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Research article

An agent-based model of the impact of computer-mediated communication on organizational culture and performance: an example of the application of complex systems analysis tools to the study of CIS

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Abstract
Organizations that make use of computer information systems (CIS) are prototypical complex adaptive systems (CAS). This paper shows how an approach from Complexity Science, exploratory agent-based modeling (ABM), can be used to study the impact of two different modes of use of computer-mediated communication (CMC) on organizational culture (OC) and performance. The ABM includes stylized representations of (a) agents communicating with other agents to complete tasks; (b) an OC consisting of the distribution of agent traits, changing as agents communicate; (c) the effect of OC on communication effectiveness (CE), and (d) the effect of CE on task completion times, that is, performance. If CMC is used in a broad mode, that is, to contact and collaborate with many, new agents, the development of a strong OC is slowed, leading to decreased CE and poorer performance early on. If CMC is used in a local mode, repeatedly contacting the same agents, a strong OC develops rapidly, leading to increased CE and high performance early on. However, if CMC is used in a broad mode over longer time periods, a strong OC can develop over a wider set of agents, leading to an OC that is stronger than an OC which develops with local CMC use. Thus broad use of CMC results in overall CE and performance that is higher than is generated by local use of CMC. We also discuss how the dynamics generated by an ABM can lead to a deeper understanding of the behavior of a CAS, for example, allowing us to better design empirical longitudinal studies.
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Introduction

Computer information systems (CIS) and the organizations they are part of are prototypical complex adaptive systems (CAS; Holland, 1995), that is, systems consisting of heterogeneous, often adaptive individuals and components that interact to collectively generate emergent patterns of behavior. That is, activities carried out by individuals create phenomena at the organizational level which cannot be foreseen by analyzing the actions of each individual in isolation (Anderson, 1999; Gilbert and Troitzsch, 1999). As with other CAS, the various direct and indirect, positive and negative feedbacks generated by the (usually non-random) interactions of the members of an organization with and through its CIS can lead to nonlinear, path-dependent dynamics at both the individual and organizational level. This can result in system dynamics that are sensitive to initial conditions, and which generate multiple equilibria or even no equilibria, but rather chaotic or other more structured 'perpetual novelty' (Holland, 1995), all characteristics of the rich behavior of CAS.

In this paper we focus on one use of CIS, computer-mediated communication (CMC), and its possible effects on organizational culture (OC) and performance. CMC is a computer system which allows people who are not physically together to exchange information (Williams, 1977). Thus, the use of CMC can promote a more widespread interaction among members of an organization (Olson and Olson, 2000). This may influence the stability of the network of individuals, who must communicate to carry out their tasks. Thus, we wish to explore how differences in the stability of contact networks could impact OC strength and, in turn, performance on tasks that require individuals communicating with other members of the organization. For instance, since the use of CMC may expand the contact-network of individuals and allow an easy change of communication partners (Olson and Olson, 2000), that drop in network stability may bring about a weak OC at early stages of the CMC use. On the other hand, increased network contacts might promote a strong culture in the long run. In any case, CMC-induced changes in OC can lead to changes in communication effectiveness (CE) (Alge *et al*., 2003), directly affecting task performance, but also leading to feedback as successful (or unsuccessful) communication leads to further changes in OC.

Traditional approaches to studying the use of CMC in organizations, or any CAS, often limit our ability to understand the full complexity of these systems, in part because the characteristics of CAS (heterogeneous agents, nonlinear mechanisms and feedbacks, adaptive agents, non-random contacts, path-dependent dynamics) violate many of the assumptions necessary to use those traditional approaches (survey research, controlled experiments, game theory – all of them using traditional statistical tools). This is important, since the absence of adequate tools to deal with complex behavior inclines researchers to ignore such issues, unnaturally limiting the scope of social research (Meyer *et al*., 2005), and in turn of CIS.

For example, there have been quantitative and qualitative studies of CMC. The quantitative studies have used Information Richness Theory (Daft and Lengel, 1986) and statistical methods to analyze the capability of certain media to effectively exchange information between individuals. The studies concluded that due to its low richness, CMC is not an appropriate medium for communicating when dealing with ambiguous problems (Sproull and Kiesler, 1986; Daft *et al*., 1987; Valacich *et al*., 1994). Since these approaches require accurate measurement of variables and (usually linear) statistical tests of the relationship between variables, the models are often overly simple, missing much of the complexity of the system and its behavior. On the other hand, other studies have used qualitative approaches to study the same phenomenon (Lee, 1994; Ngwenyama and Lee, 1997). Those studies concluded that CMC can be used to deal with ambiguous situations, since humans learn to cope with low richness media, for example, by incorporating their knowledge of the context. With qualitative approaches, the researcher may include many more variables, but the treatment of them is generally narrative, generating case-based studies. And while the case-based studies are informative, they cannot be easily generalized to other situations (McKelvey, 2002).

In addition to finding the balance between models that are too simple or too complicated, to fully understand the effects of CMC, or any CAS, we need to incorporate a temporal component in our analysis. By studying the dynamics of the use of CMC, we could answer questions like: Do individuals over time adapt their strategies for using CMC? What effects do those individual changes have on patterns of behavior? Could we incorporate some new tools in CMC that might help users reduce the time they need to develop those strategies? Some studies have begun to address those questions (Jarvenpaa *et al*., 1998; Alge *et al*., 2003; Cornelius and Boos, 2003; Kreijns *et al*., 2003; Newlands *et al*., 2003). However, a general problem with longitudinal studies is the small sample sizes they use and the few measurements of variables they take over time (Zwijze-Koning and de Jong, 2005). Additionally, since in many studies the analysis relies on the specific context of the situation, it is difficult to generalize the findings.

