Communication Cost, Attitude Change, and Membership Maintenance: A Model of Technology and Social Structure Development

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Abstract

Voluntary electronic collectives, in which a networked infrastructure supports bounded many-to-many communication, are one of the most common social structures in online contexts. Like other natural groups, features of these collectives, such as member commitment and identity, develop over time. Prior studies of group development provide some indication how voluntary collectives might operate. Psychological studies of group dynamics have considered how members' attitudes change, while structural models have examined the role of member movement in the development of voluntary collectives. However, because existing development models typically do not consider particular communication mechanisms and processes, they provide little insight into how different communication infrastructures will affect the development of voluntary collectives.

This paper integrates the processes of individual belief change and member movement in a dynamic model of voluntary collective development. Contributed messages create a composite signal, providing members with noisy and incomplete information about the collective. This information changes members' beliefs; those beliefs, in turn, are used as the basis for deciding whether or not to continue as a member of the collective. Communication costs, a feature of the communication infrastructure, affect a collective's development by moderating the process of member belief change. The processes of communication, individual belief change, and membership maintenance form a cycle that underlies the development of the collective.

To develop this theory of voluntary collective development, a dynamic, multi-agent computational model was developed, validated, and analyzed. During development, the model was calibrated based on a subset of the empirical data collected from a random sample of e-mail based Internet listservs. Using the remaining data, the model was validated, focusing on the ability of the model to accurately represent a type of structural change in social collectives. A set of virtual experiments was conducted to determine the model's predictions regarding the impact of alternative technologies on collective development. The results imply that reduced communication costs, as are expected in networked environments, slow down the development process, resulting in voluntary collectives which have more (and more diverse) members while also being less stable than traditional face-to-face associations.

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Voluntary collectives¹, in which membership and participation is a matter of personal choice, are a common social structure in online environments. However, unlike the small groups considered in prior studies of computer-mediated communication systems, voluntary collectives are dynamic structures (McGrath and Hollingshead, 1994). Some, including many that might be thought of as "required", see high rates of membership loss as individuals stop regularly looking at shared messages (Butler, 1999a; Whittaker, 1996). Some have high message volumes (Rojo, 1995; Sproull and Faraj, 1997), while many see little or no activity (Butler, 1999a). Their structural characteristics, including size, membership composition, communication volume, and topical diversity, vary significantly between (Butler, 1999a) and within particular collectives (Baym, 1993; Zernhausern & Wong, 1997). Thus while prior research on technology supported small groups may provide some insight, it does not directly address the question of how the use of new technologies affects voluntary collectives.

Face-to-face meetings, print, telephones, and electronic mail are all technologies that can support communication among members of a voluntary collective. Each has associated with it different costs and can support different communication structures. Yet communication is only part of the operation of social collectives: members join and leave, individuals' perceptions and evaluations change, and from these processes the focus and activity of the collective develop. Thus while networked environments may support more efficient communication, it is unclear how altering the communication costs and structures will affect the development of voluntary collectives.

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¹ The term 'collective' is used instead of group when referring to the current research to avoid referencing the metaphor of 'small groups' which is prevalent in existing studies of computer-mediated social behavior. As we have argued elsewhere (Butler, 1998 [paper 1]) many online social structures are not structurally similar to the prototypical small group, and misapplication of this small group model can result in inappropriate conclusions regarding the nature of these structures.

Existing streams of group development research independently consider the role of member attitude change, at the individual level, and membership movement, at the group level, on the development of voluntary collectives (e.g. Tuckman, 1965, 1977; McPhearson, 1983a,1983b,1990). The individual approach to studying social collectives is characterized by a concern with the perceptions, attitudes, and behavior of individuals within small groups. From this perspective, studies of development focus on how members of a collective change over time. (c.f. Gersick, 1988). Social collectives are seen as a context in which to consider individuals' mental state and processes (Moreland, Hogg, & Hains, 1994). Although this approach is concerned primarily with changes in individual members, some theorists have proposed models that characterize the social processes of small groups in terms of developmental stages (e.g. Hare, 1976; LaCoursiere, 1980; McGrath, 1984). The most prominent example, presented by Tuckman (1965; Tuckman and Jensen, 1977), outlines a set of phases: forming, storming, norming, performing, and adjourning.

However, sequential stage models are limited in that they are essentially descriptive models, providing a set of snapshots of a prototypical group (Tuckman ,1965; Hare, 1976; Poole, 1983). They have little to say about the mechanisms which underlie the observed changes (Gersick, 1988) and the sequential structure is a poor representation of the development process (Fisher, 1970; Scheidel & Crowell, 1964; Poole, 1981, 1983). As a result, recent work has begun developing models of the social processes which link individual attitudes and behaviors to developing features of a social collective (Gersick, 1988, 1989; Moreland and Levine, 1982; Worschel, 1996). However, because they have historically focused on small groups that, by definition, consist of a few members meeting face-to-face, these models have had little to say

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about the role of communication and communication technologies in the development processes of social collectives.

Under the structural approach, social collectives are seen not as environments for member change, but as dynamic social entities that arise within larger social systems (c.f. Carley, 1990). Structural theorists characterize this system in a variety of terms, including institutional (Blau, 1967; Etzioni, 1964; Simmel, 1955), ritual (Goffman, 1959), and competitive (Hannen and Freeman, 1977; McPhearson, 1983b; McPhearson and Rotolo, 1996) models. Development studies focus on the social processes, such as membership movement and participation, which underlie the formation and continued existence of collectives as entities. The models typically do not describe the mechanisms that link individual behaviors and the development of social collectives (Carley, 1991). Consequently, with the exception of recent work with computational models of emergent social structures (Kaufer and Carley, 1993; Carley and Wendt, 1991; Carley, 1995a, 1995b) these models, like those considered within the individual approach, do not consider the role of communication or communication technology in the development and maintenance of social collectives.

Although traditional studies of social collectives have typically not considered the impact of alternative communication infrastructures, there is a growing literature about technologysupported small groups and social collectives. Studies of group decision support systems (GDSS) and electronic meeting systems (EMS) have generally adopted the individual approach, considering how the use of new communication technologies change individuals' attitudes, perceptions, and behaviors in small groups (for review see McGrath and Hollingshead, 1994). This work provides insight into the social behaviors of individuals in networked environments. However, as with traditional studies taking this approach, it often unclear how (or if) changes in

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individual members will be reflected in the development of the collective as a whole (McGrath and Hollingshead, 1994).

In contrast, field studies of networked social collectives have generally adopted a structural perceptive, focusing not on individuals but on the processes and structure of social collectives (for review see Butler, 1999a). Through rich description, these studies provide insights into the features of collectives in networked environments. However, much of this work is focused on the project of demonstrating that "real" social activity can occur in online contexts. As a result, it fails to systematically consider how alternative technologies might differentially impact the development process in social collectives.

Drawing from both the individual and structural streams, we propose a model of voluntary collectives that considers the role played by the communication technology. Individual change, in the form of member attitude shifts, and structural change, in the form of membership movement into and out of the collective, are integrated to describe the development processes of voluntary social collectives. Communication activity within a collective acts as a signal, providing information about the emergent features of the membership of that social structure. Communication technology is seen as setting the communication costs incurred by members, costs which impact a collective. Through the communication infrastructure, that signal affects individuals' perceptions; those perceptions, in turn, underlie their decision to continue or end membership in the collective. Thus, the process of individual attitude change underlies the movement of members out of the collective, and together these changes result in the emergent features of collective composition, size, and focus.

