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Research-in-Progress

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Abstract

In this multi-method study, we combine a longitudinal field study and agent-based modeling to examine the social construction process of user beliefs of collaborative technology over time. We argue that the primary methods in the technology acceptance literature—variance-based analysis and interpretive case study—are limited in understanding the reciprocal social influence process inherent to user beliefs of collaborative technology. Drawing on Bijker's (1995) social construction of technology theory and Salancik and Pfeffer's (1978) social information processing theory, research questions regarding the social construction of user beliefs are developed. We describe the longitudinal field study and agent-based modeling employed for answering the research questions. The future steps of this research-in-progress are outlined. We discuss the implications of this study at the end.

Keywords: social construction of technology, collaborative technology, multi-method research, agent-based model

Introduction

Collaborative technology has now penetrated into organizational work practices. Many different forms of collaborative tools -- including e-mail, intranet, web-based conferencing tools, and enterprise systems -- are being used routinely in organizations to support knowledge sharing, workflow automation, and virtual organizing. Recent studies show that collaborative tools provide an important platform for innovation (Boland et al. 2007), knowledge sharing and application (Choi et al. 2010), and organizational transformation (Leonardi 2007). Therefore, organizations continue to introduce new such tools. Yet, successful introduction of collaborative tools remain a challenging task.

Past research has shown that individual's beliefs and attitudes toward such collaborative tools are socially constructed (Fulk 1993; Orlikowski and Scott 2008). Yet, precise dynamics of such social construction process is not well understood. What factors facilitate or impede the process? What factors shape the contour of such social construction process? In this study, we seek to shed some fresh light on the issue of social construction process of collaborative technology by focusing on the formation and development of user beliefs of the tool. Understanding user beliefs of collaborative technology is a unique challenge to information systems (IS) researchers as these beliefs are not only shaped by an individual user's experience with the technology but also influenced by the opinions of other stakeholders (DeSanctis and Poole 1994; Markus 1990; Venkatesh et al. 2003). The primary approaches employed by IS researchers—variance-based technology acceptance models and interpretive case studies—are either limited in examining the reciprocal and emergent social construction process or lack precise measures of user beliefs and behaviors.

Motivated by this research challenge, we develop a multi-method approach (Mingers 2002) that is specifically suited to the examination of the formation and development of user beliefs of collaborative technology over time. This approach combines longitudinal field study and agent-based modeling (Davis et al., 2007). While the former provides snapshots of the formation and development of user beliefs in the real world and provide the basis of validation of the model, the latter extends these snapshots into a continuous and precise view of the time paths of causal relationships inherent to the social construction of user beliefs by opening the black box of the social construction process.

In the remainder of this article, we first draw upon Bijker's (1995) social construction of technology theory and Salancik and Pfeffer's (1978) social information processing theory in developing our research questions. Then we outline the multi-method research approach and the future steps of this study. In the last section we discuss the implications and draw conclusions.

Theory Development

Based on analyses of the historical evolution of the bicycle, synthetic plastic, and the fluorescent light bulb, Bijker (1995) developed a theory of social construction of technology. His theory is built around two key theoretical constructs: (a) interpretive flexibility of technological artifacts and (b) closure and stabilization. First, he argues that technological artifacts are inherently flexible, which causes different interpretations by different groups of users. The time-space discontinuity between designers and users makes it difficult for users to directly communicate with designers to fully understand the designers' intentions of the technology (Orlikowski 1992). Although users engage in "interpretations" of a system utilizing various sources of evidence (DeSanctis and Poole 1994), often these interpretations result in a less than complete understanding. Individuals' understanding of the technology is always incomplete due to the asymmetry of information distribution and the distributed and situated nature of users' cognition. The interpretive flexibility of technology manifests itself through divergent opinions and perceptions of the technology among users, particularly during the early stage of technology adoption (Tyre and Orlikowski 1994; Weick 1990). Second, over time, as users gain experience with technology, they develop stable routines, norms and habits for the use of the technology. Orlikowski and Scott (2008) note that material characteristics of the technology is entangled with institutional and social contexts, producing unique sociomateriality of technology use in organizations. Therefore, users' interpretations of technology are simultaneously constituted by the physical and material characteristics of that technology and the institutional and social contexts, shaping the contour of emergent patterns of use and its meanings over time. Consequently, the technology attains a stable interpretation among users. This is what Bijker (1995) calls "closure."

