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Social learning in design teams: The importance of direct and indirect communications

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Abstract

This paper discusses the effects of direct and indirect communications on social learning and task coordination in design teams. The findings reported in this paper are based on a computational model that simulates the formation of transactive memory (TM) through social learning from direct and indirect communications. Direct communications are explicit information exchanged between team members whereas indirect communication may be opportunistic and coincidental, resulting in learning and information gained through observations of the actions of others. However, team structure mediates opportunities for communication. Three types of team structures are studied, which are differentiated on the basis of their constraints on and opportunities for direct and indirect communications across the team. The differences across the team structures are investigated through a series of simulations in which team member retention, cognitive busyness of team members, and task complexity are additional moderating variables, and task coordination and formation of TM are the dependent variables. Fewer communications to coordinate the same tasks are taken as the measure of efficient task coordination. Findings suggest that reduction in communication and learning opportunities are more detrimental to the task coordination in flat teams as compared to functional teams. Indirect communications contribute more to the formation of TM than to task coordination. Flat teams facilitate the formation of TM, whereas functional teams are more appropriate for efficient task coordination, indicating that the role of TM in mediating task coordination varies with team structure.

Keywords: Busyness; Direct Communication; Member Retention; Social Learning; Task Coordination; Team Structure; Transactive Memory

1. INTRODUCTION

The importance of communication in design teams is well recognized (Sonnenwald, 1996; Kleinsmann et al., 2007; Kleinsmann & Valkenburg, 2008). Although communication can be viewed and conceptualized in different ways (Maier et al., 2005), in the design research community, communication is generally conceptualized as the exchange of design representations across various communication media, communication tools, and communication channels in distributed and colocated settings (Del Cerro et al., 2001; Bucciarelli, 2003; Eckert et al., 2005). Beyond satisfying the information needs of communication itself, authors have been increasingly stressing the importance of social learning associated with coincidental communication occurring during the team activity (Brown & Duguid, 1996; Grecu & Brown, 1998; Bobrow & Whalen, 2002; Wu & Duffy, 2004).

Social learning refers to learning from social processes (Bandura, 1977), which include direct communication and observation. Social learning is considered particularly important to teamwork because social learning is embedded in the environment and it is as much involuntary as it is goal directed (Marsick & Watkins, 1997). In general, social learning is explained in terms of actions and observations (Tomasello, 1999; Knobe & Malle, 2002; Malle, 2005). Team members learn about the other members in the team based on the actions of the others, which are often observable (Wallace & Hinsz, 2009). The structure of the team and the available information and communication technologies may support or inhibit opportunities for observations and interactions. For example, a person may directly communicate with another person and learn about her level of expertise with a specific piece of software because they sit in adjacent cubicles and work together on the same project albeit in different roles.

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Thus, based on this direct communication afforded through spatial adjacency and project team structure, the first person knows to seek the second person's assistance in using the software. In contrast, a third person may not have directly communicated with the second person having the software skills, but he might have observed the second person working while walking by the cubicle and learns through observations that the second person uses that software. Similarly, a fourth person might only have observed (overheard) the discussion between the first person and the second person about the software to learn something about the second person's knowledge of the software, which may be useful if any assistance is needed later on. Those not located in the office would not have the opportunity for this coincidental observation or indirect communication without the assistance of social media. Thus, different modes of social learning associated with direct and indirect communication are possible in design teams, and all these forms of communication provide opportunities for learning about the skills and knowledge of others, which should affect teamwork and team performance (Cohen & Bailey, 1997), including task coordination (Cooke et al., 2000, 2004).

Design teams require actions and communications that extend beyond the design activity to prosocial aspects of teamwork (Carrizosa & Sheppard, 2000; Milne & Leifer, 2000; Akgun et al., 2006). In the absence of such prosocial characteristics, merely forming a design team consisting of people knowledgeable in their individual domains may not ensure high coordination (Candy & Edmonds, 2003). Effective teamwork requires team members to have a well-developed understanding of the team's competence and where (i.e., with whom) competences lay, which has been theorized in terms of the concept of a transactive memory (TM; Wegner, 1987; Lewis, 2003). TM is a system through which groups collectively encode, store, and retrieve knowledge (Wegner, 1987; Lewis, 2003; Akgun et al., 2006). TM allows teams to deal with tasks that require multiplicity of competence and knowledge that may not be possible for one individual to develop, manage, and organize, but can be effectively developed, managed, and organized by coordinating the specialized competence and knowledge of the team members and by assigning the right job to the right people.

Simply put, TM mediates efficient teamwork (Moreland et al., 1998; Rao & Argote, 2006; Ren et al., 2006). Communication and social learning act as a mechanism for the formation of TM (Rao & Argote, 2006). The degree to which team members have learned about each other's skills and knowledge is taken as a measure of the completeness or "density" of the TM (Ren et al., 2006). One benefit of having a complete TM is that fewer communications would be required to coordinate tasks. The team would already know the identity of those knowledgeable in a specific domain. Team members would therefore not have to spend communication cycles finding a knowledgeable person to complete a task or to learn how to complete a task when an expert in the area is available within the organization. Teams that require fewer direct communications between individuals to coordinate task work could be considered to perform more efficiently (Blinn, 1996; Entin & Sarfaty, 1999).

Studies comparing individual learning scenarios to social learning scenarios have established the coordination and TM formation benefits of social learning (Moreland et al., 1998; Ren et al., 2006). However, these studies have considered social learning as a single entity, which limits our understanding of the significance of the constituent learning modes associated with direct and indirect communication. Thus, despite the consensus that various modes of social learning exist and social learning contributes to TM formation and ultimately task coordination, there is little understanding of the differential contributions of the social learning modes to TM formation or task coordination. This research addresses this gap by comparing the differential contributions of different social learning modes associated with direct and indirect communications to TM formation and task coordination.

An improved understanding of the differential effects of the different social learning modes associated with direct and indirect communications on TM formation and task coordination benefits can help design teams reduce the cost of formal training and orientation toward TM formation and improving task coordination (Marsick & Watkins, 1997).

2. RESEARCH APPROACH AND METHOD

Because the aim of the present research is to understand the influence of social learning modes associated with direct and indirect communications on task coordination and TM formation, this research starts from the position that the project team is already staffed with specialists with rich experience in the tasks, processes, and context but who do not have knowledge of what others in the team know. Such an assumption is facilitated by a computational study, which allows isolation and controlled study of experiment parameters that are difficult to isolate in empirical studies (Conte & Gilbert, 1995; Jin et al., 1995; Carley & Gasser, 1999; Macy & Willer, 2002; Gilbert, 2004). Following are the key drivers and advantages of using a computational model for this study:

- In many prior studies on social learning in teams, the foundation of teamwork is the ability of the agents to learn from experience *about their tasks*, often modeled as information acquisition (Rodan, 2008). Across all these and other similar studies, the consensus is, as put succinctly by Simon (1991, p. 125): "All learning takes place inside individual human heads; an organization learns in only two ways: (a) by the learning of its members, or (b) by ingesting new members who have knowledge the organization didn't previously have." Rather than modeling cognitively rich agents that improve their own performance through experience, we question the type of experiences that lead to learning and the barriers to those experiences. Specifically, we model the types of social experiences gained through communication about what others know so that the agents can be more efficient at coordinating work.

- In studies with human subjects, it may not be possible to identify or create scenarios such that team members only learn about each other's and the team's competence while their knowledge of the task, process, and context remains constant.
- Constraining how and what the team members (agents in the model) learn through computational simulation ensures that the observed effects are a result of social learning modes and are not biased by learning abilities that may vary from person to person. Factors such as the kinds of assumptions team members make and how those assumptions are influenced by other sociocognitive variables such as trust and reputation may differ from person to person. These factors may diminish or exaggerate the knowledge that agents take away from a social learning experience. The use of a computational model eliminates these factors because social learning and communication opportunities can be consistently implemented as a set of rules.

The computational model has been validated in earlier studies for its usefulness and consistency (Singh et al., in press). Although sociocognitive factors such as trust and contextual factors such as proximity between the agents are likely to affect the veridicality of the reported findings, additional parameters can be modeled in future research to study their effects.

This paper studies the effect of direct and indirect communication on task coordination by considering the fundamental modes of social learning associated with direct and indirect communication; and by conducting simulations with various mediating variables (MVs) that may affect direct and indirect communication, and hence social learning opportunities, in design teams.

