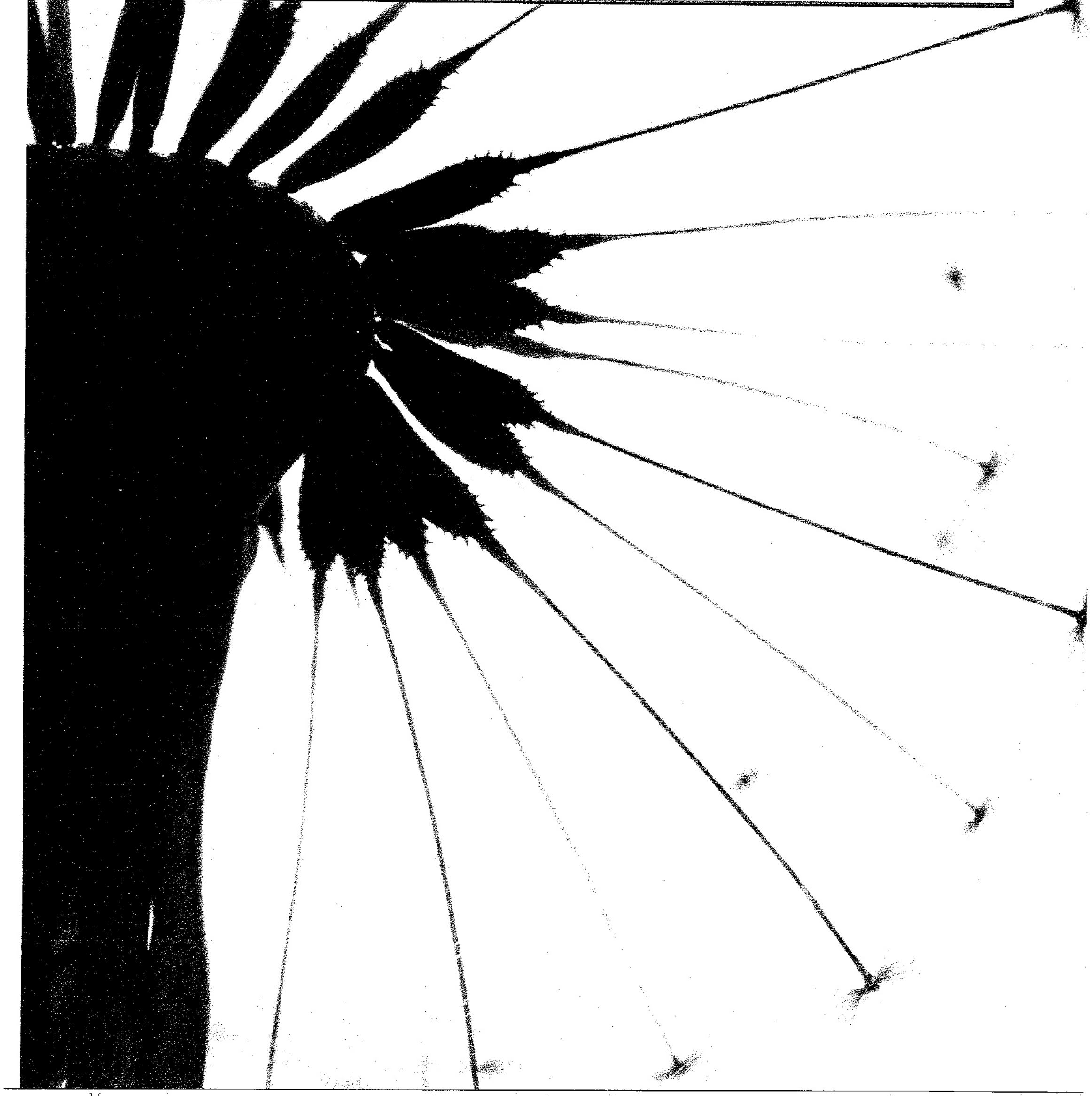
The Diffusion of Innovations

A Communication Science Perspective

EDITED BY Arun Vishwanath and George A. Barnett



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The Revolution in Diffusion Theory Caused by New Media

JAMES A. DANOWSKI, JULIA GLUESING & KEN RIOPELLE

Introduction

From the face-to-face discussions with farmers about seed corn in the 1940s grew the famous S-shaped diffusion curve. Most scholars still unquestioningly teach the classic curve, despite the fact that face-to-face communications are no longer nearly as important among a range of new media. With new media comes a different set of assumptions about the key variables that grounded the old S-shaped curve. A new form of curve emerges: the convex curve, one shaped similarly to the trajectory of a rocket launched into low-earth orbit. This chapter presents the rationale underlying this revolution in diffusion theory wrought by new media technologies. Empirical evidence comes from a study of three innovation concepts at two levels of analysis, individual and organizational units, innovations communicated mainly through e-mail and web pages about automobile engineering innovations in an organization. Herds form when people see in new media that an innovation is going to develop, and they adopt without discussion or little interaction with other individuals about the innovation. The more slowly growing S-shaped curves still explain certain types of innovation diffusion, but S-shaped curves' relegation to a more circumscribed position in the theoretical space about innovation is revolutionary and a pattern likely to continue to expand in scope.