Also note that systems with adaptive agents usually involve co-adaptation or co-evolution (Anderson, 1999), in that a change in one agent changes the 'environment' for the other agents, which in turn may adapt as well. The cascading adaptations often lead to dynamics where there is no equilibrium. For example, the successful introduction in 1981 of the IBM PC into the market created so much demand that drove other IT firms to launch equivalent products based on that technology. That lowered the price of the PC and created a *de facto* standard that profoundly affected the strategies and composition of the PC industry, which in turn set the stage for later products, standards and so on.

As mentioned above, the problems confronting research involving CIS and CMC are not unique, but are common to complex systems research in general. This suggests that by applying modeling techniques commonly used in the study of CAS, CIS researchers will be able to study phenomena that traditional behavioral methods typically cannot.

In this paper, we describe the use of one particular computational modeling technique, agent-based modeling (ABM), which is well suited to study the use of CMC, and CIS in general, in organizations. The distinguishing feature of ABMs is that they are constructed in a 'bottom-up' manner, by defining the model in terms of entities and dynamics at a micro-level, that is, at the level of individual actors and their interactions with each other and with the environment (Conte *et al*., 1997; Bankes, 2002a; Bonabeau, 2002). An ABM consists of one or more types of agents, and possibly a non-agent environment (in this paper we ignore the non-agent environment). Agents may be individuals or institutions. This flexibility makes it possible to study systems at many scales, and to integrate parts into a coherent whole. The state of an agent can include various characteristics, preferences, beliefs, memory of recent events, as well as particular social connections. Agent definitions include specification of their capabilities to carry out particular behaviors, as well as decision-making rules and other mechanisms that agents use to choose their own behaviors. Agents also may have adaptive mechanisms (learning or evolutionary) that allow them to change based on their experience. As an ABM is run, agent behavior is generated as agents make choices that determine which other agents to interact with and what to do in a given interaction. Thus, ABMs embody complex interlaced feedback relationships, leading to the nonlinear, path-dependent dynamics often observed in CAS. Note that the model's output is both the temporal patterns in the micro-behavior of agents as well as the emergent macro-level structures, relationships and dynamics that result from correlated micro-level activity.

Because ABMs are mechanistic models, they can be used to enhance our understanding of processes that can lead to the patterns we see in the systems being modeled. For example, we can explore the role of various factors that vary across organizations by explicitly representing those factors in our models at the micro-level and then observing how the model responds to variations in those factors. We also can explore alternative micro-level mechanisms, for example, agent decision rules, as well as alternative social network structures. By systematically exploring a variety of simple ABMs, constructed from different combinations of components and mechanisms, we can test hypotheses about the underlying processes that generate the data patterns we see, including both hypotheses that are suggested by theoretical assumptions about human behavior, as well as hypotheses generated by analysis of data from the field. Finally, ABMs (as with all models) can make predictions that can be tested about what to expect in situations and times not yet studied, as well as predictions about what aggregate patterns to expect in variables not yet observed, thus suggesting additional questions to ask and cases to study.

Because ABMs are dynamic, we can examine behavior of the system over various time scales, and track the state of the system during the 'transients' rather than just looking at equilibrium or other 'snapshot' states of the system. This is of particular importance when studying CAS, since in general CAS are almost always adapting and changing, and can follow different paths to multiple equilibria (Holland, 1995). Understanding the dynamics of a CAS is critical for gaining a deeper understanding of how the system being represented gets to the snapshots we get from survey data. In addition, knowing the fundamental dynamic processes that drive a CAS can suggest more effective ways to change the system's path, for example, by indicating effective policy lever points (Bankes, 1993, 2002b; Holland, 1995).

Because ABMs are computational models, they are formal, unambiguous and thus replicable and testable (Axelrod, 1997a; Axelrod and Cohen, 2000). However, they can be used to study aspects of CAS that are difficult or impossible to study using traditional analytic (equation-based or game-theoretic) techniques (Parunak *et al.*, 1998).

All of these features of ABMs contribute to their suitability as a way to study the dynamic processes that are characteristic of CAS. By including those kinds of processes in an ABM, and by constructing models that are as simple as possible, ABMs allow us to deepen our understanding of the processes and conditions that lead to patterns we generally observe in organizations, as for example the changes brought about by the introduction of or changes in a CIS.

The rest of the paper is organized as follows. The following section describes the relationships between CMC, OC, CE and task performance, and poses some hypotheses we wish to study. The next section briefly describes the ABM we developed to model CMC in organizations. Then the next section describes some experiments we carried out to explore the hypotheses posed in section 'CMC effects on OC and performance', and presents the results of computational experiments conducted using the ABM. Finally, the last section discusses the findings, the limitations of this paper and the benefits and disadvantages of the application of ABM to studies of CIS.

CMC effects on OC and performance

One definition of OC states that it is

> a pattern of basic assumptions, invented, discovered or developed by a given group, as it learns to cope with its problems of external adaptation and internal integration, that has worked well enough to be considered valid and therefore is to be taught to new members as the correct way to perceive, think, and feel in relation to those problems (Schein, 1990).

OC strength measures the variation in the different traits of a culture, due to differences in assumptions among organizational members (Denison, 1990). If individuals have heterogeneous assumptions, then the OC will be weak, whereas OC will be strong when assumptions are homogenous.

Empirical studies have shown that variation in an organization's member's network of contacts may affect OC strength (Leenders *et al.*, 2003; van Laere and Heene, 2003). The more variation in networks, the more difficult it is to establish or sustain a set of assumptions, decreasing the OC strength. On the other hand with stable networks,[1] people will exchange assumptions in small groups, which will tend to homogenize assumptions and form a strong group culture within groups of frequently interacting individuals, effectively leading to a strong OC.