3. RESEARCH QUESTIONS AND HYPOTHESES

There are several variables that we believe have a strong influence on opportunities for social learning through communication. The following are the independent variable (IV) and MVs in this study, which we will elaborate upon in the subsequent sections:

IV: Social learning modes (associated with communication opportunities) available to team members

MV1: Team structure, that is, how the team is organized

MV2: Level of member retention, that is, how many team members are retained from one project to another

MV3: Level of busyness, that is, availability of an individual to observe team activities (i.e., learn from indirect communication)

MV4: Task complexity

Although there are numerous forms of social learning, in this model, we consider three fundamental modes of social learning: learning from personal interactions (PI), learning from task observations (TO), and learning from interaction observations (IO). These forms of social learning will be operationalized to model how an individual learns about the competencies of others so that members can better coordinate their activity, which is a key factor that affects the rate at which organizations benefit from their own experience (Argote, 2005). The three fundamental modes of social learning are explained below:

1. *Personal interaction:* Personal interactions are direct communications, and these are the most direct mode of learning. Team members learn by directly interacting with other team members. Personal interactions between team members with respect to a task allow them to know about each other's competence for a given task. For example, if A talks to B about task T^1, then both A and B learn about each other's competence with respect to T^1.
2. *IOs:* When a team member has the opportunity to observe interactions between other team members, the member learns about the interacting team members without having to directly communicate with them. For example, if A observes B allocating task T^1 to C, then A may learn about the competence of B and C with respect to T^1.
3. *TOs:* A team member may also have the opportunity to observe another team member performing a task without having direct communications. For example, if A observes B performing the task T^1, then A learns about B's competence with respect to T^1.

In technology-mediated communication, the kinds of indirect and coincidental communication discussed in (b) and (c) can occur on social networking sites and groupware, where members can observe (i.e., read about) each other's activities, messages, and updates.

The relationship between direct and indirect communication and task coordination is mediated by several variables. Team structure determines the opportunities for communication and social learning. Design teams can vary across different dimensions such as size (e.g., large, medium, or small), life span (e.g., project-based temporary teams or long-term teams), location (e.g., distributed or colocated), structure (e.g., flat or hierarchical), and composition (e.g., homogenous or heterogeneous). This study distinguishes design teams with respect to the constraints and opportunities for socialization and communication, primarily categorizing teams with respect to team structure, but taking into consideration the characteristics defined across other dimensions such as location and life span. The theoretical bases for the choice of team structures studied are as follows.

Design teams are often project based (Perkins, 2005), formed from a collection of experts with specialist knowledge. Project-based design teams can take different organizational structures (Laubacher & Malone, 2002; Perkins, 2005). The organizational structure of the design teams would create differences in terms of the task allocation and social observation opportunities, which should affect the formation of TM and the ability of the team of experts to coordinate the tasks. The following three types of team structures are differentiated:

Flat teams: Flat teams have no hierarchy and no subdivisions. Such teams are generally used for consultation, taskforce, and design exploration (Katzenbach, 1993; Perkins, 2005). In general, such teams allow unconstrained social interactions and observations across all members of the team.

Distributed flat teams: With the increased use of communication technology, collaborative design teams are often distributed across geographies (Moore & Dainty, 1999; McDonough et al., 2001). Examples of distributed teams can be found in global project teams (McDonough et al., 2001). In such teams, social cliques sometimes develop, such that the team is divided into two to three colocated clusters. Thus, even if the teams are flat for the purpose of task allocation, the opportunities for social learning and indirect communication are skewed due to the physical boundaries (Allen, 1977; Fulk & Boyd, 1991; Desanctis & Jackson, 1994; McDonough et al., 2001; Kiesler & Cummings, 2002; Leinonen et al., 2005).

Functional teams: Many design teams are organized into functional subteams (Hackman, 1987; Malone, 1987; Grant, 1996; Love et al., 1998; Moore & Dainty, 1999). In such teams, the task is passed to the members from the subteams with relevant domain knowledge. Hierarchy is created in the team as the task is decomposed into subtasks and members are chosen to coordinate those tasks. A team member from each subteam emerges as the group coordinator. This member also coordinates the activities of that group with coordinators from other groups.

Besides the team structure, the project-based nature of design team means team composition, in the sense of having team members with prior experience working together, is a critical consideration (Moore & Dainty, 1999). It is often considered desirable to retain as many team members as possible from one project to another to take advantage of the social learning and TM achieved from previous projects (Hinds et al., 2000). However, it may not always be possible to retain the entire team for new projects, and hence, member retention is a critical mediating factor to consider while assessing the role of direct and indirect communications in task coordination.

Finally, in large organizations, individuals are often part of more than one design project, which means their cognitive busyness may divert their attention away from the prosocial activities of the team. The level of busyness determines an individual's availability to attend to the observable data (Gilbert et al., 1988; Gilbert & Osborne, 1989). Hence, busyness level is another mediating factor that may alter the effects of direct and indirect communications on task coordination.

Based on these three MVs, we can investigate the effects of direct and indirect communication on TM formation and task coordination. Our primary question (Q1) is the following:

Q1: How does the contribution of different social learning modes to TM formation compare across different team structures?

Although the effect of different social learning modes associated with direct and indirect communications on TM formation needs to be established (Q1), it can be argued that the opportunities for TM formation should be highest in flat teams because there are no constraints on direct or indirect communication across the team. Following a similar argument, members of functional teams should have the least opportunity to communicate and learn about each other, in particular, about the team members who are not in their functional group. Therefore, because TM is known to mediate task coordination (Moreland et al., 1998; Rao & Argote, 2006), it might be expected that teams with a higher density of TM will show more efficient task coordination. However, despite the expectation that the density of TM formation in functional teams is lowest, it is argued that functional teams will show more efficient task coordination, whereas flat teams will perform the worst. This conjecture is based on the argument that in functional teams, where agents need to coordinate the tasks within smaller and targeted groups, agents need fewer direct and indirect communications to identify the relevant task performers. When agents need to coordinate tasks across the entire team, teams should perform more efficiently if they have no constraints on direct and indirect communications. Following this argument, flat teams should be more efficient in task coordination than are distributed teams. Although the agents need to coordinate the tasks among the same number of agents, that is, the entire team, flat teams provide more opportunities for social learning and indirect communication than distributed teams. This leads to the following hypotheses:

H1a: Task coordination is higher in teams that require direct communications within functional groups.

H1b: Task coordination is highest in functional teams.

Besides the communication opportunities resulting from the team structure, busyness levels and reduction in membership retention should have negative effects on TM formation and task coordination. Busyness reduces the opportunities for learning from social observation (indirect communication). Hence, the negative effects of the reduction in social learning because of higher busyness levels should be higher in flat teams. In flat teams, the contributions of social observations to density of TM formation are expected to be higher compared to distributed flat teams and functional teams. This leads to the following hypotheses:

H2a: The reduction in the density of TM formation with the increase in busyness levels is higher in teams with greater opportunities for communications.

H2b: The reduction in the density of TM formation with increase in busyness levels is highest in flat teams.

The increase in busyness levels should decrease task coordination. Therefore, if task coordination is expected to be highest in functional teams, then the decrease in task coordination with the increase in busyness level should also be highest in functional teams. Following the same argument, the decrease in task coordination with the increase in the busyness level should be higher for flat teams when compared to distributed teams. This leads to the third hypothesis:

H3: The decrease in task coordination with the increase in busyness levels is highest in functional teams.

The pattern of variations in task coordination should similarly be affected with the reduction in team member familiarity. This leads to the fourth hypothesis:

H4: The decrease in task coordination resulting from the reduction in the level of member retention is highest in functional teams.

Because the teamwork in this research is discussed in terms of task coordination, it is important to consider the level of task complexity because task complexity would be intuitively expected to influence how much communication is needed to coordinate tasks. Therefore, Q1 and each of the hypotheses are tested across different tasks, differentiated in terms of task complexity, as explained in Section 4.5. Figure 1 shows the relationships between the IVs, MVs, dependent variables, and the hypotheses.

4. DESCRIPTION OF THE COMPUTATIONAL MODEL

The computational model is implemented in the Java Agent Development Environment. The agent society consists of team agents, who perform the work, and a client agent, who allocates the task to the team and selects one of the team agents as the team leader. Team agents interact with each other to complete a given project that requires the completion of a set of tasks. For each simulation cycle, a team agent may: perform a task, directly communicate with another agent to assign a task, or observe other agents, which results in indirect communication. Direct communication is implemented as message passing between two agents. Indirect communication is implemented as a notification message to agents from the simulation environment of an observable event, that is, an observable task or an observable interaction between any two agents. The notification message contains details of the observable event, and all the agents that are not busy in a given simulation cycle receive this notification, contingent on the team structure. Thus, opportunities for social learning occur during each simulation cycle. There is one design-related activity in each simulation cycle. This activity is task allocation, refusal to perform a task, or task completion. Agents who are not directly involved in a design-related activity may receive an indirect communication about the design-related activity, contingent on their busyness and the team structure. The key implementation details of the model are briefly described in this section.