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A Model of Voluntary Collectives

The social system considered here consists of a set of N individuals and a collective (C). Unlike recent theoretical studies of social structure, in which groups and collectives are conceptualized as emergent results (Carley, 1991,1995a,1995b; Epstein and Axtell, 1996), a social collective exists as an independent social entity which is known to the individuals within the system. The collective has internal processes that are not emergent (Figure 1). People associate with, interact with, and evaluate a collective, not as a collection of distinct, known individuals, but as a composite social 'agent'.

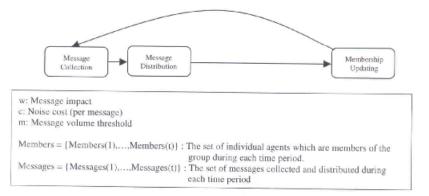


Figure 1: Collective Structure

One of the common features of social groups and associations is that there is some form of communication among the members² (Forsyth, 1990). A voluntary social collective is a socio-technical structure that supports bounded many-to-many communication among a collection of people who individually choose to contribute and be exposed to the communication activity. A collective's membership is the set of individuals (members) who are exposed to and

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² In contrast, nominal groups and psychological groups are defined in terms of individual perceptions and, in theory, may exist without inter-member communication (Forsyth, 1990). However, even for these types of social structure the underlying perceptions are the result of some sort of communication activity.

have access to the collective's communication infrastructure³. Over time, as individuals leave the collective, the membership changes. The membership list is implemented as a binary matrix in which Members_{it} is 1 if individual *i* is a member during time period t and 0 otherwise.

Communication activity within the collective occurs as messages, discrete units of communication each of which has a single topic and is distinguishable from other messages only in terms of that topic. Collective members create messages. After all of the members have made a decision about participating, the set of messages is distributed, exposing each member to the collectives communication activity⁴. The message list is implemented as a matrix in which the entries (Message_{it}) are set as [0,1] values indicating a message topic if individual *i* sent a message during time period *t* and -1 otherwise⁵. The set of non-negative values in a column of the Message matrix (Message_t) describes the communication activity within the collective during time period *t*. After all of the members have processed the messages, updated their evaluation of the collective, and made a decision about maintaining their membership, the collective's membership list is updated. Members are only removed from the membership list if they explicitly decide to terminate their membership. Consequently, once an individual agent is added to a group's membership it remains a member, and sees all group messages, until it takes explicit action to terminate its connection with the group⁶. This processes of message gathering,

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³ Although this definition of membership may seem limited to collectives which make use of computer-mediated communication systems, it can also describe more traditional settings. For example, one might define membership in a hobby group in terms of attendance of a minimal number of meetings. This is the face-to-face equivalent of maintaining exposure and access to the collective's communication infrastructure.

⁴ Although this process is described in terms of 'distributing' messages it is implemented by having all member agents process each entry in the message list. Thus, while there is no transfer of data to members, all members are exposed to each of the messages.

For modeling convenience individuals are restricted to sending at most one message per period.

⁶ Future models might also consider the dynamics of collectives in contexts, such as Lotus notes or USENET, which make use of pull technologies. In those cases, maintaining membership is not a passive activity; exposure to communication activity occurs only as the result of repeated active decisions by the individual.

distribution, and membership adjustment (Figure 1) forms a cycle which iterates once per time period.

Collectives make use of various communication infrastructures. Traditional social collectives rely on face-to-face meetings, tightly knit networks of interpersonal contacts, or paper-based print media. Audio, video, and real-time text conferencing, e-mail distribution lists, and groupware (e.g. Lotus Notes and USENET) are all technologies which can support voluntary social collectives. The technologies used within a collective determine the communication costs incurred by its members. Different technologies allow for different forms of communication, resulting in different costs and structures. A collective's noise cost (c), message impact (w), and message threshold (m) reflect the features of the technological infrastructure. Noise cost (c) is the cost incurred by a member as a result of processing a message that is outside the individual's interests (i.e. noise). The value of this parameter is modeled relative to normalized signal benefit, a value that represents the maximum net benefit the individual receives from processing an interesting message. In this implementation, the normalized signal benefit is fixed at 1, and noise cost is set in terms of the percentage of this value (c.g., noise cost = X implies that the costs incurred processing noise are X% of the normalized signal benefit). Message impact (w), or the weight given to single units of communication as individuals learn about the group, is set as [0,1] value. Message threshold (m) is the number of messages of interest a member can receive in a day before the benefits of those messages are outweighed by the costs of processing them. Within different infrastructures, the features of communication vary, and as result different collectives have different cost and impact structures.

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Although they are identifiable social entities, voluntary collectives also have emergent features. Communication is not the result of a unified activity, but rather the action of individual members. Membership is maintained not by a coordinated process, but by the choices of independent individuals. People involved with voluntary collectives contribute messages, process other messages, and, based on their perceptions and expectations, decide whether to continue or maintain their membership (Figure 2). This three stage cyclic model of communication, learning, and action is similar to those proposed by Turner (1988) and Carley (1991) as underlying the development of emergent social structures.

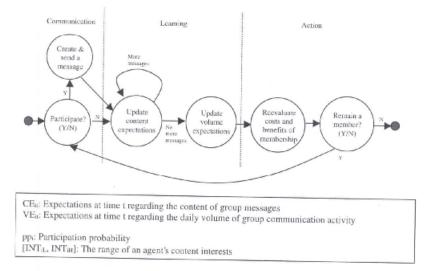


Figure 2: Individual Structure

Individuals participate in a collective's communication by constructing messages which are then sent to the other members. Following prior work on participation in social groups (Skvoritz, 1988) and information sharing in decision-making teams (Wittenbaum and Stasser, 1996), each individual's message contribution behavior is modeled as the result of an

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independent stochastic process. An individual chooses to contribute a single message in a time period with a given probability (pp), which may vary between individuals but does not change over time. Upon choosing to participate, an individual creates a message, selecting a topic from his interests. The message is then passed to the collective for distribution to the members.

In this implementation of the model, an individual's interests are represented here as a range of values ($[INT_{I}, INT_{H}]$) which define an arc within a collective's circular [0,1] topic space. A message is constructed by selecting a random value from a uniform distribution over this range.

An individual's relationship with a social collective develops over time (Moreland and Levine, 1982). As they are exposed to a collective's activities, members' expectations about the focus (CE_{it}) and volume of activity (VE_{it}) change. Content expectations are implemented here as a matrix of [0,1] values in which CE_{it} is individual *i*'s expectation in time period *t* regarding the probability that future messages in the collective will be of interest to him. Volume expectations (VE_{it}) are positive values representing individual *i*'s expectations at time *t* about a collective's future daily message volume.