The contact networks of individuals can be influenced by CMC, since use of CMC can alter the communication patterns in an organization. Previous research has shown that CMC has the potential to provide the tools for enhancing the flow of information among members of an organization (Gurbaxani and Whang, 1991; Fulk and DeSanctis, 1995). People who might otherwise not communicate, might do so by exploiting the advantages of CMC (Olson and Olson, 2000). Barriers such as distance, difference in time, availability of the other party are only a few of the many problems CMC tools can address. CMC also helps continue exchanges of information which began in face-to-face meetings, but were interrupted because the participants normally work at different locations. And chatrooms, internet forums, Wiki's, and so on, are all new ways for people to virtually meet and exchange information, creating new communication partners, even if people have never met face-to-face.

However, the availability of CMC does not guarantee that people will necessarily communicate with different partners from the ones they normally do, it just makes it possible to do so. This suggests that CMC may be used in two different ways: (1) when an individual uses CMC to communicate with the same partners over time, we call this situation a *local use of CMC*; and (2) when CMC is used to communicate with new or changing partners, we call this a *broad use of CMC*. Thus, local use of CMC will generally result in stable contact networks, whereas broad use will result in unstable networks.

Thus because CMC can alter contact networks, and the degree of stability in contact networks can affect OC strength, local and broad use of CMC may affect OC differently. However, the relationship may not be simple, especially when considering the differences over time. Two plausible hypotheses are the following:

H1a: At an early stage of development of an organizational culture, a broad use of CMC promotes a weaker culture than a local use of CMC.

H1b: At a late stage of development of an organizational culture, a broad use of CMC promotes a stronger culture than a local use of CMC.

At an early stage of development of OC, the stable contact network resulting from local use of CMC will quickly lead to homogenization of assumptions and a resulting strong OC. With broad use of CMC, resulting in an unstable contact network, people will have the chance of exchanging assumptions among a more diverse set of members, which can make it more difficult to develop common assumptions, resulting in an OC that is weaker than with local use of CMC. On the other hand, later in the development of OC, since broad use of CMC involves many more members, it might foster a stronger OC than a stable network, if there have been a sufficient number of contacts and changes of culture. For example, some studies of the use of CMC in newly created work groups show that indeed some traits of a culture become stronger, that is more homogeneous, as people interacts through CMC over a sufficient number of interactions (Jarvenpaa *et al.*, 1998; Burke and Chidambaram, 1999).

The possible effect of CMC use on OC strength is important because some qualitative case-based and quantitative studies have suggested that a strong OC can enhance the performance of an organization. That is, a strong OC increases the CE needed by individuals when accomplishing their tasks (Chatman, 1988; Denison, 1990; Chin *et al.*, 2002; Smith and Rupp, 2002), where CE is defined as the ability of a medium 'to permit quick, accurate, and meaningful exchanges' of information (Burke and Chidambaram, 1999). That is, common assumptions tend to homogenize how members understand and handle their work-related problems, which facilitates communication (Clark, 1996; Chin *et al.*, 2002; Cornelius and Boos, 2003). A high CE enhances the possibility of reaching a mutual understanding when members of the organization communicate through CMC. This increased CE in turn will increase performance (Burke and Chidambaram, 1999).

Thus CMC use may not only affect OC strength, as stated in Hypotheses H1a and H1b, it may also affect organizational performance, as summarized in the following hypotheses:

H2a: At an early stage of development of an organizational culture, a broad use of CMC promotes longer task-completion time than a local use of CMC.

H2b: At a late stage of development of an organizational culture, a broad use of CMC promotes shorter task-completion time than a local use of CMC.

where task-completion time is the measure of performance we consider in this paper.

That is, per hypothesis H1a, at an early stage of OC development a broad use of CMC promotes a weaker OC than local use of CMC, which in turn will lower CE and thus increase task-completion time. Conversely, from hypothesis H1b we expect that at a later stage of OC development, broad CMC use will result in a strong OC and thus in increased CE and shorter task-completion time.

Figure 1 summarizes the relationships between CMC, contact network stability, OC strength, CE and organizational performance. Note that in this study we assume local and broad use of CMC lead to stable and unstable networks, respectively (A1), whereas the other relationships (P1, P2, etc.) are represented by processes in the ABM described in 'An ABM of CMC, OC and performance'.

Note also that besides the influence of OC strength on CE (P2 in Figure 1), CE can affect OC strength (P4), because members of an organization need to effectively exchange information in order to develop a culture (Schein, 1985; Axelrod, 1997b). Thus, CE influences the development of OC and the strength of OC impacts CE. This bi-directional feedback loop, commonly found in CAS, can generate nonlinear dynamics in the system as a whole.

Finally, note that in this study we focus on the relationships between organizational culture, CE and the ability of individuals to carry out tasks, not on whether the organization has found the 'right' tasks for its members to carry out, that is, with respect to profits, market-share or other factors that lead to long-term survival of the organization as a whole.

Thus in our study, the overall best culture is generally homogenous, leading to good CE across a range of individuals and tasks that is as broad as possible. This is different from the focus of March's model of exploitation *vs* exploration (March, 1991), which was concerned with the potential cost of homogeneity when an organization is faced with trying to find innovative solutions (i.e. in our terms, tasks to carry out) that meet performance criteria defined by an external environment.