4.1. Team structure

The three types of team structures are implemented by defining the task allocation and social observation conditions. In

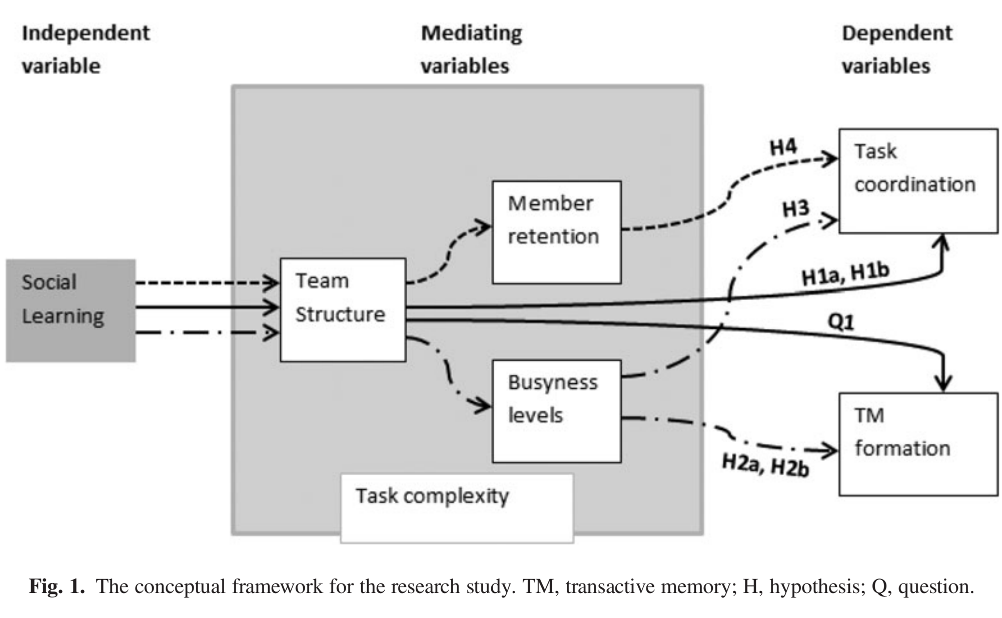

Fig. 1. The conceptual framework for the research study. TM, transactive memory; H, hypothesis; Q, question.

flat teams, there are no constraints on direct and indirect communications across the team. In distributed teams, team members can have direct communication with all other team members, but their ability for indirect communication, that is, observations, is limited to their social groups. Agents in functional teams are constrained to have direct and indirect communications within their own functional groups only, apart from the group coordinator who can directly communicate with the coordinators of other functional groups.

4.2. Agent learning

Rather than modeling cognitively rich agents that improve their own performance through experience, the model implements the types of social experiences, that is, direct and indirect communications that have significant influences on individual learning, and how cumulative individual experience increases individual proficiency when agents have the ability to learn from others (Reagans et al., 2005) about what others know so that the agents can be more efficient at coordinating work (Wegner, 1987). The model adopts the mechanisms of learning based on actions and observations (Tomasello, 1999).

The social learning mode of PI occurs when agents are directly communicating with other agents to perform a design-related task, and the social learning modes of IO and TO occur when agents are not engaged in any design-related task and are instead observing other agents working. Social learning in agents is implemented as rules based on assumptions on the type of knowledge about another agent that could be gained from each mode of social learning (see Table 1). An agent's availability to attend to the observable data is mitigated by the level of busyness (see Section 5.2.3).

Table 1. *Learning assumptions corresponding to learning opportunities*

Learning Mode	Condition (IF)	Deduction (THEN)
Personal interaction, direct communication	If an agent A^1 allocates a task T^1 to another agent A^2	Then A^2 knows that A^1 does not have the competence to perform task T^1
Personal interaction, direct communication	If an agent A^2 gives feedback to another agent A^1 that had allocated task T^1 to A^2	Then A^1 knows about A^2's competence for T^1
Personal interaction, direct communication	If an agent A^3 receives a task T^2 from another agent A^2	Then A^3 knows that A^2 has the competence to perform the task preceding T^2 (i.e., T^1) according to the task dependencies
Interaction observation, indirect communication	If an agent A^1 observes another agent A^3 allocating task T^3 to a third agent A^4	Then A^1 knows that A^3 does not have the competence to perform task T^3
Task observation, indirect communication	If an agent A^1 observes another agent A^5 performing task T^4	Then A^1 knows that A^5 has the competence to perform task T^4

4.3. Simulating TM formation

As agents communicate, they construct their TM. The development of their TM involves learning about the competence of each agent for each of the different tasks the team needs to perform. The competence details for an individual agent are termed the agent competence model (ACM), and collectively, the ACMs within an agent for all other agents form a TM. The TM formed by each agent may be different from the TM of another agent because the agents will have different opportunities for direct and indirect communications.

Competence is measured as the ratio of the number of times an agent successfully provides a solution for a given task to the number of times that task is allocated to the agent. The default value is taken as 1/2 because, unless it is known *a priori*, there is an equal likelihood that a given agent may or may not have competence in any of the given tasks. Thus, perceived competence tends to move toward either 0 or 1. As an example, at simulation cycle t, agent A^1 performs a task T^1, which was allocated to it in simulation cycle $t-1$. Let an agent A^2 be the observer, who at simulation cycle t – 2 had (1/2 as the value against T^1 for A^1's ACM. Thus, based on the observations in simulation cycles $t-1$ and t, the updated value against T^1 for A^1's ACM will be (2/3), which is an increase in the competence value. In contrast, if in simulation cycle t, A^1 shows failure to perform T^1, the updated value would be (1/3), which is a decrease in the competence value. Another agent A^3 might be busy in simulation cycle t and hence may not be able to update its ACM of A^1 because it could not observe the design activity in that simulation cycle.

4.3.1. Implementing TM

The TM is represented as an $m \times n$ matrix, where m is the total number of tasks and n is the total number of agents. For example, if there are altogether m tasks to be performed, then the ACM of a team agent A^1 will represent A^1's competence in each of the m possible tasks. The collection of the ACMs of all n team agents, that is, A^1 to A^n, will form an agent's TM, that is, the TM will have $m \times n$ values.

4.3.2. Using the TM for task allocation and handling

To allocate a task, agents directly communicate to the agent having the highest competence for the given task, and if an agent that has received a task has the competence to perform the task, it will. When the simulation starts (at time $t = 0$), all the agents have the same default value (1/2) for the competence in each task. This assumption can be relaxed if there is prior knowledge about each agent's skills. Given this assumption, agents initially allocate the task to a random agent.

Once the agents have gained experience working with each other, there will be differences in known competence of the agents in a given task, gained through both direct and indirect communications. If more than one agent has the highest competence value, the agent allocates the task at random to any one of the agents from this short list.

Agents propose solutions based on their own competence and the range of acceptable solutions for the agent that allocated the task, that is, the task allocator. The task performer looks up in its TM the competence details of the task allocator corresponding to the given task. For the selected solution to be accepted, the solution must also overlap with solutions acceptable to the task allocator. Once the agent has identified a short list of solutions that it can provide and that are also acceptable to the task allocator, it can choose any of the solutions from the short list, provided the chosen solution has not already been proposed in the same project. Because the agent constantly updates the task allocator's ACM as soon as it gets a feedback, the task performer is able to adapt the solution to suit the task allocator. Thus, teams with a well-developed TM are expected to perform faster.

4.4. Measuring TM formation

Density of TM formation is measured as a ratio of the number of TM matrix elements for which the values are different from the initial values by the end of the simulation. At the start of the simulation, because each agent starts with a default value for each element in the matrix, the values in each element will change only if the agent has learned it through direct or indirect communications.

For example, let there be 10 agents in the team and a total of 10 tasks to be performed by the team. In that case, the TM is represented as a 10×10 matrix such that there are 100 elements in the TM. When the simulation starts, all the elements have a default competence value $= 1/2$. As the agents interact with and observe each other and the task, they learn about each other's capabilities in the different tasks and update the values of the corresponding elements in the TM. By the end of the simulation, let us assume that 60 of these values were updated, such that the value of each of these 60 elements is different from 1/2. Thus, the TM formation in this case is 60%.

Each agent maintains a separate TM, which it updates based on its own direct and indirect communications. Therefore, by the end of the simulation, each agent's TM will be different. However, overlap and similarities across the TM of the agents are likely. The overall TM formation for the team is calculated as an average TM formation for each agent in the team. For example, in a team of 10 team agents, if 4 agents have 60% TM formation, 4 agents have 40% TM formation, and 2 agents have 50% TM formation, then the overall TM formation for the team is 50%.

4.5. Modeling tasks

Gero (1990) classifies design tasks as routine and nonroutine, depending on the exploration of the design space. Brown (1996) suggests another additional dimension for classification of design tasks, namely, parametric/conceptual designs, based on the explication of the attributes that specify the desired design solutions. In this model, two types of parametric design tasks are simulated (simple tasks and complex tasks), such that they are differentiated in terms of the potential values for the attributes that specify the design problem, as shown in Figure 2.

Simple tasks are tasks with unique solutions such that any two agents performing the same task will provide the same solution. All that the agents need to know is "who knows what." For example, tasks such as drafting and parametric dimensioning of standard structural elements are simple tasks because any two individuals performing the same task will provide the same solution.

For simple tasks, the task handling has sequential hierarchy and dependency (see Fig. 2a). There is a predefined set of tasks, such that one task leads to another. Because the solutions to simple tasks are unique and there are no parallel dependent tasks, the solutions for simple tasks are not subject to any compatibility check. For example, if an agent has completed task T^2, the next task to be performed is always T^3. Initially, the client allocates the first task on the basis of solutions proposed by agents in the team that express interest in leading the first task. Thereafter, the agents coordinate among themselves to pass on the resulting task to other agents before the set of tasks is complete. If an agent has knowledge in its TM of the competence of a specific agent to complete a task, the agent immediately assigns the task to that agent through direct communication. If the agent has no knowledge in its TM of which agent could complete a task, it randomly chooses an agent and sends a direct communication to inquire if that agent can complete the task. It continues to communicate directly with agents until an agent accepts the task. During each direct communication event, the agent updates its ACM about agents who could and could not complete the task. Each direct communication requires one simulation cycle. Agents that are not involved in the direct communication in that cycle may have the opportunity for observations or indirect communication, contingent on their busyness levels and the team structure. Once the last task is completed, the client is informed of the completion, closing the project simulation.