In addition to their primary function of supporting the collective's activities, the messages also serve a secondary purpose of providing information about the collective's focus. As a member of a collective, an individual is exposed to messages. Based on this exposure, individuals then change their expectations about the collective's focus and level of activity. This change in beliefs about the collective is implemented as a reinforcement process (Hunter, Danes, and Cohen, 1984), where the change in an individual's content expectations (ΔCE_{it}) is determined by:

 $\Delta CE_{it} = rw[CE_{i(t-1)}][1 - CE_{i(t-1)}]$

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where *w* is the message impact parameter, which is inherited from the collective, and r denotes the individual's reaction to the message; r = 1 if the message is of interest, and r = -1 otherwise. A message is deemed interesting when its topic (MsgTopic) falls within the arc defined by the individual's interest parameters (INT_{iL} and INT_{iH}). When multiple messages are distributed in a time period, the change in content expectation is computed separately for each message. After all messages have been received, volume expectations for the time period (VE_{ii}) are set to the observed mean message volume for all previous time periods.

Individuals' expectations about the future activities of a collective underlie their assessment of the rewardingness of membership (Moreland and Levine, 1982). After adjusting their beliefs in response to being exposed to a set of messages, individuals assess the expected costs and benefits of continued membership. This assessment takes into account the expected benefit from messages that are of interest to the individual, a benefit that is subject to limits. Individuals have strict limits on the time available to them. As more time and attention is 'spent' processing messages, the remaining time is more valuable. Thus as the amount of interesting materials increases, the incremental net benefit of an additional interesting message in the same time period is lower. The assessment also considers the costs incurred as a result of processing uninteresting, or noise, messages. Expectations of the content and volume of activity (CE_{it}, VE_{it}) and the known costs of processing messages within the collective's communication infrastructure (m,c) are combined to assess expected costs and benefits of continued membership. This assessment is implemented with the following formula:

 $E_{it} = E(CE_{it}, VE_{it}; c, m) = (-1/2m)(CE_{it}VE_{it})^2 + (CE_{it}VE_{it}) - c((1 - CE_{it})VE_{it})$

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The first two terms $[(-1/2m)(CE_{it}VE_{it})^2 + (CE_{it}VE_{it})]$ indicate the total expected net benefit due to messages which are expected to be of interest. The final term $[-c((1-CE_{it})VE_{it})]$ is the expected costs due to noise messages.

Individuals' assessment of the costs and benefits determines their willingness to maintain membership in a collective (Moreland and Levine, 1982). If the expected net benefit is positive, the individual will choose to remain a member; otherwise she will choose to terminate membership and leave the group. Membership termination is modeled as the individual choosing to send a signal to the collective, requesting removal from the membership list.

Within a social system individuals and collectives interact, and from those interactions arise the emergent features of collectives. Individuals pass messages to a collective, the collective then passes those messages on to its members (including the sender). After responding, members then may request that the collective remove them from the membership list, an action which results in the individual not being exposed to future messages.

The individual (Figure 2) and collective (Figure 1) processes are different components of a social system containing a single collective with an initial membership of N (Figure 3). This system can be described in terms of a communication infrastructure, represented by the noise cost (c), message impact (w), and message threshold (m) parameters; a participation structure, represented by the distribution of participation probabilities (pp_i) in the population of individuals; and an interest structure, represented by the population distribution of individual interests⁷.

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⁷ In the current implementation, a uniform interest structure is assumed. A maximum interest range is specified. For each individual a interest range length is selected randomly from a uniform distribution bounded by 0 and the specified maximum. A interests base point' is also selected, from a [0,1] uniform distribution. The range and base point are then used to specify the individual's interest range [INT_{iL} = BasePoint, INT_{iH} = BasePoint + Range]

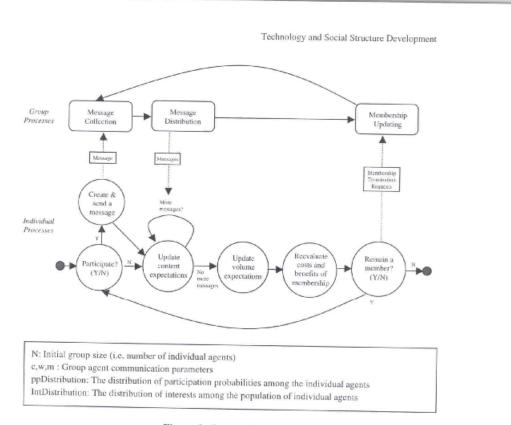


Figure 3: System Structure

The current implementation of this composite system is lockstepped. All individuals perform an action before anyone moves to the next step in the process. Within a given step, the individual agents are executed in a fixed sequence. After the individuals have completed a step, the collective performs any relevant activities. All individuals make a choice about contributing messages, create messages, and send them to the collective before the messages are distributed to the membership. Likewise, all individuals decide about continuing membership before the collective updates the membership list and starts accepting new messages.

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Development of Voluntary Social Collectives

As members are exposed to communication within a collective, their beliefs about the collective change. Developing beliefs alter individuals' assessments of the benefits of being part of the collective, changing their level of commitment and possibly causing them to end their membership (Moreland and Levine, 1982). Member movement changes the composition and size of a collective's membership, which is reflected in the development of its aggregate interests and the focus of its communication activity. These changes, in turn, affect the development of remaining member's beliefs.

The simultaneous development of member commitment and the structural features of a collective's membership is a result of the cycle of individual and structural change processes. As the following example illustrates, these development processes can be seen in the proposed model of voluntary social collectives⁸. The mean commitment level among members converges to a stable value (Figure 4).

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⁸ The example was the result of a single run of the model (as coded in Appendix A) with the following parameters: N = 75 ; PartProb = 0.0749; w = 0.05; c = 0.1; m = 5 ; INTRange = 0.6132. These results were chosen as representative after running a virtual experiment which systematically varied w,c,and m and randomly varied N, PartProb, and INTRange.

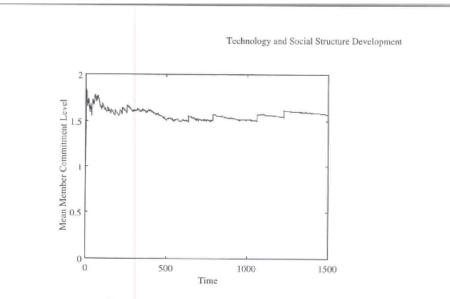


Figure 4: Mean Member Commitment

Changes in the mean level of member commitment with a voluntary social collective arise from two processes. The smooth progression of the mean toward a stable point is the result of core members commitment converging on a common value, while the abrupt shifts are the result of peripheral members terminating their membership.

The trajectories of individual's commitment development illustrate how these two processes play out within a social collective (Figure 5).

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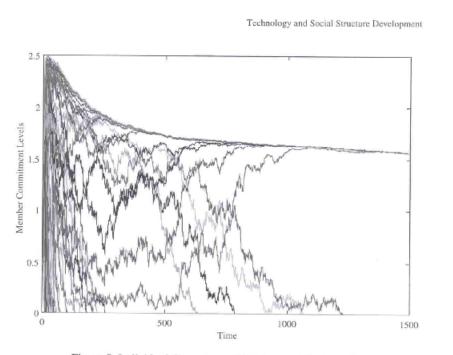


Figure 5: Individual Commitment Development Trajectories

Jumps in the mean level of member commitment occur as individuals who have lower commitment choose to end their membership. These abrupt shifts occur in tandem with the convergence of remaining members' commitment to a common level, as a result of their development of strong beliefs about the content of future communication activity.