An ABM of CMC, OC and performance

In this section, we describe an ABM that implements the conceptual ideas and mechanisms outlined in the previous section. We tried to build an ABM that is as simple as possible, since it is easier to understand and explain a phenomenon using a simple model rather than a complicated one (Axelrod, 1997a). The ABM is an *exploratory*

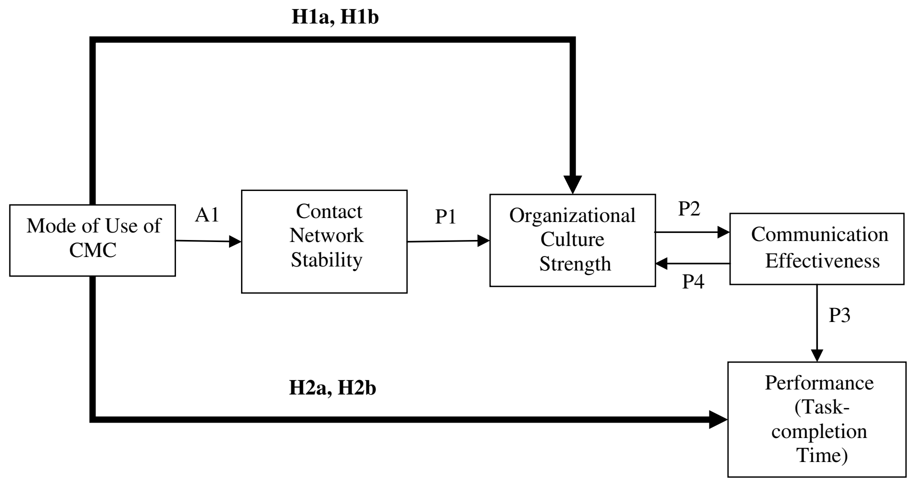

Figure 1 Relationships among variables in hypotheses H1 and H2.

model (Bankes, 1993), in that we use it to carry out computational experiments to increase our understanding of how a system of the type it models behaves, rather than trying to explicitly model any particular organization or particular individuals and their use of CMC. As such the model includes stylized representations of (1) agents communicating with other agents to complete tasks; (b) an OC consisting of the distribution of agent traits, changing as agents communicate; and (c) the effect of OC on CE. The following paragraphs describe the details of the model that are important for understanding the experiments carried out to analyze the hypotheses presented in 'CMC effects on OC and performance'. For full details, additional hypotheses, computational experiments and related empirical studies and validation, see Canessa and Riolo (2003) and Canessa (2002).

In short, the model consists of a given number of agents which belong to an organization. The organization assigns a series of tasks to each agent. To accomplish a task, an agent must successfully communicate with a given number of agents in a given sequence. Thus, each task consists of a number of *task-steps* an agent must complete. Some task-steps may be carried out by the agent itself, without having to communicate with another agent. To complete most task-steps, an agent must send a message to another agent (receiver) and receive a response from that receiver agent. Thus besides completing their own tasks, agents also must attempt to respond to messages from other agents. An agent's performance on a given task is the total number of *time-steps* it takes to complete a task, that is, the number of time-steps necessary to send the messages to other agents, corresponding to the task-steps, plus the times-steps it takes to receive back the responses to those messages.

Every time an agent completes a task, the organization assigns a new one to it. This new task might involve contacting the same agents as in the previous task, or the organization might change the identity of the agents that must be contacted. If a task involves contacting the same agents, the agent is using CMC locally; if the task involves contacting different agents, the agent is using CMC broadly.

Each agent has a culture (i.e., a set of cultural attributes) represented by an array of 10 numbers, each number representing the agent's trait for a particular attribute. The more similar the culture of the sender and receiver of a message, the more likely they are to have a successful communication (the more likely the receiver agent will answer the incoming message). Additionally, as part of this communication process, the culture's of the sender and receiver become more similar.

Table 1 summarizes the key details of the sequence of activity in the ABM, as well as the specific values of the parameters of the model we set for this study.

Note that processes outlined in 'CMC effects on OC and performance' (see Figure 1) are embedded in various components and mechanisms in the ABM. Regarding A1 (that the mode of use of CMC impacts network stability), the organization assigns a task, which might or might not involve contacting the same agents, which dictates whether agents use CMC in local or broad mode.

Regarding P2 (impact of OC strength on CE), we operationalized CE as the probability that an agent will answer the incoming message from another agent. Since the difference in culture between individuals partly determines common understanding between them, CE is a function of the difference in culture between two agents:

$$CE_{jk} = 1/(1 + \mathrm{e}^{(\sum_{i=1}^{N}|T_{ij}-T_{ik}|)\alpha-\beta})$$

where T_{ij} is the *ith* dimension of the culture of agent '*j*' and T_{ik} is the *ith* dimension of the culture of agent '*k*' and N $(=10)$ is the number of cultural dimensions. The constants α and β simply adjust the shape of the sigmoid curve. CE takes a value very close to one (provided we set a sufficiently large β) when there is a perfect match between the cultures of both agents; CE decreases toward zero as the difference between the cultures increases. In this study, α was set to 0.25 and β to 5.0.

Regarding proposition P3 (the impact of CE on task-completion time), the higher CE, the higher the probability the agents will successfully communicate when one sends a message to another, which in turn will lower the number of time steps needed to complete tasks.

Proposition P4 (the impact of CE on OC) was embedded by making the probability that a receiver adopts the culture

Table 1 Model actions and important details of the ABM

Stage	*Actions carried out by the ABM*	*Explanation/details*
1	Initialization of the simulation	Create an organization with 240 agents and assign a task involving 10 contacts (10-step task) to each agent Assign the values of the initial culture to each agent, sampling from a normal distribution N(0, 10)
2	Select at random without replacement agent A from a list of all the agents	The model uses random number generators (RNG) and we replicated each experiment 30 times using different seeds for the RNG
3	Allow agent A to send messages for its current task	Each agent works to complete only one task at a time and the organization assigns it a new task only after the agent finishes the current task
4	Answer the incoming messages for A until no incoming messages remain or until A processes 10 messages	The incoming messages from other agents are processed in FIFO order. The agents have a maximum number of incoming messages they can process per stage (in this case 10) Agent A will answer the message with probability CE, which is proportional to the difference in culture between sender and receiver (see discussion of assumptions for details regarding CE) If A fails to answer, the sender will try again on the next step
5	Change agent A culture	Following Axelrod's (1997b) cultural model, each agent's culture is represented by a list of 10 numbers, one value for each trait. Agent A will adopt one trait of the culture of the sender with probability proportional to CE
6	See whether A's task is complete. If the task is complete:	The task is complete when A has received answers to all outgoing messages required for that task
	(a) Compute the number of simulation steps A used to complete the task (b) Assign a new task to A	With probability P_{CI} the organization changes the identity of the agents involved in completing the new assigned task and with probability P_{CS} the sequence in which the contacts must be made (see discussion of experimental conditions)
7	Repeat stages 2 through 6 until all agents have gone through that process	
8	Compute the outputs of the model	The model computes the Average task-completion time for the organization (ATCTO) and the Overall organizational culture strength (OOCS) (see 'Experiments and results' for details)
9	Repeat stages 2 through 8 for as many simulated time steps as specified	We specified 3000 simulated time steps per replication

