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Modeling Information Equality:
Social and Media Latency Effects on Information Diffusion

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In this study, we build and test a stochastic, agent-based model of information diffusion, called dFusion. The model incorporates diffusion research and social network analysis into a framework that is consistent with the findings of digital divide and knowledge gap research. Using three separate real-world datasets, our model demonstrates clear causal relationships between social structure, communication network structure, and the degree of "information equality" (relatively equivalent speed of access to salient information) within a given social network. By focusing on differential, rather than absolute, speed of access to information, we hope to create an evaluative framework for information technology investment that accurately and comprehensively predicts the effects of such interventions on social equality.

We live in the "information age." This assertion has developed over the last few decades from a radical reconceptualization of society and power to a cliché often mouthed by marketers, politicians, and academics alike. It appears to be one of the few points on which nearly all contemporary social theorists agree.

But what, exactly, does this assertion mean? The answer differs from theorist to theorist. Castells (2000a, 2000b, 2001a, 2001b) points to the confluence of three trends: the growing power and pervasiveness of ICTs, the emergence of a global economy, and the increasing social value of free and

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open communication. To Castells, these factors combine to produce a new social structure that abandons traditional hierarchies for a network model.

Ball-Rokeach (Gibbs, Ball-Rokeach, Jung, Kim, & Qiu, in press; Loges & Jung, 2001; Matei & Ball-Rokeach, 2002) positions information, instantiated in the act of “storytelling,” at the center of power relations between individuals, community organizations and global institutions, facilitated by both mass and interpersonal communication media. In her communication infrastructure (CI) model, information is envisioned as the key that allows individuals to achieve crucial personal goals, such as understanding, orientation, and play, both individually and socially.

Bell (1999) distinguishes today’s “post-industrial society” from the past industrial society on the basis of the shift from a Marxian “labor theory of value” to a more current “knowledge theory of value” (p. xvii). Information has supplanted labor as the building block of modern societies. Its superiority, he argues, rests in its reflexivity (knowledge begets more knowledge, unlike labor) and in its potential role as a collective good, rather than a scarce resource.

While these theorists, and others, may have different models for discussing the role of information *vis-à-vis* social, political, and economic institutions, each agrees that information, and its exchange, are now fundamental. It follows that access to information – who learns what, and when – is key, especially as the gap between information “haves” and “have-nots” threatens to grow continually wider. This threat is tacitly addressed in our legal institutions (e.g., laws against insider stock trading), newer social conventions (e.g., file sharing, blogging), and explicitly acknowledged by some communication theorists (Deroian, 2002; Himanen, 2001).

In this study, we address the political ramifications of information-as-currency in interpersonal communication networks. Specifically, we are interested in measuring *information equality,* defined as the extent to which members of a society or social network have access to equivalent information at relatively equivalent speeds. The degree of information equality possessed by a network can be understood as an emergent property generated by the information latencies within that network. Specifically, we identify two network properties, social structure and the communication infrastructure, that impact information latency. We label their effects, respectively, as social latency and media latency.

In an ideal network, every node would have the capacity to communicate instantaneously with every other node. In the real world, however, social barriers limit the number of possible interlocutors to whom a given person may have access. The emergent effect of this limitation is an overall lag in the speed with which information can traverse an entire social network – hence, social latency. Similarly, technological limitations and unequal access to, and use of, communication media produce media latency at the network level.

Policy Considerations

The effects of social latency and media latency on a network’s information equality have profound policy consequences. Digital divide research (Haythornewaite, 2001; Jung, Qiu, & Kim, 2001; Loges &

Jung, 2001; Mansell, 1999; Sidorenko & Findlay, 2001) has previously identified social consequences of the unequal distribution and use of communication media. One policy issue arising from this, specifically from knowledge gap research (Tichenor, Donohue, & Olien, 1970), has been the tendency of newer communication technologies to widen the inherent social inequalities in the system.

The authors point to a number of contributory factors at work in creating this differential effect, including communication skills (attributed to better education — a socioeconomic attribute), existing knowledge, relevant social contact, the nature of the mass medium itself, as well as selective exposure, acceptance, and retention of information. Of particular interest for this paper, research found that the social subsystems that benefited the most tended to be those that started with the greatest advantage.

The knowledge gap hypothesis has come under criticism from several quarters since it was first proposed, especially the privileging of certain types of information (news and public affairs were the original information topics measured). Gaziano and Gaziano (1999), for example, argue that knowledge gap research has yielded inconsistent results because researchers “combine and confuse concepts from different perspectives that vary in levels of analysis and assumptions” (p. 118). However, although the application of this hypothesis to research is confounded by these limitations, the premise that new ideas and technologies can increase, rather than close, the gap between information haves and have-nots remains a vital consideration for any research, such as ours, focused on the impact of ICTs on social networks. Indeed, the policy considerations arising from the knowledge gap hypothesis have found an ally in research concerning the digital divide.

Following the formative years of the World Wide Web, several studies (Basil, Brown, & Bocarnea, 2002; Haythornewaite, 2001; Hoffman, Novak, & Schlosser, 2000; Jung, et al., 2001; Katz & Rice, 2002; Lenhart, 2000; Loges & Jung, 2001; Mansell, 1999; Sidorenko & Findlay, 2001) showed that there were significant differences in terms of access to and use of the Internet pertaining to certain key demographic measures — namely, gender, education, race, age, locale, and income — as well as disparities between post-industrial societies and the so-called “developing world.” These observations gave rise to the digital divide debate, in which one side argued that disparity would narrow as diffusion increased, and the other side argued that social inequities would only increase with time. Traditional measures of access support the first group, showing gaps narrowing in recent years across incomes, race, and education, and disappearing completely with regard to gender (Howard, Raine & Jones, 2001; Katz & Rice, 2002; Lenhart et al., 2003; Nie & Erbring, 2000).

However, proponents for social equity challenge these findings (Norris, 2001; Schiller, 1999) and question whether diffusion of technology is a meaningful measure. Jung, et al. (2001; also see Loges & Jung, 2001; Walther, Slovacek & Tidwell, 2001), for instance, have created an Internet connectedness index (ICI) which reveals continuing inequalities in terms of the intensity and satisfaction of Internet use despite the narrowing gap in basic access. This dissatisfaction with using access to technology and time spent using technology as unqualified barometers of social equality is a theme we echo in our own research. Rather than simply exploring new technology’s impact on the *speed* at which members of a network receive information, we are concerned with examining the *differential rates* of access to information; we are looking for lingering social inequities beneath the surface appearance of uniform benefit.