According to social information processing theory (Salancik and Pfeffer 1978), co-workers' and team members' beliefs and behaviors can be an important mechanisms by which such social construction of technology take place.

Specifically, co-workers influence an individual's beliefs, attitudes, and behaviors through overt expressions of their attitudes, interpretations of events, and provision of standards for judging the appropriateness of particular behaviors and for appropriately rationalizing workplace activities (Fulk, 1993, p.924).

Social construction of technology will play a particularly salient role in constructing individual users' beliefs about collaborative technology because it is specifically developed for multiple users. Furthermore, collaborative tools can be easily configured to accomplish diverse types of tasks -- such as e-mail, file sharing, bulletin boards, and conferencing -- it is more likely that it invites more diverse and often conflicting interpretation of technology by different individuals (Alavi et al. 2002). Therefore, as individuals work together to perform a task, they not only process the task and develop social relationships with each other during that process (Hackman and Morris 1975), but also develop norms and collective beliefs about the ways in which they communicate with each other (Alavi et al. 2002; McGrath et al. 1993; Yoo and Alavi 2001).

The social construction theory of technology suggests that the process by which individuals' beliefs are formulated and how it influences the emergence of sociomaterial practices of the organization follows a non-linear, dynamic and reciprocal process. That is, individuals' beliefs and actions shape the group or organizational outcomes, while at the same time, such collective outcomes simultaneously enable and constrain individuals' beliefs and actions (Miller and Page 2007). The dynamic and simultaneous interactions between individual and collective levels produce unpredictable and emergent outcomes of social construction process. What is not well understood in this process is the process by which the contour of sociomaterial practices emerges through this dynamic and emergent process.

In order to close this gap in the literature, we ask the following research questions:

Research Question 1: How do the initial divergent individual beliefs of technology influence the emergent pattern of social construction of technology, and how the emergent social construction of technology simultaneously influence individuals beliefs of technology?

Research Question 2: How does the nature of social structures among individuals influence the emergent patterns of social construction of technology, and how the emergent social construction of technology simultaneously influence the nature of social structures among individuals?

Research Question 3: What factors influence the temporal shape of the emergent patterns of social construction of technology?

Research Methods

In order to answer these research questions, we need to quantitatively trace the temporal contour of the evolution of user beliefs over time, evaluating the time-dependent relationship between beliefs of each user and other team or organizational members. We combine the analytical advantages of longitudinal field study and agent-based modeling in satisfying these methodological requirements (Mingers 2002). The longitudinal field study provides the empirical observation of one version of the social construction process in the real world. Grounded in this empirical observation, an agent-based model is constructed to enable simulated experiments of various versions of the social construction process (Davis et al. 2007). By comparing simulation results from different experimental treatments, we expect to gain rich insights regarding the causal pathways in the formation and development of user beliefs of collaborative technology.

Longitudinal Field Study

We have collected the longitudinal data from one hundred and eighteen executives from a large U.S. federal government agency. These executives participated in the study as part of an executive development program at a major state university. The sample comprised 65 males and 53 females. The average age was 49. Twenty-two subjects had bachelor's degrees, 71 had master's degrees, and 2 had PhDs. Twenty-three individuals had other types of degree, such as law and community college degrees. They were divided into 18 teams, each of which consisted of 6-7 individuals.

The teams worked on a task involving a complex community planning and development project for a rural city in a Mid-Atlantic state (population 35,000). Each team was to assume the role of consultant team to the mayor of the city and develop a specific strategy to increase the home ownership rate from the current 38% to 51% (or greater) within 10 years. At the conclusion of the 10-week project, each team was to submit a report to the mayor containing specific recommendations on the attributes of the customers (e.g., age and income mix), financing options, annual housing production levels (new construction and/or rehabilitation of old construction), as well as specification of resource levels, sponsors, and partners. All teams were given census, demographic, and economic data for the city and the surrounding region. Other relevant data were provided by the mayor's office, including statistics on employment, crime, education, and the city's housing and community development profiles.