Note that one time-step for one agent consists of one pass through stages 2–6.

of the sender of the message proportional to CE (Axelrod, 1997b; Canessa and Riolo, 2003).

Before conducting experiments with the ABM, we carried out extensive verification and validation of the model. For details see Canessa (2002) and Canessa and Riolo (2003). That included performing sensitivity analyses of the various values of the parameters we set in the experimental runs. For example, we made a sensitivity analysis of the parameters α and β and the resulting curve used to compute CE. The analyses showed that those changes did not significantly impact the conclusions drawn from the model (Canessa, 2002; Canessa and Riolo, 2003).

Experiments and results

In order to explore the behavior of our ABM, with a focus on testing the hypotheses described in 'CMC effects on OC and performance', we carried out computational experiments under two conditions shown in Table 2.

For the condition labeled LUC ('Local use of CMC'), the probabilities P_{CI} and P_{CS} are set to 0.2, that is, every time the organization assigned a new task to an agent: (a) there was a 20% probability the organization would change the sequence in which the agent had to communicate with the corresponding agents for completing its task, and (b) there was a 20% probability the organization would change the identity of the agents that the agent must

Table 2 Experimental conditions. P_{CI} is the probability the identity of agents to contact is changed from task to task assigned to an agent, P_{CS} = probability the sequence of contacts is changed

Experimental condition	Parameter values
LUC – Local use of CMC	$P_{CI} = P_{CS} = 0.2$
BUC – Broad use of CMC	$P_{CI} = P_{CS} = 1.0$

contact for accomplishing the task. For the condition labeled BUC ('Broad use of CMC') those probabilities are set to 1.0. Hence, LUC represents a situation in which agents work throughout the simulation mainly with the same agents and contact agents in about the same sequence. In contrast BUC represents a situation in which agents work throughout the simulation mainly with different agents and a different sequence of contacts.

Each run of the ABM was continued for 3000 time steps, and the runs were replicated thirty times using different seeds for initializing the random number generators. The output values described below were then averaged over the 30 runs.

In this paper, we focus on two outputs of the model that are most relevant for testing hypotheses H1 and H2:

(a) ATCTO – Average task-completion time for the organization, which is the number of simulation time steps needed to complete tasks, averaged over all tasks completed by all agents in a given time step. Recall that we only measure the time steps an agent uses to communicate with other agents, thus focusing on the difficulty of communication, not on the individual's own work required to carry out a task.

(b) OOCS – Overall OC strength, which measures the strength of the OC by calculating the variance for each of the dimensions of the culture for the entire organization, combining them using the following expression:

$$OOCS = 1/\left(1 + \sum_{i=1}^{N} \sigma_i^2\right)$$

where σ_i^2 is the variance of cultural dimension i and N ($= 10$) is the number of cultural dimensions. Note that the stronger the culture, the smaller the variation and thus the closer OOCS will be to one. This calculation agrees with Denison's definition of cultural strength (Denison, 1990), which he operationalizes as the standard deviation of the different OC traits measured by a survey instrument.

Figure 2 shows ATCTO for local and broad use of CMC, averaged over the 30 replications for each experimental condition.

In general, task-completion time increases at the beginning of the simulation reaching a maximum and then it begins to asymptotically decrease toward a lower equilibrium value. This happens because the first completed tasks among all the tasks that the organization assigns are the ones that take agents a shorter time to complete. (Although the shortest tasks involve the same number of steps as the rest, they take a shorter time because the tasks consist of a number of steps that agents can complete by

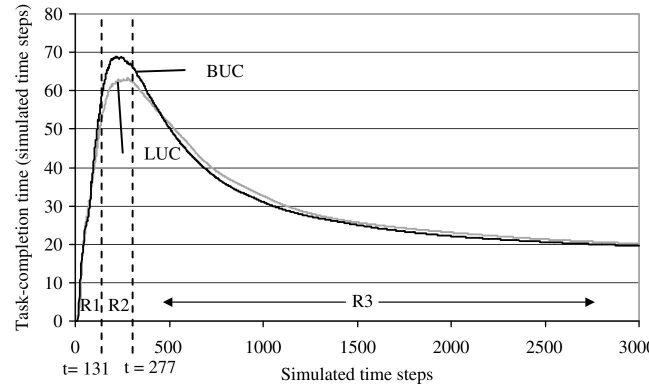

Figure 2 Task-completion time (ATCTO) for a 10-step task for local (LUC) and broad (BUC) use of CMC (average over 30 replications).

themselves without having to communicate.) As the run proceeds, agents begin to complete more complicated tasks, which increases the mean task-completion time. However, at the same time, the OC begins to homogenize, making it easier for agents to understand each other, that is, increasing CE. This shortens the task-completion times, decreasing ATCTO. Finally, the culture homogenizes as much as the conditions allow and the system approaches a stable value, with additional fluctuations due to the random processes involved.