Problem Statement

In his sweeping assessment of research across multiple disciplines, the National Science Foundation's co-director of Human-Centered Computing, William Bainbridge (2004), states that "understanding semantic approaches to cultural systems would enable the engineering of culture, to accelerate the rate of invention in valued fields, and to learn how to fit difficult species of technology into harmoniously functioning ecologies. This is one of the profound revolutions that technological convergence would create" (p. 174).

The proposed research illustrates one example of Bainbridge's profound semantic revolution, the over-time study of e-mail content using semantic-network analysis of full texts. This is done to better understand the diffusion of information and communication technologies (ICTs) in organizations. A focus on message content can be considered the primary distinguishing feature of the discipline of communication compared with other social sciences. The next most central focus in communication studies is focus on the networks of who communicates with whom as messages are exchanged. Moreover, it is considered important to analyze messages and interpersonal networks *over time*. The most developed theory about communication over time is diffusion of innovations theory (Rogers, 1962, 1971, 1983, 1995, 2003). The 2003 edition alone is cited in over 15,000 scholarly works. Nevertheless, comparatively little research has studied diffusion *within* organizations. Most diffusion research that involves organizations looks at them as the unit of analysis as they on the whole adopt innovations among other organizations. In contrast, the current study examines the diffusion of an interconnected set of six innovations within an organization.

In conducting the proposed multi-level investigation, the current study is grounded in a widely useful theoretical and methodological approach to a variety of research problems: network analysis. Showing the wide scope of a network perspective, Barabasi (2002) asserts that everything in human experience is linked to everything else through networks. In communication studies, networks have been analyzed spanning levels of analysis (Castells, 1996), some examples including from nations as nodes linked by their annual telephone call volumes (Barnett, 2001; Danowski, 2000), to networks among cultures constructed from cross-posted discussion list messages (Choi & Danowski, 2002), to networks of information industry mergers and acquisitions (Danowski & Choi, 1998; Chon, Choi, Barnett, Danowski & Sung-Hee, 2003), to networks of sub-disciplines according to co-membership in divisions of a professional association (Barnett & Danowski, 1992), to individuals' e-mail networks (Danowski & Edison-Swift, 1985; Diesner, Frantz & Carley, 2005), to news story word networks (Danowski, 1993a; Corman, Kuhn, McPhee & Dooley, 2006), to concept cooccurrences across discussion forum posts (Danowski, 1982), to individuals' cognitive networks from open-ended survey responses (Rice & Danowski, 1991, 1993; Danwoski, 1993b), studying such things as perceptions of voice mail.

Network Theory and Network Analysis

It has become widely recognized in this decade that the network perspective reflects the fundamental structure of social processes. Borgatti and Foster (2003) show the exponential growth curve for studies on social networks in Sociological Abstracts, reviewing nearly 200 studies of social networks and organizations at both the inter- and intra-organizational levels. Organizational and communication scholars have addressed the emergence of knowledge networks in global organizations and their relationships with information-technology-driven organizations (Contractor & Eisenberg, 1990). Researchers have been developing sophisticated computational simulation models for testing hypotheses about networks and information diffusion, changes in individual and group knowledge and interaction networks, the dynamics of cultural influence networks, and how shared beliefs evolve, focusing on their co-evolution with information technology (Carley & Krackhardt, 1996; Carley, 1996; Contractor, Zink & Chan, 1998; Harrison & Carroll, 2002). *The New York Times* (Eakin, 2003) is even publishing articles about the popularity of network theory, and there are best-selling books on the topic (Gladwell, 2000; Barabasi, 2002; Buchanan, 2002; Johnson, 2001; Watts, 1999, 2003; Strogatz, 2003). Physicists have conducted numerous studies of networks and various social practices, modeling them in high-order mathematical network terms (Newman, 2002).

Network theory, as it has been applied to the study of human behavior and relationships, is comprised of multiple theoretical approaches. Monge and Contractor (2001, 2003) state that there are 10 families of theories that have been used to explain the emergence, maintenance, and dissolution of communication networks in organizations. With a long tradition in sociology, organizational theory, and anthropology, network analysis is a form of structural analysis with theory and methods intimately linked (Monge & Contractor, 2001; Rogers & Kincaid, 1981; Bernard & Ryan, 1998; Borgatti & Foster, 2003). The analysis technique is most often used to discover the pattern of interpersonal communication in a social system by determining who talks to whom, and investigating structural and relationship properties of networks (Valente, 1995, 1996; Cross, Borgatti & Parker, 2002). Monitoring emerging networks identifies where greater leverage can be gained for channeling diffusion resources (Cotrill, 1998; Carley, 1995). Although inter-organizational networks are not of direct focus in the current research, there is a stream of studies that investigate inter-organizational network predictors of organizational adoption of innovations (Davis, 1991; Haunschild, 1993; Palmer, Jennings & Zhou, 1993; Powell, Koput & Smith-Doerr, 1996; Geletkanycz, Boyd & Finkelstein, 2001; Gulati & Westphal, 1999; Westphal, Seidel & Stewart, 2001).