Several state-sponsored and non-governmental organizations (NGOs) have attempted to address these issues by upgrading, expanding, or democratizing the media infrastructure of communities. These agencies range from the Bill & Melinda Gates Foundation (http://www.gatesfoundation.org) to the World Links for Development Program (http://www.world-links.org), and the United Negro College Fund (http://www.uncf.org). As the knowledge gap and digital divide research shows, the degree to which such efforts can be characterized as successful largely depends on the evaluative mechanisms and criteria employed by the researchers.

We believe that these efforts suffer from three principal limitations: focus on media latency at the expense of social latency; lack of an evaluative mechanism that accounts for information equality within the network under study; and lack of adequate predictive power to confidently invest in change. It is our aim to address these limitations by developing a diffusion of information model that encompasses both social and media latency as independent variables and predicts information equality as a dependent variable. Specifically, we incorporate diffusion research and social network analysis into an agent-based predictive model.

Diffusion Research

Diffusion of innovation research (Granovetter, 1978; Rogers & Shoemaker, 1971; Valente, 1996), and its less common theoretical sibling, diffusion of information research (Rogers, 2000; Wellman & Berkowitz, 1988), consider the multi-level processes whereby messages, attitudes and behaviors are spread through a social system.

Rogers (2003) classifies members of social systems based on the degree to which an individual is relatively earlier to adopt an innovative idea than other members. Of interest from a political standpoint is the observation, mirroring the findings of knowledge gap research, that earlier adopters tend to have higher socioeconomic status than later ones. Specifically, they tend to have more years of formal education, are more likely to be literate, have higher social status, and possess a greater degree of social upward mobility.

It is important to note that this social stratification is understood to be an *effect*, as well as a *cause,* of diffusion processes. In the words of Rogers (2003), "the consequences of the diffusion of innovations usually widen the gap between the audience segments previously high and low in socioeconomic status" (p. 443). This observation is directly relevant to a network's information equality; to the extent that differential rates of access to communication create separate information classes (i.e., haves and have-nots), these classes tend to map onto preexisting socioeconomic strata.

Diffusion research also focuses on the concept of salience, or the perceived importance of a message to an individual in a network. Researchers such as Rogers (2003) have demonstrated that the perceived salience of a message or innovation has a measurable impact on whether the message is relayed or the innovation is adopted. This is a concept we incorporate into our model, with a variation. Valente (1996) distinguishes between innovation with respect to an individual's personal social system and innovation with respect to the entire network. We apply this bifurcation to our measure of salience, distinguishing between "personal salience" (the degree to which a message is perceived as relevant to an individual) and "network salience" (the degree to which a message is perceived as relevant to the entire network).

We are hardly the first researchers to apply a political lens to diffusion research. Deroian (2002), for instance, suggests "some political implications of social network formation with regard to diffusion of innovation" (p. 845). Rogers (2000), reviewing news diffusion research to date, suggests that "future attention could be given to connecting investigations of news diffusion with such theoretically driven research areas as knowledge-gaps" (p. 573). This is exactly the theoretical fusion we strive to accomplish.

Social Network Analysis

Social network analysis encompasses a growing field of methodological and theoretical approaches to communication dynamics within a network of nodes, usually conceived as a group of individuals (Burt, 1992; Monge & Contractor, 2003). One of the distinguishing characteristics is that it analyzes communication within a network, based primarily on the emergent structures of links between the nodes, rather than on the qualities of the nodes themselves.

We echo this emphasis in our own model. Most agent-based models in social sciences focus on the way that nodal attributes change as a result of the attributes of other nodes in their immediate environments (Bhargava, Kumar & Mukherjee, 1993; Watt & VanLear, 1996). By contrast, we are primarily interested in modeling message flow as a function of the emergent structures of social links throughout the network.

Another concept we borrow from social network analysis is the distinction between strong and weak ties (Granovetter, 1973; Krackhardt, 1992). Strong ties represent close friendships and family ties, while weak ties represent acquaintances and other lower-intensity relationships. While strong ties are a greater predictor of contact (Koku, Nazer & Wellman, 2001), weak ties have been shown to be "stronger" sources of salient information due to their non-redundancy (Granovetter, 1973). We incorporate both of these observations into our model.

Agent-Based Modeling

Typically, research on the diffusion of a message through a network has been conducted through field experiments. This usually entails fielding questionnaires after the fact and attempting to reconstruct the path of a given message through a network, or at least to assess how many individuals had received the message at various discrete points in time (Rogers, 2000). This methodology is insufficient to our needs for a variety of reasons. First, we are attempting not only to observe message diffusion, but to *predict* it, based on two top-level independent variables (social and media latency). Second, we are dealing with extremely large networks consisting of thousands of nodes. Field experimental research on a network of this size would almost certainly require a sampling methodology, and would therefore miss many of the finer details of a network's social structure – one of our primary predictive variables.

Researchers like Moody (2002) argue that relational activity occurs at discrete points in time, rather than in static networks. Accordingly, our research – unlike traditional diffusion research – requires dynamic measurement of a message as it travels through a system; creating a daunting experimental task. Finally, we aim to create a model that may be applied to a broad variety of social networks, and thus we demand a tool with a great degree of flexibility. This last point addresses a problem that has dogged diffusion research for years; as Rogers (2000) observes, the majority of diffusion research has not been broadly generalizable due to the procedural idiosyncrasies of data collection.

The method we choose to best address these needs is agent-based modeling. Sometimes referred to as cellular automata (CA) modeling (there are some differences between the two terms, but it is difficult to draw a clear distinction [Reynolds, 1999]), this method relies upon a computer simulation in which individuals ("agents") interoperate within a given environment according to a set of predefined rules.

This methodology has previously been applied, albeit rarely, to diffusion processes. Bhargava, et al. (1993) created a cellular automata model for predicting the successful diffusion of new products in various markets. Similarly, we employ a stochastic, rather than a deterministic, model. This is an essential feature because, as Bhargava, et al. write, "in realistic social systems, uniform patterns are rarely seen to persist" (p. 90). Corman (1996) also suggests the viability of this methodology when he writes, "stochastic cellular automata . . . rely on transition probabilities or apply decision rules as constraints on random behavior. Such models describe the innovation diffusion process" (p. 194).