The combination of individual and structural change also results in several emergent phenomena that are consistent with prior conceptual models of social collective development. For example, the minimum level of member commitment, another indication of a collective's development, is expected to suddenly shift (Figure 6).

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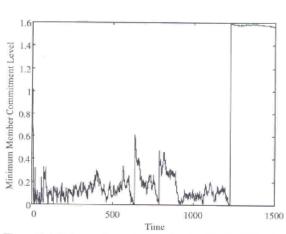


Figure 6: Minimum Commitment Level with the Collective

This shift in the minimum level of commitment may underlie significant changes in the operation of the collective, not unlike the development phases proposed by Tuckman (1965) or the transitions observed by Gersick (1988, 1989).

Another feature of social structure development seen in this example is the emergence of an interest focus. Although it is common to refer to a social collective's 'interests', especially in discussions of online collectives (Baym, 1993; Kollock and Smith 1997), even in formally managed settings, collective communication activity is actually the aggregate result of members' individual choices. The true focus or interests of a collective are not a monolithic construct, but an emergent one which arises from the actions of its members. As a collective's membership develops, the distribution of interests among the members changes (Figure 7).

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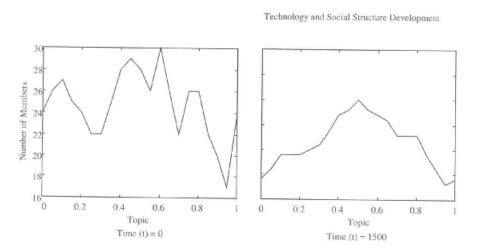


Figure 7: Development of a Collective's Interest Distribution

In the extreme, a collective's membership becomes stable. When stability is reached the distribution of interests⁹ is roughly normally distributed (Figure 7). Thus, although there is no formally defined interest specification, a collective still develops an interest focus as a result of member and structural change processes.

Model Calibration

Calibration is the process of adjusting a computational model to reflect the features of empirical data. This process provides a conceptual reference point for validation and analysis of the model. Calibration of the voluntary collectives model is based on empirical data from a sample of e-mail based Internet¹⁰ listservs. These collectives utilize Internet-based electronic mail and a centralized mailing list to enable individuals to broadcast text-messages to other members. Although there may be an individual who is responsible for maintaining the technical infrastructure (i.e. the listowner) the sampled collectives are unmanaged, voluntary collectives.

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⁹ A modeled collective's interest distribution is characterized by determining the number of members with interests at twenty equally spaced points within the collective's [0,1] topic space.

Individuals are free to enter, leave, or send messages as they please. Listowners take no formal steps to restrict membership or message content.

From a population of approximately 70,000, an initial set of 1066 listservs was created. This initial sample was stratified, to ensure that it spanned a range of topic and member communities. One third focused on work-related topics. One third focused on personal topic (hobbies, lifestyles, etc.). The remaining collectives were associated with topics that mixed work-related and personal interests (e.g geographic locations).

The initial sample was filtered through a multiple stage confirmation process that screened out managed collectives, i.e. moderated listservs and those with formal new member screening. This selection process also verified that each listserv was mechanically functional, able to provide the needed data, and available for inclusion in the study (for more details on sample selection process see Butler, 1999a). The result of this process was a sample of 217 listservs. 192 of these collectives provided data that could be used to construct measures of membership change and communication activity.

For a 130 day period, between July 23, 1997 and November 30, 1997, communication and membership data was collected for each listserv. The communication data consisted of all messages, which were aggregated to create collective-specific archives of all communication activity that occurred during the observation period. During the data collection period a copy of each collective's membership list was requested daily. These lists were archived to create a record of the changes in collective membership during the observation period (for more details on data collection procedures see Butler, 1999a and Butler, 1999b).

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¹⁰ The relevance of the Internet here is that it is a public network environment. This is to be contrasted with an organizational network in which participation in a collective is limited to a relatively small number of organization members.

The message and membership archives characterize the structural features of the listservs. Measures of these structural features serve as the basis for calibrating the model. The empirical data was used to construct measures of daily communication volume and percentage membership loss. Daily communication volume was calculated by determining the total number of messages distributed to the members during the observation period and dividing that by the number of days (i.e. 130). Percentage membership loss was determined by counting the number of people who left the listserv during the observation period and normalizing it by the number of members present on the first day of the observation period (i.e. the collective's initial size)¹¹. These measures were used to assess two aspects of the sampled online collectives: the distribution of communication volumes and membership loss was also assessed (see Butler, 1999b for more analysis of the relationship between structural features of online social collectives).

From the full sample of listservs¹², 100 were randomly selected to be the calibration sample and the remaining 92 listservs were used as the validation sample. Calibration was performed with a series of sessions. Each session involved simulating 100 collectives and comparing the resulting distributions and relationships with data from a randomly selected subset of 100 listservs from the empirical sample. In each calibration run, one or more of the model settings were modified to better reflect the features of the observed collectives. Also, to better represent the state of the empirically observed collectives, all of which were known to be at least four months old, each calibration run included two phases. The first phase, a 100 time period

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¹¹ Membership loss could not be calculated by simple subtraction (initial size – final size) because these collectives also had members entering during the observation period, a process that is not considered in the current computational model.

computational model. ¹² In several cases there were major problems creating the structural measures due to the presence of membership management activities (i.e. manipulation of the membership by the listowner) or the occasional presence of nonstandard message formats. The cases were dropped, leaving a total sample of 192 listservs.

initialization phase, was run to represent a collective's prior history. The second phase, with 130 time periods, was then run and the results compared with data from the online collectives.

The initial calibration run was performed with the following model settings:

Model Setting	Value
N	100
c	0.33
w	0.05
m	15
ppDistribution	Fixed @ 0.005
Interest range distributions	Uniformly distributed between 0 and MaximumInterestRange, a value which is chosen for each group from a uniform distribution between 0.25 and 0.75
Initial CE(0) distribution Initial VE(0) distribution	Uniformly distributed between 0.5 and 1 Fixed @ 1

Table 1: Model Settings for Calibration Run #1

The distribution of initial content expectations (CE(0) distribution) was set based on the premise that voluntary members would, at least early on, have positive expectations regarding the collective's communication content. Individuals are therefore assumed to initially expect at least a majority of the communication activity to be of interest (i.e. CE(0) would be distributed between 0.5 and 1 for the initial members). Similarly, it is assumed that individuals would not voluntarily join which they expect to have no communication activity. Consequently, initial volume expectations (VE(0)) were set at 1 to indicate a uniform initial expectation of one message per day.

