Effects of social learning and team familiarity on team performance

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ABSTRACT

This paper describes the relationship between the modes of social learning and level of team familiarity, i.e. agents that have worked together before, on team performance. A computational model is implemented under a set of typical social learning modes in a team environment. In this model, agents can learn from personal interaction with other agents and the tasks, and by observing interaction among other agents and the tasks. Agents in the team are considered domain experts, which means the task knowledge is pre-coded. Agents learn about each others competence (i.e., who knows what), which leads to the formation of a team mental model. Agents that have team familiarity are expected to have developed each other's mental model to the extent facilitated by the available learning modes. Simulations are conducted with team familiarity and learning modes as parameters. Simulation results indicate that team performance is positively correlated with social learning and team familiarity. Implications of the findings on managing information exchange within teams are discussed.

KEYWORDS

Groups and teams, social learning, mental models, prior-acquaintance, team performance, agent-based modeling.

1. INTRODUCTION

Performing a task in a team environment is different to working in isolation. Agents, when assigned individual tasks in a team environment, need a well-developed mental model for the task, process, context and of the team for effective team performance [1, 2]. A group of individual experts may not lead to a high performance team [3]. Individual experts need to know about each other's expertise for efficient task allocation and utilization of the knowledge distributed across the team under the presumption that each has the knowledge required to perform the task but that no one person has all of the knowledge or time to complete all of the tasks. This knowledge about each other is achieved through social interactions and observations. During these social interactions and observations, the ability of individuals to identify other individuals as intentional beings similar to them allows team members to make assumptions about each other and their actions, facilitating social learning, and learning about each other's mental states. Social learning contributes to the formation of a team mental model (TMM) [1, 2], which is taken here as an individual agent's knowledge of its own competence and the competence of all other agents in the team to perform the different tasks. In a typical team environment the social learning modes include: (1) learning from personal interaction with the task and other agents, (2) learning by observing interaction among other agents, and (3) learning by observing another agent interact with a task [4].

When agents work on the same project, depending upon what learning modes are available to them, they build a mental model of each other. When some of these agents with prior acquaintance (team familiarity) are part of another project team, this pre-existing mental model of each other should enhance team performance. This paper discusses the relationship between modes of social learning, team familiarity and team performance based on empirical results from simulations of a flat team with learning modes and team familiarity as the parameters. Agents in the team are considered domain experts, which means the task knowledge and process knowledge is pre-coded. Agents learn about each other's expertise (i.e. who knows what), which leads to the formation of a TMM. Team performance is measured in terms of the number of messages exchanged for the task to be completed. Higher team performance is correlated with lower numbers of messages exchanged.

Section 2 summarizes prior work on team mental models and team performance. References to other agent-based models of learning in teams are provided to highlight the lack of comparative studies on the influence of modes of social learning on team performance. Section 3 briefly describes the computational model developed to include the modeling decisions and implementation details. Section 4 describes the experiment matrix that presents the set of simulations conducted. Section 5 discusses the simulation results and a discussion and implications of these results are discussed in Sections 6, 7 and 8.

2. Background

The ability of humans to understand others as intentional beings similar to ones self, allows individuals to learn from social interactions and third party observations [5]. In a team environment, where members are brought together by common goals [6], often the intentions behind task allocation and handling are similar. Team members use this assumption of common goals and intentions to learn about each other through different modes of social learning. Social learning is important in the formation of TMMs, influencing the team performance. Separate studies have been conducted to investigate the relationships between TMMs and team performance [2, 7, 8], and different modes of social learning have been reported [4]. Literature on team familiarity [9] and transactive memory systems [10] has established the positive correlation of mental models with team performance. However, the contribution of the different modes of social learning on development of TMMs needs further investigation. Agent-based models of teams have been used for team based learning, cooperative learning, collaboration and problem-solving studies [4, 11, 12, 13, 14, 15]. Specific studies have been conducted on models of social interaction but little comparative study has been reported on the influence of different learning modes (assumptions based on personal interaction vs observation) on team performance and formation of TMM.