We also draw upon the Bass diffusion model (Bass, 1969) in building our own. Although Bass relied on an ordinary differential equation (ODE) model rather than an agent-based model, his equation included a coefficient accounting for the external effects of the communication media themselves. To our knowledge, Bass' is the only diffusion model prior to our own which explicitly accounts for this factor.

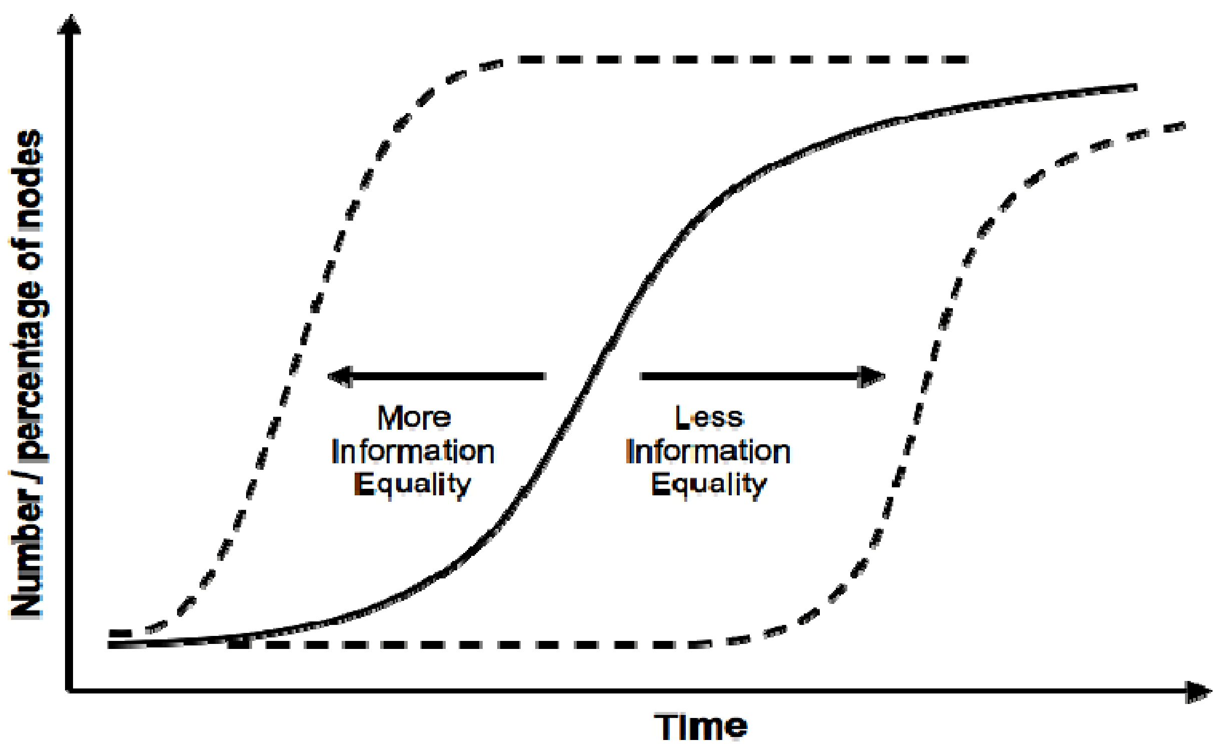
Study Purpose

The purpose of this study is to build and test a preliminary model with the capacity to predict the information equality of social networks, applicable to a variety of groups such as regions, states, etc., using input data regarding social structure and communication media infrastructure. Using such a model, a state or NGO with a budget dedicated to improving the communicative capacity of a given social network could test the effect of different strategies tailored to the network at hand before spending a cent on technology. For the moment, our purpose is to validate the model, rather than create a tool for policy decision-making, a task we leave for the future. In this light, we choose to focus exclusively on interpersonal communication, reserving the effect of mass media for future enhancements to the model.

Our aim in building this model is to examine the emergent effects of social and media latency on a network's overall degree of information equality. Our heuristic for observing information equality is quite simple. As researchers have noted, information diffuses neither universally nor uniformly through a network (Valente, 1995; Wellman & Berkowitz, 1988). As a result, nearly all diffusion processes follow a characteristic "S-curve" over time (Bhargava, et al., 1993; Rogers, 2000); a few initial adopters or message recipients are followed by a sudden upsurge of mainstream adopters, followed finally by a smaller number of later adopters. This curve tends to trail off asymptotically as it approaches maximum diffusion – it rarely reaches 100% of all possible adopters or recipients.

We argue that the shape of the S-curve for information diffusion is a veritable map of the gulf that separates information haves from have-nots. To the extent that a few nodes have access to salient information long before the majority, a network lacks information equality. By contrast, the sooner the majority of nodes receive information, the higher a network's level of information equality. This can be observed in the shape of the S-curve, as shown in Figure 1. Greater information equality will "pull" the curve to the left, while lower information equality will "pull" it to the right. A higher information equality network would be one in which the curve rises sharply and then tapers off as all the members receive the information at about the same time. A lower information equality network would be one in which the curve rises extremely gradually, as only a few members receive information; and long before the majority.

Figure 1. **Diffusion Curves With Greater and Lesser Degrees of Information Equality**



The research heuristic, then, involves measuring the impact of two independent variables, social and media latency, on the information equality of a given network. We aim to develop a model that will first recreate the S-shape of the diffusion curve, and then predict variations in the shape of the curve as a result of changes in the component factors of social and media latency. Specifically, our research questions are:

- Is the degree of information equality dependent on the interpersonal communication infrastructure (media latency)?
- Is the degree of information equality dependent on the social network structure (social latency)?
- Is the degree of information equality dependent on the interaction between the interpersonal communication infrastructure and the social network structure?

Our present task is not to predict the information equality of any specific network, but rather to test the effectiveness of our model. To that end, we apply it to three separate datasets, culled from the Metamorphosis Project (2002 Data Set), The Pew Internet and American Life Project (March-May 2002 Data Set), and the UCLA World Internet Study (2002 Data Set). We have chosen these three sources for a variety of reasons. First, they represent some of the most comprehensive, publicly available datasets regarding the use of ICTs within social environments. Second, each of these datasets represents a large-scale population, which is essential given that geographical relationships factor into our model, and that our project addresses emergent macro-level structures of information flow. Finally, the data that comprise these sets include both relative and absolute usage information for both ICTs and face-to-face communication, each of which is essential to our model.