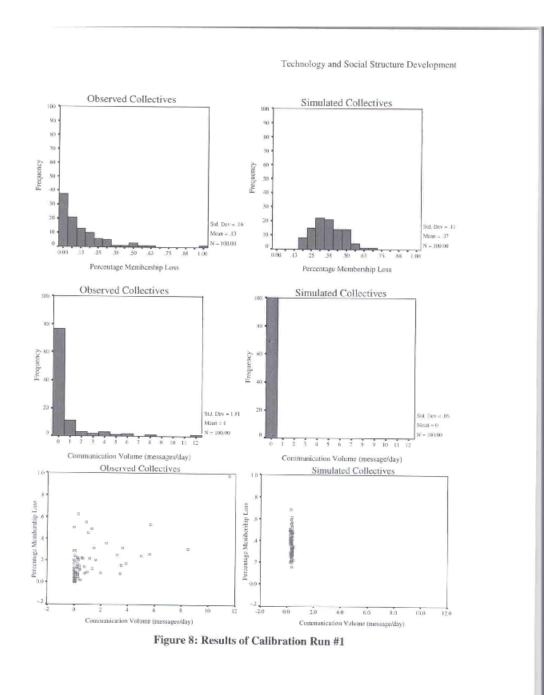
As described above (and in Butler, 1999a), the sample of e-mail based Internet listservs was selected to ensure that the sampled collectives varied in terms of the member populations that they drew from. This variation is most clearly reflected in the range of topics represented in the sample. However, it is also likely to result in interest ranges varying within the collectives, with some being attractive to individuals with narrow, well-defined interests and others

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appealing to individuals with a wider range of interests. This diversity within the sample is reflected in the setting of the interest range distribution. The largest interest range within a collective is randomly selected from a uniform distribution between 0.25 and 0.75. Then within each run the individual's interests ranges are set by selecting one end point from the topic space (uniform distribution) and selecting an interest range size from a uniform distribution between 0 and the modeled collective's maximum interest range. These settings represent variety in interest structures at both the individual and population level.

Overall, the empirical results from the online collective are not well represented by this instantiation of the model (Figure 8 & Table 2).

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		Observed	Collectives	Simulated (Collectives
		Percentage fembership Loss	Communication Volume (messages/day)	Percentage Membership Loss	Communication Volume (message/day)
Mean		.125	.770	.368	.330
Median		.078	.062	.366	.328
Mode		.000	.000		.328
Std. Deviation		.164	1.806	.105	.059
Skewness		2.342	3.679	.360	.011
Std. Error of Skewness		.241	.241	.241	.241
Kurtosis		7.533	15,808	~ 230	249
Std. Error of Kurtosis		.478	.478	.478	.478
Percentiles	25	.000	.000	.287	292
	50	.078	.062	.366	.328
	75	.198	.456	455	.366
	3		ist. The smallest value is N = 100		

Table 2: Distribution Statistics for Calibration Run # 1

	Observed	Simulated
Pearson's Correlation	0.629*	-0.203*
Spearman's Rho	0.688*	-0.198*

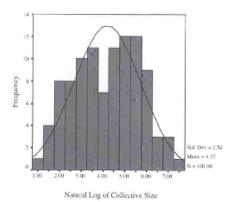
N = 100

Table 3: Relationship between Communication Activity and Membership Loss

Unlike the observed data, in the computational collectives both percentage membership loss and communication volume are normally distributed (Figure 8). In addition, the predicted relationship between these measures is negative, not positive as in the empirical data (Table 3). *Calibration Run #2: Size Distribution*

One of the most unrealistic aspects of the model settings used in the first calibration run is the use of a single value for membership size among the computational collectives (N = 100). In the empirical sample the initial collective sizes vary according to a log-normal distribution (Figure 9).

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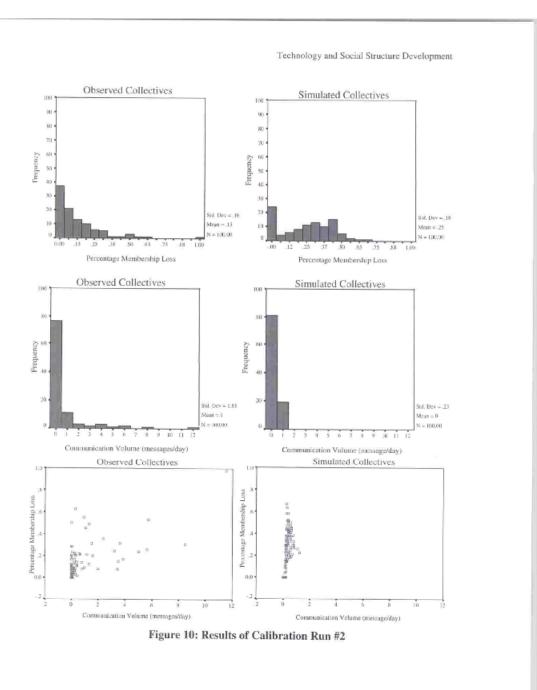




To more accurately reflect this aspect of social collectives, the second calibration run was performed with initial membership sizes (N) drawn from a log-normal distribution with a mean of 4.17 and standard deviation of 1.54. All other model settings were unchanged (see Table 1). Although the result of this instantiation of the computational model are a closer match

with certain aspects of the empirical data, there remain several significant differences (Figure 10, Table 4, and Table 5).

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		Observed	Collectives	Simulated (Collectives
		Percentage Membership	Communication Volume	Percentage Membership Loss	Communication Volume
		Loss	(messages/day)		(message/day)
Mean		.125	.770	.246	316
Median		.078	.062	.262	.267
Mode		.000	.000	.000	-183
Std. Deviation		.164	1.806	.184	.230
Skewness		2.342	3.679	.061	1.179
Std. Error of		.241	.241	.241	.241
Skewness					
Kurtosis		7.533	15.808	-1.021	2.051
Std. Error of		.478	.478	.478	.478
Kurtosis				0.08	1110
Percentiles	25	.000	.000	.043	.141
	.50	.078	.062	.262	.267
	75	.198	.456	.399	.433
	a	Multiple modes ex	in. The smallest value α N = 100		.4.57

Table 4: Distribution Statistics for Calibration Run # 2

	Observed	Simulated
Pearson's Correlation	0.629*	0.519*
Spearman's Rho	0.688*	0.682*

N = 100

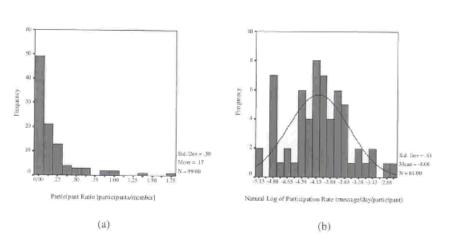
Table 5: Relationship between Communication Activity and Membership Loss

Use of an empirically derived distribution of initial collective sizes resulted in a predicted relationship between percentage membership loss and communication that is similar to the observed relationship (Table 5). However, the membership loss and communication volume distributions in the population of computational collectives are structurally different that the results seen in the empirical data (Figure 10).

Calibration Run #3: Participation Distribution

The settings used in the first two calibration runs assume that participation is uniformly distributed among all members of the collective. However, in the observed listservs, participation is concentrated among a subset of the membership (Figure 11).