Team members were assigned so that no members were co-located in the same geographic office to avoid face-to-face meetings among team members while working on the task. The project data were made available to the teams on a multimedia database of a collaborative technology. This tool, referred to as Alpha system in this paper, provided features such as a multimedia database, threaded discussion, and workflow automation. Participating executives were unfamiliar with Alpha system. They were, therefore, extensively trained in its use during the two-week residential module of the program prior to the team project. They were provided access to Alpha system on a server at the university through a toll-free telephone number. To further support the use of Alpha system by the participating executives, telephone technical supports by professional consultants were provided. The use of Alpha system was voluntary.

Three different user beliefs about the collaborative technology were measured: perceived usefulness (PU), perceived ease of use (PE), and behavioral intention (BI). The questions were adopted from the original instrument developed by Davis (1989). Both PU and PE were measured twice, at the end of the second week (T1) and at the end of the tenth week (T2). Other group members' perceived usefulness (OPU) and perceived ease of use (OPE) were calculated as the average of their self-reported PU and PE, respectively, for both T1 and T2. BI was measured at T1. We also measured subjective norm (SN) at T2 to assess the strength of group cohesion. The measurement of SN was adapted from Taylor and Todd (1995). Users' self-reported usage (USE) was measured at T2, using two items.

Agent-Based Modeling

Agent-based modeling is a computational simulation tool widely adopted by social and organizational researchers to understand how individual actors' attributes and behaviors interact and collaboratively create social or organizational level outcomes. Rather than reducing a real world phenomenon to variables and relationships among variables, agent-based modeling uses agents, interactions among agents, and an environment to represent social processes. Agents are individual actors in a social process. They are described by attributes and behavioral rules. Attributes are the internal states of agents (Epstein and Axtell, 1996). They can be fixed (e.g., gender) or modified over time (e.g., wealth). Behavioral rules are the schemata governing an agent's attributes and behaviors. They are a set of input/output statements that link an agent's perception of the world to changes in its internal state or actions (Drazin and Sandelands, 1992). Interactions are the mutually adaptive behaviors of agents. They arise as agents recurrently apply their behavioral rules. The reciprocal social influence process is an example of interactions among collaborative technology users. The environment is the medium for agents to operate in and interact with (Epstein and Axtell, 1996). It can represent landscapes or abstract structures such as collaborative work.

The agent-based modeling can complement and extend the longitudinal field study in three important ways. First, while the longitudinal data capture time-dependent causal pathways by a few snapshots of the social construction process, the agent-based model allows us to continuously and precisely track the evolution of this process with a built-in clock. Second, unlike data collection in the real world that is constrained by physical, legal, or ethical concerns, the agent-based model offers us significant control in the measurement and manipulation of crucial variables. We can implement and examine a wide range of experimental treatments. Third, compared with the longitudinal data analysis, the agent-based model provides a more natural scheme for the examination of the social construction process of user beliefs. Rather than infer this process from individual user's perceptions, we can directly observe how agents' interactions enact this social process.

Although agent-based modeling involves simulation, it is not aimed at providing an accurate replication of the real world. The goal of agent-based modeling is to employ simple computational parameters and algorithms to operationalize a social process, allowing researchers to gain deeper understanding of the real world by observing the results generated by simple algorithms (Axelrod, 1997). Reflecting this goal, a well-established approach in the agent-based modeling community is to use strings of symbols (e.g., numbers or letters) to represent agents and the environment (e.g., Holland, 1995; March, 1991). This approach allows researchers to use a consistent syntax encoding the key elements of a social process while abstracting away real-world nuances.

We followed this approach in developing the agent-based model for this study. In our model collaborative technology users are the agents. The number of users in each simulated team, *n,* is defined as a variable so that we can conduct experiments regarding team size. Each user is represented by a string of numbers. Each number in the string can be interpreted as a work practice that is supported by a technology feature of the tool. Therefore, the length of the string, *l*, signifies the total number of features in the tool; it is intended to reflect the technology complexity. We define *l* as a variable in order to evaluate the impact of technology complexity on user beliefs. Each number in a worker's string takes an initial value of 0, indicating no use of the tool. The numbers can remain 0 or change to 1 over time as a result of belief changes. The 1 value indicates uses of the particular feature of the tool.