Complex tasks are tasks for which solutions may vary from person to person depending upon their expertise level are considered complex tasks. These tasks require hierarchical decomposition (see Fig. 2b). These tasks are similar to the complex architectural and engineering design problems that require decomposition according to functions, structures, or (modular) subsystems (Eppinger & Salminen, 2001). For a given task, multiple solutions may exist and an agent working on a task may only find some of the solutions that lie within their competence range, where the competence range of an agent is the range of solutions that an agent can provide or assess for a given task. The competence range is a proxy for the degree of skill for an agent. Two agents assigned the same task may provide different solutions because they may have different competence ranges for the same task. The task per-

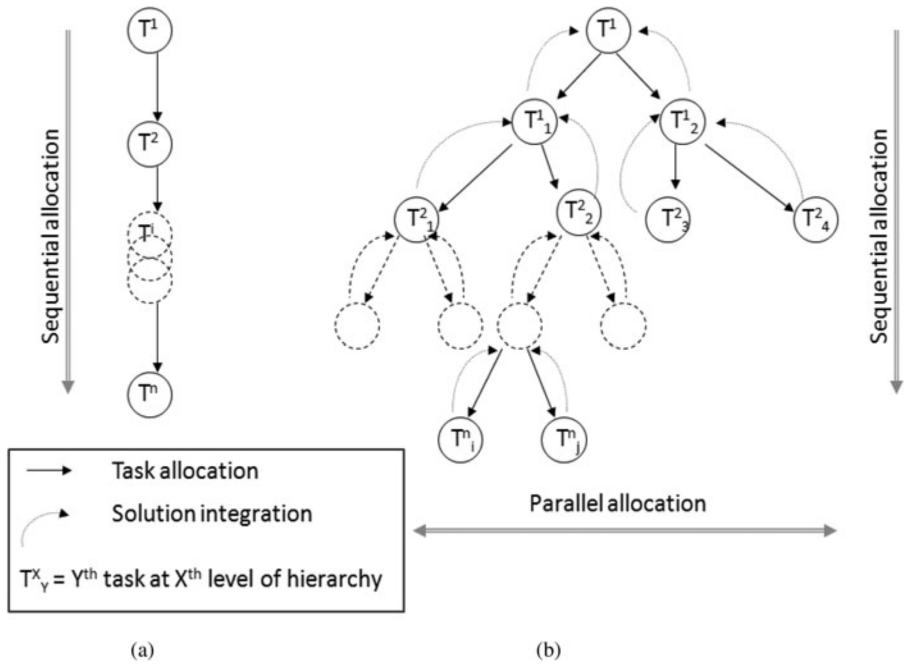

Fig. 2. Model task complexity for (a) simple tasks and (b) complex task.

formers (agents) need to know the solution space acceptable to the evaluator (some other agent or the client) to prevent providing a solution incompatible to the task allocator. Agents learn about the acceptable solution space of others as they interact and communicate with them. Similarly, the client has a desired range for the overall solutions. The team agents are required to collectively generate a solution that falls within the client's acceptable range. The teamwork involves coordination and evaluation of the subsolutions such that all the subsolutions are compatible.

For the complex tasks, one subtask may branch out into multiple subtasks. Solutions to all the subtasks need to be compatible. Hence, such tasks require solution integration and compatibility check. This may require reallocation of the same tasks to the same or some other agent. The solutions are evaluated at the integration stage, following a top-down approach, that is, the solutions for higher-level tasks are completed first. Initially, the client approves the overall acceptable solution range (e.g., an acceptable solution for T^1 in Fig. 2b). The team leader, appointed by the client on the basis of an expression of interest, considers this approved range as the boundary limit when evaluating the solutions for the corresponding subtasks, that is, T^1_1 and T^1_2. Once the team leader approves subtasks provided by other agents, those agents consider the approved solution as a benchmark to reset the acceptable solution range for the solutions to be coordinated at the next lower level, that is, T^2_x $(x = 1, 2, 3, 4)$. This cycle continues until all the tasks are decomposed into the lowest levels. If the integrated solution exceeds the boundary conditions, the agent evaluating and coordinating the integrated solution, that is, the evaluator, chooses one of the subsolutions to be reworked. For example, if the solutions proposed for T^1_1 and T^1_2, each performed by different agents, do not fit together when evaluated in terms of the solution accepted earlier for T^1, then one of the two tasks, T^1_1 or T^1_2, needs rework. This cycle of task evaluation and rework continues until the subsolutions are compatible at each level. The direct communications between agents to coordinate tasks are otherwise identical to the agent communications for simple design problems as are the social learning opportunities and indirect communications when an agent is not performing design work (has no assigned task).

5. SIMULATION DETAILS

5.1. Experiment matrix

Table 2 shows the experiment matrix. To investigate Q1 and H1, experiments were conducted to ascertain the contributions of different learning modes associated with direct and indirect communications to TM formation across the different team structures. These simulations were conducted with busyness level = 0 and membership retention = 100%. Thereafter, simulations were conducted with varying busyness levels to test hypotheses H2a, H2b, and H3. Simulations with varying levels of member retention were conducted to test H4. All the simulations were conducted with each task type to study the effects of task complexity on the simulation results.

5.2. Overview of the simulation

5.2.1. *The simulation loop*

At the start of the task cycle, the client invites expressions of interest from all the agents. Agents who can perform the

Table 2. *Experiment matrix*

	Team Structure				
Learning/Communication Modes	Member Retention	Busyness Levels	Task Type	Measures	Comments
√			√	TM & TC	To investigate Q1, H1a and H1b across both task types (TC is task coordination)
		√	√	TM & TC	To test H2a, H2b and H3 across both task types
	√		√	TC	To test H4 across both task types

Note: TM, transactive memory; TC, task complexity.

"firstTask" propose solutions for the first task and express interest to lead the hierarchical set of tasks for complex tasks. Based on the proposals, the client chooses one of the agents to lead the tasks. Thereafter, the agents communicate with each other to identify experts and coordinate the task allocation and handing as described in Section 4.5.

A single simulation run consists of two simulation rounds: a training round and a test round. In the training round, agents start with default (experimenter-defined) values for the ACM and none of the agents has any TM formed at this stage. A training round is needed to simulate member familiarity, such that some or all agents can be retained in the test round, simulating the level of member retention. Once the training round is completed, the test round is run. All the agents retained from the training round to the test round carry over the TM formed during the training round. Changes to the TM from the training round are used as the basis for TM formation. Measurement of task coordination is based on the results from the test round. For each scenario, the results are based on 60 simulation runs, which was found to give acceptable statistical confidence level ($>$ 99%) in the results using split-half *t* tests.

5.2.2. *Simulating member retention*

The level of membership retention is taken as the number of agents retained from the previous project, such that if all the agents are the same in the training round and the test round, the level of membership retention is 100%. If the membership retention is 100%, all the agents retain their TM. If the membership retention is less than 100%, new agents are introduced into the team, such that each new agent acquired in the team replaces an agent that was part of the training round. For example, let there be 10 agents, A^1 to A^{10}, who were part of the team in the training round. If the desired membership retention in the test round is 80%, then the new team has 8 agents retained from the training round and 2 new team agents, for example, $A^{3'}$ and $A^{7'}$, such that they replace the other 2 agents, A^3 and A^7, that were not retained from the training round.

Although all new agents (i.e., $A^{3'}$ and $A^{7'}$) start with a default TM, the agents retained from the training round (i.e., A^1, A^2, A^4, A^5, A^6, A^8, A^9, and A^{10}) reset their ACM of the agents that have been replaced (i.e., A^3, A^7) while retaining the ACM for the rest of the agents (i.e., A^1, A^2, A^4, A^5, A^6, A^8, A^9, and A^{10}). That is, the retained agents retain part of their TM, whereas the other part (i.e., related to A^3 and A^7), is reset to default values (to be used for ACM of $A^{3'}$ and $A^{7'}$).

5.2.3. *Modeling busyness levels*

Busyness is implemented as the probability that an agent is not able to sense the observable data, that is, does not notice the indirect communication. Observable situations associated with indirect communication include interactions among other agents (IO) and task performance by some other agent (TO). The busyness levels are varied in the training round itself and not in the test round. The effects of busyness on the level of TM formation are measured in the training round. Busyness levels in the training round should effect the task coordination during the corresponding test round. Hence, the mediating effects of busyness levels on task coordination are measured in the test rounds.

6. SIMULATION RESULTS AND DISCUSSION

6.1. Effects of communication

Figure 3 shows the contributions of different social learning modes associated with direct and indirect communications to TM formation across different team structures. Relative contributions of the learning and communication modes are obtained by juxtaposing the results from simulations with the following learning cases:

- PI + IO + TO: All learning modes of social learning are available to the agents.
- PI + IO: None of agents can observe others perform the tasks.
- PI: All agents learn only from personal interactions, that is, only direct communications.