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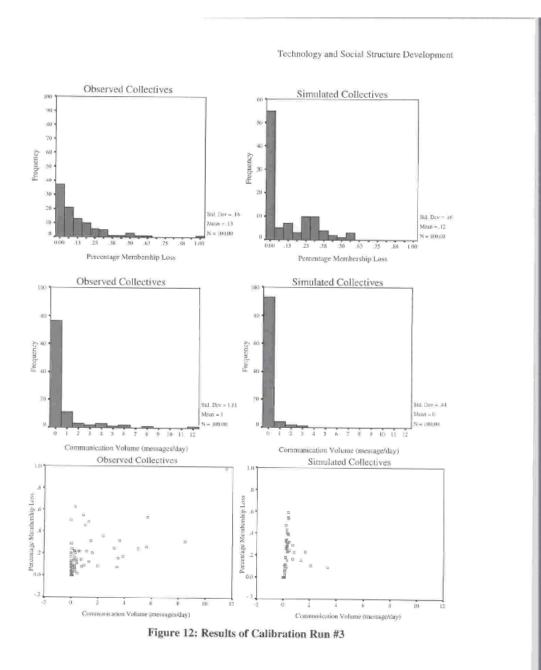


In the third calibration run, the participation structure for a collective is constructed in two steps. In the first step, a participation ratio is selected from an exponential distribution with a mean of 0.17^{13} (Figure 11a). The participation ratio, which is the proportion of individuals who will contribute any messages to the group, is used to probabilistically label individual agents as non-participants (participation probability (pp) = 0) or participants (pp > 0). The individual agent's participation probability is then set as a fixed value which is drawn from a log-normal distribution with a mean of -4.08 and standard deviation of 0.53 (Figure 11b). Otherwise, the model parameters were identical to those used in calibration run 2.

The results of the third calibration run (Figure 12, Table 6, and Table 7) indicate that this instantiation of the computational model is incrementally more similar to the empirical data.

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¹³ As Figure 11 clearly indicates, there is an outlier in the distribution of participation ratios (11.57). This collective was not included in the calculation of the mean participation ratio used to calibrate the model.



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		Observed Collectives		Simulated (Collectives
		Percentage Membership Loss	Communication Volume (messages/day)	Percentage Membership Loss	Communication Volume (message/day)
Mean		.125	.770	.119	.226
Median		.078	.062	.000	.099
Mode		.000	.000	.000	.000
Std. Deviation		.164	1.806	.160	444
Skewness		2.342	3.679	1.115	4.735
Std. Error of Skewness		.241	.241	.241	.241
Kurtosis		7.533	15.808	.116	27.177
Std. Error of Kurtosis		.478	.478	.478	.478
Percentiles	25	.000	.000	.000.	.015
	50	.078	.062	.000	.099
	75	.198	.456	.250	.275
	2	Mulaple modes e	xist. The smallest value is N = 100	stuwn	

Table 6: Distribution Statistics for Calibration Run # 3

	Observed	Simulated
Pearson's Correlation	0.629*	0.290*
Spearman's Rho	0.688*	0.851**

N = 100

Table 7: Relationship between Communication Activity and Membership Loss

Although the relationship between the volume of communication activity and membership loss was slightly affected it remains positive (Table 7). The distribution of communication volumes was slightly more right-skewed, while the percentage member loss distribution shifted to the left (Figure 12).

Calibration Run #4: Communication parameters

Unlike initial size and participation structure, the communication parameters (noise cost, message threshold, and message impact) are unobservable. In the initial model calibration runs, these settings were chosen arbitrarily. However, in the fourth, and final, stage of model calibration these model settings were varied. Values incrementally higher and lower then the settings used in prior calibration runs (see Table 1) were used to select the parameter values

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which resulted in distributions of percent member loss and daily volume which most accurately reflect the empirical observations. Model threshold values of 2, 5, and 8 were used to represent a range of message thresholds. These values were chosen because cover a low to high level of activity relative to the levels of message activity seen in the listservs (Mean daily activity ≈ 0.2 messages/day; Maximum mean ≈ 3 messages/day). Likewise, the noise cost is varied to reflect situations in which the cost of noise is low (0.1) and those in which the cost of unwanted messages is directly comparable to the benefit received from messages of interest. Finally, the message impact parameter is set at 0.01, 0.05, and 0.09 to model situations in which messages are seen as providing weak, medium, or strong indications of the content of future communication activity.

Each of the 27 (3x3x3) communication parameters combinations were used for 100 groups. Each condition was then compared, both with one another and with the empirical data to characterize the impact of the communication parameters, and select the condition which best fit the data.

						W				
		0.01	0.05	0.09	0.01	0.05	0.09	0.01	0.05	0.09
0.10	Mean	0.03	0.12	.0.12	0.02	0.12	0.16	0.05	0.11	0.16
0.10	Median	0.00	0.00	00.0	0.60	0.00	0.01	0.00	0.00	0.00
0.33	Mean	0.05	0.12	0.19	0.06	0.20	0.17	0.05	0.12	0.19
0.32	Median	0.00	0.00	0.19	0.00	0.21	0.12	0.00	0.00	0.18
1.00	Mean	0.08	0.18	0.18	0:08	0.17	0.21	0.08	0.20	0.19
1,00	Median	0.03	0.18	0.16	0.05	0.15	0.20	0.03	0.16	0.20
			M = 2.0	3		M-<0	0		10-00	

Table 8: Mean and Median Values for the Distribution of Percentage Membership Loss in Computational Collectives

By comparing the percentage membership loss distribution location measures (mean and median) for a variety of model settings (Table 8) with the empirically observed data (mean = 0.125; median = 0.078), the model settings of c = 1.0, m = 5.0, and w between 0.01 and 0.05 were selected. To further refine these settings, a supplementary calibration run was performed

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with the settings of c = 1.0, m = 5.0, and w = [0.01, 0.02, 0.03, 0.04, 0.05]. All other model settings were identical to those used in calibration run 3. For each of the 5 combinations 100 collectives were simulated.

	W						
	0.01	0.02	0.03	0.04	0.02		
Mean	0.09	0.11	0.13	0.17	0.17		
Median	0.05	0.07	0.09	0.13	0.15		



Based on the results of the secondary calibration run (Table 9), the message impact parameter (w) was set at 0.02.

The structure and location of the distribution of percentage membership loss results from the computational collectives is comparable to that observed in the empirical data (Figure 13, Table 10, and Table 11).

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Model Setting	Value
N	Log normally distributed [LN(4.17,1.34)]
c	1.0
W	0.02
m	5
ppDistribution	Ratio of Participants (i.e. pp > 0) to Members is exponential with = 0.17;
Interest range distributions	All participants have the same participation probability (drawn for the group from a log normal distrubition [LN(-4.03,0.53)] Uniformly distributed between 0 and MaximumInterestRange, a value which is chosen for each group from a uniform distribution between 0.25 and 0.75
Initial CE ₀ distribution	Uniformly distributed between 0.5 and 1
Initial VE ₀ distribution	Fixed @ 1

Table 12: Model Settings for E-mail Based Internet Social Collectives

Calibration used empirical data about structural change and communication activity in e-mail based Internet listservs to identify a baseline set of parameters for the computational model of social collective development. These settings provide a reference point for the subsequent validation and analysis of the model.

Model Validation

Validation is the process of comparing the results of a computational model with empirical data for the purposes of testing the model. Unlike calibration, in which the parameters of the model are adjusted to identify the most appropriate settings, during validation the proposed parameters and processes are taken as given, the model is run, and the outcomes are compared with empirical data. The results of this process provide information about how well, and under what conditions, the computational model accurately represents the intended phenomena.