Positional, relational, and cultural traditions in network analysis originate from the classic, seminal structural concepts developed in sociology and anthropology by theorists such as Durkheim and Radcliffe-Brown, and from organizational theorists such as Weber, Parsons, and Homans (Monge & Contractor, 2001). In organizations, this approach sometimes focuses on formal structures. Other researchers have used network analysis to describe the communication links in organizations regardless of formal position. This network structure is often referred to as the informal network and places emphasis on the dynamic and constantly changing nature of the links, based on repetitive patterns of message flow or the network's emergent properties. From the cultural perspective, networks are seen as socially constructed through a series of communicative interactions in which shared meanings emerge that constrain and enable interactions. Work done from this tradition has focused on semantic networks or word networks to examine message content and the structure of meanings in communicative interactions (Danowski, 1982, 1993b; Monge & Eisenberg, 1987).

Networks are increasingly seen as patterns of communication (Borgatti, 2008) about a variety of topics such as friendship or social interaction, technical or professional advice, and the sharing of new ideas or techniques (Scott, 1991, 2000; Wellman, 1983). Typically, networks are constructed by asking respondents to name others with whom they communicate, sometimes specifying a particular topic. These traditional survey research methods for gathering network data have restricted the ability of researchers to examine networks dynamically, or to investigate large networks that cross social systems.

In contrast, the current study uses methods that tap the capabilities of information technology infrastructure to overcome these restrictions in the main data collection phases by analyzing organizational e-mail content and e-mail distribution networks gathered by ICT procedures that recover historical information as well as collect real-time data. Our study focuses on the organizational communication networks enabled by information technology infrastructure. We research the diffusion of innovation in IT-supported networks of practice. Of particular relevance to this research are recent studies of the social construction of innovation networks. Poole and DeSanctis (1990) have examined how actors and structures in a social system influence each other in a recursive relationship. In a longitudinal study conducted at a U.S. public works department, the duality of this relationship was empirically validated using the output from simulation techniques in comparison with actual network evolution (Contractor, Whitbred, Fonti, Hyatt, O'Keefe & Jones, 2000). Harrisson and Laberge (2002) explored the process of diffusion of a socio-technical innovation among workers of a large microelectronics firm. Network analysis revealed how innovation is constituted and the communicative form it takes by tracing the chain of arguments and responses. Burkhardt and Brass (1990) demonstrated in their study how the diffusion of an innovation altered the network structure based on knowledge and information individuals possessed about the innovation. Torenvlied and Velner (1998) investigating resistance to the introduction of ISO quality standards in a transport company found that contagion of resistance in an informal trust network is a significant barrier in diffusion of innovations.

Network Models of Diffusion

Networks are important to the diffusion of innovation (Debresson & Amesse, 1991) because they posit that the ties between individuals influence the spread of an innovation. Most diffusion models are contagion/epidemic/cohesion/relational models where information about innovation is passed from one person to another through direct contact. Valente (1995, 2005) identified only six studies that exist in the public domain that utilized network models of the diffusion of innovation with both network data and time of adoption data. He reanalyzed data from three of the studies to demonstrate how relational network models, structural network models, threshold and critical mass models aid our understanding about how ideas, products, and opinions "take off" and spread with varying speed through a social system. Valente (1995) conceptualized a network threshold model that is both relational and structural and provides a more accurate measure of a person's innovativeness. He calls out the need for more network and diffusion research that measures adoption over time while collecting network data (Valente, 2005).

Network Growth and Decay

Most research treating diffusion of innovations from a network perspective has considered networks as static. Nevertheless, as Borgatti and Foster (2003) point out, the research on change in network structure is rich in examining the evolution of group structure, including empirical investigations of network change (Barnett & Rice, 1985; Burkhardt & Brass, 1990; Burt, 2000; Shah, 2000; Barnett, 2001), and general mathematical models of change (Doreian & Stokman, 1997; Snijders, 2001), as well as agent-based simulation studies reviewed by Macy and Willer (2002). Nevertheless, because of the difficulty of simultaneously collecting network data and time of adoption data, the testing of network threshold and related models of diffusion have remained limited.

In short, while network approaches to diffusion have been infrequent, even less researched has been diffusion in online organizational environments. The broad question of the current study is: Do different diffusion models emerge within the online organization compared with the traditional societal diffusion context?

