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Using Multi-Agent Simulation to Explore the Contribution of Facilitation to GSS Transition*

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Abstract

Significant prior research has shown that facilitation is a critical part of GSS transition. This study examines an under-researched aspect of facilitation—its contributions to self-sustained GSS use among group members. Integrating insights from Adaptive Structuration Theory, experimental economics, and the Collaboration Engineering literature, we formalize interactions of group members in GSS transition as strategic interactions in a minimum-effort coordination game. The contributions of facilitation are interpreted as coordination mechanisms to help group members achieve and maintain an agreement on GSS use by reducing uncertainties in the coordination game. We implement the conjectured coordination mechanisms in a multi-agent simulator. The simulator offers insights into the separate and combined effects of common facilitation practices during the lifecycle of GSS transition. These insights can help the Collaboration Engineering community to identify and package the facilitation routines that are critical for group members to achieve self-sustained GSS use and understand how facilitation routines should be adapted to different stages of GSS transition lifecycle. Moreover, they indicate the value of the multi-agent approach in uncovering new insights and representing the issue of GSS transition with a new view.

Keywords: *Collaboration Engineering, GSS facilitation, multi-agent model, coordination game*

* Robert O Briggs, Gert-jan de Vreede and Anne Massey were the accepting editors.

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"A word processor that is immediately liked by one in five prospective customers and disliked by the rest could be a big success. A groupware application to support teams of five nurses that initially appeals to only one nurse in five is a big disaster." (Grudin, 1994, p. 101).

1. Introduction

Group support systems (GSS) transition, a central concern of Collaboration Engineering (CE), is the process that starts when some members of a team express interest in using a GSS and ends when the team of users has become self-sustaining (Briggs et al., 1998). The Adaptive Structuration Theory (AST) (DeSanctis and Poole, 1994) suggests that GSS transition occurs through the interplay among technologies, social structures, and human interaction. When a GSS is first introduced into a group, the group goes through an appropriation process by which members examine the technology structures and *agree on* when and how to use them, and eventually *stabilize* the appropriation (Dennis et al., 2001). An important implication of AST is that to codify and package best practices of GSS facilitation, CE researchers need to understand not only facilitation functions in technology and task management, but also how facilitation contributes to a self-sustained agreement among group members regarding GSS use.

Achieving continuous agreement among group members is a unique challenge to GSS transition (Grudin, 1994). To streamline the terminology, we refer to the GSS transition with the agreement challenge as "self-sustained GSS use" in the rest of this paper. GSS are suites of collaborative software tools that combine communication, computer, and decision technologies to support problem formulation and solutions in teamwork (DeSanctis and Gallupe, 1987; Briggs et al., 2003). Most GSS are only useful when a high percentage of team members use them. For single-user systems, this problem does not apply. For expensive organization-wide systems, top management can step in to force the technology transition (Rogers, 1983; Cooper and Zmud, 1990; Lucas et al., 1990; Grudin, 1994), however, if the financial impact is less salient (Briggs et al., 2003), top management may not be motivated to intervene in GSS transition. Moreover, GSS users tend to be inter-divisional, inter-organizational, or industry-level collaboration teams. A top-down solution may not be applicable to such teams. Because of this unique challenge in GSS transition, technology transition theories that either focus on individual users or organizations cannot be readily applied to the context of GSS (Gallivan, 2001).

Several studies have recognized that self-sustained GSS use should be viewed as a critical mass problem, because it is consistent with the notion that "some threshold of participants or action has to be crossed before a social movement 'explodes' into being" (Oliver et al., 1985, p. 523; Fichman, 1992; DeSanctis and Poole, 1994; Gallivan, 2001). Theories of critical mass emphasize management of interactions between actors (Oliver et al., 1985; Markus, 1987). Based on the notion of critical mass, AST indicates that human interactions underlying self-sustained GSS use can be characterized as interdependent decision making in that the degree to which members believe that other members know and accept the use of GSS positively affects their expected value of GSS (Markus, 1987; DeSanctis and Poole, 1994). Taken together, the critical mass view and AST imply that the challenge of GSS transition is essentially a problem of managing interdependencies between decision-making of GSS users. In other words, self-sustained GSS use boils down to a coordination problem, as coordination is defined as "managing dependencies between activities" (Malone and Crowston, 1994, p. 90).

A central premise of the coordination theory is that in order to overcome the coordination problem, additional activities must be performed (Crowston, 1997). These activities, called coordination mechanisms, serve primarily to manage interdependencies between actors and thereby help actors cross the threshold required for a social movement to explode into being (e.g., self-sustained GSS use). Prior research from the laboratory and the field implies that GSS facilitation practices are in effect coordination mechanisms that help to manage the interdependent decision making of GSS users. For example, a number of studies have shown that restricting process structure, a common facilitation practice, is effective in producing agreement on GSS use (e.g., Wheeler and Valacich, 1996; Dennis et al., 2001). This finding implies that one of the coordination mechanisms embodied by facilitation is limiting the number of alternatives available to a group. While the literature has accumulated implicit evidence on how facilitation contributes as a coordination mechanism in GSS transition, few have explicitly explored the theoretical explanation and empirical implications of such mechanism. This knowledge gap can prevent CE researchers from identifying and packaging important facilitation routines, and consequently impair the effectiveness of the CE approach in promoting self-sustained success with GSS. To this end, the first research question of this study is:

- How do facilitation practices, as coordination mechanisms, intervene with the interdependent decision making of GSS users and thereby contribute to GSS transition?

In addition, a study about the coordination mechanisms in self-sustained GSS use can help us recognize the dynamic and adaptive aspects of GSS facilitation. Scripted facilitation has been criticized for a lack of adaptability (Anson et al., 1995). This can be attributed to the focus on technology and task management in extant CE practice. Compared with human interaction, task and technology characteristics are much more stable over time and, thus, facilitation routines for task and technology management rarely entail a dynamic dimension. On the other hand, group-level agreement on GSS use is an emergent property; it arises *over time* from the coordination of interdependent individual decisions about GSS use. Thus, facilitation practices, as coordination mechanisms, need to be adapted to the dynamic patterns of human interaction. An understanding of adaptive facilitation practices can help explain why an organization would eagerly embrace a GSS for two years and then abandon it (Briggs et al., 2003). Therefore, the second research question of this study is:

- How should GSS facilitation be adapted—given the dynamic process of interdependent decision making inherent in GSS—and, thereby, stabilize GSS use?

The dynamic, adaptive, and emergent characteristics of GSS transition make multi-agent modeling a proper approach for this study. The multi-agent framework is a lens through which we can see how interactions among adaptive individuals in a dynamic environment give rise to group level behaviors such as self-sustained GSS use. The interface between GSS transition and a multi-agent framework is in many ways natural and inevitable. At an abstract level, both deal with similar conceptual issues such as dynamic change, adaptation, and evolution of interacting parts in a system. Both seek answers for similar questions such as what are the multiple pathways by which structures can emerge, stabilize or change in systems? Ultimately, we employ the multi-agent simulator as a tool to uncover new insights and ask new questions that can help researchers perceive the issue of GSS transition in a fresh light.

In the remainder of the paper, we first discuss the theoretical development and our propositions about contributions of facilitation as coordination mechanisms in self-sustained GSS use. Following the theoretical section, we describe the design, the calibration and the validation of the multi-agent simulator. Next, we discuss the experimentation in the multi-agent simulator and the insights gained through the experimentation process. Then, we suggest how the findings from multi-agent simulator can contribute to the CE literature and how the simulator can be utilized by the CE community to create knowledge.

2. Theoretical Development

In this section, we first discuss major technology transition models to provide background information for our study. Then, by borrowing insights from coordination theory, economics, and prior research on GSS, facilitation, and Collaboration Engineering, we formalize the human interactions underlying GSS transition as strategic behaviors in a game-theoretic coordination game (Roth, 1995; Van Huyck et al., 1990; Camerer and Knez, 2000; Knez and Camerer, 1994; Cachon and Camerer, 1996; Chaudhuri et al., 2001). The contribution of facilitation is theorized as interventions during the course of the game.

2.1. GSS Transition

The obvious starting place for discussing GSS transition is the stream of research on user acceptance of new technology. In the information system (IS) literature, models of technology acceptance are probably among the most mature research areas. Since several studies have provided thorough reviews of technology acceptance models (e.g., Venkatesh et al., 2003), our discussion here will highlight the main findings and focus on the connection between the individual-level acceptance models and GSS transition.