As expected, findings show that TM formation is higher in flat teams, compared to distributed teams and functional teams. These results are consistent with the reported challenges in role clarity, task coordination, and teamwork in distributed work groups (Cramton, 2001; Huckman & Staats,

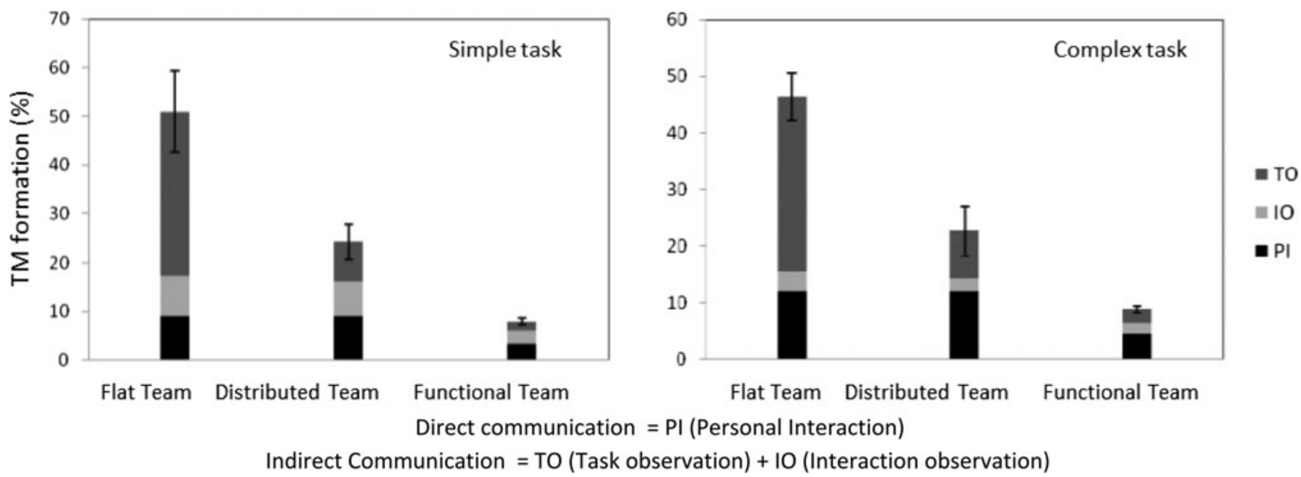

Fig. 3. The density of transactive memory formation as a consequence of differing team structures and modes of learning and communications for both simple and complex tasks.

2011; Staats, 2011). Our findings indicate that, in team environments with greater opportunities for communications, indirect communications play a major role in TM formation. Because flat teams have no subgroups or internal boundaries that obstruct observations, indirect communications contribute more to TM formation than do direct communications.

Figure 4 shows the contributions of different learning and communication modes to task coordination across different team structures. The task coordination measures are normalized for this analysis, such that the worst task coordination across all the simulations (maximum number of messages) is considered 1 and higher coordination is shown as increasing. (This normalization is inverse to a standard normalization because the maximum number of messages indicates worst coordination, and hence that is taken as the reference point, i.e., 1.) For each case, the normalized coordination value is obtained by dividing this maximum value by the number of messages in each case. For example, if worst case has 147 messages, and best case has 32 messages, then normalized coordination for the best case is 147/32.

Simulation results show that teams perform more efficiently when they have opportunities for both direct and indirect communications (PI + IO + TO). Nonetheless, different modes of indirect communications have differential contributions to task coordination. TO contributes more to task coordination than IO. In terms of coordinating simple tasks, the role of indirect communications in improving task coordination is more significant in flat teams. In terms of coordinating complex tasks, there is no noticeable difference in the coordination across the team structures for most cases. However, overall the results indicate that, in general, functional teams perform more efficiently than flat teams, partly supporting hypotheses H1a and H1b.

The results from simulations conducted to investigate Q1, H1a, and H1b suggest that indirect communications, that is, both IO and TO contribute to the density of TM (see Fig. 3) and to the task coordination (see Fig. 4). Across

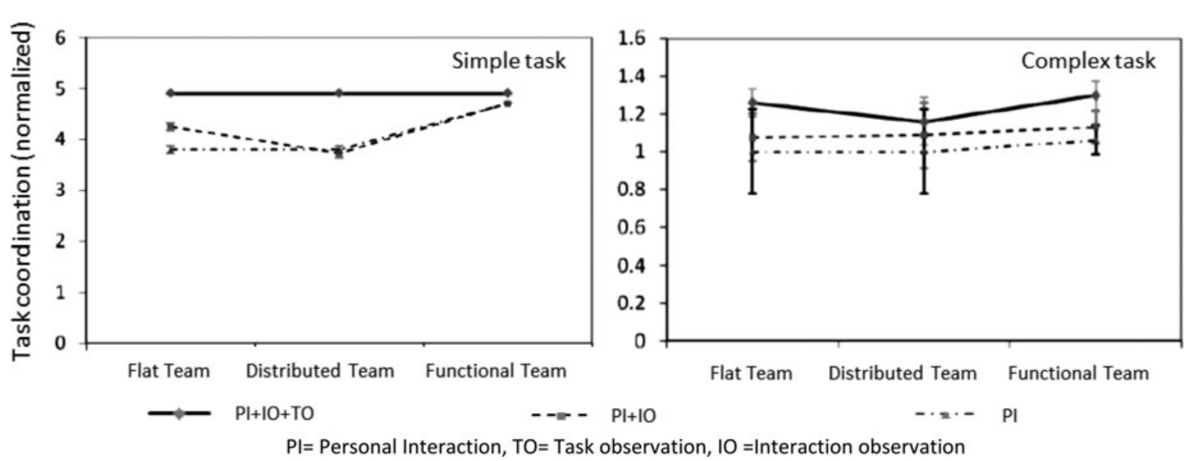

Fig. 4. Task coordination as a consequence of differing team structures and modes of learning and communication for both simple and complex tasks.

both measures, the contributions of TO are higher than IO. The differences across the learning cases are higher for TM formation than for task coordination, indicating that indirect communications contribute more to TM formation than to task coordination.

We should have expected that an increase in TM formation due to increasing opportunities for indirect communications should be followed by a corresponding increase in task coordination. However, this was not the case, as increasing opportunities for indirect communication had a milder effect on improving task coordination even as TM formation increased. This discrepancy could be explained in terms of what is described as "importance," a key characteristic of team mental models, a construct related to TM (Badke-Schaub et al., 2007). TM is formed as agents develop ACMs of all other agents in the team. However, not all ACMs are equally critical to task coordination. For any agent in the team, it is more important for it to identify and develop ACMs of those agents that it will need to directly communicate and coordinate the tasks with, and it may not matter much to task coordination if the agent is not able to know about the competence and skill levels of the rest of the agents.

Knowing *a priori* what will be important in the TM may not always be possible in real-world cases because of the iterative and emergent nature of design and hence the lack of clarity in what (and whose) knowledge could have been important. Therefore, the "efficiency of TM" is introduced as a measure to assess indirectly the formation of an important TM. The efficiency of the formed TM is defined as the ratio of the task coordination to the total amount of TM formed (see Table 3).

As seen in Table 3, regardless of the experiment scenarios and the variations in member retention or task complexity, functional teams are more efficient in the formation of an important TM. In functional teams, agents primarily communicate with agents within their own task groups, and that is where most of the task coordination is needed. This explains why functional teams are efficient in developing important TM. This also explains why global projects are still successful despite distributed work groups with lower overall density of TM formation. Organizing larger project teams into smaller work groups reduces the task coordination efforts and TM requirements at the team level by splitting the coordination requirements and reinstating the significance of the methodical organizational breakdown structure (Sosa et al., 2004).

6.2. Effects of busyness

As expected in hypothesis H2a, the reduction in the density of TM formation with the increase in busyness levels is higher in teams with greater opportunities for communications. Simulation results support H2a. Accordingly, the observed negative effects of higher busyness levels on TM formation are highest in flat teams and lowest in functional teams, as shown in Figure 5, supporting H2b. The reduction in TM formation with the increase in busyness levels shows a similar pattern across all team structures regardless of the task type, which is demonstrated in Figure 6.

Figure 7 shows the effects of busyness on task coordination across both task types at 100% member retention. In Figure 7 task coordination is represented through negative numbers because coordination is measured in terms of the number of messages (direct communications), such that fewer messages correspond to higher task coordination. In the computational model, the number of messages taken by the team is an indicator of the time taken to complete the task. Teams that require fewer messages complete the task faster. A marginal decrease in task coordination with an increase in busyness levels is observed across all team structures, providing insufficient evidence to support or refute hypothesis H3, that higher busyness levels have greater effects on the task coordination in functional teams.

The variations across the team structures resulting from higher busyness levels are higher on TM formation than on the task coordination, which is consonant with the earlier conclusion that indirect communications have a greater effect on the density of TM formation as compared to task coordination.