Diffusion of Innovations Theory

Research on the diffusion of innovations spans almost six decades (Griliches, 1957; Nyblom, Borgatti, Roslakka & Salo, 2003) and includes more than 5,000 studies. No other field in the behavioral and social sciences represents more effort by more scholars in more nations (Rogers, 2003). An innovation can refer to new knowledge, to new technologies such as information technologies, product improvements or manufacturing technologies, or to a new process for doing work in organizations. While there is a large body of extant research about innovation based on product or process life cycle (Utterbeck, 1994; Fine, 2001), this study is grounded in the theoretical and methodological traditions in communication and social network research.

There are a few diffusion studies that look at organizational adoption of ICTs (Markus, 1987, 1990; Mahler & Rogers, 1999). For example, researchers studying the adoption of enterprise resource planning software in Europe found that factors affecting late adoption differed from those explaining early adoption (Waarts, van Everdingen & Hillegersberg, 2002).

Our focus on measuring diffusion via ICT data does not suggest that face-to-face interaction is unimportant to diffusion. Following the findings of

Haythornthwaite and Wellman (1998), who reported that social network data on media use among members of a co-located research group showed that pairs with closer ties used more media to communicate, we assume that to some extent ICT-based networks are correlated with face-to-face network structures, although in the current study we hypothesize that interpersonal communication is less important to diffusion in heavily used ICT organizational environments than it is in less mediated social systems.

One of the most robust findings from the diffusion of innovation literature is the S-shaped cumulative adoption curve (Rogers, 1995), called in the marketing literature the "Bass Model" (Bass, 1969, 1980). The curve results from a simple plot of the cumulative number of adopters of an innovation on the Y-axis against some fixed period of time along the X-axis. Henrich (1999) names a second kind of curve, r-shaped or r-curves. These begin convexly with a maximum growth rate and then slowly taper off toward equilibrium; the difference between the two kinds of curves is shown in Figure 1.

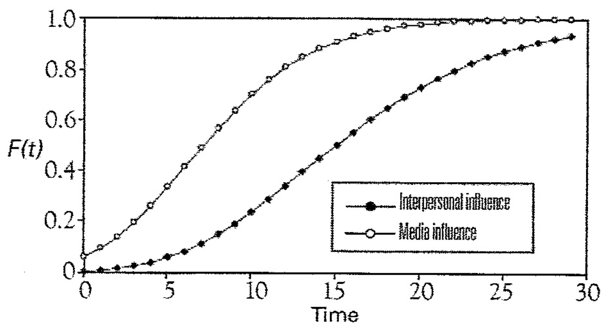


Figure 1

Scholars such as Hägerstrand (1952), Bowden (1964, 1965), Bass (1969), Hanneman (1969), Carley and Svoboda (1996), and Henrich (1999) have developed computational models to simulate the diffusion of innovations under various conditions and parameters that produce these curves as a graphic summary of the diffusion process over time. Most such curves are S-shaped.

In contrast, Rosenkopf and Abrahamson (1999) report "bandwagon" production factors resulting in more r-shaped or convex diffusion curves. These predictors include: (1) greater number of media messages, (2) more ambiguity of innovation efficiency/effectiveness, (3) more messages about number of adopters, and (4) more messages about status of adopters. We expect higher values for these variables in organizational environments when diffusion is primarily via ICT, in the current study via e-mail. E-mail "media" would seem to typically produce large numbers of messages about innovations in organizations. New product innovations, such as those studied in the current research—new car features in the concept stage—have associated uncertainties. There is less common understanding of the overall concept of the innovations, how these will be engineered, how feasible it will be to integrate them across different car platforms, and how much they will cost to build. These uncertainties link with Rosenkopf and Abrahamson's second predictor of convex diffusion curves. In the current study these aspects of the innovations are quite ambiguous in terms of efficiency and effectiveness. In fact, one innovation was eventually terminated because of negative performance in these areas.

Consistent with the third predictor, e-mail provides information about the number of adopters through the CC: function. It is the norm in the organization to CC: members of the work group, key people in other work groups, and members of the steering committee for the innovations. In this way individuals have increasing messages about the number of adopters as more e-mail about the innovations is produced when individuals begin to adopt the innovations and e-mail about them. The fourth predictor, adopter status, is highly visible because widely used e-mail "signatures" provide clear status information. Thus, all four of the conditions Rosenkopf and Abrahamson (1999) specify for convex diffusion curves are met in the organizational innovations studied in the current investigation.

Others theorize about the causes of rapid-growth convex curves for diffusion in terms of herd behavior (Geroski, 2000) leading to information cascades. Herd behavior (Choi, 1997) is taken from animal behavior observations. Once lead members of the herd begin to stampede in a particular direction, the other members quickly follow suit with no knowledge of environmental conditions except that the lead herd animals are moving. In a stock market, for example, once enough investors sell or buy stocks rapidly, other investors follow in a herd-like manner with no information other than sufficiently large numbers indicating other investors are making a move, making it unquestionably important to mimic. This makes the resulting adoption curve such that it has a very rapid growth over time followed by a tapering off as laggards follow.