Most theories and models about technology acceptance are focused on an individual user as the unit of analysis. The basic premise underlying these models is that an individual's reactions to using information technology affect his or her intentions to use the technology, which consequently influences the actual use of the technology (Venkatesh et al., 2003). Based on the premise, different models have theorized a range of determinants of intention and/or use of technology. For example, the Technology Acceptance Model (TAM) (Davis, 1989; Davis et al., 1989) posits that perceived usefulness and perceived ease of use are of the primary user reactions to technology. They mediate the effects of external variables such as system characteristics and development process on intention to use a new technology. In the IS literature, TAM has been recognized as the most influential model explaining information technology acceptance (Venkatesh and Davis, 2000). In addition to the constructs defined in TAM, other models have proposed constructs such as attitude toward behavior, motivation to use technology, perceived behavioral control, affect toward use, and self-efficacy.

Although most of the technology adoption models focus on individual user intention/usage, they hint at the importance of human interaction to technology transition by defining social influence (i.e., subjective norm) as a determinant of intended or actual use of technology. For example, based on the Theory of Reasoned Action and the Theory of Planned Behavior, the original TAM was expanded to take into account other people's influence on a focal person's intention or usage (Venkatesh and Davis, 2000). Specifically, the social influence factor, called subjective norm, is defined as a "person's perception that most people who are important to him think he should or should not perform the behavior in question" (Fishbein and Ajzen, 1975, p. 302). This construct provides a rationale for us to explore human interactions in GSS transition. One thing to note is that the human interaction underlying subjective norm is different from that for coordination. First, subjective norm is a one-way interaction—others influence the focal user—while coordination involves two-way interaction—others influence and are influenced by the focal user. Second, subjective norm affects how a focal user perceives the value of a technology, not the actual utility of the technology. In contrast, coordination in GSS transition affects how much value users gain from the technology.

TAM has been employed in a few GSS studies. Researchers often find that TAM has limited applicability to group-level technology transition. For example, Dasgupta et al. (2002) adapted constructs from TAM to a laboratory study about the acceptance of a GSS application in an education setting. Contrary to the prediction of TAM, their findings showed that perceived usefulness has a negative impact on actual system usage. In another field study about GSS transition, Briggs et al. (1998) had to extend and modify constructs of TAM in order to account for the rich dynamics they observed in a group setting. They produced the Technology Transition Model (TTM) as an extension of TAM. In a later study, Briggs et al. (2003) summarized the main limitation of TAM: it does not account for how interactions among group members may lead to an agreement of GSS use and how the agreement can be sustained over time. The limitations of TAM and other individual-focused models necessitate alternative approaches or theories to study GSS transition. Among the alternatives, Collaboration Engineering and the critical mass view are particularly relevant to this study.

Collaboration Engineering is an approach that specifically focuses on acceptance and use of GSS. Rather than focusing on an individual user's perception, intention and use of technology, CE shifts attention to a key enabler of GSS transition, facilitation. CE researchers recognize that an essential difficulty in GSS transition is the lack of ongoing intervention provided by professional facilitators. To address this problem, CE researchers have attempted to codify and package best practices of facilitators so that practitioners can execute the facilitation routines on their own. Currently, CE researchers have documented approximately 70 such packaged facilitation routines (Kolfschoten et al., 2006), and have observed their effectiveness in achieving self-sustained GSS success in the field (Kolfschoten et al., 2006).

Critical mass has been suggested by several studies as an alternative perspective through which to examine GSS transition. For example, Fichman (1992) and Gallivan (2001) both proposed the critical mass theory as a more appropriate framework than TAM in explaining group level acceptance of technology. Grudin (1994) identified critical mass as a unique challenge to GSS transition. In AST, DeSanctis and Poole (1994) pointed out that the interdependence among GSS users' values and behaviors is consistent with the notion of critical mass. Although few researchers have developed their suggestions into formal research models, they contribute to the literature by calling for research attention on the interactions of GSS users rather than the intention/use of individual users. These studies motivate our focus on the coordination of GSS users and the coordination mechanisms brought about by facilitation practices.

A review of the technology acceptance literature reveals that self-sustained GSS use is a promising yet under-researched area. Up to now, few studies have formally characterized the coordination during GSS transition and how facilitation moderates the dynamics of coordination and eventually leads to self-sustained GSS use. Based on AST, Figure 1 illustrates the complementary relationship between this study and the literature. Among technology, task, and human interaction, TAM and CE have offered insights into the impact of technology and task structures on GSS transition, while our focus is on the path from human interaction to GSS transition and the moderating effect of facilitation on the path. Below, we first theorize on the interdependent human interactions during GSS transition and then discuss the contributions of facilitation.

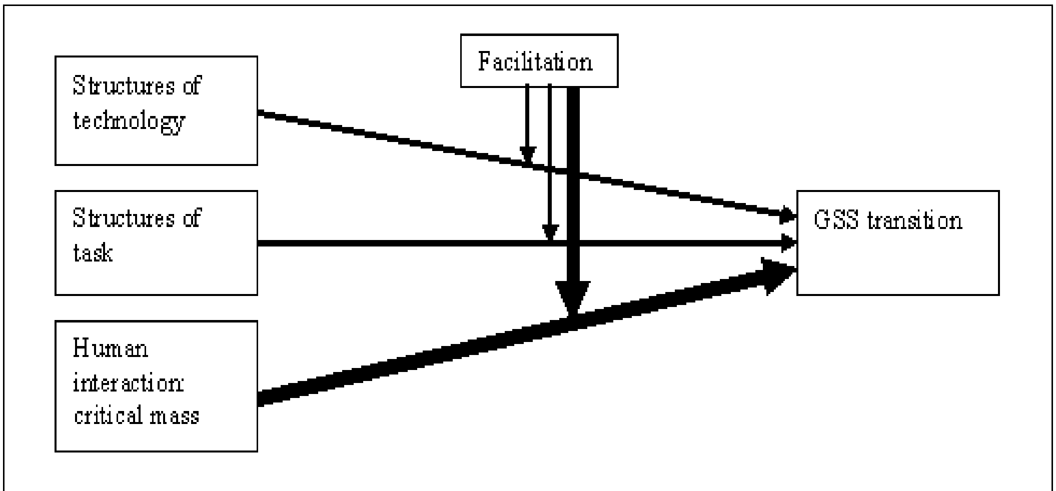

Figure 1. The Complementary Relationship between This Study and the Literature

Notes: The thin arrows are the focus of TAM and CE literature, while the thick arrows are the focus of this study.

2.2. Coordination of GSS users

As discussed in the introduction, achieving self-sustained GSS use can be articulated as a coordination problem for GSS users. In order to understand how facilitation contributes to the emergence and stabilization of the group-level agreement on GSS use, we need to first characterize the interdependent decision making of GSS users. Economic and social scholars have developed a family of coordination games to mathematically analyze the interdependencies among individuals and derive the group level outcomes. Among the family of coordination games, we employ a minimum effort coordination game with Pareto-ranked equilibria (see Appendix A for a tutorial), because it allows us to take into account the complexities in a GSS context, such as task/technology fit and asymmetry among group members in terms of effort invested in GSS use. Specifically, we characterize group members' decisions about GSS adoption as the dilemma between reserving one's own effort or investing the effort in adopting the GSS and taking the risk of wasting their effort if not enough coworkers adopt the same GSS. Meanwhile, because the efficiency of GSS varies across different tasks, in order to gain the most benefit, members have to simultaneously recognize the most efficient GSS for a given task and adopt the system together. In repeated play of this game, individuals adjust their choices based on the payoff of their past decisions. This allows self-sustained GSS use to emerge or collapse based on the dynamic interaction of individual decisions over time.

Experimental economists find that it is extremely difficult to achieve coordination success in minimum effort games with Pareto-ranked equilibria (see Weber, 2006 for a review). In relation to GSS transition, this means that it is difficult to achieve self-sustained GSS use. This finding helps to explain why GSS tend to be self-extinguishing (Briggs et al., 2003). To prevent coordination failure, economists have recognized two general interventions. The first intervention is to mechanistically focus players' beliefs on a particular equilibrium, usually through pre-play communication (Cooper et al., 1992). This intervention helps players accept the risk of coordination and agree to choose the Pareto optimal action. The second intervention is to reduce the tension between individual risk and group efficiency by changing the payoff structure of a coordination game (Cooper et al., 1990; Van Huyck et al., 1990). This approach makes the Pareto optimal action less risky and more attractive and, thereby, induces more coordination success. Based on prior findings of interventions in the minimum-effort coordination game, the premise of this paper is that the coordination mechanisms of GSS facilitation intervene with the interdependent decision making of GSS users by (1) reducing uncertainty about other members' choices of GSS feature (i.e., help members accept the risk of coordination) and (2) reducing uncertainty about the potential value of a chosen GSS for a given task (i.e., make the Pareto optimal action less risky). The section below elaborates on this premise.