The collaborative work characterizes the environment of our agent-based model. We assume that the users take a divide-and-conquer approach and break down the collaborative work into individual tasks for each user. Each individual task is represented by a string of numbers. The numbers in the string represent the productive work practices of applying or not applying the technology features. The length of a task string is *k*, signifying task complexity. Each number of a task string takes an initial value of 0 or 1 with equal probability. The values in a task string remain constant. Identical values on the same dimension of a user's string and its task string indicate that the user's IT-based work practices are productive. This gives us a way of measuring work performance. By setting *l* being equal to *k,* we can model a situation where the tool can perfectly support the task. However, by setting *l* being smaller than *k,* we can model a situation where the tool is inherently less than desirable to fully support the task. The latter case can be used in order to understand the social construction process of technology under a situation where a defective system is being deployed.

Consistent with the longitudinal field study, user beliefs are encoded as three attributes of the user agents: perceived usefulness (PU), perceived ease of use (PE), and behavioral intention (BI). Values of these three attributes vary between 0 and 1. The initial value of a user's PU is a random number drawn from a normal distribution. This random number allows us to simulate the divergent nature of initial user beliefs. The mean and standard deviation of the normal distribution will be calibrated from the longitudinal data. During the model play, each user's PU is updated by its work performance, which is measured as the percentage of values in the user's task string correctly represented in the user's string. During each clock tick of the model play, each user will compare its current work performance with the average performance in the past. This user will then increase or decrease its PU according to its performance gains or losses. To capture the possible variations of users' technology attitude, we randomly assign users to one of three types: positive, neutral, or negative attitude. When a user with a positive technology attitude achieves performance gains, the user's PU substantially increase with slight improvements in performance. Therefore, its PU is updated according to the concave function:

Updated PU = current PU + square root of performance gain[1]

For a neutral attitude user, performance gains will lead to the updated PU value according to the linear function:

Updated PU = current PU + performance gain.

For a negative user, the user's PU increases only after sustained level of performance improvements with a significant time lag. Thus, its PU is updated according to the convex function for performance gains:

Updated PU = current PU + performance gain squared.

Meanwhile, if a positive user experiences a performance loss, the decrease of PU comes only after persistent poor performance with a significant time lag. Thus, its PU is updated according to the convex function:

Updated PU = current PU - performance loss squared

For a neutral user, its PU is updated as:

Updated PU = current PU - |performance loss|

For a negative user, the PU drops only with a slight performance decrease. Thus, its PU is updated according to the concave function:

Updated PU = current PU - square root of |performance loss|

[1] Since performance gains or losses are percentage values, their square roots are always greater than their squared values.

The specific functional forms in the above equations should not be interpreted as any precise mapping of attitude changes in the real world; instead, we attempt to use them as simple computational representations of the three broad different trajectories of attitude change of different users. For example, a user with an initial PU as 3 and a performance gain of 0.04 will update her PU from 3 to 3 + 0.2 = 3.2 if the user has a positive technology attitude. The same initial PU and performance gain values will result in an updated PU as 3 + 0.04 = 3.04 if the user has a neutral attitude. For a user with a negative technology attitude, the same initial PU and performance gains will lead to an updated the PU as 3 + 0.0016 = 3.0016.

The initial value of a user's PE is a random number drawn from a normal distribution. This simulates the initial divergent individual beliefs. The mean and standard deviation of the normal distribution will be calibrated from the longitudinal data. To represent the possible variations of user learning speed, we randomly assign users to three learning types: fast learners who have a concave learning curve (to represent rapid initial learning), regular learners who have a linear learning curve, and slow learners who have a convex learning curve (to represent significant initial learning curve). During each clock tick of the model play, a fast learner's PE is updated according to the concave function:

Updated PE = current PE + square root of current PE

For regular learners, the PE is updated according to the linear function:

Updated PE = current PE + initial PE

For slow learners, the PE is updated according to the convex function:

Updated PE = current PE + current PE squared

The social influence among users is represented by the behavioral rule: if a user's PU or PE is different from other members' average PU or PE, the user will adjust its beliefs according to:

