of cost-benefit tradeoffs that are relevant. Network changes are not without cost, and may call for financial investment and human adjustment. Thus, the desired changes in network structure have to be evaluated in terms of the cost of bringing them about, as our model does. In sum, the model presented here could form the basis for potentially very valuable managerial tools with which to understand and influence the diffusion of new products and technologies.
It should also be pointed out that our model brings out some ethical challenges to the manager who may be interested in re-engineering his customer network. If human relationships are the basis for enduring social networks, especially in a consumer market, how appropriate it is to talk in terms of “engineering?” This is an issue that deserves to be considered in depth, although any meaningful discussion of the topic is beyond the scope of this paper.

Conclusion

The contributions and implications outlined above serve to demonstrate the potential value of explicitly modeling diffusion curve parameters in terms of underlying network structure. This paper sought to add value to the diffusion and network literature in marketing in three ways:

1. by making it possible to infer diffusion potential from directly measurable network properties;
2. by “unpacking” the diffusion process into innovation and imitation processes that form the building blocks of contagion; and
3. by developing a holistic structural model of network diffusion which integrates the several network properties that have hitherto been studied separately.

Apart from providing an alternative approach to the estimation of diffusion curve parameters, our method offers greater managerial leverage by identifying concrete ways in which the network may be “re-engineered” in order to facilitate diffusion. The fact that diffusion curve parameters may be prospectively estimated from network structure also lends a distinct advantage over traditional models in which $p$ and $q$ are estimated post hoc. In the current business and societal context of rapid technological change and continuous innovation, research interest in diffusion processes remains strong (Rogers, 2003). Especially in the high-technology sectors of the economy, such as the internet and telecommunications, both networks and the diffusion of innovations are central issues. Against this background, the model outlined here is intended to pave the way towards a rigorous integrated treatment of networks and the mathematical modeling of diffusion.

Notes

1. This is the reason why we have crafted our arguments in terms of postulates (which, following Webster’s Dictionary, we take to mean established rules or principles which form the premise for a train of reasoning), rather than in the traditional form of hypotheses. Our position is that both conceptual and empirical support is already available for each of the postulates taken separately; thus, our concern is neither to present new theoretically derived hypotheses nor to lay the groundwork for empirical testing. Rather, we take the postulates as already enjoying some measure of empirical support, and hence justifying their use as premises in our task of developing an integrative analytical model. Thus, our purpose in briefly re-stating the arguments leading up to the postulates is only to summarize the arguments that already exist with some empirical support. This is not to say that all empirical issues have been settled with respect to the postulated relationships, simply that our goal in this paper is to advance the analytical modeling effort rather than the agenda of empirically testing theoretically derived hypotheses.

2. In a general sense, our equations are relevant to the Ciba Geigy case. TeleSession enabled Ciba Geigy to lower $T^*$. The lowering of $T^*$ was accomplished by increasing the average
centrality and the network range of the network. According to our analysis an increase in these two would lead to an increase in the INP, or the innovative potential of the network, which in turn would lead to a larger number of early adoptions, and thus speed up the diffusion. If our model is parameterized, then it can perhaps provide directions for resource allocations. The details provided in the HBS case on Ciba Geigy does not permit such a calibration. However, such a calibration may be carried out in future applications.

References


Further reading

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