2.3. GSS Facilitation

According to Hayne (1999, p. 73), facilitation is defined as:

1. to make easier or less difficult; help forward; an action, a process;
2. a set of factors or behaviors carried out before, during, and after a meeting to help a group achieve its goals;
3. moving from the known to the unknown.

It is implied that facilitation is not confined to services provided by professional facilitators. Any factor or behavior that helps a group achieve GSS transition can be considered facilitation, regardless whether it is brought about by a facilitator, a trainer, a leader, or a software program. Our theorization of facilitation is in this broad sense.

Past research has shown that there are multiple approaches for facilitation to affect GSS acceptance and use. We summarize the facilitation routines observed in prior studies in Table 1. Among the variety of facilitation approaches, we identify and focus on four basic practices. The first is GSS championing (e.g., Nunamaker et al., 1991; George et al., 1992), which can be performed by a facilitator or a group leader. This practice can boost users' enthusiasm and the perceived effectiveness of GSS and thus promote GSS use. The second practice is restricting GSS choices (e.g., Hayne, 1999; Dennis et al., 2001), usually done by using highly restrictive software. This practice "forces" members to achieve self-sustained GSS use by minimizing alternative ways of GSS use. The third practice is task and technology help (e.g., Griffith et al., 1998; Dennis and Garfield, 2003). This is usually provided by professional facilitators. By directly intervening in how users employ GSS to perform tasks, facilitators can improve task/technology fit and enable members to leverage more benefits from GSS. The fourth practice is training (e.g., Dennis et al., 2001; Dennis and Garfield, 2003), which can be provided by a trainer or a facilitator. By educating members about the structures and use of GSS, "it moves the group more quickly down the gradual path to the stabilization of appropriate structures and habitual routines" (Dennis et al., 2001, p. 173).

The four basic facilitation practices can be mapped onto the two general interventions of coordination failure in a minimum-effort game: (1) reducing uncertainty about other members' choice of GSS feature and (2) reducing uncertainty about the potential values of chosen GSS for a given task. Specifically, both championing and restricting reduce the uncertainty about others' GSS use by increasing members' willingness to coordinate and mechanically focusing members' choice on a few GSS features, respectively. Meanwhile, task and technology help reduces the uncertainty about the value of a chosen GSS for a given task by directly intervening with the task and technology match during group meetings. Training reduces the same uncertainty by enabling group members to make sensible use of GSS for a given task on their own. The mapping from the common facilitation practices to interventions of a minimum-effort coordination game (see Figure 2 for an illustration) indicates that:

Table 1: GSS Facilitation Practices[1] Identified in the Literature

Study	GSS Facilitation Practices
Nunamaker et al., 1991; George et al., 1992	* Reduce technical complexity by initiating and terminating specific software tools (3) * Training (4) * Champion/sponsor of GSSs (1)
Dickson et al., 1993	* Chauffeur-driven support (helps the group with the technology) (3) * Facilitator-driven support (helps the group with the process and the technology) (3)
Clawson et al., 1993	* Selects and prepares technology (3) * Creates comfort with technology (3) * Understands technology and its capabilities (4)
Anson et al., 1995	* positively influence people's perceptions of GSS effectiveness (1) * help people better understand and organize their use of GSSs (3, 4)
Orlikowski and Yates, 1995	* Metastructuring, i.e., direct intervention into GSS use process (3)
Niederman et al., 1996	* encourage GSS adoption through good matching of tools to tasks (3) * demonstrate GSS's added value (1) * provide "low-key" technology that allows group members to focus on tasks (3)
Griffith et al., 1998	* ensure the advantages of GSSs are accessible to group members (3) * run the technology for group members (3) * assist those members who are not masters of the technology (3)
Boiney, 1998	* Explain the use and purpose of GSS capabilities and options (4)
Hayne, 1999	* Selecting the technology that fits a group's goal (3) * Take care of logistics of technology use (3) * Restrictiveness (2)
Niederman and Volkema, 1999	* Explain operations of GSS (4)
Dennis et al., 2001	* Direct intervention into GSS use process (3) * Restrictive GSS (2) * Training (4)
Vreede et al., 2002a, b	* Choose and prepare GSS technology (2) * Introduce GSS to users (4) * Being available during GSS use process (3) * Structure the GSS use process (3)
Dennis and Garfield, 2003	* Starting the GSS (3) * Training (4)

Notes: numbers in parentheses indicate the basic facilitation practices they relate to. 1. champion; 2. restrict choice; 3. task and technology help; 4. training.

[1] We only focus on the facilitation practices related to GSS transition. Facilitation relates directly to the problem being discussed in a group meeting is not the focus of this study.

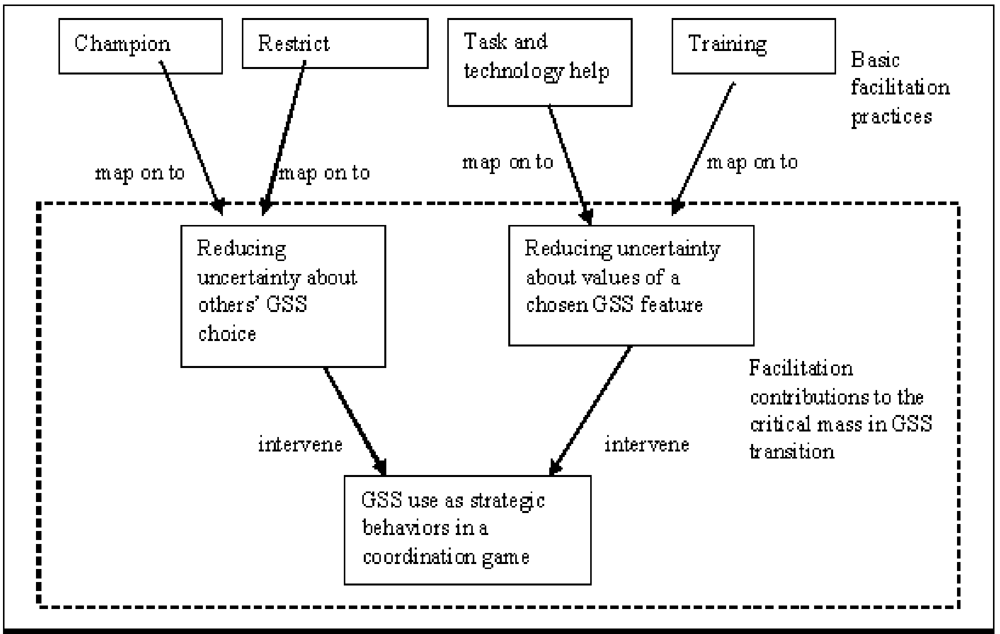

Figure 2. The Multiple Pathways of GSS Facilitation

Proposition 1: Facilitation as a coordination mechanism can induce self-sustained GSS use by reducing uncertainties through multiple pathways.

Due to the multiple pathways for achieving self-sustained GSS use, the effectiveness of facilitation practices may vary at different points in the GSS transition lifecycle. Facilitation practices that directly change how GSS users perceive or use the technology in tasks may be more effective in the initial phase of GSS transition, because they do not require users to spend time learning functions of GSS. On the other hand, facilitation practices that help users truly understand GSS may be more effective in the long run, because they sustain GSS use by stabilizing the habitual routines of GSS users (Johnson and Rice, 1987; Dennis and Garfield, 2003). For example, restricting may work better than training to initiate GSS use, because it mechanically forces GSS users to adopt the same system

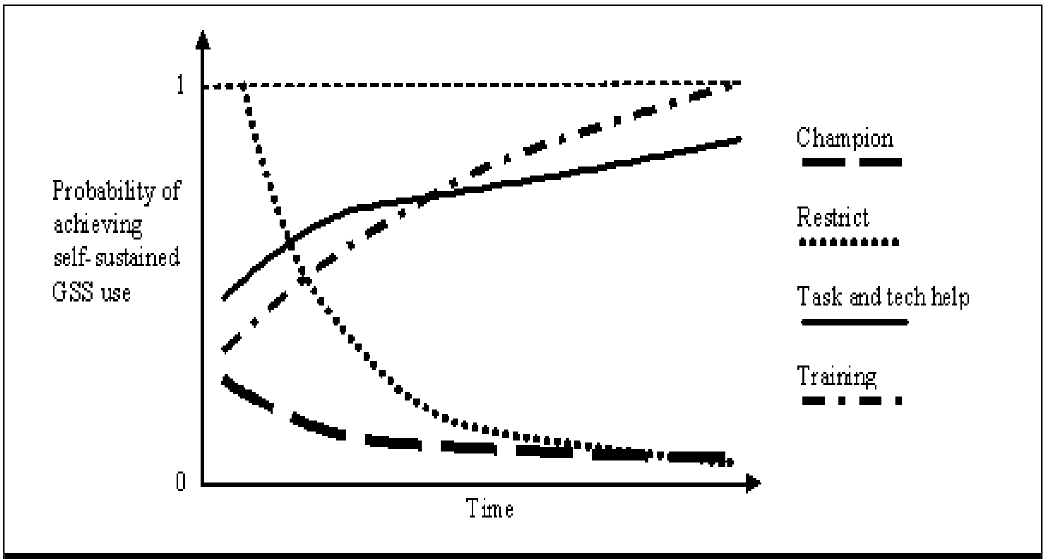

Figure 3. A Possible Pattern of Effectiveness of Different Facilitation Practices in GSS Transition Lifecycle

Notes: The shapes of the function lines are fictional; they are not part of our proposition.

rather than gradually helps users voluntarily choose the same GSS. However, in the long run, training may become more effective, because training empowers GSS users to make sensible use of the technology without the ongoing intervention of facilitators. Figure 3 shows a possible pattern of effectiveness for different facilitation practices over time.