A computational model has been developed to study the role of different modes of social learning on the formation of a TMM in varied team environments. In this model team environment can vary in terms of team structure, level of team familiarity among team members and situational factors such as busyness and attrition. Variations in the team environment is expected to influence the amount of social learning and hence the TMM and team performance. This paper reports on simulations in which the level of team familiarity is the only team environment parameter that is varied, and modes of learning are the only agent parameters that are varied. Once the influence of team familiarity across different learning modes is understood other parameters can be varied in future simulations.

3. Computational model

3.1 Modeling decisions and implementation

A computational model based on modeling team members as agents is adopted. A schematic representation of the simulation environment is given in Figure 1. All the agents within the team are sub-set of a predefined agent population. Each agent in the agent population has a unique ID and they must register with the Simulation Controller. At the time of registering with the Simulation Controller each agent registers its domain expertise areas and affiliations (task groups / social groups). A single agent can have expertise in multiple domains such that multiple agents may have expertise in the same domain. At the start of the simulation, a sub-set of the agent population is chosen as the team. The composed team has all the relevant expertise to complete the task.

The computational model is implemented in the Java Agent Development Environment (JADE). Agents chosen into the team must register with the DF (Director Facilitator) agent, predefined in the JADE environment to provide "yellow page" services to other agents. If there is attrition (a member leaves the team) or acquisition (new member joins the team) the member must deregister or register with the DF agent. Thus, at each cycle, the DF agent maintains the list of current team members. This list is accessed by the Simulation Controller to maintain the team composition and to ensure that required expertise is there within the team at any given time. At the start of task cycle, the Client agent calls for a bid for the first task to all agents that are members of the team at that time. Once the lead agent is chosen by the client the team members interact within themselves to complete the task before informing the client of the completion of the task.

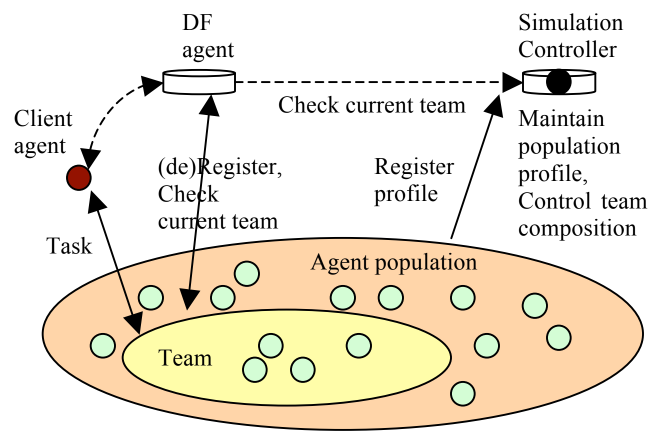

Figure 1. Simulation environment

Details of the model are as follows:

3.1.1 *Agent communication*

Agent interaction in the team is in the form of message passing. Agents exchange messages based on FIPA [16] protocols. In the simulations reported in this paper agents exchange messages to: (a) allocate tasks; (b) inform the source agent that the task is done; and, (c) send refusal messages to convey their inability to perform the task.

3.1.2 *Social observations*

Any information exchange in JADE is through message passing. Hence, even the social observations are implemented in the form of a message received by the observing agent. When an agent interacts with a third agent or with the task a duplicate message is sent to the observer agent, which is marked to be identified as a social observation. This message contains the ID of the interacting agents and the contents of interaction.

3.1.3 *Agent's knowledge base*

An agent's domain knowledge is fixed, i.e., for a specific input and required task, agents either know the solution or do not have any knowledge of the solution. In the case where the solution is not known, agents refuse the task.

Agents know all the task dependencies i.e. if an agent can perform a task, then it knows the next task that needs to be performed. The protocol for the task handling is also known to all the agents. When the team is initially formed, apart from the knowledge of their own capabilities, agents do not know capabilities of other agents or "who knows what", i.e., the TMM is not developed. Once the simulation is started agents develop the TMM through different modes of learning.

Implementation: When an agent is initialized, it has a default agent mental model (AMM) for all the agents in the agent population. This AMM consists of: (a) role identifier; (b) counters for P, the number of times the agent has performed the given task; and, (c) T the number of times a task has been allocated to the agent.

The ratio P/T gives an agent's competence value for a given role corresponding to a task. For each agent there are as many competence values as the total number of roles. When the agent is initialized, the default value for P is 1 and T is 2 because, with no prior information, there is an equal chance that an agent may or may not have competence in the given role.