6.3. Effects of membership retention

In hypothesis H4, it was expected that the decrease in task coordination resulting from the reduction in the level of member retention is highest in functional teams. Figure 8 shows that the findings reject H4. In absolute terms, the decrease in task coordination resulting from the reduction in membership

Table 3. *Measuring efficiency of transactive memory (task complexity is normalized)*

Task	MR	Flat Teams	Distributed Flat Teams	Functional Teams
S	100%	0.18 = (9.33/50.98)	0.38 = (9.33/24.30)	1.17 = (9.33/7.96)
S	66%	0.08 = (4.08/50.98)	0.16 = (3.99/24.30)	0.88 = (7.00/7.96)
S	17%	0.05 = (2.70/50.98)	0.11 = (2.65/24.30)	0.74 = (5.79/7.96)
C	100%	0.05 = (2.40/46.34)	0.10 = (2.21/22.56)	0.27 = (2.47/9.02)
C	66%	0.02 = (1.08/46.34)	0.05 = (1.08/22.56)	0.23 = (2.10/9.02)
C	17%	0.02 = (1.05/46.34)	0.04 = (1.00/22.56)	0.23 = (2.10/9.02)

Note: S, simple task; C, complex task; MR, membership retention.

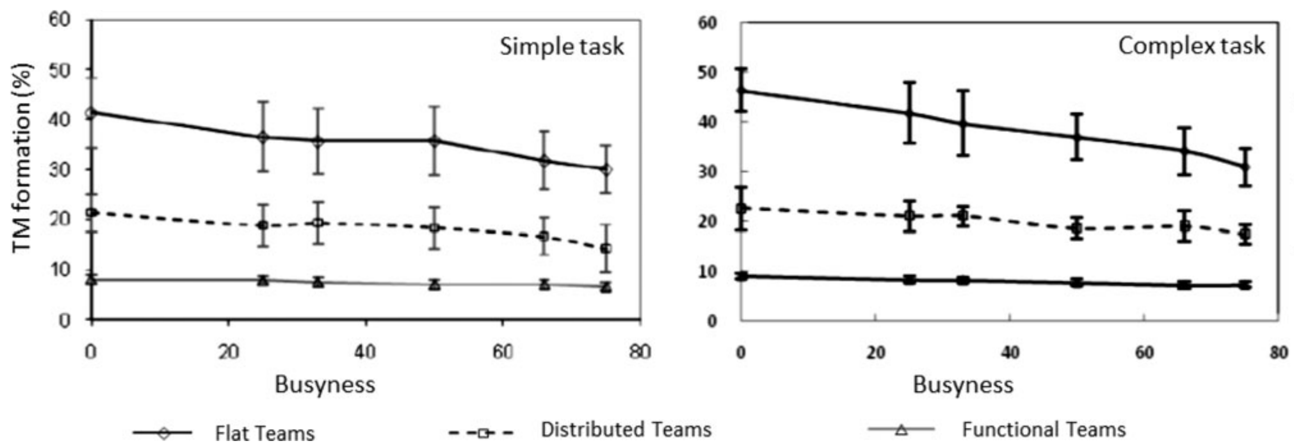

Fig. 5. The effect of team structure and busyness levels on transactive memory (TM) formation for a complex task.

retention is higher for flat teams and distributed flat teams than that for the functional teams. However, in relative terms, this increase in task coordination caused by the increase in member retention across the different team structures may be comparable. The scope of improvement in the task coordination of functional teams is lower because functional teams show higher efficiency of formed TM, resulting in high task coordination notwithstanding the levels of membership retention or busyness of the team members. In functional teams, even at lower levels of membership retention, which means lower predeveloped TM, the agents' search space for the relevant task experts is narrowed within the corresponding task group rather than the entire team. This smaller search space compared to the flat teams or distributed flat teams inherently reduces the effort in communicating and coordinating the tasks, giving functional teams a greater efficiency in task coordination.

The higher scope of increase in task coordination with the increase in member retention in flat teams highlights another important aspect of TM formation. Indirect communications not only allow knowing who knows what but also allow agents to know who does not know what without having to directly communicate and ask around. This allows narrowing of the search space through a process of elimination, which becomes more critical in flat teams than in functional teams. Thus, in a team environment, it may be important not only to identify relevant knowledge sources but also to know which sources to exclude in time-constrained situations. Indirect communications can play an important role in gaining such information.

The findings from simulations with membership retention and team structures are in agreement with the recent findings from Staats (2011), who found that the team familiarity gained under differential conditions (e.g., team structure) have differential effects on task coordination. Staats found variations in the quality of familiarity gained across distributed and colocated team members. The variations can be attributed to the variations in the scope for direct and indirect communications, and hence, the variations in the opportunities for social learning.

In summary, indirect communications contribute more to TM formation than to task coordination. Teams with greater

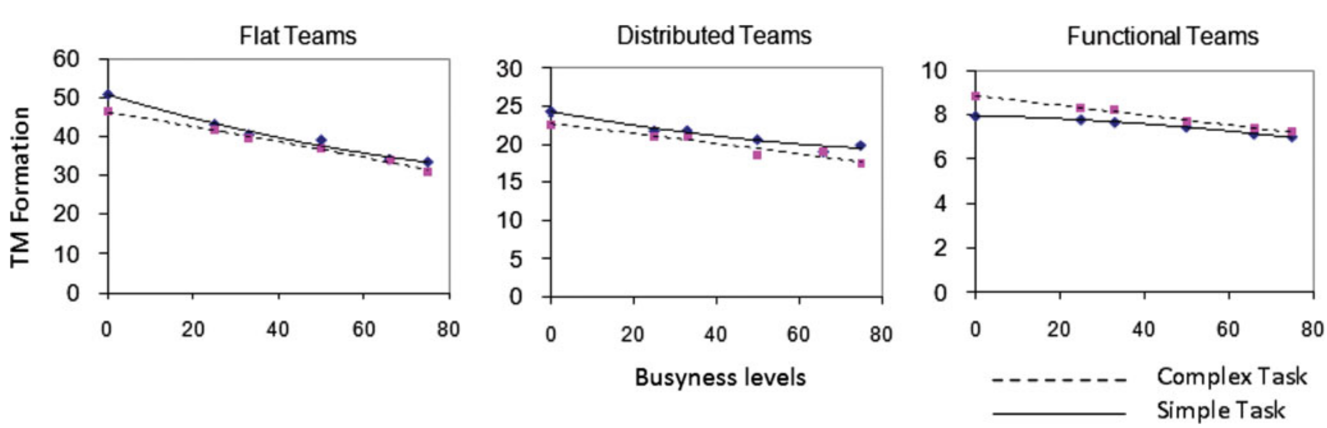

Fig. 6. The effect of busyness levels, team structure, and task type on level of transactive memory (TM) formation. [A color version of this figure can be viewed online at http://journal.cambrige.org/aie]

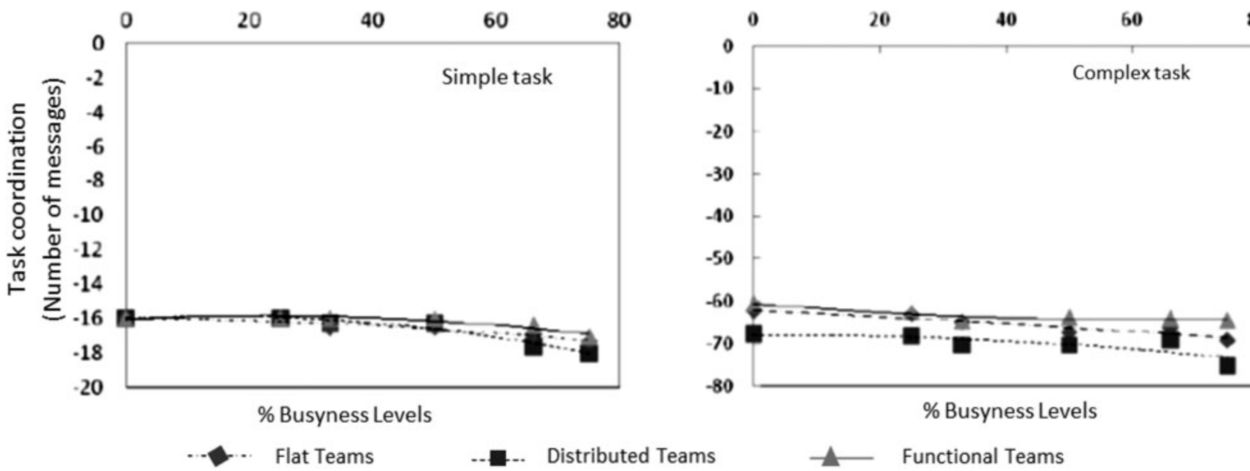

Fig. 7. The effect of team structure, busyness levels, and task type on task coordination, measured as the negative of the number of messages (values closer to zero indicate higher coordination).