We propose that the underlying interpersonal communication network is not dense and interlocking throughout this process, but instead is highly constrained, which, in network terms, manifests as simple center/periphery structures or highly radial networks in which the contacts of individuals do not communicate with one another. In information theory terms the former type of network structure is entropic while the latter type is negentropic. Negative entropy is the opposite of entropy or equal distributions of events. In contrast, negative entropy is a result of constraints on all possible events. The more constrained a situation, the higher the negative entropy. In information theory, negative entropy means the same as information, the reduction of uncertainty or of entropy. In a network, if all nodes were completely connected to all other nodes, this would be the most entropic pattern. If, on the other hand, the network had a central hub with contacts emanating from it, which were not connected to each other, this would be a pattern showing high negative entropy. For short, we refer to negative entropy as negentropy.

It is reasoned that the primary cause of the logistic curve is face-to-face interpersonal communication in which individuals embody a contagion or epidemic process where they discuss with others their experience with the innovation and decide whether or not to adopt it. In the famous hybrid seed corn diffusion example (Griliches, 1957), it took years for the interpersonal contagion process to unfold into the S-shaped curve. This appears to be a generalizable notion (Dixon, 1980), consistent with Geroski's (2000) theory that direct, unmediated interpersonal contact as the basis for passing of innovation information results in an S-shaped curve.

Geroski theorizes that the contrasting r-shaped modified exponential curves occur because of information cascades. When individuals adopt an ICT innovation without having to go through the learning curve themselves, but make their adoption decision based on the experiences of the early adopters, time of adoption speeds up compared with the contagion-based S-curves. Geroski posits three phases to such information cascade or bandwagon adoption: (1) initial choice of early adopters between technology variant A and B, (2) lock-in (Arthur, 1989) on A, (3) bandwagon or information cascade effect. Bass (1969) proposed early on (see Figure 1) that some innovations rely heavily on interpersonal communication and therefore have the S-shaped curve while other innovations involve more use of the media for innovation-relevant messages, resulting in the convex r-curves. Rosenkopf and Abramson's (1999) information cascades theorizing provides more specific reasons for its occurrence and does so in communication terms.

With the ubiquity and sophistication in logging of e-mail ICTs, researchers can take more advantage of automated monitoring of communication to investigate organizational innovations. Although this has been discussed for some time in the literature (Danowski, 1982, 1988) such methods have diffused slowly.

Additionally, this research addresses five shortcomings of traditional diffusion research. Those studies: (1) are piecemeal, descriptive, and retrospective, (2) relate a single variable to diffusion, (3) collect data from error-rich self-reports, (4) rarely include both time of adoption and network data; Valente (1995, 2003) identified only six such studies (e.g. Danowski, 1976), and (5) give little theoretical attention to why ICTs may change diffusion processes.

The logistic function defines the S-shaped curve. It can be defined as:

$$P(t) = \frac{1}{1+e^{-t}} = \frac{1}{1+\exp(-t)} = (1+\exp(-t))^{-1}$$

where the variable P denotes a population or sample and t is *time*.

Hypotheses

Based on the literature and reasoning discussed, we propose the following hypothesis:

> H: Diffusion curves for IT-based innovations will be convex rather than S-shaped.

Methods

Organization and Innovations Studied

This study was conducted among an American automobile company's product engineering staff across its global network. The innovations were initially a package of two sets of products with a single overall name that was created to be a new feature across a range of the company's vehicles. The number of engineers involved was approximately 2,000.

ICT Studied

Communication about the innovations occurred in a variety of modes, but the most tractable was e-mail about the innovation. Monitoring all relevant electronic mail over time overcomes limitations of cross-sectional, self-report data, which includes considerable errors introduced by respondent memory processes and their ability to report only gross summary features of their communication messages about an innovation. To avoid such problems, this study created a procedure by which the over time e-mail content of individuals was monitored both historically and in real time over a two-year period. The organization exclusively used Microsoft Outlook for e-mail with approximately 400 servers with up to 4,000 users each. The first step in establishing the monitoring procedure was to create a new Outlook rule that a participant would apply once on his Windows PC so that it would search all historical e-mails stored by individuals for key words associated with the innovations and forward these e-mails to a dedicated server—and also forward all relevant e-mails in real time during the course of the study, from January 2005 to December 2007.

A major discussion about deploying this procedure was among the executives and corporate attorneys to ensure confidentiality, respect for the personal privacy of the participants and compliance with the legal systems of employees from different countries. After an in-depth review by the company's lawyers from multiple countries, the process was approved as an opt-in choice, an approach more characteristic of Europe than the USA. In all cases, participation was voluntary and employees could stop participating at any time. Participants were asked to run rules in Microsoft Outlook to enable automatic forwarding of e-mail to a "dummy e-mail address" on a secure server designated to store the study data. Therefore, study participants were fully aware that their e-mail was being monitored for the study. When they composed an e-mail, they also could see the dummy e-mail address in the CC line and delete it if for some reason they did not want a particular e-mail to be part of our study data.