> **Proposition 2:** Different facilitation practices can have varied effectiveness in initiating and sustaining GSS use during the lifecycle of GSS transition.

In summary, an integration of AST, experimental economics, and GSS research suggests that facilitation practices, as coordination mechanisms, intervene with the interdependent decision making of GSS users by reducing the uncertainties in the coordination problem; effectiveness of facilitation practices may vary during the lifecycle of GSS transition due to the different pathways for facilitation to induce self-sustained GSS use. The propositions offer a basis for CE researchers to evaluate the causal mechanisms underlying the common facilitation practices (P1), and to understand how to adapt them to the dynamic process of GSS user coordination during GSS transition (P2).

3. Method

We employ multi-agent modeling to examine the contributions of facilitation to self-sustained GSS use. A multi-agent model (also called bottom-up modeling or artificial social systems) is an emerging paradigm to analyze how heterogeneous, autonomous behaviors of actors/agents generate global macroscopic regularities of social phenomena (Epstein, 1999). In a multi-agent model, "fundamental social structures and group behaviors emerge from the interaction of individuals operating in artificial environments under rules that place only bounded demands on each agent's information and computational capacity" (Epstein and Axtell, 1996, p. 4). Essentially, multi-agent modeling helps us understand how repeated interactions among actors give rise to collective behaviors in an entire system. It has been employed to study a variety of social, economic, and organizational issues such as information diffusion and social change (Carley, 1991), exchange of goods in a market (Epstein and Axtell, 1996), media and organizational culture and performance (Canessa and Riolo, 2003), transactive memory in teams (Ren et al., 2006), and knowledge transfer in organizations (Cataldo and Carley, 2001).

Compared with traditional social science paradigms such as statistical estimating and differential equations, a multi-agent framework has five unique characteristics. First, it takes a bottom-up approach. Rather than seeking a centralized control mechanism for orderly behaviors of a system, a multi-agent framework explores whether *decentralized* interactions among autonomous actors can lead to system-level regularities. Second, a multi-agent framework assumes that actors engage in adaptive rather than fully rational behaviors (Axelrod, 1997). Actors with limited information and foresight optimize their strategies through interacting with others. Third, a multi-agent framework allows heterogeneity among actors, whereas traditional social scientists often suppress agent heterogeneity in order to make their models tractable (Epstein and Axtell, 1996). Fourth, multi-agent modeling focuses on dynamic processes that produce or disrupt equilibria rather than the static nature of equilibria (Epstein and Axtell, 1996). Last, traditional statistical or multi-equation modeling assumes linear, deterministic, or independent relationships among parameters, whereas a multi-agent framework explicitly takes into account nonlinear, nondeterministic, and interdependent interactions among multiple levels of actors. These unique characteristics make it a valuable approach to examine the decentralized, dynamic, and adaptive human interactions underlying GSS use and the multiple pathways for facilitation to induce critical mass to spur GSS transition.

In addition, the computational modeling approach offers several advantages compared with laboratory experiments or field studies. First, it gives researchers precision and control in the measurement and manipulation of crucial variables. As pointed out by Conway et al. (1959, p. 105), "in physical experimentation stochastic variability is, by definition, that which lies beyond the control of the experimenter; simulated experimentation, the stochastic variability, like every other feature of the model, is deliberately and explicitly placed there by the constructor. Second, it is a more manageable way to study time-dependent and time-consuming processes such as GSS transition. A computer simulation can collect longitudinal data more efficiently than a lab or field study (Arrow et al., 2000). Moreover, as dynamic patterns are not easily described verbally, a computer simulation can visually present important temporal features of a process in a step-by-step manner (Drazin and Sandelands, 1992). Third, a computational approach provides a very effective method to answer "what if" questions (Romme, 2004). Researchers can explore a wide range of possible contingencies that are hard to implement in lab experiments or field studies due to legal, ethical, or practical reasons. Last but not the least, in order to translate theories and concepts to computational programmable systems, we have to specify the causal mechanisms underlying facilitation practices and critical mass of GSS transition. This makes computational modeling a very helpful approach for CE researchers to identify the causal elements of packaged facilitation routines.

Of course, due to the complexities of reality, it is not possible to mimic every aspect of the real world in the computational environment. Therefore, we must, to quote Simon (1990, p. 7), "separate what is essential from what is dispensable in order to capture in our models a simplified picture of reality, which nevertheless will allow us to make inferences that are important to our goals." The goal of our multi-agent simulation is neither normative (it does not assume idealistic rationality) nor descriptive (it does not replicate the rich details of a GSS supported work group), but exploratory. If the simulation produces results that can inform the causal mechanisms or adaptive aspects of common facilitation practices, it gives us some grounds to believe that the multi-agent modeling method is a useful approach to uncover new insights about GSS transition issues. By excluding many factors, we can be sure that their presence does not cause the observed output. What is lost in the level of detail is gained in the degree of control over the research environment (Prietula et al., 1998). Thus, we take a parsimonious approach in the multi-agent modeling and only simulate the factors that are both essential to our research questions and well understood in the literature.

In general, the multi-agent model is an artifact constructed within the design science approach (Hevner et al., 2004). It is not aimed to be a full-grown information system that can be used in practice. Instead, the artifact provides a way for the GSS transition problem to be conceived by CE researchers. As Simon states, "Solving a problem simply means representing it so as to make the solution transparent" (1996, p. 132).

3.1. The Multi-Agent Model Design

Based on the theory of multi-agent modeling (Epstein and Axtell, 1996), interactions among GSS facilities, users, and facilitation practices are reduced into four building blocks of a multi-agent model: agents, properties or attributes of agents, environment, and behavioral rules. The first building block, *agents*, is the actors in a system. In our model of work groups, agents are members of a work group. The number of agents in the model is controlled by the parameter, group size.

The second building block, p*roperties or attributes* of agents, is their internal states and characteristics. In our model, agents have three attributes: belief about others' GSS use (referred to as belief), probability of task/technology fit (referred to as task/tech fit), and learning. Belief represents the uncertainty of other members' GSS choice. It is a value ranging from 0 to 1, with higher values meaning lower uncertainty. Belief of each agent is randomly drawn from a normal distribution with mean 0.75 and standard deviation 0.2 (more details later on the calibration of these values). If the random draw produces a number less than 0 or greater than 1, we set it to 0 or 1, respectively. Task/tech fit reflects the uncertainty about the potential value of a chosen GSS for a given task. It varies from 0 to 1, with higher values for lower uncertainty. Learning reflects members' true understanding about GSS functions. It is a value from 0 to 1, with a higher value for better understanding. The initial value of learning is randomly drawn from the uniform distribution between 0 and 1 to represent a diversity of users' familiarity with GSS. In general, the value of task/tech fit equals learning, unless agents receive task and technology help (more details on this facilitation rule later). This represents the situation where members' ability to match task with GSS is based on their understanding of the technology, unless there is direct intervening from a facilitator.

The third building block, the *environment*, is the medium over which agents operate and interact. It is separate from the agents but interacts with them. In our model, the environment represents the GSS. It offers benefits (payoffs) to agents based on the coordination outcome. If agents achieve agreement about GSS use, each agent receives a GSS payoff. If agents fail to adopt the same GSS, those who did not choose to use the GSS receive a defector payoff (representing their reserved effort), and those who attempted to use the GSS receive a loser payoff (representing their wasted effort). In the framework of a minimum-effort coordination game, the GSS payoff is always higher than the defector payoff, which in turn is higher than the loser payoff (Skyrms, 2004). Following the payoff structure of the coordination game and based on model calibration results, we assign the payoff values as shown in Table 2.