The measures of our success will be:

- The degree to which our model predicts S-curve diffusion patterns for each of these datasets.
- The extent to which the dependent variable, information equality, responds to changes in social and media latency, the independent variables.

Method

Our agent-based modeling software, called dFusion, predicts the diffusion of a message through a network by first proposing initial conditions for the network, and then proposing rules governing the ways in which individual nodes within the network may interact.

The initial conditions consist of nodal, relational and environmental attributes. The values for these attributes are determined stochastically at the network level, based on quantitative analysis of the three datasets. Nodal attributes include sociodemographic variables, as well as geographic positioning within a square matrix of 200 x 200 cells. Relational attributes assign and define the links between these nodes, relying in part on their geographic proximity.

Environmental attributes map the external variables onto the social network. In this model, sources external to the network include the media vehicles and the message conditions. For present purposes, we are only modeling the use of two communication media: e-mail and phone/face-to-face. We create this dichotomy because these media fall on opposite ends of several relevant axes. Researchers have identified particular qualities that distinguish traditional forms of interpersonal communication from newer forms of computer-mediated communication like e-mail. Prior research (Flanagin & Metzger, 2001) has been conducted upon synchronicity, presence, and the ability to multicast. We merge phone and face-to-face because they exhibit similar characteristics for the axes under analysis.

E-mail is an asynchronous medium, while phone and face-to-face contact are synchronous. E-mail is a low-presence medium, offering users little sense of "being there," while phone and face-to-face contact are higher presence media. E-mail is a multicasting medium, while phone and face-to-face contact are far more likely to occur on a one-to-one basis. Finally, e-mail is a new and only partially diffused medium that requires specialized knowledge to operate, while phone and face-to-face contact are available to almost everybody. Each of these distinctions plays a key role in determining which medium an individual node will use to communicate with another node in our model. Finally, we assign the message values corresponding to its levels of network salience and personal salience.

Once the initial conditions are established, we then set rules stating the conditions under which a given node will attempt to relay the message, to whom the node will relay it, which communication vehicle it will use for dissemination purposes, and finally, whether the recipient of the message is available. The decisions made are dependent upon the network conditions describing the nodes and relations, which are derived from the datasets. For example, the choice of whether to use e-mail is contingent on whether the sender and recipient have access to the Internet, a factor which is determined for each node in each model network. The rules thus followed are what Monge and Contractor (2003) call "metarules":

> a metarule may specify that the rules of interaction may depend on agent's [sic] attributes, thus allowing for the possibility that different agents in the network follow different rules, potentially at different times (p. 87).

The agent-based model is then activated by the introduction of messages with varying degrees of personal and network salience and run under the varying conditions described by the different datasets. The computational modeling technique with stochastic variables requires that we run the same model multiple times and then generate averaged "realized" values selected from a probability distribution. Each run of the model thus constructs a unique network created stochastically from the input variables. The emergent outputs, realized as diffusion curves, are then aggregated over the multiple runs.

A more thorough accounting of the logic matrix behind dFusion is attached as Appendix A. Both the version of the software discussed in the present paper (v.0.1.1.b) and the most current version of the software are available for download from http://www.d-fusion.org.

Despite dFusion's complexity and its sensitivity to input data from real-world datasets, we acknowledge that the model has some considerable limitations. Its inability to distinguish between more than two modes of communication is an obvious one, the lack of mass media as a parallel information distribution system is another, and its inability to account for sociodemographic variables is yet another. We address these and other shortcomings, as well as potential improvements to the model in the discussion section of this paper.

Following our application of the dFusion software to our datasets, a series of Kolmogorov-Smirnov (K-S) goodness-of-fit tests (Chakravarti, Laha, & Roy, 1967; Massey, 1951) were conducted to evaluate whether or not specific pairs of curves may reasonably be assumed to come from the same distribution. Specifically, the tests measured difference between specific pairs for each set of runs described in the results section. These methods allow us to quantitatively test our hypothesis that variations in social and media latency would produce diffusion curves that are significantly different from each other.

Curve-fitting was also conducted to estimate the goodness-of-fit of the resultant S-curves produced by our model, testing our program's capacity to reproduce classic diffusion patterns. Due to the diversity of opinion and methodology reflected in the diffusion literature, however, we find a broad variety of equations and models (Mahajan & Muller, 1979; Teng, Grover, & Güttler, 2002; Valente, 1993) to define an ideal S-curve, ranging from the logistic (Dimmick & Wang, 2005), exponential, and polynomial (Sharif & Ramanathan, 1982); to the Gompertz (Dixon, 1980) and mixed-influence (Bass, 1969; Mahajan & Peterson, 1985) models. We chose to compare the resulting S-curves from our model to higher-order polynomials to establish their validity.

An alpha level of .05 was used for all the statistical tests.