Once the e-mail data collection process was approved, the academic researchers received IRB approval from the two universities at which the PI and Co-PIs for this NSF grant were located based on a procedure to protect privacy used by Danowski and Edison-Swift (1985) to convert all names in the e-mails to numbers known only to the corporate staff who collaborated in this anonymizing activity. While the corporate research team knew the identities of all named individuals in the e-mails, the academic researchers had no knowledge of these identities. IRB applications were submitted for exempt status for the research, meaning that, because no identifying information was known to the academic researchers, the research was exempt from the need to obtain informed consent.

The first analysis step was to deploy the Outlook rule to the project manager's e-mail going back nine years. The academic researchers then conducted a network analysis of the who-to-whom network from these e-mails to identify the most central individuals using Negopy (Richards & Rice, 1981). The program found one large group, evidence of a negentropic center/periphery structure (see Figure 2). Because Negopy computes the geodesic distance scores among all pairs of nodes in each group, in this case one, comparable centrality information was available for all nodes in the network. This information was presented to the corporate researchers who used this information along with other considerations to choose 298 target individuals for the e-mail harvesting.

The 298 targets were initially sent an e-mail requesting their participation and application of the Outlook rules. Thirty-eight chose to voluntarily participate, for a participation rate of 13%. Follow-up by project staff noted that potential users did not wish to have their e-mail monitored in this fashion because of uncertainty around what it would find and how it would be used, even though most were aware that all corporate e-mail was monitored in real time for "illegal" activity words. Nevertheless, we captured non-participant e-mail that included one of the 38 people who participated on their To: From or CC: list on each e-mail. We found that capturing all innovation e-mails, many having long forwarding chains, from only 1% of the 2,000 project engineers was sufficient to capture e-mails of approximately 1,900 individuals exchanging approximately 45,000 e-mails. As a result we constructed a two-year time series of e-mails about the innovations.

Results

Figures 2–7 show the results for the six innovation diffusion curves. SPSS 18 Curve Fitting procedure was used. It does not have the convex shape as one of its fitting options, but we are more interested in whether the logistic curve explains the most variance. The contrasting curve we will use is the cubic curve. There are many different shapes to the cubic curve, and one of them is the convex curve. Once examining the statistical evidence one can look at the shapes of the curves and visually see whether the cubic functions are the particular kind of interest, convex curves. All of the various curves fitted are statistically significant at ($p < .000$), although the variance explained varies. For the adoption of innovation #1 by organizational units, shown in Figure 2, the logistic curve explained 59% of the variance over time, while the cubic form $f(x)=ax^3+bx^2+cx+d$ explained 97%. For the adoption of innovation #1 by individuals, shown in Figure 3, the logistic curve explained 79% of the variance, while the cubic explained 99%. For the adoption of innovation #2 by organizational units, shown in Figure 4, the logistic curve explained 34% of the variance, while the cubic explained 61%. For the adoption of innovation #2 by individuals, shown in Figure 5, the logistic function explained 93% of the variance, while the linear, cubic, and quadratic each explained 97%. For the adoption of innovation #3 by organizational units, shown in Figure 6, the logistic curve explained 72% of the variance while the cubic curve explained 98%. For the adoption of innovation #3 by individuals, shown in Figure 7, the logistic function explained 81% of the variance and the cubic function explained 97%. Combining the statistical results with the visual curve identification, there is consistent evidence of convex r-curves explaining more variance than logistic S-curves, supportive of the hypothesis. At the organizational level, the cubic functions explain nearly six times more variance than at the individual level.