Table 2: Payoffs of the GSS Facility

		The Collective Choices of Other Agents	
		GSS	Other Technology
Individual Agent's Choice	GSS	GSS Payoff (10)	Loser Payoff (0)
	Other Technology	Defector Payoff (3)	Defector Payoff (3)

Notes: Numbers in parentheses are the values used in the simulation.

The last building block, *behavior rules*, defines the movements, interactions, and changes of internal states of agents and the environment. To this study, behavioral rules are the most important component of the multi-agent model because they reflect our conjectured mechanisms underlying the facilitation practices in GSS transition. We implement four behavioral rules to represent the four basic facilitation practices identified in the literature: the champion rule, the restrict rule, the task and technology help rule, and the training rule.

The champion rule increases the average belief of agents by a certain percentage set by the simulator users. For example, if belief of agents was initially drawn from a normal distribution with mean 0.75, and the increase percentage was set to 20 percent, the champion rule will increase the distribution mean to 0.95. Thus, uncertainty of others' GSS use is reduced, and agents are more likely to choose the GSS. The restrict rule also affects belief of agents, but in a different fashion. When the restrict rule is in effect, belief of agents is changed from its current value to 1 (i.e., uncertainty about others' GSS choice is minimized). This reflects the empirical finding that restricting can mechanically focus members' beliefs on particular GSS features by limiting the choices available.

The task and technology help rule increases the value of task/tech fit to 1 regardless of agents' learning. It reflects the direct intervening of facilitators to help members choose appropriate GSS features for a given task. The training rule increases the value of learning at a fast speed. It represents the effect of training on improving members' true understanding of GSS use. The other three facilitation rules also improve learning, but at a slower speed. This mimics group members' independent learning as a "by-product" of using GSS. The actual values of the learning speed with training or without training are set by the simulator users. Table 3 aligns the basic facilitation practices and their corresponding behavioral rules in the model.

In a round of the model play, agents simultaneously make a choice to use GSS or not, receive payoff based on their choices and the collective choice of the group, and then update their belief and learning.

When agents make a choice about GSS use, they calculate the expected value of using GSS with the following equation:
Expected value of GSS = (my belief of others' choice) ^ number of other agents * GSS payoff * task/tech fit[2]

Essentially, the equation above captures two things: the payoff of GSS use and the likelihood of GSS use by the whole group. The payoff of GSS use is defined in Table 2. The likelihood of GSS use encompasses two uncertainties: (1) whether other members will choose the same GSS and (2) whether the chosen GSS fits the task at hand. In the equation, the first uncertainty is calculated as the focal agent's belief of others' choice raised to the power of the number of other agents. The second uncertainty is reflected by the task/tech fit variable.

[2]The value of task/tech fit equals the learning value, unless the task and technology help rule is in effect.

Table 3: Alignment between Previous Observations and the Behavioral Rules

	Previous Observation	**In the Agent Model**
Champion	Increase members' enthusiasm and perceived effectiveness of GSS (e.g., Nunamaker et al., 1991; George et al., 1992)	Increase the average belief of agents about others' GSS use
Restrict	Mechanically focus members' choice on particular GSS features (e.g., Hayne, 1999; Dennis et al., 2001)	Increase belief of agents about others' GSS use to 1
Task and Technology Help	Intervene in the task and technology match during group meetings (e.g., Dickson et al., 1993; Clawson et al., 1993)	Increase the task/tech fit value to 1
Training	Educate members about the functions of GSS (e.g., Boiney, 1998; Dennis and Garfield, 2003)	Increase learning at a greater speed than the other facilitation rules

If the expected value of GSS is greater than the defector payoff, the agent will choose to use the GSS. Otherwise, the agent will choose to defect (not use the GSS). If all of the agents choose to use the GSS, the round results in GSS use. On the other hand, if some agents choose not to use GSS, the round results in coordination failure. Agents will receive payoffs according to Table 2.

At the end of each round, agents update their belief and learning based on the outcome. If the round achieves GSS use, each agent updates his or her belief using the following calculation:
*Updated-belief = current-belief + ((1 – current-belief) * belief-changing-speed)*

The above equation captures the concave effect of a GSS use outcome; that is, every time the group of agents achieves GSS use, their belief about others choosing the same GSS in the future increases. Meanwhile, the marginal effect of each additional GSS use outcome decreases as the belief value approaches 1.

If the round results in coordination failure, agents update their belief using:

*Updated-belief = current-belief – (current-belief * belief-changing-speed)*

This equation reflects the convex effect of coordination failures. Specifically, agents reduce their belief that others will adopt the GSS when they fail to achieve GSS use. The impairing effect of coordination failure diminishes as the belief value approaching 0.

Meanwhile, if the training rule is in effect, agents will update their learning using:

*Updated-learning = current-learning + ((1 – current-learning) * learning-speed-with-training)*

If the training rule in not in effect, agents will update their learning with:

*Updated-learning = current-learning + ((1 – current-learning) * learning-speed-without-training)*

Both learning update equations produce concave learning curves: each round of model play helps agents to be more experienced in choosing the appropriate GSS for a given task; the more experienced agents become, the less improvement they can make with each additional round of model play. As discussed earlier, the learning speed is faster when the training rule is in effect. The different learning speeds are reflected by the different parameters (learning-speed-with-training vs. learning-speed-without-training) in the two equations.

The decision, belief, and learning update functions of the model indicate that the behavior of agent is adaptive rather than fully rational. Each agent only has information about his or her own belief and learning ability. Each has no knowledge of the global distribution of others' beliefs or learning. After each round of game play, agents only know their own choice and the collective outcome. They do not know the specific choice of any other agent. Unlike fully rational actors, who would directly reach an equilibrium in the coordination game based on mathematical analysis of the payoff structure, agents in our model gradually converge to an equilibrium of the coordination game by adjusting their choices based on the history of the game play.

The simulator user can control the number of rounds in the game play. A greater number of rounds mimics a longer time span of GSS transition. The simulator has the capability to turn a certain facilitation rule on or off at any point in a simulation session. Thus, as the users of the simulator, we can examine whether a particular facilitation rule or a combination of several facilitation rules can induce self-sustained GSS use and how their effectiveness changes at different points in the GSS transition. Our multi-agent simulator is created in Netlogo (Wilensky, 1999), and its interface is shown in Figure 4. The interface comprises five main areas: model controls, experiment controls, calibration parameters, facilitator practices, and the display.