The computational model of social collective development was validated using structural change data from the 92 listservs that were not used for calibrating the model. The model was

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validated using a variation of the correlated inspection approach (Law & Kelton, 1991). The empirically observable model settings, initial collective size (N) and the participation structure (as described by the participation ratio and participation probability), were set based on the data from a single listserv in the validation sample. The communication parameters (noise cost (c), message weight (w), and message threshold (m)) and initial conditions (CE₀ and VE₀) were set based on the results of model calibration. Based on these model settings, 10 model runs were performed. For each run, the remaining unobservable model setting, the variation in the collective's member interest ranges (INTRange), was randomly selected from a uniform distribution between [0.25,0.75]. The mean percentage membership loss and mean daily communication volume for the set of 10 computational collectives were then recorded as the predicted structural outcomes. This process was repeated for each listserv in the validation sample.

Comparison of the predicted and observed outcomes with paired t-tests indicates that, overall, there is not a statistically significant difference between the model's membership loss predictions and the empirical data (H₀: $\mu_{predicted} = \mu_{observed}$; p = 0.263). There is a significant difference between the predicated and observed values for communication activity (H₀: $\mu_{predicted}$ = $\mu_{observed}$; p < 0.01). As was observed during the calibration process, the model under-predicts the communication activity ($\mu_{predicted} = 0.408$ and $\mu_{observed} = 0.795$).

OLS regression analysis of the membership loss error (Table 13) indicates that the model is most accurate for collectives with low membership loss. The model also tends to overstate the membership loss when applied to larger and more active collectives.

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	Dependent Variable						
	Membership	Loss Error	Message Volume Error				
	Unstandardized	Standardized	Unstandardized	Standardized			
Intercept	0.051***		0.0251				
Initial Size	0.00012**	0.209**	0.0013***	0.242***			
Observed Message Volume	0.025***	0.301***	-0.7585***	-1.011***			
Observed Membership Loss	-0.818***	-0.882***	-	-			
Adjusted R ²	0.572		0.9	55			

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Table 13: OLS Regression Analysis of Computational Model Error

The results of error analysis, along with graphical inspection of the relationship between the error and empirically observed levels of activity, imply that model error is greatest when it is applied to collectives with high levels of communication activity (> 3 messages per day). However, because the distribution of activity levels in online voluntary collectives has been seen to be highly skewed (Butler 1999a) this error should not significantly bias conclusions when considering the majority of these social structures.

The validation and error analysis results indicate that the model provides reasonable predictions for membership loss. Furthermore, they imply that the model is most accurate for collectives in the range of sizes and activity levels that are most common. Thus, the computational model can be seen as providing an accurate representation of the structural development of these social collectives.

The Impact of Communication Cost on Collective Development

One of the most often discussed features of networked communication environments is their ability to reduce the costs of communication (Sproull and Keisler, 1990). By reducing the costs of message transmission, networks can enable messages to be sent that in more costly traditional settings, such as group meetings or print publications, would have gone undistributed. Computer-mediated systems also change the way people process communication, affecting both the incremental costs of receiving a desirable message and the costs incurred as a result of noise.

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Networked environments also reduce the importance of many economies of scale, allowing communication to take place in smaller units. Rather than having a two-hour meeting or sending a multi-page newsletter, collective communication can take the form of shorter messages.

Different infrastructures lead to different communication costs for the members of voluntary social collectives. Different costs affect the development of the collective in several ways. Communication costs and structures affect the development of individuals' perceptions by altering the impact of individual units of communication activity on the individuals' beliefs about the collective. If communication activity is large-grained and expensive, the impact of any given unit on a member's beliefs will be greater. Lower processing costs also affect development by altering individuals' assessments of expected net benefits of continued membership. This, in turn, may alter when, or if, individuals choose to end their membership. Thus, changing communication costs have the potential to affect collective development.

A virtual experiment was performed with the computational model to assess the expected impact of different communication infrastructure on the development of social collectives. The experimental conditions were created by systematically varying the communication parameters, noise cost (c), message weight (w), and message threshold (m). Noise cost was set at 0.33, 1.0, or 3.0. Message weight was set at 0.005, 0.02, or 0.1. Message threshold was set at 2, 5, or 8. The values were chosen to represent a range of communication infrastructures. To anchor the analysis, the experimental settings included the values identified during calibration as most appropriate for e-mail based Internet groups. The remaining model settings and the initial conditions were set as determined during calibration (c.f. Table 12).

For each condition one hundred collectives were modeled. To simulate a year, runs were 365 time periods long, not counting the initialization stage of 100 time periods. However, rather

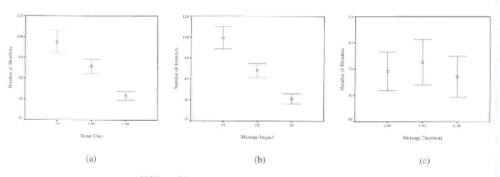
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than comparing conditions in terms of time to membership stability, an outcome that takes years for most of the modeled collectives, measures of membership size and stability were considered. Size, measured in terms of the number of members, was considered, because it is an important structural feature of a voluntary social collective. Larger collectives provide members with larger audiences and, potentially, more sources of information and support.

Stability is the likelihood of individuals leaving the collective. In voluntary collectives, members are free to leave whenever they choose. Individuals end their membership when they expect the costs of continued membership to outweigh the benefits. Collectives regularly experience shocks in the form of events, both internal and external, that have the potential to alter the membership of the collective. A collective can be seen as more stable if its membership is less likely to leave in the face of these shocks. Examination of preliminary results indicated that differences in individual members' evaluation of the group were due primarily to differences in their expectations about the content of activity (and not expectations about volume) (Figure 2). The lower a member expectations about the probability of future message usefulness, the lower her assessment of membership benefits would be, and the higher the chances that he would leave the group if a shock occurs. Stability can thus be measured in terms of the minimum content expectations among a collective's members.

Measures of size and stability were recorded for each of the 100 computational collectives in each condition. The model results were then analyzed in a series of ANOVA models.

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[95% confidence intervals for collective size after 365 time periods]

Figure 14: Effects of Communication Features on Collective Size

Lower costs and message weights result in larger collectives. Voluntary social collectives operating in contexts with lower relative noise costs see less membership loss, and as a result they are larger than those in which the relative cost of processing noise is higher (F = 42.514; p < 0.001) (Figure 14a). The effect of relative noise cost on collective size is a consequence of altering the minimum acceptable signal to noise ratio. When faced with lower relative costs of processing noise, individuals are willing to tolerate a higher proportion of unwanted messages. Thus the threshold at which individuals choose to end their membership is lower. This slows down the rate at which members filter out, resulting in larger collectives.

Collectives in which the impact of individual messages on member beliefs is lower are also larger (F = 54.220; p < 0.001) (Figure 14b). Lower message impacts reduce the rate at which individuals' beliefs about a collective change. This, in turn, slows down the rate at which members either leave the collective or become fully committed. In addition, there is a significant interaction between noise cost and message impact (Figure 15). In contexts with lower noise costs, the impact of decreasing message weights on collective size is greater.