Note that the difference in the time series between LUC and BUC is small, but is statistically significant in many periods. The magnitude of this difference can be varied by changing some parameters of the model, for example, increasing the number of task-steps in the tasks. However, the interpretation of the difference remains unaltered and is the important aspect we will explain in the next paragraphs.

To better analyze the dynamics of ATCTO, we divided the graph in three regions. Table 3 presents some representative statistics for each region. In region one (R1: $t = 0$ to $t = 131$), the two time series are very similar. In general, except for a few isolated points of the time series, the t-statistics for assessing the statistical significance of the difference in task-completion time between local and broad use of CMC (ATCTO local use – ATCTO broad use) are well above 0.05. For example, at time $t = 80$, the difference in task-completion time between LUC and BUC is only 1.14 and is not statistically significant. This happens because the agents initially have different cultures, and there have not been sufficient time steps for much homogenization of the culture. Since agents are initially maximally heterogeneous, it is irrelevant whether agents interact most of the time with the same agents (LUC) or with different agents (BUC), since CE will be low in both cases, leading to similar task-completion times. Thus in R1, at a very early stage of development of the OC, hypotheses H2a is not supported: a broad use of CMC does not promote a significantly longer ATCTO than local use of CMC. However, to some extent this reflects high initial heterogeneity in the agents.

Table 4 shows the difference between the overall OC strength (OOCS) for the two modes of use of CMC (OOCS LUC – OOCS BUC), averaged over the three regions, and the results of testing whether that difference is positive. For Region 1, the average difference is positive, meaning that at

Table 3 Task-completion time for some representative times for the three regions depicted in Figure 2

Time (simulated time steps)	*Value of ATCTO (average over 30 replications SD in parentheses)*		*Difference in ATCTO (ATCTO LUC – ATCTO BUC, P-values in parentheses)*
	Local use of CMC (LUC)	*Broad use of CMC (BUC)*	
80 (R1)	32.35 (9.80)	31.21 (8.92)	1.14 (0.64)
132 (change R1 → R2)	50.62 (9.71)	55.81 (11.05)	−5.19 (0.058)
218 (R2)	62.29 (6.84)	68.96 (9.05)	−6.67 (0.002)
277 (change R2 → R3)	62.80 (7.53)	67.21 (9.66)	−4.41 (0.0532)
279 (R3)	63.27 (7.99)	67.23 (9.93)	−3.97 (0.0934)
1000 (R3)	32.61 (8.06)	30.98 (7.81)	1.63 (0.43)
2000 (R3)	23.06 (3.77)	22.12 (3.36)	0.94 (0.32)
3000 (R3)	20.13 (2.77)	19.56 (2.57)	0.57 (0.41)

Table 4 Average difference in overall organizational culture strength (OOCS) between local (LUC) and broad (BUC) use of CMC, for the three regions depicted in Figure 2

Region	*Average difference in OOCS (OOCS LUC – OOCS BUC, SD in parentheses)*	*T-stat for testing if difference is positive*
R1 ($t=0$–131)	0.000044 (0.00015)	3.40 (df = 131, *P*-value = 0.0004)
R2 ($t=132$–277)	0.00036 (0.00019)	23.40 (df = 145, *P*-value = 0.0000)
R3 ($t=278$–3000)	−0.00054 (0.0009)	31.04 (df = 2722, *P*-value = 0.0000)
Last 60 data points	−0.00056 (0.00025)	17.57 (df = 59, *P*-value = 0.0000)

an early stage of development of the OC, a broad use of CMC promotes a weaker culture than a local use. Thus, hypothesis H1a is supported.

In Region 2 (R2: $t=132$ to $t=277$), Figure 2 shows the difference in task-completion time (ATCTO) between LUC and BUC is considerable. At $t=132$, the difference in task-completion time is – 5.19 and is statistically significant (*P*-value = 0.058, see Table 3). Inside Region R2 all the differences are consistently statistically significant, with associated *P*-values ranging from 0.002 to 0.005. Note that a negative difference means that inside this region the tasks requiring LUC take a shorter time to complete than tasks requiring BUC. This happens because in the LUC runs, sufficient time has elapsed since the start of the simulation so that the culture has been able to homogenize within the stable network of agents, because agents interact mainly with the same agents. In contrast, in the BUC runs, the time elapsed since the start of the simulation is insufficient to homogenize the culture, because agents are constantly interacting with different agents. Therefore, the more homogeneous culture resulting from a stable network of contacts, promoted by LUC, allows a higher CE and shorter task-completion time than the less homogeneous culture of the unstable network of contacts, promoted by BUC. Thus, hypotheses H2a is supported: at an early stage of development of OC, a broad use of CMC promotes longer task-completion times than a local use of CMC.

Examining Table 4, we can see that for the period that corresponds to Region 2, the difference between OOCS for LUC and BUC is positive and statistically significant, which means that the culture developed under LUC is stronger than the one under BUC. Therefore, hypotheses H1a is supported.

Finally, in Region 3 (R3: $t=278$ to $t=3000$), we see from the results presented in Table 3 that ATCTO for BUC is shorter than for LUC, but the differences are not statistically significant. However, Figure 2 shows that after the first part of Region 3 the time series of ATCTO corresponding to BUC lies below the one for LUC. Though the differences are small, these results suggest the performance of the agents in this period is better in BUC rather than in LUC. We believe this is because BUC is able to promote a more widespread homogeneous culture than LUC. That is, since agents interact with a far more diverse set of agents in BUC, the organization is able to incorporate the individual cultures of a larger number of agents into the OC.

To examine the long-run behavior of the model, we assumed the last 60 data points of the time series of ATCTO are representative of the long run behavior of the system, as suggested by Figure 2. Figure 2 shows that both time series asymptotically approach stable values as time advances. Thus we performed a paired difference test using those last 60 data points of the task-completion time series corresponding to LUC and BUC. Table 5 shows the results of those tests for 10-step task, that is, the data from Figure 2, and for tests on similar runs on 40-step tasks (time series not shown).