Adjusted PU = Updated PU * (1 – subjective norm) + Others' PU * subjective norm

Adjusted PE = Updated PE * (1 – subjective norm) + Others' PE * subjective norm

Subjective norm (SN) in these equations is a variable varying between 0 and 1. SN allows us to conduct experiments assessing the moderating effect of subjective norm. To model the uneven distribution of information about other users' beliefs, we implement a variable, communication bandwidth (CB), to control the proportion of other members' beliefs correctly observed by a focal user. CB is defined as a variable ranging from 0 to 1, where 0 indicates that individuals do not receive any signal about others' beliefs and 1 indicates a situation where no signal loss takes place. Thus, a user's perceived beliefs of others are calculated as:

Other's PU = average PU of other members * communication bandwidth

Other's PE = average PE of other members * communication bandwidth

Each user's behavioral intention (BI) is a linear combination of its PU and PE according to the equation:

BI = PU * PU-beta + PE * PE-beta

PU-beta and PE-beta will each be drawn from a normal distribution. The mean and standard deviation of each normal distribution will be calibrated from the longitudinal data.

Users adopt the tool's features with probability equal to their BI. That is, during each clock tick of the model play, each 0 in a user's string can changes to 1 with probability BI while each 1 in the user's string can change to 0 with probability (1 – BI).

Interactions in the agent-based model are the reciprocal social influence process among users. They arise as users recurrently apply the social influence behavioral rule.

In addition to user beliefs, we also track users' technology use behaviors by measuring IT adoption rate over time. This IT adoption rate can be measured as the average IT use intensity (i.e., percentage of users adopting a tool feature on average) or the average tool feature use rate (i.e., percentage of tool features adopted by a user on average). These two measures produce identical result. The agent-based model design is summarized in Table 1 and depicted in Figure 1.

We have implemented the agent-based model using the Netlogo toolkit (Wilensky, 1999). An internal clock is built in the agent-based model to simulate the flow of time. At each tick of the clock all agents were given the opportunity to execute their behavioral rules once. A simulation session will include multiple clock ticks mimicking the duration of a collaborative technology use process.

Table 1: Summary of the agent-based model design

Model element	**Real-world counterpart**	**Computational representation**
Agents	Users	A total of *n* users, with each user represented by a string of *l* numbers
Agent attributes	User beliefs	PU, PE, and BI; these values vary between 0 and 1; PU is updated by users' work performance gains or losses; PE is updated by learning
Agent behavioral rule	Social influence among users	Agents adjust their beliefs (PU, PE, and BI) according to other members beliefs. The degree of adjustment is dependent on the subjective norm and communication bandwidth.
Interaction	Reciprocal social influence process	As each user recurrently applies the behavioral rule, the reciprocal social influence process arises in time and space.
Environment	Collaborative work	Collaborative work is divided into individual tasks. Each user's individual task is represented by a string of *k* numbers