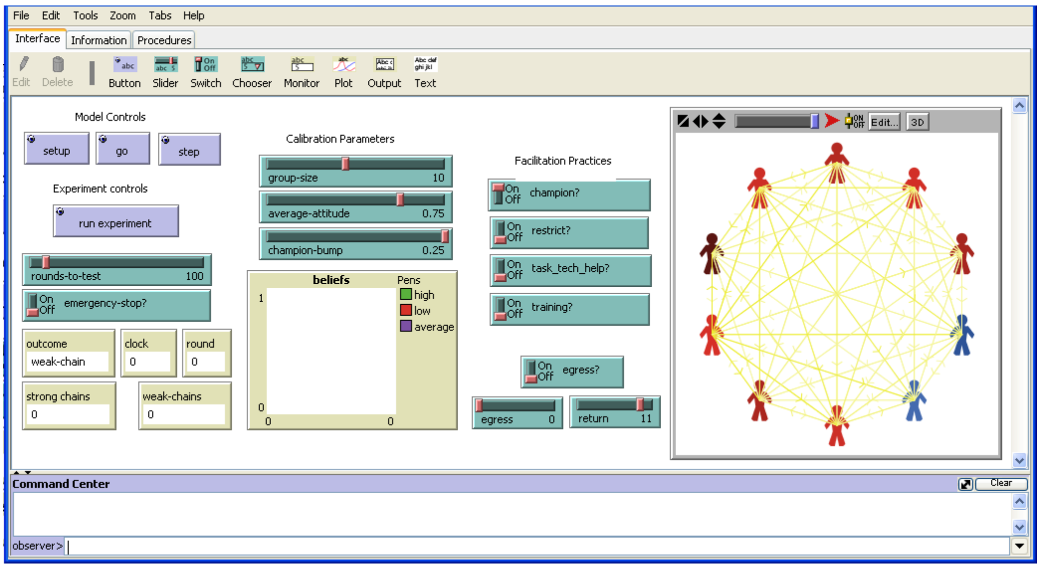

Figure 4. The Interface of the Simulator

The *model controls* are used to set up and run an individual experiment. A simulator user will first determine under what conditions he would like to test for the model and then set up the experiment. To run one round, the user hits the "go" button. To slowly proceed through a round, the user uses the step button to see the interactions at each stage. In the *experiment controls* section, a user can run many rounds and look at the aggregated results. As discussed above, the user will set up the conditions to be tested and the number of rounds to test the model on. The monitors in the lower left of the interface show the cumulative results. The *calibration parameters* are part of the experimental conditions but have been tested based on previous literature. Users can modify these values to see for themselves how group size and initial starting beliefs change the nature of the outcomes. The justification for the specific variable settings in our simulation is discussed in detail in the model calibration section. The *facilitator practices* are what we are exploring in this paper. Each practice can be turned on or off at any time and in any combination. The *display* is a window on the experiment, which shows each agent as a person shape. The colors of the agents show their choice in the game: A red agent has chosen NOT to use the GSS and a blue player has chosen to use the GSS. In addition, the brightness of the agents indicates how adamantly they made the decisions. For instance, a barely visible red agent is more likely to switch to blue than a bright red agent. Each agent also has an outward link to every other player and an inward link from every other agent. These links maintain each agent's current belief about how likely he thinks the other agent is to choose a GSS in question. The brightness of the lines is a visual clue to show the strength of the belief. The display updates after each round in a simulation session to reflect the current state of the simulation.

3.2. Model Validation

"Learning" from research using a computational model requires two stages. The first stage is to understand the behavior of the simulator itself in terms of the properties and behavioral rules. This is the focus of the section above on model design. The second stage is to translate learning from the simulation to learning about the actual process. This is generally viewed as the focus of the validation process. Validation "is the process of building an acceptable level of confidence that an inference about a simulated process is a correct or valid inference for the actual process" (Van Horn, 1971, p. 247). Rarely will validation result in a "proof" that the simulation is a correct or "true" model of the real world. The two important characteristics of the validation problem are:

1. The objective is to validate a set of new insights rather than the mechanism that generated the insights.
2. Validation is problem-dependent. There is no such thing as "the" appropriate validation procedure (Van Horn, 1971).

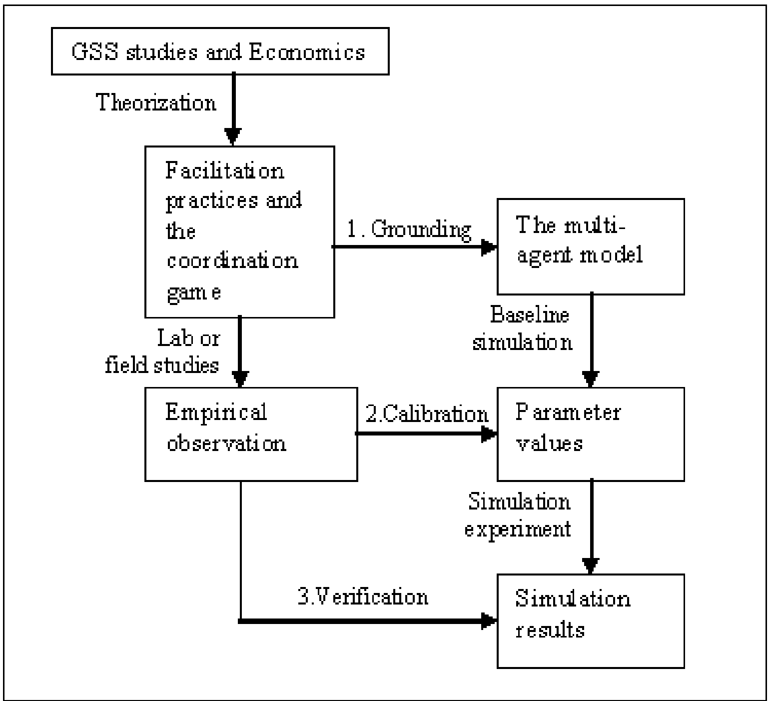

Figure 5. The Three-Stage Validation Process

In social science, an approach that has been recommended and performed in a number of simulation studies (e.g., Naylor and Finger, 1967; Weitzel et al., 2006; Carley, 1996; Kane and Alavi, 2007) is a three-stage validation process (see Figure 5 for the process in our study). The first stage is grounding. It focuses on the reasonableness of the causal relations in the simulation model and the fit of the model with existing theories. The grounding of our multi-agent model was largely addressed in the discussion about GSS transition, the coordination challenge, and facilitation practices. The behavioral rules of the simulation model are specifically based on the facilitation routines identified in the literature, and the interaction among agents is rationalized by the well-established coordination game theory in economics.

The second stage of the validation process is calibration. It is an iterative process of improving the fit of the parameter values in the model to the empirical observations available. The parameters of our model include *group size, GSS/defector/loser payoffs, the mean and standard deviation of belief and the belief changing speed*. These parameters define the context of GSS facilitation rather than directly represent the facilitation rules. Although variations of the parameter values do affect the simulation results, they are not the focus of our research questions. In the calibration process, we seek the set of parameter values that allows us to see the significance of different facilitation practices and variations of their effectiveness over the lifecycle of GSS transition.

To calibrate reasonable values for the parameters, we ran the simulation model 1000 times for each of the possible combinations of different values of the parameters (see Johnston, 2006 and Johnston, 2007 for more details). We then compared the results to findings taken from the last 17 years of experimental research in coordination within different size groups in minimum-effort games (Van Huyck et al., 1990; Camerer and Knez, 2000; Knez and Camerer, 1994; Cachon and Camerer, 1996; Chaudhuri et al., 2001; Weber, 2006). Out of the possible configurations of parameter values, the setting with the mean belief 0.75, the standard deviation 0.2, the belief changing speed 0.75, GSS payoff 10, defector payoff 3, loser payoff 0, and group size 10 produced the best fit with the prior findings.

The last stage is verification, which is the process of demonstrating the reasonableness of the simulation results and the fit of the results to real world observations. Because there is rarely an existing real world counterpart for every simulated condition, we cannot demonstrate the consistency of all variations in the simulation and all real world conditions (otherwise, we do not need to use simulation). Verification usually involves showing—for at least a few versions of the simulated system and the comparable conditions in real world—that the simulator produces results not inconsistent with the performance of the real system. Certainly, the match between a few variations of simulation and real world conditions does little to establish the virtue of other variations of the model. Thus, this widely applied and accepted test is essentially a null test: a model that failed to pass would be exceedingly suspect, but a model passed is not proved to be valid (Conway et al., 1959). Ultimately, verification is aimed at improving our faith in the insights gained from the simulation.

We perform model verification after conducting experiments with the multi-agent simulation. For the results produced by the simulation experiment, we look for comparable empirical findings in the literature and see whether the implications from the simulation and the empirical findings are consistent. More details on model verification are presented at the end of the results section.

As indicated by Figure 5, the three-stage validation process is not an isolated step in our research program. Instead, it is a persistent concern throughout this study and, thus, the process of validation is “embedded” as part of the theoretical development (grounding), model design (calibration), and result discussion (verification).

3.3. Experimentation in the Multi-Agent Model

We conduct a full factorial design experiment to explore the separate and combined effects of the facilitation rules. The goal of the experiment is twofold. First, we intend to gain insights into the propositions about facilitation practices. Second, we attempt to illustrate the value of the multi-agent simulation as an approach to gain new knowledge and ask new questions about the GSS transition issue. Table 4 lists the dimensions and the levels of each dimension of the factorial design experiment. This design results in 92,160 factorial conditions for the simulation experiment. A factor worth mentioning is egress of facilitation. This dimension of the factorial design is intended to test the sustainability of facilitation practices. By terminating the facilitation rules at different points in the GSS transition lifecycle, we can see how effective the facilitation rules are in inducing self-sustained use of GSS.

The outcome measure of the experiment is the likelihood of achieving self-sustained GSS use (i.e., the number of sessions achieving GSS use in the last round divided by the total number of sessions in a factorial condition). By comparing the likelihood values across different factorial conditions, we can assess the impact of different facilitation practices under varied settings of the model variables.