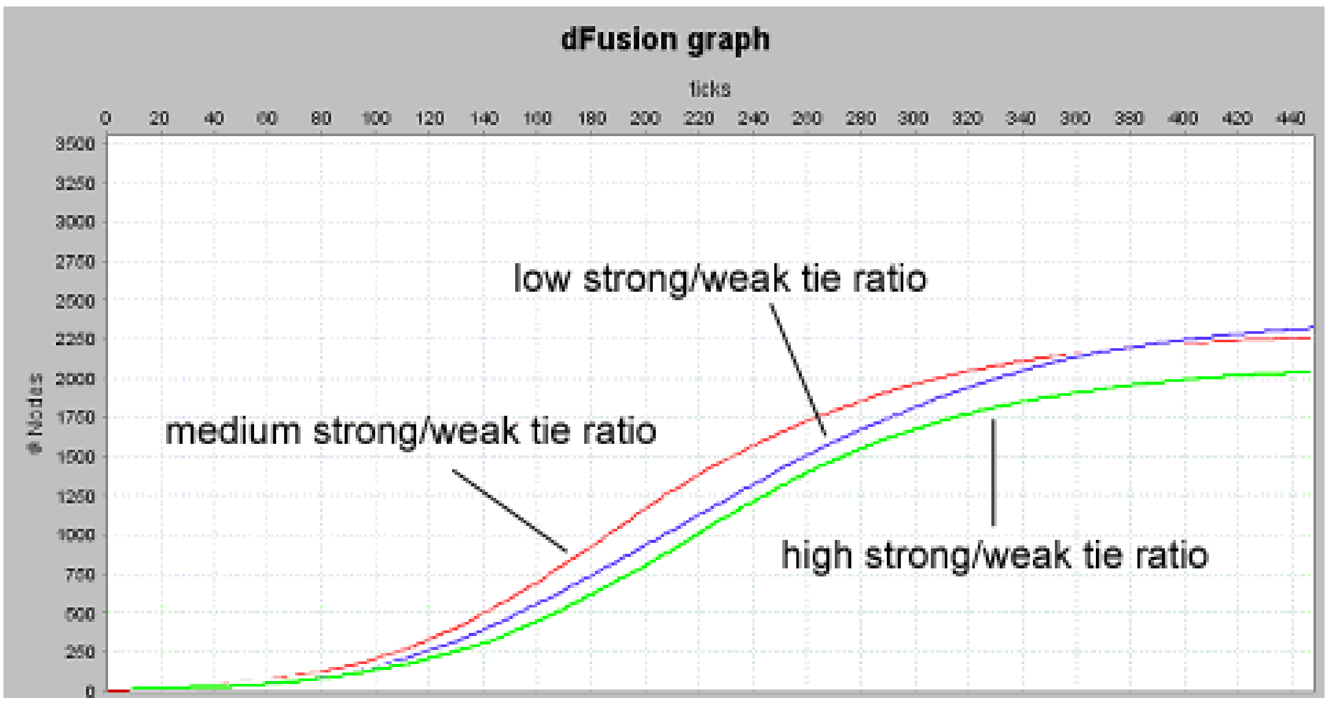
Results

The agent-based model was run for all three datasets. Each dataset was subject to analysis under several permutations of variable values. Specifically, message salience was biased towards high personal salience for half the runs and towards high network salience for half the runs. Social latency was varied between three levels (low, medium and high ratio of strong to weak ties) for half the runs, and controlled for the other half. Similarly, media latency was varied between three levels (corresponding to e-mail usage penetration) for half the runs and controlled for the other half. As a result, each dataset was run with 12 variable permutations at the outset.

The results were markedly consistent across all three datasets. For ease of presentation, we shall only discuss the findings from the Pew Internet and American Life Study here, which are representative of the overall findings. The graphs for the remaining two studies, the UCLA Internet World study and the Metamorphosis Project, are available on request.

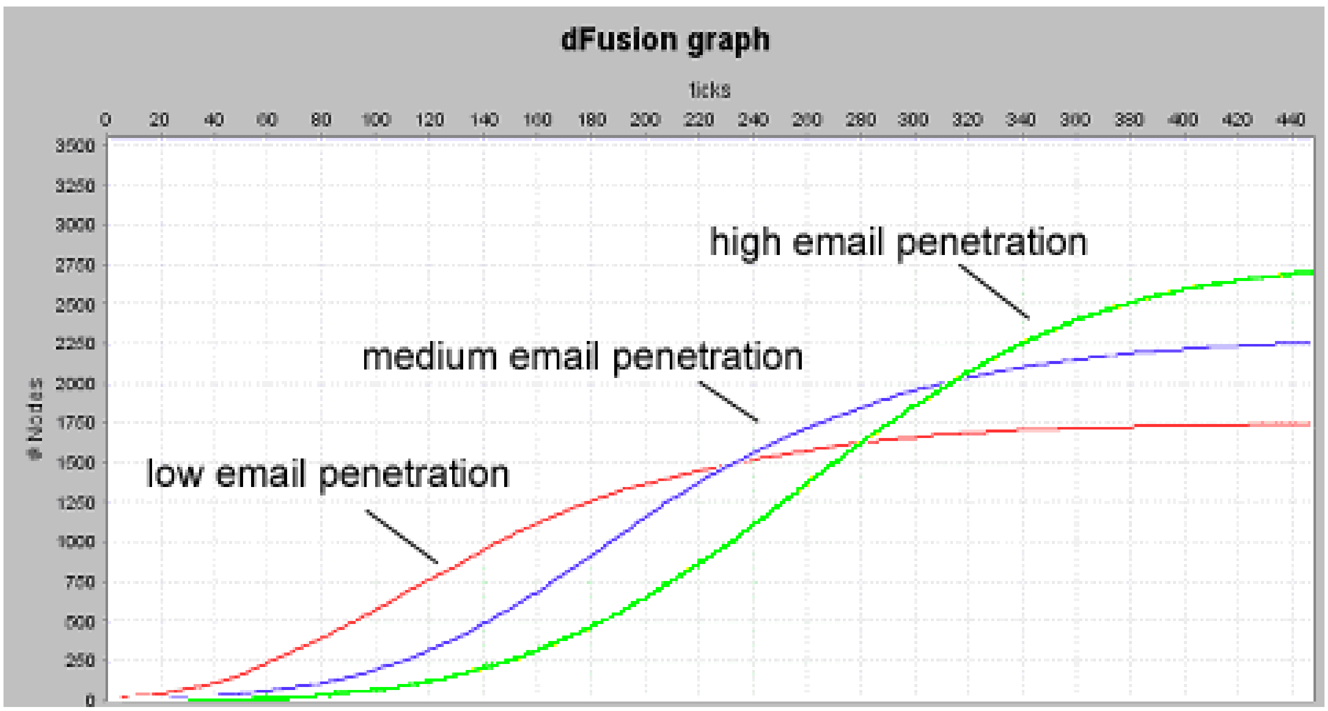
For messages with relatively high network salience, increases in the ratio of strong ties to weak ties led to reduced diffusion of the message, as seen in Figure 2. The information equality of the curve varied as well; however, it did not vary consistently in one direction. The curve demonstrated greatest information equality, moving furthest to the left, in the case of medium-level strength of ties ratio.