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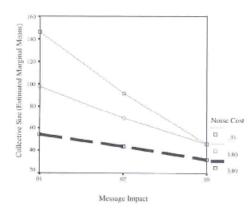
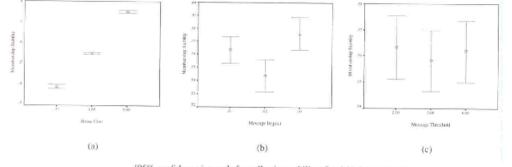


Figure 15: Interaction of Message Impact and Noise Cost

However, the model does not predict that message threshold will have a significant impact of a collective's size, (F = 0.471; p = 0.625) (Figure 14c).

Lower costs and impacts also result in less stability. Voluntary collectives operating in infrastructures with lower noise costs are less stable (F = 2761.603; p < 0.001) (Figure 16a).



[95% confidence intervals for collective stability after 365 time periods]

Figure 16: Effects of Communication Features on Collective Stability

As with size, message threshold does not have a significant effect on collective stability (F = 0.181; p = 0.835) (Figure 16c). However, the effects of message weight on collective stability

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are more complex (Figure 16b). Based on the trajectory of their belief development, individuals can be classified in one of three categories: leavers, committed core, and peripheral members. Leavers, who are not actually interested in the collective, are characterized by a strictly declining content evaluation trajectory. Given enough time, these individuals all leave the collective. The committed core consists of those members who have consistently high and increasing evaluations of the communication content. Their content evaluation trajectories are strictly increasing. Peripheral members are characterized by evaluation trajectories that are first decreasing, then increasing. Early on, peripheral members are only interested in a subset of the collective's activity. As a result, their content evaluation decreases over time. However, as the collective's topic focus develops, peripheral members' evaluations improve. Given enough time, peripheral members' evaluations increase to the level of that of the committed core.

Early in the development of a collective, the members all have relatively high expectations. As time passes, leavers and peripheral members lower their expectations of the content and committed core members increase theirs. As the leavers work their way out, their commitment drops and with it the overall stability of a collective. Thus, early on leavers undermine a collective's stability. Furthermore, after these individuals leave, the peripheral members keep stability low. Then as the peripheral members' evaluations of the collective recover, their expectations increase and with them the stability of the collective. Reduced message impact decreases the rate at which individuals' beliefs change, slowing down the rate at which leavers exit a collective, the committed core forms, and peripheral members' evaluations fall and recover. As a result, reducing message impact alters the rate at which a collective's stability develops.

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The non-linear pattern seen in Figure 16b is the result of "catching" collectives in different stages of development. In the low message impact condition, a reduced rate of belief change results in many leavers having not yet worked their way out of a collective. In the high impact condition, stability is higher because the leavers have end their membership and the peripheral members have recovered. In the moderate condition, most of the computational collectives have lost the leavers, but because the rate of belief change is reduced, there has not yet been time for the peripheral members to recover. As a result, stability in these collectives is lower than the low impact condition, because the peripheral members have had time to 'reach bottom', and lower than the high impact condition, because they have not had enough time to recover.

Communication features, such as message impact and noise cost, significantly affect both member and structural development processes in voluntary social collectives. As the impact of a message increases, individual beliefs form more rapidly. As noise processing costs increase, members demand more focus from collectives. Consequently, in contexts with higher message impact and noise costs, member and structural development proceeds more quickly, resulting in smaller, more stable collectives. In contrast, in the presence of reduced message weight and noise costs, as are expected in networked environments, member and structural development processes take more time, resulting in larger, less stable collectives. Thus while networked environments may make communication more efficient by reducing communication costs, they may slow down the development of voluntary collectives, and as result be the site of significantly different social structures.

Discussion

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The theory presented here draws from research on belief change and social structure to model the intertwined processes of member and structural development in voluntary social collectives. In some ways these collectives may seem different than the task groups which have been the focus of past research. In the structures considered here membership, specifically exposure to communication activity, is the result of individual choice. In addition, activity was assumed to be interest-based. This is in contrast to the task or decision oriented formal groups, such as production and management teams, that have been the focus of prior research.

In spite of these apparent differences, the model presented here is applicable for management researchers. On one hand, the process model of voluntary social collective development is useful because it tells us something about a type of social structure which plays an important role in the flow of information within and between organizations (e.g. Goodman and Darr, 1998; Van Hippel, 1988). As organizations, both public and private, spend more on information technology with the goal of facilitating information flow, it becomes increasingly important to understand how features of the technology and the social processes of collective development interact. This theory is also important for researchers interested in more traditional task and decision-oriented groups. Although formal membership in traditional teams may be the result of managerial action, it is often the case that exposure to communication activity is the result of individual choice. In addition, the process of developing beliefs about a formal team's activities and goals is likely to be driven by exposure to communication activity, much the same way belief about content develop in voluntary social collectives. Hence, future work should consider how the proposed theory might be applied for describing development of traditional teams and groups in dynamic organizational environments.

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Although the model provides a basic description of core elements of collective development, there are several areas that warrant further attention. One such area is the participation model. The participation model is similar to those used in prior studies of small group participation and information sharing. An individual's probability of contributing to the communication stream is fixed and determined exogenously. Individual's contributions are limited to one per time period. Message topics are randomly chosen through a process that is independent of the prior activity within the group. Development of a more detailed model of communication activity and participation would provide potentially useful insights into the link between member beliefs, communication activity, and membership movement and their role in the development of social collectives.

Another aspect of the model that would benefit from additional development and analysis is the introduction of members. The current model focuses on membership loss. While this is likely to be an important mechanism for determining the composition and focus of voluntary social collectives, it is, in some sense, only half the story. A more complete model of membership movement would also consider the role that the inflow of new members plays in the structural development processes considered here.

Finally, it must also be recognized that voluntary collectives do not exist in a social vacuum. The development processes considered here take place within a social system in which there are other collectives. However, as with studies of the development of single collectives, discussions of larger social systems provide little insight into how a changing communication infrastructure might alter the development of these systems (for notable exceptions see Carley, 1995a, 1995b, Carley and Wendt, 1991). Combination of this and other work which considers the role of communication technology, with explicit models of social system dynamics, such a

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those proposed by McPhearson (1983b) and McPhearson and Rotolo (1996), would allow researchers to consider the role that technology plays in altering the dynamics of complex organizations and societies.

Conclusion

Over time, the processes of individual attitude change and membership movement combine to shape both a collective's true interests and member perceptions of that focus. Although networked environments are seen as speeding up communication, reducing the costs of communication may actually slow down these processes which underlie important aspects of voluntary collective development. Lower communication costs and small units of communication reduce the pressure on individuals to reach confident conclusions about continuing membership. Members who would have left quickly under conditions of high cost, instead remain in the collective. As a result, networked collectives are expected to be larger, more diverse, and less stable, having lower minimum and average member evaluations, than collectives that rely on face-to-face communication.

New communication technologies change the ways members of groups, associations, and organizations communicate with one another. Yet having the capability for communication does not necessarily mean that it will occur. Based on their perceptions of the social context, individuals decide which collectives and people they will interact with. However, in addition to providing new means for communication, these technologies also alter the way individuals receive and process information about the social structures in which they are members. This, in turn, affects perceptions of the social context and alters how communication patterns change over time. Thus while new technologies may increase the mechanical efficiency of communication, it is the secondary effects on perception and evaluation of collectives that may

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ultimately underlie the development of the structures in which social communication actually occurs.

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ultimately underlie the development of the structures in which social communication actually occurs.

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