Table 4: The Factorial Design Experiment		
Dimension	**Level**	**Number of Levels**
The champion rule	Present, Absent	2
The restrict rule	Present, Absent	2
The task and tech help rule	Present, Absent	2
The training rule	Present, Absent	2
The percentage Increase of belief resulted from the champion rule	10%,15%, **20%**, 25%	4
Learning-speed-with-training	0.6, 0.65, 0.7, **0.75,** 0.8, 0.85	6
Learning-speed-without-training	0.2, 0.3, 0.4, **0.5**	4
Total rounds of game play	6, 7, 8, 9, 10, 11,**12,** 13, 14,15	10
Egress of facilitation after the specified round	1, 2, 3, 4, 5, 6	6
Total Number of Factorial Conditions		92,160

Notes: The numbers in bold are the set of variable settings we selected for result reporting

4. Results

We performed 100 sessions of simulation in each of the 92,160 factorial conditions. To scope down the results for reporting, we first selected a subset of factorial conditions that could effectively represent variations in facilitation effects. Specifically, we chose the factorial conditions with 20 percent as the increase in belief resulted from the champion rule, 0.75 as the learning-speed-with-training, 0.5 as the learning-speed-without-training, and 12 as the total rounds of game play. Conditions with other settings of the variables either did not generate enough variations for further examination, or produced results that were consistent with the selected subset.

In the selected subset of factorial conditions, we identified several interesting patterns in the simulation results. First, 11 out of the 16 possible combinations of the facilitation rules can induce GSS use. However, their effectiveness varies. Each facilitation rule alone is generally ineffective in producing self-sustained GSS use. Among all the combinations of two facilitation practices, the restrict rule and the task and technology help rule together are associated with the highest likelihood of a GSS use outcome. A combination of at least three facilitation practices can always induce some GSS use outcomes. We list the 16 combinations and their experiment outcomes in Table 5. In the table, each row with a non-zero likelihood outcome represents an effective portfolio of facilitation practices to induce GSS use. By the model design, we know precisely the causal pathway underlying each practice in the facilitation portfolios. Overall, findings in Table 5 offer a fine-grained understanding of the relative effects of the multiple pathways for facilitation to induce GSS use.

When allowing facilitation rules to terminate in the middle of a simulation session, we found that the sustainability of the facilitation rules varied. In general, the training rule enhances the sustainability of other facilitation rules. As shown in Table 6, the likelihood of reaching self-sustained GSS use tends to be higher when the training rule is present before we terminated all the other facilitation rules. We performed two-sample proportion tests to compare the likelihood of achieving self-sustained GSS use with and without the training rule (see Table 6 for the *p* values). Moreover, the longer the training rule remained in a simulation session, the more likely a self-sustained GSS use outcome occurs. For example, for the combination of the restrict, task and technology help, and the training rules, facilitation egress after the first round failed to result in any self-sustained GSS use outcome, while egress after the second round generated a 30 percent GSS use outcomes.

Table 5: Experiment Results of Combinations of the Facilitation Rules

Restrict	Champion	Task and Tech Help	Training	Likelihood of GSS Use
		yes	yes	1%
		yes		0
			yes	0
				0
	yes	yes	yes	2%
	yes	yes		4%
	yes		yes	0
	yes			0
yes		yes	yes	100%
yes		yes		100%
yes			yes	6%
yes				4%
yes	yes	yes	yes	99%
yes	yes	yes		100%
yes	yes		yes	4%
yes	yes			7%

Notes: "yes" means presence of the rule, while a blank cell means absence of the rule.

Table 6: Experiment Results with Egress of Facilitation Rules

Restrict	Champion	Task and Tech help	Training	Likelihood of GSS Use			
				Egress after Round 1		Egress after Round 2	
				%	*p*	%	*p*
		yes	yes	0	na	0	na
		yes		0		0	
			yes	0	na	0	na
				0		0	
	yes	yes	yes	5	0.37	7	0.04*
	yes	yes		4		2	
	yes		yes	0	na	0	na
	yes			0		0	
yes		yes	yes	0	na	30	0.002**
yes		yes		0		13	
yes			yes	0	na	6	0.15
yes				0		3	
yes	yes	yes	yes	22	0.006**	91	0.13
yes	yes	yes		9		86	
yes	yes		yes	1	0.5	3	0.65
yes	yes			1		4	

Notes: "yes" means presence of the rule while a blank cell means absence of the rule. * for significance at 0.05 and ** for significance at 0.01.

The varied sustainability of the facilitation rules motivated us to ask a new question: Does the timing of the presence of a facilitation practice modify its sustainability? We conducted a follow-up experiment with the facilitation rules present in the last two rounds of a simulation session (see Table 7 for results). We found that the timing of the presence of facilitation matters. When facilitation is made available in the last 2 rounds of a simulation session, the likelihood of achieving a GSS use outcome tends to be much lower than in the cases when the facilitation rules are present in the first two rounds of a session. This implies that the earlier GSS users can receive facilitation, the better the GSS transition outcome may be. Results in Table 7 also indicate that the restrict rule becomes pivotal in the late presence of facilitation. Meanwhile, the training rule does not seem to make much difference when made available later in a simulation session. An insight gained here is that later in the GSS transition process, when users' belief in GSS use has been substantially "damaged" by coordination failures, the facilitation practices that boost users' belief are more important than those that help them understand the technology.

Table 7: Experiment Results of Late Presence of the Facilitation Rules

Restrict	Champion	Task and Tech Help	Training	Likelihood of GSS Use
		yes	yes	0
		yes		0
			yes	0
				0
	yes	yes	yes	0
	yes	yes		0
	yes		yes	0
	yes			0
yes		yes	yes	5%
yes		yes		1%
yes			yes	3%
yes				3%
yes	yes	yes	yes	3%
yes	yes	yes		6%
yes	yes		yes	2%
yes	yes			1%

Notes: "yes" means presence of the rule, while a blank cell means absence of the rule.

Table 8: Model Verification

Findings in Real World Settings	Findings in the Simulation Conditions
GSS facilities are self-extinguishing (Briggs et al., 2003)	Absence of the facilitation rules results in zero GSS use outcome
Some initial training alone is ineffective in inducing GSS transition (Dickson et al., 1993)	Presence of the training rule alone results in zero GSS use outcome
A combination of training and restrictive GSS can lead to self-sustained GSS use (Hayne, 1999)	A combination of the training and the restrict rule can induce 6% likelihood of a GSS use outcome
Experiential learning is important for users to adapt GSS to their work processes (Dennis and Garfield, 2003)	The training rule can enhance the sustainability of other facilitation effects
Organizations would eagerly embrace a GSS facility for two years and then abandon it (Briggs et al., 2003)	Several facilitation portfolios (e.g., the restrict rule, or the restrict and the task and technology help rules combined) cannot produce self-sustained GSS use after the facilitation rules are terminated
Early presentation of a GSS to users is important (Orlikowski, 2000)	Facilitation provided in the first two rounds is more effective in inducing self-sustained GSS use than that provided in the last two rounds of a simulation session

Taken together, the findings help us achieve the two goals for multi-agent simulation. First, they offer us a more sophisticated view of the contributions of facilitation to self-sustained GSS use. We not only gain insights into the relative effect of different portfolios of facilitation practices (in relation to P1), but also recognize that the effects may vary depending on the available duration and timing of the facilitation practices (in relation to P2). Second, the findings indicate the value of the multi-agent modeling approach. The fact that we could conduct a large-scale full factorial design longitudinal experiment shows that the multi-agent simulation is a manageable approach to study dynamic social processes. The follow-up experiment about the late presence of facilitation rules further indicates that the multi-agent method is effective in answering “what if” questions.

As the last stage of the model validation, we revisit the GSS literature to look for comparable findings for the simulation results. As discussed earlier, it is usually impossible to find a real world counterpart for every condition in the simulation. Thus, we perform the model verification for a selected set of results for which we could identify related findings in the literature. The comparison between the simulation and the empirical results is presented in Table 8. In general, we do not see any significant inconsistencies between the two sets of findings. The model verification enhances our confidence in the insights gained from the multi-agent model.

5. Discussion and Conclusion

In this study, we apply the multi-agent framework to understand the contributions of facilitation as a coordination mechanism in GSS transition. By formalizing the interdependent decision making of GSS users as strategic behaviors in a minimum-effort coordination game, we interpret the contributions of facilitation as interventions to coordination failures in the game play. We develop a multi-agent simulator to gain insights into the propositions about facilitation practices. Through the simulation experimentation, we find separate and combined effects of the basic facilitation practices at different points in a GSS transition lifecycle.

The findings from the multi-agent simulation offer several important implications for CE research and practice. First, CE researchers can employ the multiple pathway view of the facilitation practices to examine the causal mechanisms underlying best facilitation practices identified in the field. Recognizing the specific causal pathways helps CE researchers to codify the core and most effective collections of facilitation routines. Second, this study calls for attention to the adaptive dimension of facilitation routines. The simulation results show that some facilitation practices such as restricting GSS use may be effective in initiating GSS use, but not in sustaining the facilitation benefit. In contrast, facilitation practices such as training may not appear to be helpful when used alone, but are very important for sustaining GSS use in the long run. Moreover, our findings imply that initiating an agreement of GSS use at the beginning of GSS transition is easier than correcting coordination failures later in the transition process. These findings suggest that packaged facilitation routines should include an additional component: the schedule for administering different facilitation practices. Based on an understanding of effectiveness of facilitation practices at different points in the GSS transition lifecycle, the schedule can vary the duration and intensity of different facilitation routines. This schedule can greatly enhance the adaptability of the CE approach to the dynamic nature of human interactions.