Figure 2. Individual Adoption of Innovation #1

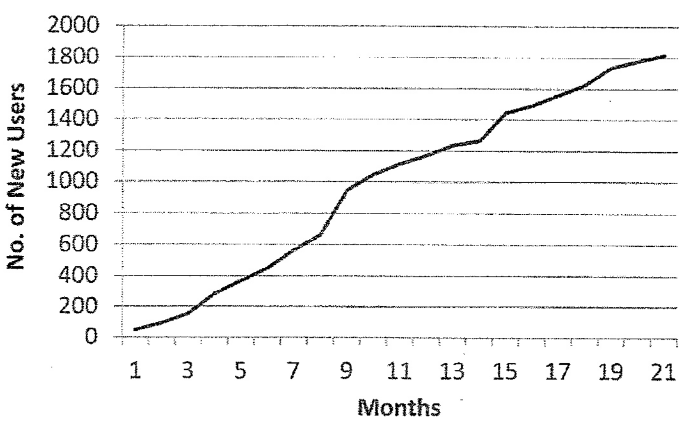


Figure 3. Individual Adoption of Innovation #2

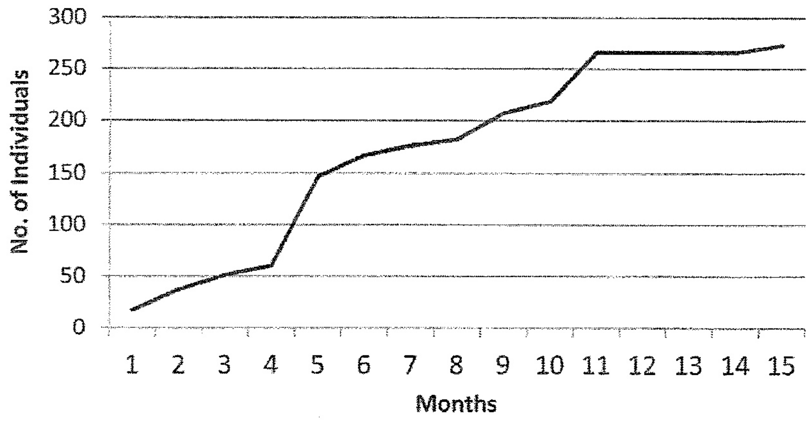


Figure 4. Individual Adoption of Innovation #3

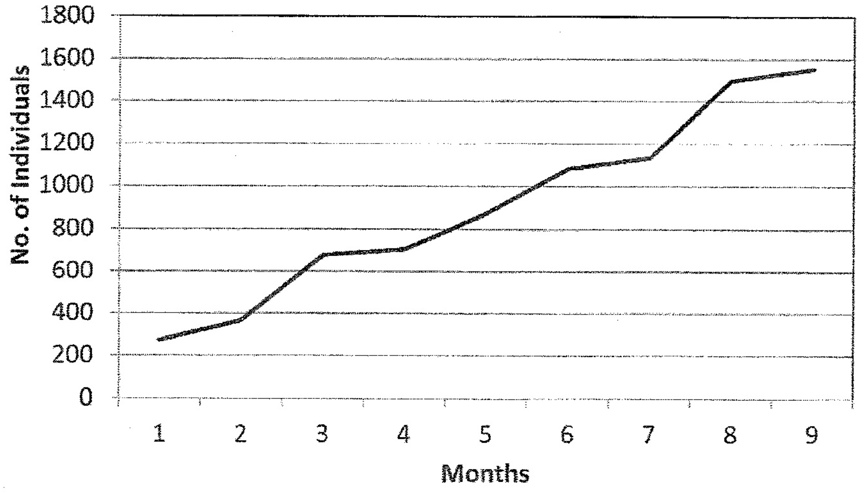
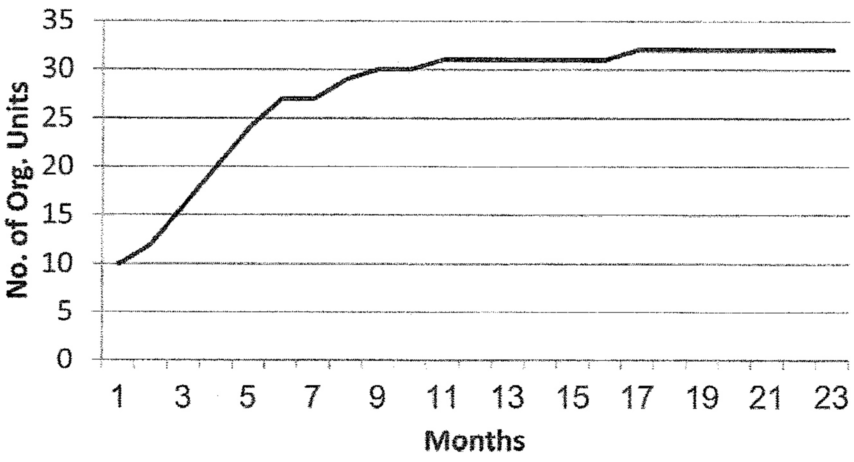