***Figure 2*. High network message salience, varying ratio of strong to weak ties**



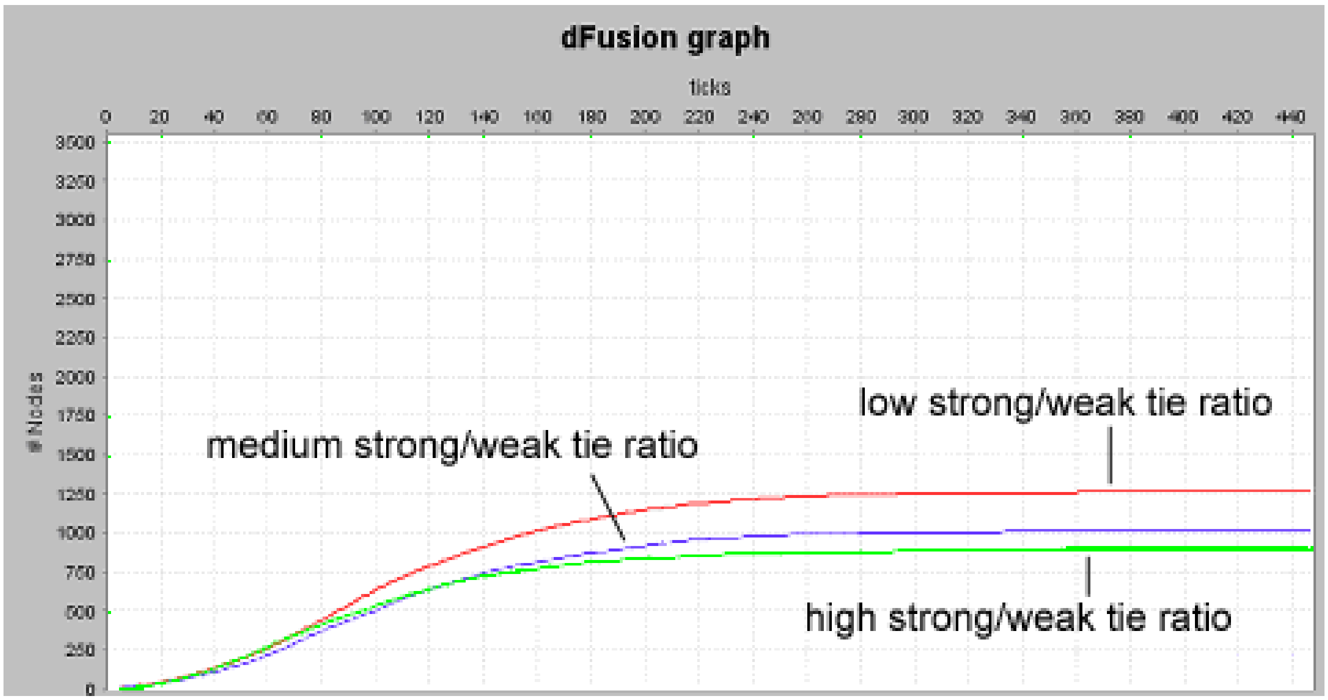
For messages with relatively high network salience, increases in the penetration of e-mail led to increased diffusion of the message, as seen in Figure 3. Additionally, the curve moved to the right, demonstrating lower information equality, with increased e-mail usage in the network.

***Figure 3*. High network message salience, varying penetration of e-mail**



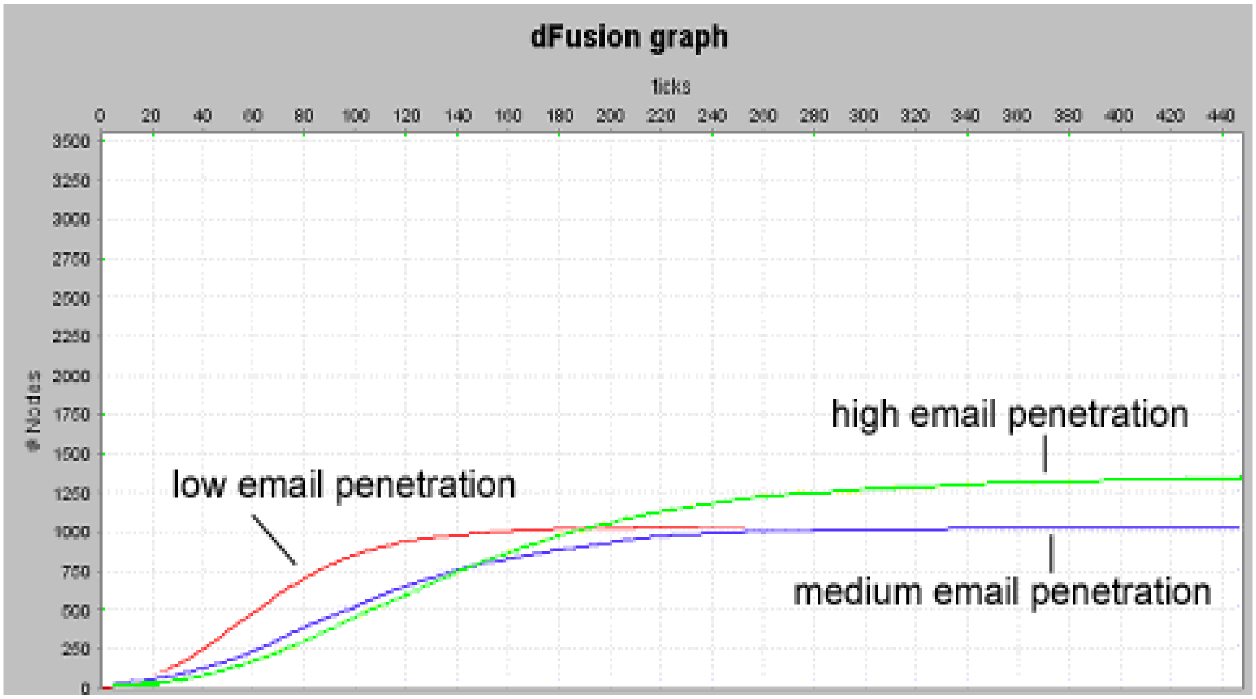
For messages with relatively high personal salience, increases in the ratio of strong ties to weak ties led to reduced diffusion of the message, as seen in Figure 4. The curve moved to the right, indicating reduced information equality, with an increased ratio of strong to weak ties in the network.

***Figure 4*. High personal message salience, varying ratio of strong to weak ties**



For messages with relatively high personal salience, increases in the penetration of e-mail led to increased diffusion of the message, as seen in Figure 5. The curve moved to the right, indicating reduced information equality, with an increased ratio of strong to weak ties in the network.

***Figure 5*. High personal message salience, varying penetration of e-mail**



In all cases, a message with relatively higher network salience achieved greater diffusion as compared to a message with relatively high personal salience. We can observe this result by comparing graphs 2 and 4, and graphs 3 and 5.