The theoretical development and the multi-agent model of this study contribute to the literature in several ways. First, to our knowledge, this study presents the first formal characterization of the coordination problem during GSS transition. It also develops the critical mass view suggested by prior studies (e.g., DeSanctis and Poole, 1994; Grudin, 1994; Gallivan, 2001). By articulating self-sustained GSS use as a coordination problem, we are able to draw on a rich body of literature from behavioral economics. To some extent, this study serves as a bridge between the CE literature and the game theory in economics. The minimum-effort coordination game framework and the propositions about facilitation’s contributions open up the “black box” of the impact of human interactions on GSS transition and the moderating effect of facilitation practices. By mapping the common facilitation practices of the two general interventions to coordination failures in the minimum-effort game, we offer a fine-grained view of the multiple pathways underlying how facilitation results in self-sustained GSS use.

A second contribution of this study is the multi-agent simulator. The simulator is essentially an artifact developed based on the design science approach (Hevner et al., 2004). Following the fundamental principle of design science (Hevner et al., 2004), we demonstrate a valuable approach to gain knowledge and understanding of a design problem (in this study, packaging the best practices of facilitation) through the building and application of the simulator. Although the findings from the simulator cannot be applied in a strict numeric sense, they help us realize nuances of GSS facilitation that are difficult to identify in either laboratory or field studies. For example, by designing facilitation behavioral rules in the multi-agent model, we achieve an in-depth understanding about how facilitation may affect GSS use by modifying the inputs to the decision, belief, or learning functions of agents. Moreover, when conducting experiments in the simulator, we identify new questions (e.g., the timing of the presence of facilitation) and perform immediate follow-up research. This would be difficult to pursue with other research approaches. We believe that the multi-agent simulator is a valuable tool for the CE community to gain new insights and pose questions from new angles. Subsequently, it improves the effectiveness of the CE community by extending the value of the best facilitation practices to more GSS supported work processes.

5.1. Limitation and Future Work

This study represents the starting point of our inquiry into the dynamic and adaptive characteristics of GSS transition with multi-agent simulation. At the current stage, the multi-agent model is still an oversimplified version of real world processes. While the simplification is necessary to accommodate the exploratory nature of the study, it leads to several limitations of this paper.

First, this study leaves out some important factors in the GSS context such as group cohesion and power. A next step for our inquiry is to incorporate these important factors. For example, a possible way to implement group cohesion in the multi-agent model is to utilize social network techniques. We can employ the link functions in Netlogo to represent social links among agents. Then, group cohesion can be measured as the strength and density of the social links. We anticipate that group cohesion has a positive effect on self-sustained GSS use, because strong social links among agents help improve their belief about others' GSS use intention. The social network approach is also a potential way to implement power in the multi-agent simulation. Power may be measured as the degree of centrality of each agent in the social network. An interesting question regarding power is whether it moderates the contribution of facilitation to GSS transition. One conjecture is that participation of powerful people in GSS transition may enhance the effectiveness of facilitation because they increase the willingness of other members to adopt the technology.

Second, we fixed several parameter values (e.g., group size and payoffs) in the current simulation in order to focus on the variables that are most relevant to our research questions. In the future, we plan to relax the parameter values to test their impact on the GSS transition outcome. For example, with respect to group size, experimental economic studies already provided some evidence that coordination is harder to achieve in larger groups (Weber, 2006). We anticipate that GSS use will be more difficult to reach and sustain as group size increases, because each additional member introduces more heterogeneity in interest or effort in GSS use. In addition, regarding payoffs, an interesting aspect to explore in future work is to vary the discrepancy between the GSS and defector payoffs. The discrepancy affects the tension between individual risk and group efficiency (Cooper et al., 1990; Van Huyck et al., 1990). We expect that the higher the GSS payoff relative to the defector payoff, the more likely agents will achieve GSS use, because the relatively higher GSS payoff makes GSS use a more appealing choice.

Another common concern of the computational approach is that the results seem to be "pre-determined" by the model design. It is true that the results are logical consequences of the model construction (otherwise, there is serious internal validity problem of the computational model). However, this does not mean that the new insights that emerged and the new questions asked during the model building and application processes could be predicted based on the initial model design. Once researchers understand how the behavioral rules in our model can generate the results, the value of our model in uncovering new insights and representing issues in a fresh new light is realized.

As one of the first studies looking at the coordination problem in GSS transition, this paper shows the relevance of the subject and the need for further research. The theoretical development and the multi-agent simulation are exploratory in nature. They warrant future work that can more precisely describe and predict the effect of certain facilitation practices on self-sustained GSS use and, thereby, improve the performance of the CE approach.

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Appendix A: Tutorial on Coordination Games

The basic form of a coordination game, usually called pure coordination game, is characterized by complete symmetry between players, between strategies and between equilibria (Mehta et al., 1994). A classic example of pure coordination game is the game of “Heads and Tails” from Schelling’s seminal work (1960). In the game, multiple players write down either “heads” or “tails.” If they simultaneously write down the same word, each is paid some given amount of money. If they write down different words, they receive nothing. In this pure coordination game, players have the same payoff structure, the same strategies (“heads” or “tails”) and the same expected value if either “heads” or “tails” becomes their unanimous choice.

The pure coordination game has been refined in several ways to represent more complex situations. One family of refined coordination games is called minimum effort games (Van Huyck et al., 1990; Camerer and Knez, 2000; Knez and Camerer, 1994; Cachon and Camerer, 1996; Chaudhuri et al., 2001). In a minimum effort game, players have to invest some effort to achieve a potential payoff, but the actual payoff to all players is tied to the effort of the person who contributes the least. A simple example of minimum effort games is a chain-building exercise. In the game, each member of a group is responsible for building one link of the chain. Each member can either invest $1 to build a weak link or invest $10 to build a strong link. After each member has independently decided whether to build a weak or strong link, the links are joined into a chain and the strength of the chain is tested. The chain is only as strong as the weakest link; that is, the chain is strong if all the links are strong or weak even if only one weak link is present. Each member in the group earns $5 if the chain is weak or $30 if the chain is strong. Thus, a person who chooses to build a weak link earns $4 regardless of the choices of others whereas a person who chooses to build a strong link may either lose $5 or earn $20 depending on others’ actions. The chain-building exercise demonstrates an essential difficulty in coordination: the dilemma between protecting individual resources or investing the resources towards a group goal, but taking the risk of losing individual investment.

One distinct feature of this type of minimum effort game is that coordination can still occur at separate outcomes, such as strong link building and weak link building in the chain-building exercise. However, there are obvious differences in potential benefits of outcomes. The coordination games with such asymmetric benefits of outcomes are often referred to as coordination games with Pareto-ranked equilibria. Here, an equilibrium (or pure-strategy Nash equilibrium) is a game outcome in which no player can gain anything by being the only person to change his/her choice (Gibbons, 1992). When we order the equilibria of a coordination game by their potential benefits to the whole group, we get Pareto-ranked equilibria. The equilibrium with the highest potential benefit is called the Pareto optimal equilibrium (Gibbons, 1992). Experimental economists find that players often fail to choose the Pareto optimal equilibrium in a coordination game even if the Pareto ranking is salient (Camerer, 2003; Van Huyck et al., 1990, 1991; Cooper et al., 1990, 1992). They attribute the result to strategic uncertainty. That is, players either do not interpret the Pareto ranking correctly or they are uncertain about other players’ interpretation. Coordination games with Pareto-ranked equilibria reveal another difficulty in coordination: uncertainty about potential benefits of outcomes. Table A1 shows a comparison between the minimum-effort coordination game with the pure coordination game.

Table A1: Comparison of Coordination Games

	Example	Symmetry between Strategies	Pareto-Ranked Equilibria	Types of Uncertainty
Pure coordination game	Heads and Tails	Yes players invest the same amount of effort and have the same payoff	No all equilibria of the game are equally good.	Uncertainty about other players’ choice
Minimum effort game	Chain building exercise	No players can invest different amounts of effort and get different payoff	Yes some equilibria of the game offer more benefits than others.	(1)Uncertainty about other players’ choice (2)Uncertainty about the rank of a equilibrium

About the Authors

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