The AMM is represented as an M-dimensional vector of competence values of the M roles within the team. The TMM is represented as an M × N matrix **E**, where N is the total number of agents. Each element E_{ij} represents the competence of the jth agent for the ith role, such that $0< E_{ij} <1$.

Updating AMM and TMM: When an agent receives a positive feedback on another agent's competence, both P and T are incremented by one. In the cases where a negative feedback is obtained, then only the T value is incremented by one.

3.1.4 Agent Learning

Agents learn as they interact with their environment that includes the task and the other agents. This interaction with the environment includes the observations that the agents make based on the sense data available to them. Agent's learning is limited to the TMM, which is primarily learning "who knows what". Agents can learn from their personal interaction with other agents and through observations, Figure 2. Only the task-related interactions in the team are considered. In terms of task handling, all agents in the model consider other agents to be similar to themselves in their intentions and goals. This means: (a) if an agent has the competence to perform a task, it will; (b) agents always intend to allocate a task to an agent that it believes has the highest competence to do the task; and, (c) agents will refuse to do a task only if they do not have the competence to do it. These assumptions about others' intentions and goals allow agents to learn about each other's mental states as they interact with their environment. Learning is rule-based, as given in Table 1.

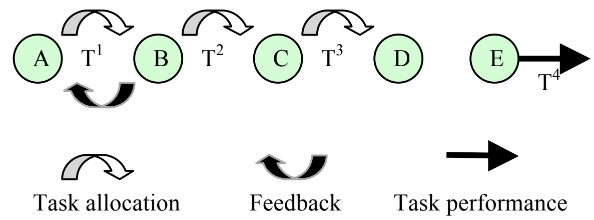

Figure 2. Learning opportunities in a team environment (symbols are defined in Table 1).

Table 1. Learning assumptions corresponding to learning opportunities shown in Figure 2

Condition (IF)	Deduction (THEN)
If an agent A allocates a task T^1 to another agent B	then B knows that A does not have competence to perform task T^1
If an agent B gives a feedback to another agent A that had allocated task T^1 to B	then A knows about B's capability at T^1
If an agent C receives a task T^2 from another agent B	then C knows that B has the competence to perform the task preceding T^2 (i.e. T^1) as per the task dependencies
If an agent A observes another agent C allocating task T^3 to a third agent D	then A knows that: C does not have the competence to perform task T^3.
If an agent A observes another agent E performing Task T^4	then A knows that E has the competence to perform the task T^4

3.1.5 Task handling

Using the AMM/TMM, agents select which agent should be assigned the new sub-task. Agents allocate the sub-task to the agent with the highest competence value for the role corresponding to the sub-task. Where multiple agents have the highest value of competence, then an agent is selected at random from the short-listed agents. New sub-tasks are obtained by looking up the task dependencies as pre-coded in the agent's knowledge base. Figure 3 is the activity diagram for a typical agent.

3.1.6 Attrition and member acquisition

It is possible that agents leave the team mid-way through the project. Attrition of agents may necessitate the acquisition of new agents into the team to ensure that necessary domain expertise is maintained. This change in team composition may affect team performance. Hence, an agent attrition factor has been implemented.

Implementation: The rate of attrition is modelled as the probability that an agent or a given percentage of agents from the team will leave the team in a cycle of the simulation. The agent or agents that exit the team is chosen randomly. The Simulation Controller ensures that, at any given time, there is at least one agent for each role within the team. If the attrition of an agent leaves the team without some expertise on a specific role, another agent with that expertise is immediately introduced into the team. In the simulations reported in this paper, the attrition rate is kept constant at zero. These will be varied in future work.