Figure 5. Organizational Unit Adoption of Innovation #1



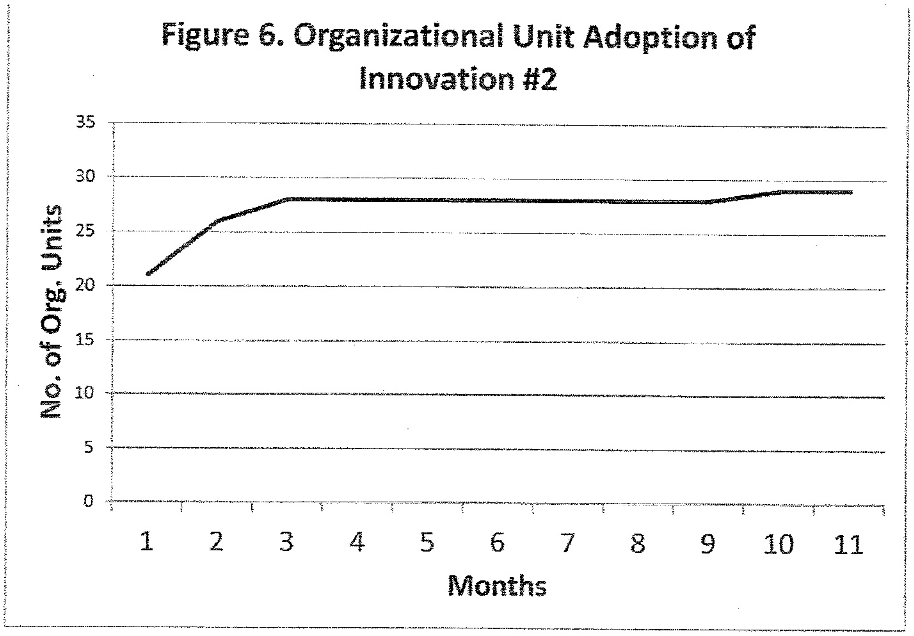


Figure 6. Organizational Unit Adoption of Innovation #2
No. of Org. Units
0
5
10
15
20
25
30
35
1
2
3
4
5
6
7
8
9
10
11
Months

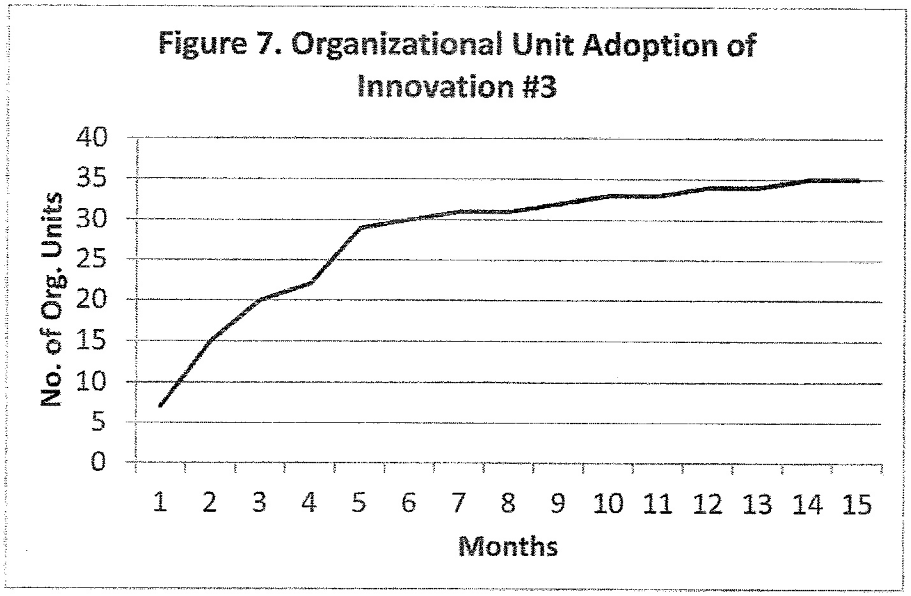


Figure 7. Organizational Unit Adoption of Innovation #3
No. of Org. Units
0
5
10
15
20
25
30
35
40
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
Months

Discussion

This study found support for the hypothesis that innovations diffused through heavy use of ICTs would have a convex r-curve rather than the traditional S-curve. The classic contagion/cohesion models of diffusion of innovations that involve growing chains of interpersonal interactions for an S-curve of adoption to slowly build do not appear. Instead, a rapidly accelerating convex r-curve develops. This represents a major shift in expecting how innovations may diffuse in increasingly ICT-based environments. There is a more rapid ramp-up of adoption without much direct interpersonal communication, rather than the traditional slow-building S-shaped curves due to the need for potential adopters to directly communicate with earlier adopters and one another in deciding whether to adopt. In the ICT-based global space, one can therefore expect more rapid diffusion of more innovations more quickly over time than in the previous pre-ICT world.

The theoretical rationale is that the ICT studied e-mail allows for herd behavior, otherwise known as information cascade effects. This is perhaps because by examining e-mail headers users can see who the early adopters are and their choices about ambiguous innovations in terms of efficiency and effectivness. They also see the onset of the next phase, the lock-in of others on this choice. Once observing this, there is no need to have interpersonal communication in deciding to adopt, and people quickly decide to join herd movement. Reasons include that with e-mail individuals not only see who is adopting what when and their organizational status but see emerging herd movements that they join. In addition, some adoption may be mandated by management. The nearly six times greater convexity at the organizational level may be in part a result of this mandate factor, but another likely factor may be herd observation of early adopters within an organizational unit. In this study, examination of six diffusion curves showed all of them to be convex r-curves and not S-shaped, therefore supportive of the hypothesis. Future research can see to what extent ICT innovations in other organizations follow this pattern and, more widely, whether ICT innovations among large global populations have more convex than S-shaped diffusion curves.

Note

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