The results from the Kolmogorov-Smirnov tests can be seen in Table 1. For the purposes of brevity, in this table we refer to the curves according to a naming convention consisting of the table number they appear in followed the color by which they are represented. For instance, the curve with a low strong-to-weak tie ratio in Figure 2 is referred to as 2Blue. The results are not obtained from the same distribution, but support the hypothesis that each curve is unique.

***Table 1*. Kolmogorov-Smirnov Goodness-of-Fit Test**

Comparison between	D	P-value
2Red-2Green	0.2316	.000
2Green-2Blue	0.3474	.000
2Red-2Blue	0.2717	.000
3Blue-3Red	0.4076	.000
3Red-3Green	0.3653	.000
3Blue-3Green	0.2450	.000
4Blue-4Green	0.5523	.000
4Green-4Red	0.6303	.000
4Blue-4Red	0.5323	.000
5Blue-5Red	0.5791	.000
5Red-5Green	0.5434	.000
5Blue-5Green	0.4388	.000

The results from the curve-fitting are shown in Table 2. The resulting coefficients of multiple determination (R^2) suggest a high degree of explained variance; the corresponding F-Ratios are also provided. We conclude that the curves resulting from the simulation exhibit similarities to higher-order polynomials.

***Table 2*: Curve-Fitting to Higher-Order Polynomials**

Curve	10th Order Polynomial		5th Order Polynomial	
	F	R2	F	R2
2Red	38563453	0.99*	194043	0.99*
2Green	23173926	0.99*	405820	0.99*
2Blue	17798465	0.99*	136531	0.99*
3Blue	38563453	0.99*	194043	0.99*
3Red	12644556	0.99*	394702	0.99*
3Green	41067396	0.99*	313006	0.99*
4Blue	10691913	0.99*	162350	0.99*
4Green	9854749	0.99*	120500	0.99*
4Red	23035468	0.99*	93932	0.99*
5Blue	10691913	0.99*	162350	0.99*
5Red	410641	0.99*	11655	0.99*
5Green	8800826	0.99*	357590	0.99*

* Significant at the .05 level

10th Order Polynomial: Y = a*x^10+b*x^9+c*x^8+d*x^7+e*x^6+f*x^5+g*x^4+h*x^3+i*x^2+j*x+k
5th Order Polynomial: Y = a*x^5+b*x^4+c*x^3+d*x^2+e*x+

Discussion

This study had very promising results, according to both qualitative and quantitative methods of analysis. As Corman (1996) writes:

> *[C]ommunication scholars should not make the mistake of putting CA models completely under the stricture of traditional, formal statistics. CA models are amenable to testing, but the interpretation of social processes as automata, and the intuitive comparison of automatic to actual communication, are equally worthwhile for communication researchers (p. 209).*

Consequently, Corman (1996) recommends an interpretive method relying upon the “qualitative judgments of the modelers and other observers” (p. 207). The vital question regarding the model is, “Does the automaton look, sound, and/or behave like the phenomenon in question?” (p. 207).

Our model does, indeed, look, sound, and behave like the phenomenon in question. In order to produce a model capable of predicting information diffusion patterns through a social network, we incorporated findings from diffusion research and social network analysis into a framework that coupled social latency with media latency as high level independent variables and replicated the findings of knowledge gap and digital divide research. Our criteria for success were the degree to which the resulting diffusion curves resembled the S-curve typical of diffusion processes, and the degree to which the shapes of the curves, representing information equality, would vary as a function of changes to the component variables of social and media latency.

By these standards, our model was quite successful. Under a variety of different initial conditions corresponding with the unique network properties described by our three datasets, the model consistently produced diffusion curves with the “S-shape" described by Rogers (2000) and Bhargava, Kumar and Mukherjee (1993). Furthermore, by making changes to the initial values in our tests, we were able to predict diffusion patterns with visibly different degrees of information equality. These findings are supported quantitatively through the curve fitting analyses in the first instance, and through the K-S tests in the second.

These findings support our assertion that the degree of a network’s information equality is dependent on both social latency and media latency. Additionally, they support Granovetter’s (1973) contention regarding the “strength of weak ties;” as the ratio of weak to strong ties rises in our model, the overall message diffusion level increases. Most importantly, they offer promise that stochastic, agent-based models of information diffusion can serve a vital role in predicting the social effects of new technologies before resources are committed to upgrading the interpersonal communication infrastructure.

Apart from validation of the methodology, the dFusion software produced some interesting results that may shed some light on the diffusion process itself, particularly on the event of the introduction of an ICT into a community. Newer communication technologies may lead to greater message diffusion overall, but they also produce greater inequality in the short term. Diffusion is greater for socially relevant messages than for personal ones. These findings suggest some important implications for community development programs.

Communities with strong ties are inherently less “information equal” than those with a greater portion of weak links. Networks comprised of weak ties tend to produce higher message diffusion and lower latency. The implication for community development projects is that creating links, be they personal or organizational, to new resources outside of the community itself is just as important as strengthening intra-community ties.

Partial e-mail diffusion initially leads to less information equality, but this counterintuitive result may differ depending on the level of technology diffusion. Our current study only tested networks with e-mail diffusion rates limited to the range of 20-60% (which were the numbers suggested by our real-world datasets). Future research should examine the changing information equality within a network given the introduction of a new communication technology. The research should follow this introduction to near universal adoption in order to understand the full range of social implications associated with innovative ICTs.

For messages with high personal salience, marginal increases in the adoption of new ICTs does not lead to greater information diffusion, but rather to lower information equality. This suggests that people substitute the new technology for face-to-face communication within their existing social network, widening existing social gulfs between “haves” and “have-nots.” In the short to medium term, therefore, community development programs should not expect ICTs to either improve the social equality of a target community or speed diffusion of personally salient messages.

Changes in the communications network infrastructure can produce more variance in overall message diffusion than changes in social structure, but only for high network salience messages. Arguably, many of these high network salience messages would, in many real world networks, already be diffusing through mass media, which our current model does not address. Therefore, while improvements in the ICT infrastructure can have important implications for communication campaigns that aim for mass reach, campaigners should moderate their overall diffusion expectations and watch for counterintuitive – and counterproductive – effects on a personal level.