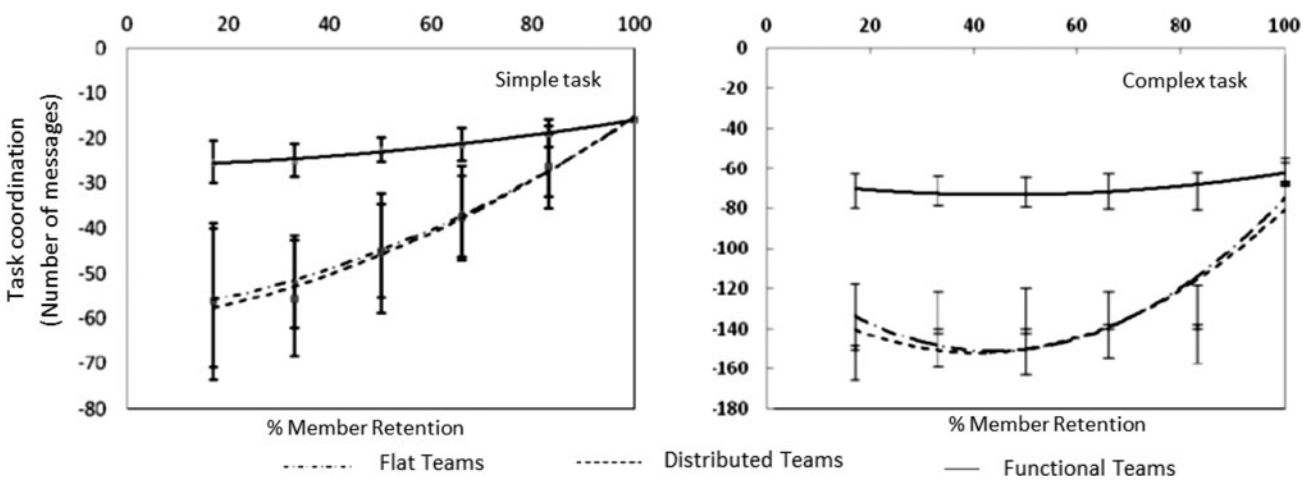

Fig. 8. The effect of team familiarity and team structure on task coordination, measured as the negative of the number of messages (lower negative numbers indicate higher task coordination).

opportunities for communications will show higher improvements in TM formation. Task coordination is faster if the teams are organized as functional teams, whereas TM formation is higher in flat teams. This indicates that although TM mediates task coordination, there is a limit to the value of TM, at which point the importance of the TM becomes critical to task coordination. Organizing teams into functional teams may reduce the need for high levels of TM formation to achieve task coordination.

7. CONCLUSIONS

The findings reported in this paper are applicable to design teams working on tasks where task coordination is the key performance barrier rather than the creativity or novelty of the design outcomes. The simulation results demonstrate the importance of indirect communications in teams toward TM formation, a prerequisite for effective teamwork. The main contribution of this paper is to establish that the different social learning modes associated with direct and indirect communications resulting from different team structures have differential effects on TM formation and task coordination. The paper also establishes the need to distinguish important elements in a TM. An important TM is found to have stronger mediating effects on task coordination as compared to the mediating effects of TM.

These findings suggest that flat teams allow the highest levels of TM formation, wherein the team members have greater access to direct and indirect communications with all other team members. However, higher levels of communication may not necessarily increase team efficiency. Simulation results show that functional teams are most efficient in terms of task coordination, where the direct and indirect communications are primarily limited to the functional group. The efficiency of functional teams is a result of communication that directly contributes to the formation of an important TM. An important TM contains knowledge of competence of those team members whose roles are directly related to the tasks and who must communicate directly to coordinate the tasks with each other. Our results provide further confirmatory evidence of the necessity of aligning organizational communication alongside product functionality and architecture (Sosa et al., 2002, 2004). The observed differences in the efficiency of formed TM based on direct and indirect communications are congruent with Gino et al.'s (2010) findings that direct experiences lead to higher task performance, mediated by TM formation. However, it must be noted that Gino et al. (2010) studied the effects of direct and indirect task experiences, not communications, on team creativity and not on task coordination.

Based on the findings, it is recommended that in scenarios where task coordination is critical but team retention is low (or personnel turnover is high) functional teams should be preferred. If the team is likely to be retained for longer term or for multiple future projects, and variations in the task are expected, then flat team structures should be adopted, at least in the norming phase (Tuckman, 1965). At the same time, for the projects and activities aimed as team-building exercises, team members should have more opportunities for direct and indirect communications, for which colocated flat teams are more suited. In addition, the workload distribution of team members should be managed to ensure sufficient opportunity for them to follow team members' activities. Distributed teams constrained by other factors can reinforce the social interaction and observation opportunities through technological and communication media where all team communications, updates, and activities are available to all the team members, facilitating indirect communications. Therefore, in distributed flat teams, how the team communication is organized and facilitated through social media (Wilson et al., 2011) will play a critical role in TM formation.

To conclude, this paper discusses the effects of direct and indirect communications on task coordination and TM formation resulting from variations in team structure. The reported findings are based on computational studies that simulate scenarios wherein social learning modes associated with direct and indirect communications, team member retention, and cognitive busyness levels are varied along with the team structure. Findings indicate that indirect communications contribute more to TM formation than to task coordination. Flat teams show higher TM formation, whereas functional teams are more efficient in task coordination, suggesting that the role of TM formation in mediating task coordination varies with the team structure. However, the underlying assumptions in the model and the simplifications of the simulation scenarios resulting from controlled parameters need to be considered in interpreting the results. In particular, it is important to note that although literature shows that less communication to achieve the same set of tasks indicates higher task coordination, it is acknowledged that less communication in teams may not be advantageous in the long term (Katz, 1982). We need to distinguish between communication to coordinate tasks and communication to learn about each other's competencies so as to form TM. This is an important distinction. When teams need to be efficient, they should be able to achieve task coordination with the least amount of communication (Entin & Sarfaty, 1999). However, in order to ensure that they can continue to be efficient, the team members should continue to communicate about their knowledge and capabilities as much as they can, so that the level of knowledge about roles and capabilities remains high. Indirect communications and flat team structures are particularly important in this team-building and TM formation objective.

REFERENCES

Akgun, A.E., Lynn, G.S., & Yilmaz, C. (2006). Learning process in new product development teams and effects on product success: a socio-cognitive perspective. *Industrial Marketing Management 35*, 210–224.

Allen, T.J. (1977). *Managing the Flow of Technology*, Cambridge, MA: MIT Press.

Argote, L. (2005). Reflections on two views of managing learning and knowledge in organizations. *Journal of Management Inquiry 14(1)*, 43–48.

Badke-Schaub, P., Neumann, A., Lauche, K., & Mohammed, S. (2007). Mental models in design teams: a valid approach to performance in design collaboration? *CoDesign 3*, 5–20.

Bandura, A. (1977). *Social Learning Theory*. New York: General Learning Press.

Blinn, C.K. (1996). Developing high performance teams. *Online 20(6)*, 56.

Bobrow, D.G., & Whalen, J. (2002). Community knowledge sharing in practice: the eureka story. *Reflections 4*, 47–59.

Brown, D.G. (1996). Routiness revisited. In *Mechanical Design: Theory and Methodology* (Waldron, M., & Waldron, K., Eds.), pp. 195–208. Berlin: Springer–Verlag.

Brown, J.S., & Duguid, P. (1996). Stolen knowledge. In *Situated Learning Perspectives* (McLellen, H., Ed.), pp. 47–56. Englewood Cliffs, NJ: Educational Technology Publications.

Bucciarelli, L.L. (2003). *Engineering Philosophy*. Delft: Delft University Press.

Candy, L., & Edmonds, E. (2003). Collaborative expertise for creative technology design. *Proc. Design Thinking Research Symp.*, University of Technology, Sydney.

Carley, K.M., & Gasser, L. (1999). Computational organization theory. In *Multiagent Systems: A Modern Approach to Distributed Artificial Intelligence* (Weiss, G., Ed.). Cambridge, MA: MIT Press.

Carrizosa, K., & Sheppard, S. (2000). The importance of learning styles in group design work. *Proc. 30th Annual Frontiers Education* (Vol. 1). Washington, DC: IEEE Computer Society.

Cohen, S.G., & Bailey, D.E. (1997). What makes teams work: group effectiveness research from the shop floor to the executive suite. *Journal of Management 23*, 239–290.

Conte, R., & Gilbert, N. (1995). Computer simulation for social theory. *Artificial Societies: The Computer Simulation of Social Life*. London: UCL Press.

Cooke, N.J., Salas, E., Cannon-Bowers, J.A., & Stout, R.J. (2000). Measuring team knowledge. *Human Factors 42*, 151–173.

Cooke, N.J., Salas, E., Kiekel, P.A., & Bell, B. (2004). Advances in measuring team cognition. In *Team Cognition: Understanding the Factors That Drive Process and Performance* (Salas, E., & Fiore, S.M., Eds.). Washington, DC: American Psychological Association.

Cramton, C.D. (2001). The mutual knowledge problem and its consequences for dispersed collaboration. *Organization Science 12(3)*, 346.

Del Cerro, G., Lemee, J., Mar, E., Wei, C.S., Weiman, C., & Wortzell, A. (2001). Assessing communication modes in design project teams. *Proc. 31st Annual Frontiers in Education Conf.*, pp. 287–294.

Desanctis, G., & Jackson, B. (1994). Coordination of information technology management: team-based structures and computer-based communication systems. *Journal of Management Information Systems 10*, 85–110.