As can be seen, both for 10-step and 40-step tasks, the average difference is positive and highly statistically significant, which means that indeed at the end of the simulation BUC promotes a shorter task-completion time

Table 5 Results of paired difference test for verifying the statistical significance of the difference in task-completion time (ATCTO) for LUC and BUC using the last 60 data points

	10-step task	*40-step task*
Average of differences in ATCTO LUC – BUC ($N=60$)	0.353	1.969
SD of differences in ATCTO LUC – ATCTO BUC ($N=60$)	1.866	0.562
Value of t-stat	10.34	27.14
P-value	1.16×10^{-24}	5.05×10^{-35}

Table 6 Summary hypothesis tests

Region	*Hypothesis*			
	H1a	*H1b*	*H2a*	*H2b*
R1 ($t=0$–131)	Supported		Not supported[a]	
R2 ($t=132$–277)	Supported		Supported	
R3 ($t=278$–3000)		Supported		Supported[b]
Last 60 data points		Supported		Supported[b]

[a]Too near initial state of model.
[b]We found an interaction effect of length of task on the relationship between mode of use of CMC and task-completion time.

than LUC. Although the differences are small, as Figure 2 shows, those differences are statistically significant since the variability of the time series within and across runs is small. The large number of steps since the start of the simulation allows a high homogenization of the culture, which consistently increases CE and decreases task-completion time.

Also note that the difference for 40-step tasks was larger than the one for 10-step tasks, as corroborated by the t-statistic for assessing the significance of the difference between differences of 10-step and 40-step tasks (t-stat$=19.11$, df$=118$, P-value$=6.37\times10^{-38}$). Thus, the long run improvement in task-completion time of BUC over LUC increases with the number of steps in tasks. This increase reflects the amplification of the improved CE of each contact by an increased number of contacts required for completing long tasks. The longer the communication chain, the stronger the effect of the mode of use of CMC on the overall communication process will be. We can conclude that in the long run, hypothesis H2b is supported, especially for tasks involving many contacts.

Table 4 shows that in Region 3 the difference between OOCS for LUC and BUC is negative overall, meaning that BUC generates a stronger culture than LUC for later stages in the development of the OC; for both Region 3 and the last 60 data points of the model runs, the difference is negative and statistically significant. Thus, hypothesis H1b is supported: at late stages of development of OC, a broad use of CMC promotes a stronger OC than a local use of CMC.

The summary of our results in Table 6 show that overall, the hypotheses we posed in 'CMC effects on OC and performance' were confirmed. There was just one situation in which a hypothesis was not supported: the task completion times over the early part (R1) of the runs. In this region, there was no significant difference in task completion times resulting from broad *vs* local use of CMC, contrary to H2a. However, that outcome probably reflects the lack of time to overcome the particular starting conditions in our computational experiments.

Discussion

The results of the computational experiments described in 'Experiments and results' suggest a number of patterns and dynamics that can be generated by systems that embody mechanisms like those in our ABM. For example, if individuals use the properties of CMC that help overcome the barriers of time and distance, and as a result they frequently change communication partners, the development of a strong OC might take longer than if people use CMC only to contact the same smaller group of other individuals. This also will be reflected in decreased CE between individuals and in the increased time they will need to complete tasks that require efficient communication of potentially ambiguous information. However, this decrease in OC strength and CE is likely to disappear once people have sufficient time to adjust to each other, through additional CMC acts. When members have adjusted to each other, resulting in a stronger OC, the difference in task-completion time between LUC and BUC is small. This point agrees with empirical studies that have shown that the level of mutual knowledge among members of virtual organizations can impact performance (Jarvenpaa *et al.*, 1998; Cornelius and Boos, 2003; Hersleb and Mockus, 2003; Kreijns *et al.*, 2003). Further, the dynamics of task-completion time the ABM generates suggest that when enough time has elapsed, the task-completion time for broad use of CMC can become shorter than for local use. Although the difference is small, it suggests that an organization might perform better in the long run if it encourages a broad use of CMC. This will be especially important if the organizational tasks require frequent changes in the individuals who must collaborate to carry them out or require long communication chains.

The different outcomes observed at different times during our ABM runs indicate that incorporating a temporal dimension in studies of CIS in general, and of CMC in particular, can be crucial for understanding and predicting the behavior of such systems. The rapid rise and slow decline in ATCTO in Figure 2, along with the change in relative position of the time series of ATCTO between LUC and BUC, suggest that we need to sample many data points if we want to appreciate the difference in performance between LUC and BUC over time in the real system. Similarly, the long time it takes the system to approach a stable performance level suggests that care must be taken when trying to assess the 'equilibrium' performance of such systems.

Also note that the dynamics generated by our ABM model can shed light on results from empirical studies that are puzzling and seemingly inconsistent with each other. For example, the analysis of a longitudinal study (Burke and Chidambaram, 1999) involving the use of CMC illustrates this point. The authors study how media richness affects CE and task performance over time. In the case of asynchronous CMC (like e-mail), they show that after a total of 5 hours of collaboration of subjects toward completing a common task, the 11 groups of subjects increased their average perception of CE; however, analysis shows that the difference in CE is not statistically significant. The authors conclude that perhaps the short time of the experiment did not allow subjects to better know each other, which might have increased CE and permitted a better performance, and they suggest that a better experiment should last for at least some months. They argue that since CMC has a low richness, it takes more time for individuals to acquire a mutual knowledge. Those conclusions agree with our findings of the ABM. In our ABM agents need time to adjust to each other for increasing CE and performance. Therefore, our ABM suggests that an empirical longitudinal study of CMC, CE and performance should last sufficiently long for individuals to overcome the initial conditions of the experiment.