However, this study is only the beginning of a long process. As Corman (1996) notes, “any good model-building effort involves refinement of the model to make it more consistent with observed phenomena” (p. 205). While our current model successfully predicts changes to a network’s information equality based on social and technological variables, the scope of those input variables is still rather limited. In order to make the model “more consistent with observed phenomena,” and thereby to offer more actionable recommendations to community development programs and other information diffusion campaigns, we plan to augment it considerably before testing it further. Among the biggest changes we hope to incorporate into future versions of dFusion are:

- Inclusion of more sociodemographic variables (e.g., race, age, gender) as nodal attributes. These variables should influence the model according to patterns predicted by social network analysis (e.g., homophily) and digital divide research.

- Expansion of interpersonal media channels beyond the current dichotomy. While we are confident in the decision to focus on e-mail and phone/face-to-face in our current model, a more diverse array of communication vehicles (e.g., instant messaging, discrete face-to-face interaction) would clearly increase its verisimilitude.

- Inclusion of mass media. Television, radio, print media, and the Web play fundamental roles in diffusion of information, even viewed at an interpersonal level. Understanding the interplay between these media and interpersonal media will be essential in building a comprehensive model of information diffusion.

- Mobile nodes and geographic clustering. In our current model, nodes inhabit fixed positions within cells, and their locations within the grid are determined randomly at the outset of each model run. In order to tailor the model more effectively to networks under consideration, we plan to geographically cluster nodes based on actual population data, and to allow the nodes to move in space over successive time intervals.

- Dynamic nodal and link attributes. In the real world, the attributes of nodes (e.g., age, education) and links (e.g., strong vs. weak ties) change over time, often as a result of events within the network. Future versions of our model should reflect this potentiality.

- Complex message attributes. Currently, dFusion only allows a single message, introduced at a single moment, with a single probabilistic score for each salience type. Future versions of the model will allow multiple messages, introduced at separate discrete moments, each with additional attributes tailored to interact with nodal attributes (e.g., messages regarding retirement plans are more likely to appeal to older individuals).

- Behavior adoption. Our current model is focused exclusively on information diffusion. This is only the first step in Rogers' (2003) five-step diffusion of innovation process. Future versions of the model will aim to predict attitudinal and behavioral changes as well.

- Naturalistic time and space coordinates. Our current model relies upon a monolithic timetable for all nodes and a square 200 x 200 geographic grid. Future versions of the model will incorporate more realistic geography, and account for differential schedules (i.e., time zones) for different nodes and regions.

Finally, we aim to verify our model by conducting controlled field experiments designed to assess the relationships between social latency, media latency and information equality. Micro-level analyses of actual diffusion processes will ultimately aid us in constructing a model that can successfully and consistently predict emergent macro-level diffusion patterns within a broad variety of social and communications networks.

Appendix A

<u>dFusion v.0.1.1.b Algorithmic Walkthrough</u>

The dFusion algorithm is composed of three distinct processes: spawning, linking and seeding. First, the program spawns the social network by assigning locations and attributes to nodes. Then it assigns links between them. Finally, the program seeds the network with one or more messages, the path of which will be determined by decisions made at the nodal level. The emergent communication pattern cannot be predicted or predetermined by the user. This process is repeated a set number of times, and the resulting data are aggregated and averaged to produce a single set of output data for a given set of input data. A somewhat simplified version of the algorithm is described below; the program containing the full algorithm can be downloaded from http://www.d-fusion.org.

A. Spawning

1. The user assigns variable parameters for the process, including total number of nodes, the links-to-nodes ratio, and the ratio of weak to strong links. The first two parameters will be fixed for all “runs” of the program, while the weak-to-strong ratio will vary from run to run according to a normal distribution around the input value.

2. The program creates a square grid comprised of 40,000 cells – each representing a distinct geographic location.

3. Nodes are added to this grid. Each node is assigned a location and individual attributes which govern ICT usage, as discussed below. Any given node may or may not have access to e-mail, and the ones which do are given a set usage frequency. The percentage of nodes with e-mail access is a fixed value assigned by the user, and the frequency of e-mail use for any given node is determined according to a normal distribution around a mean parameter assigned by the user.

B. Linking

1. The program assigns non-directional links between random pairs of nodes, until the links-to-nodes ratio is met.

2. The list of links is then sorted by geographical distance, from shortest to longest.

3. Each link in the list is assigned a value of “strong” or “weak,” according to a probability derived from the ratio established by the user at the outset. Once the target number of strong links has been reached, the remainder (which represent the greatest geographical distance) are all weak. This process ensures that shorter geographic distances between nodes will be more likely to result in strong links.

4. Each node creates its own list of strong and weak links it shares with other nodes.

C. Seeding

1. A message is created, with intrinsic personal and network salience values (each ranging from 0-5) determined by the user. Each node which receives the message will assign its own salience scores to the message, based on a normal distribution around the input values.

2. This message is seeded to a set number of randomly chosen nodes within the network.

3. At this point, the program starts a “clock” which will last for a user-defined number of “ticks.” Each tick represents an opportunity for any given node to send or receive the message. We conceive of a tick as roughly equivalent to a duration of 15 minutes for the purposes of this study.

4. Nodes begin to relay messages to other nodes, using phone or e-mail. Messages can’t travel from a set sender to a set receiver more than once, and a node cannot send a message back to the node it received it from.

5. If a node receives a message more than once, it increases its network salience score for the message by a user-determined increment. However, both salience scores a node assigns to a message decrease with every tick of the clock.

6. If either the personal or the network salience score a given node assigns to a message is greater than 2.5, the node will attempt to relay the message.

7. The sum of the personal and network salience scores a given node assigns to a message determines what percentage of addressable links it will attempt to relay the message to.

8. Once a node determines a given number of recipients for its message, it must choose which recipient nodes to address. Nodes sharing strong links are more likely to be chosen as recipients if the sending node's ratio of personal to network salience scores is higher. Other that this bias, recipient node assignations are random.

9. If both the sender and recipient nodes use e-mail, the sending node has a choice of which medium to use. If not, phone will be used.

10. The higher the number of recipients a sender would like to reach, the higher chance it will choose e-mail as its vehicle. This is because phone can only reach a single recipient per tick, but e-mail has no limit on the number of potential recipients per tick.

11. Once a node has determined whether, to whom, and via which medium it will send a message, it actually sends the message. If it uses e-mail, it will wait until the next tick determined by the node's user-determined e-mail frequency score. If it uses phone and more than one recipient is chosen, these recipients will be cued, and contacted one-per-tick until the cue is empty.

12. This process continues until the message ceases to circulate through the network, or until the user-defined number of clock ticks is reached.

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