Eckert, C., Maier, A., & McMahon, C. (2005). Communication in design. In *Design Process Improvement: A Review of Current Practice* (Clarkson, J., & Eckert, C., Eds.), pp. 232–261. London: Springer.

Entin, E.E., & Sarfaty, D. (1999). Adaptive team coordination. *Human Factors 41*, 312–325.

Eppinger, S., & Salminen, V. (2001). Patterns of product development interactions. *Proc. Int. Conf. Engineering Design*, Glasgow.

Fulk, J., & Boyd, B. (1991). Emerging theories of communication in organizations. *Journal of Management 17*, 407–446.

Gero, J.S. (1990). Design prototypes: a knowledge representation schema for design. *AI Magazine 11(4)*, 26–36.

Gilbert, D.T., & Osborne, R.E. (1989). Thinking backward: some curable and incurable consequences of cognitive busyness. *Journal of Personality and Social Psychology 57*, 940–949.

Gilbert, D.T., Pelham, B.W., & Krull, D.S. (1988). On cognitive busyness: when person perceivers meet persons perceived. *Journal of Personality and Social Psychology 54*, 733–740.

Gilbert, N. (2004). *Agent-based social simulation: dealing with complexity.* Accessed April 10, 2008, at http://www.soc.surrey.ac.uk/staff/ngilbert/ngpub/paper165_NG.pdf

Gino, F., Argote, L., Miron-Spektor, E., & Todorova, G. (2010). First, get your feet wet: the effects of learning from direct and indirect experience on team creativity. *Organizational Behavior and Human Decision Processes 111*, 102–115.

Grant, R.M. (1996). Toward a knowledge-based theory of the firm. *Strategic Management Journal 17*, 109–122.

Grecu, D.L., & Brown, D.C. (1998). Dimensions of machine learning in design [Special Issue]. *Artificial Intelligence for Engineering Design, Analysis and Manufacturing 12.*

Hackman, J.R. (1987). The design of work teams. In *Handbook of Organizational Behavior* (Lorsch, J., Ed.). Englewood Cliffs, NJ: Prentice Hall.

Hinds, P.J., Carley, K.M., Krackhardt, D., & Wholey, D. (2000). Choosing work group members: balancing similarity, competence, and familiarity. *Organizational Behavior and Human Decision Processes 81*, 226–251.

Huckman, R.S., & Staats, B.R. (2011). Fluid tasks and fluid teams: the impact of diversity in experience and team familiarity on team performance. *Manufacturing & Service Operations Management 13(3)*, 310–328.

Jin, Y., Levitt, R.E., Christiansen, T., & Kunz, J.C. (1995). The virtual design team: modeling organizational behavior of concurrent design teams. *Artificial Intelligence for Engineering, Design Analysis and Manufacturing 9(2)*, 145–158.

Katz, R. (1982). The effects of group longevity on project communication and performance. *Administrative Science Quarterly 27*, 81–104.

Katzenbach, S.D., Jr. (1993). The discipline of teams. *Harvard Business Review 71*, 111–120.

Kiesler, S., & Cummings, J. (2002). What do we know about proximity and distance in work groups? In *Distributed Work* (Hinds, P., & Kiesler, S., Eds.), pp. 76–109. Cambridge, MA: MIT Press.

Kleinsmann, M., & Valkenburg, R. (2008). Barriers and enablers for creating shared understanding in co-design projects. *Design Studies 29(4)*, 369–386.

Kleinsmann, M., Valkenburg, R., & Buijs, J. (2007). Why do(n't) actors in collaborative design understand each other? An empirical study towards a better understanding of collaborative design. *CoDesign 5(1)*, 1–15.

Knobe, J., & Malle, B.F. (2002). Self and other in the explanation of behavior: 30 years later. *Psychological Belgica 42*, 113–130.

Laubacher, R., & Malone, T.W. (2002). *Temporary Assignments and a Permanent Home: A Case Study in the Transition to Project-Based Organizational Practices*. Cambridge, MA: MIT Sloan School of Management.

Leinonen, P., Jarvela, S., & Hakkinen, P. (2005). Conceptualizing the awareness of collaboration: a qualitative study of a global virtual team. *Computer Supported Cooperative Work 14*, 301–322.

Lewis, K. (2003). Measuring transactive memory systems in the field: scale development and validation. *Journal of Applied Psychology 88*, 587–604.

Love, P.E.D., Gunasekaran, A., & Li, H. (1998). Concurrent engineering: a strategy for procuring construction projects. *International Journal of Project Management 16(6)*, 375–383.

Macy, M., & Willer, R. (2002). From factors to actors: computational sociology and agent-based modeling. *Annual Review of Sociology 28*, 143–166.

Maier, A.M., Eckert, C.M., & Clarkson, P.J. (2005). A meta-model for communication in engineering design. *CoDesign 1(4)*, 243–254.

Malle, B.F. (2005). Folk theory of mind: conceptual foundations of human social cognition. In *The New Unconscious* (Hassin, R., Uleman, J.S., & Bargh, J.A., Eds.). New York: Oxford University Press.

Malone, T.W. (1987). Modeling coorditation in organizations and markets. *Management Science 33*, 1317–1332.

Marsick, V., & Watkins, K. (1997). Lessons from informal and incidental learning. In *Management Learning: Integrating Perspectives in Theory and Practice* (Burgoyne, J., & Reynolds, M., Eds.), pp. 295–311. Thousand Oaks, CA: Sage.

Mcdonough, E.F., Kahn, K.B., & Barczak, G. (2001). An investigation of the use of global, virtual, and colocated new product development teams. *Journal of Product Innovation Management 18*, 110–120.

Milne, A.J., & Leifer, L.J. (2000). Information handling and social interaction of multi-discplinary design teams in conceptual design: a classification scheme developed from observed activity patterns. *Proc. DETC'00: 2000 ASME Design Engineering Technical Conf.*, Baltimore, MD.

Moore, D.R., & Dainty, A.R.J. (1999). Integrated project teams' performance in managing unexpected change events. *Team Performance Management 5(7)*, 212–222.

Moreland, R.L., Argote, L., & Krishnan, R. (1998). Training people to work in groups. In *Theory and Research on Small Groups* (Tindale, R.S., & Heanth, L., Eds.), pp. 37–60. New York: Plenum.

Perkins, S. (2005). Building and managing a successful design team. *STEP-Magazine*. Accessed at http://www.stepinsidedesign.com/STEPMagazine/Article/28410/0/page/1

Rao, D.R., & Argote, L. (2006). Organizational learning and forgetting: the effects of turnover and structure. *European Management Review 3*, 77–85.

Reagans, R., Argote, L., & Brooks, D. (2005). Individual experience and experience working together: predicting learning rates from knowing who knows what and knowing how to work together. *Management Science 51*, 869–881.

Ren, Y., Carley, K.M., & Argote, L. (2006). The contingent effects of transactive memory: when is it more beneficial to know what others know? *Management Science 52*, 671–682.

Rodan, S. (2008). Organizational learning: effects of (network) structure and (individual) strategy. *Computational & Mathematical Organization Theory 14*, 222–247.

Simon, H. A. (1991). Bounded rationality and organizational learning. *Organization Science 2*, 125–134.

Singh, V., Dong, A., & Gero, J.S. (in press). Developing a computational model to understand the contributions of social learning modes to task coordination in teams. *Artificial Intelligence for Engineering Design, Analysis and Manufacturing.*

Sonnenwald, D.H. (1996). Communication roles that support collaboration during the design process. *Design Studies 17(3)*, 277–301.

Sosa, M.E., Eppinger, S.D., Pich, M., Mckendrick, D.G., & Stout, S.K. (2002). Factors that influence technical communication in distributed product development: an empirical study in the telecommunications industry. *Engineering Management, IEEE Transactions on Engineering Management 49(1)*, 45–58.

Sosa, M.E., Eppinger, S.D., & Rowles, C.M. (2004). The misalignment of product architecture and organizational structure in complex product development. *Management Science 50*, 1674–1689.

Staats, B.R. (2011). Unpacking team familiarity: the effect of geographic location and hierarchical role. *Production and Operations Management*. Advance online publication.

Tomasello, M. (1999). *The Cultural Origins of Human Cognition*. Cambridge, MA: Harvard University Press.

Tuckman, B. (1965). Developmental sequence in small groups. *Psychological Bulletin 63(6)*, 384–399.

Wallace, D.M., & Hinsz, V.B. (2009). Group members as actors and observers in attributions of responsibility for group performance. *Small Group Research 40*, 52–71.

Wegner, D. (1987). Transactive memory: a contemporary analysis of the group mind. In *Theories of Group Behavior* (Mullen, B., & Goethals, G.R., Eds.). Berlin: Springer–Verlag.

Wilson, H.J., Guinan, P.J., Parise, S., & Weinberg, B.D. (2011, July–August). What's your social media strategy? *Idea watch, Harvard Business Review*.

Wu, Z., & Duffy, A.H.B. (2004). Modeling collective learning in design. *Artificial Intelligence for Engineering Design, Analysis and Manufacturing 18*, 289–313.

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