Other papers better address the issue of dynamics, for example, (Jarvenpaa *et al*., 1998), which studies CMC over a period of 57 days, taking measurements at two time points. That paper found an increase in CE and task performance in groups which adequately used CMC, that is, initially used CMC to build a common personal knowledge and trust among members. Thus, that study allowed sufficient time for subjects to overcome the initial conditions of the experiment. However, with two observations it is still not possible to characterize the dynamics as linear or not, and it is not possible to know what the results indicated about the long-term behavior of the individuals. Since our ABM suggests that the use of CMC may exhibit nonlinear behavior, it may be worth designing empirical longitudinal studies of CMC taking at least three measurements of variables over time.

Thus one strength of ABM is that it is one tool we can use to gain insights into the dynamics of CAS. We then can use those insights to help design empirical studies, and to help design and then evaluate policies in real-world settings. For example, organizations may want to know how much time it may take for individuals to increase their CE and performance when using CMC for accomplishing tasks, for example, when introducing the use of CMC in a new setting, for a different set of people or for a new set of tasks. Understanding the kind of dynamics that can happen when such changes are introduced can help the organization know what to expect, for example, an early decline followed by later improvements.

While ABM and all formal models, in and of themselves, increase our knowledge about the behavior of any system consisting of similar processes, to use such models to make inferences about particular real-world systems requires model validation. However, model validation, for ABM or any other kinds of models of CAS, is not trivial (Bankes, 1993; Grimm *et al*., 2005; Grimm and Railsback, 2005).

For exploratory models of CAS, one approach to model validation is to focus on relational equivalence (Axelrod, 1997a). In general it is impossible to expect to match the detailed behavior of CAS to the real system – there are just too many stochastic, unpredictable and changing processes and factors to include in a simple, understandable model (Bankes, 1993; Holland, 1995). Instead, validation can be done by matching patterns and relationships between the model and the system being modeled, rather than trying to match details (Axelrod, 1997a; Grimm and Railsback, 2005). That is, we assess whether the general behavior of the model matches that of the real system. For example, if the model shows that as we increase the value of a parameter, we observe an increase in an output variable of the model, then a similar change in the corresponding 'parameter' in the real system should result in a similar change in a corresponding measured variable of the real system. In the case of the present ABM, an empirical survey-based study indicated that the stronger the OC of an organization, the higher CE may be among individuals who use CMC for task-related communication (Canessa, 2002). This agrees with the result of the ABM; as the OC becomes stronger, CE increases.

Note also that with 'bottom-up' models like ABMs, validation can be carried out not only on the output of the model, that is, matching the time-series output of the model to the corresponding times series of data from the real world system, but validation also can be done on the 'micro level' processes that determine agent behavior. For example, in our ABM, the mechanisms embedded in the agents are a representation of results of empirical studies. For instance, the decision of agents to first process incoming messages related to their own tasks, and then answer the other messages in FIFO order, reflects the situation which normally happens in organizations (Canessa, 2002).

Finally, for all models, but especially for models of CAS, it is important to keep in mind that the kind and extent of validation required depends on the inferences to be drawn from the use of a model (Oreskes *et al*., 1994; Rykiel, 1996; Grimm and Railsback, 2005). The question is not 'Is the model valid?' but rather 'Is the model valid for supporting conclusion X?' In the case of our ABM, since there exists a relational equivalence for the relationship between OC strength and CE of the use of CMC, it is appropriate to say that we expect that in a real organization, a strong OC may promote a more efficient use of CMC for dealing with ambiguous situations. On the other hand, it would be

Table 7 Some benefits and limitations of ABM and empirically based research

	Agent-based computational modeling	*Empirically-based research*
Benefits	• Large sample sizes • Can do controlled experiments, one cannot do in the real system • Can thoroughly study dynamics of the system • Can easily change level of analysis	• Longitudinal studies can study dynamics of the system • Can achieve validity by using data collected from the real system
Limitations	• Requires model validation • Model may be difficult to validate • Study may be difficult to replicate in the real system	• Small sample sizes • Limited number of observations over time, attrition of subjects, etc., hinders studying dynamics of the system with longitudinal studies. • Uncontrolled errors limit validity

inappropriate to use the model to predict how much a given increase in OC strength would augment CE.

In conclusion, the computational experiments we have described in this paper illustrate one example of how Complexity Science tools, in this case an ABM, can lead to new and deeper insights into the behavior of individuals utilizing CMC and into the resulting emergent aggregate behavior of the overall organization. We think that the analyses made possible by an ABM can provide guidance for empirical research efforts and to support hypotheses regarding relations among variables that can be then tested using other research methods. Additionally, since we normally cannot experiment with real organizations, the ABM allows us to conduct experiments we may never be able to do in reality. However, we must acknowledge that validation issues pose problems in achieving all of those benefits.

More generally, as with any other modeling technique, ABM has advantages but also limitations as compared to empirical approaches. Table 7 summarizes some of the benefits and limitations of using ABM and empirically based research. As we can see the benefits and disadvantages of the two approaches seem complementary. ABM may circumvent a problem of empirical research and vice-versa. This is why we advocate the use of a combined research approach, as suggested in this paper and carried out in Canessa (2002) and Canessa and Riolo (2003). The building of the ABM, the validation of it based on real data and experiments, and the computational experimentation done with the ABM, all allowed us to gain a deeper understanding of the real system, especially of the dynamics. No single approach could have done that. This is important, since the absence of adequate tools to deal with dynamics commonly exhibited by CIS in human organizations, and CAS in general, inclines researchers to ignore such issues, unnaturally limiting the scope of CIS and all research on human systems (Meyer *et al*., 2005).

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Note

1 For this study, we define a stable network of contacts as a network in which, over time, individuals usually keep the same communication partners. On the other hand, an unstable network is characterized by a frequent change in communication partners.

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