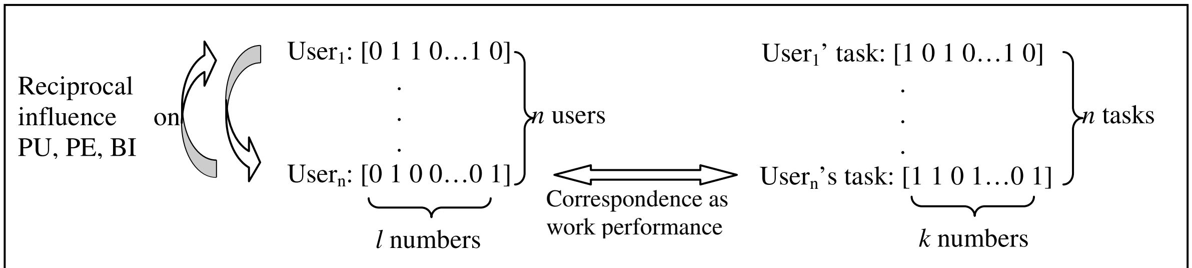

Figure 1: Overview of the agent-based model

Preliminary Results

At this point we have made several interesting observations from a preliminary analysis of the longitudinal field data. First, a correlation analysis indicates a lack of agreement among group members on PU ($r = 0.128$, $p>0.05$) and PE ($r = 0.019$, $p>0.05$) of the Alpha system at the early stage of usage (T1), but clear agreements among their PU ($r = 0.254$, $p<0.05$) and PE ($r = 0.246$, $p<0.05$) in the later stage (T2). This suggests the critical role of reciprocal social influence in the social construction of user beliefs. Second, when regressing users' self-reported usage (USE) to their beliefs, we found that only PU ($\beta=0.26$, $p<0.01$) and PE ($\beta=0.44$, $p<0.001$) at T2 were significant predictors of long-term USE. This implies that the social construction of user beliefs can diminish the intention-behavior correlation found in uses of single-user technology applications (e.g., Davis, 1989). Third, when comparing user beliefs across different time, we noticed a sharp decrease of PU (a 44% drop from T1 to T2). To our knowledge, this substantial change of user beliefs was not triggered by any dramatic event in the executive teams. We believe that it manifests the intriguing nature of the social construction process: recurrent subtle changes of individual beliefs through reciprocal social influence can collapse into an unintended or unforeseeable shift of users' shared beliefs of collaborative technology.

Next Steps

Following the longitudinal data analysis, we will perform a few tasks in the agent-based model. First, we will calibrate the mean and standard deviation of PU-beta and PE-beta according to the statistical estimates from the longitudinal data analysis. The distributions of users' initial PU and PE in the longitudinal data will inform the setting of the mean and standard deviation of the initial PU and PE values in the agent-based model.

Second, we seek to validate the agent-based model by conducting additional tests (Davis et al. 2007). One test is to set the values of team size (*n*), technology complexity (*l*), task complexity (*k*), subjective norm, and communication bandwidth according to the longitudinal data, and then see whether the formation of user beliefs produced by the model simulation correspond to the results from the empirical data analysis. A second test is to see whether by setting both subjective norm and communication bandwidth at 0, the simulation results are consistent with the findings from technology acceptance models on single-user technology applications (e.g., Davis, 1989). Although a few matches between the simulated and the real world versions of the social construction process does not establish the virtue of other variations of the simulated world, it will improve our confidence in using the simulation results to gain new insights regarding user beliefs of collaborative technology.

After model validation, we intend to perform a series of experiments in the model to evaluate the impacts of individuals' attitude toward technology, learning ability, team size, technology complexity, social norm, and communication bandwidth on user beliefs and uses of groupware. We can further manipulate the initial value of PE and PU under varying situation, to understand the impact of initial training and change management for the emerging contour of social construction of technology. In analyzing the simulation results, we will focus on an aspect of the results uniquely available from the simulations: the continuous and precise view of the time paths of these impacts. These simulations can provide insights into how the social construction process emerges and evolves over time and how its evolving process is contingent on contextual factors such as team size or communication bandwidth.

To fully leverage agent-based modeling, we intend to implement two further manipulations in the model. First, we will give users more complicated tasks (setting k larger than l) to understand the situation where the technology was "over-promised". Second, we will allow users to form discretionary social ties by incorporating social network structure among individuals. This enables us to evaluate the role of social networks in the emerging pattern of social construction of collaborative technology.

Conclusion

The primary objective of this paper was to explore the ways we can study dynamic, emergent and non-linear process of social construction of collaborative technology and the reciprocal relationship between the individuals' beliefs of technology and the collaborative workforce's shared beliefs of the tool. It was posited that at the early stage of collaborative technology use, users would have multiple, and possibly conflicting, interpretations of the tool. However, it was further posited that as individual users observe others' usage patterns and exchange their own beliefs about the system with other users, a stable sociomaterial practice would emerge over time. We believe that various initial conditions can influence the temporal contour of the emerging pattern of social construction of collaborative technology. To explore our research questions, we are conducting a multi-method study, combining a longitudinal field study and an agent-based modeling.

The potential results of this study can offer several implications to managers who want to implement collaborative technology in organizations to improve the quality of communication and coordination among their collaborative workforce. First, they will help managers to recognize the "social" nature of the tool. That is, the success of collaborative technology implementation is dependent not only upon the design characteristics of the system, but also upon the formation of successful social environments that are positive toward the technology. Second, the potential results can inform managers the effective strategies for directing a social construction process of collaborative technology toward favorable outcomes. Orlikowski et al. (1995) demonstrated that a carefully orchestrated management intervention can be effectively used to achieve the intended outcomes of the system by molding the social construction process of collaborative technology. As such, managers need to carefully develop collaborative technology implementation plans paying special attention to how social information about the technology is formed and conveyed among intended group of users.

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