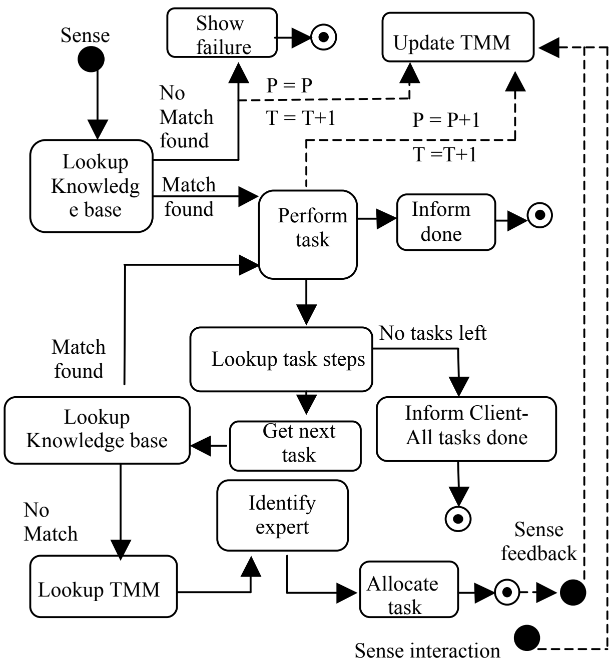

Figure 3. Activity diagram for a team agent

3.1.7 Team structure

In general teams are either termed as "flat" or "hierarchical" based on their structure and interaction. Flat teams have no hierarchy and no sub-divisions. These kinds of teams are generally used in consultation, task-force and design exploration. Experts are drawn from multiple disciplines and there are no nominated leaders. A leader may emerge over time based on the interactions adopted by the team.

Many work teams are organized into hierarchies. They have nominated leaders and are divided into expertise-based sub-teams [8]. In such teams the task is passed to the sub-teams with relevant expertise.

Implementation: Team structure has been implemented by constraining the interaction among agents and allocation of design tasks. In simulations, nominated leaders can be specified or a leader can be chosen at the run-time [17]. Run-time leaders are chosen by the client-agent through a bidding process. In the simulations reported in this paper only flat teams are considered.

3.1.8 Busyness

In a team, agents can learn from the observations they make based on the sense data available to them. This observable sense data includes agent-task interactions and agent-agent interactions. But this learning is subject to their attention. If an agent is busy (may or may not be with the current task) when the observable data is available, then the observation is not made in that instance. A "Busyness" factor is introduced for agent's attention to observable data.

Implementation: Busyness is implemented as the probability of an agent at any given cycle being able to sense the observable data available in that cycle. In the simulations reported in this paper, busyness factor is kept constant at zero. These will be varied in future work.

3.1.9 Team familiarity

When a new project team is formed, it is possible that some of the team members may have a prior acquaintance. This team familiarity means that agents have a partially-developed AMM of known agents at the start of the simulation.

Implementation: Team familiarity is implemented as the percentage of team members that are carried from one project onto the next project.

In the simulations reported in this paper, the same project is repeated in the next cycle. This means that if all the agents are retained from one project to the other, i.e., if team familiarity is 100% and if all agents have identified the expertise of other agents, then the task should be completed with the theoretically lowest possible number of messages exchanged.

3.2 Model validation

Three types of validation of computational social models are discussed in the literature [18, 19], which include: (1) comparing the observed simulation data to actual predictable data for known cases; (2) comparing the observed social behaviors to expected behaviors, which is typical of social groups; and (3) docking the implemented tool against a similar tool by comparing the observed behaviors from simulations using the two different tools.

This model has been validated by comparing observed data against predictable data for known cases i.e. cases for which values can be theoretically calculated, and demonstrating observable behaviors comparable to typical social behavior. The simulations conducted for model validation has been reported elsewhere [20].

4. Experiment setup

In experiments reported in this paper, six different values of team familiarity and four different learning cases were used. The four different learning cases are (1) Learning only from personal interactions with the other agents (PI)

(2) PI + Learn about other agents by observing them perform tasks (TO) (3) PI + Learn about other agents by observing them interact with each other (IO), and (4) PI+TO+IO. A total of 24 (6x4) simulations were run, Table 2. Each of these Monte Carlo simulations was run 120 times.

A team of 12 agents was used. In a given simulation, all agents were identical. The team needed to complete a sequential task consisting of 7 sub-tasks, and the knowledge distribution in the team was such that for 6 of the 7 sub-tasks, there are 2 agents that can perform the same sub-task. Each time a sub-task is allocated two messages ("call for proposal" and feedback) are passed. The minimum number of messages that must be exchanged is 15 (7x2 messages for task handling + 1 message for informing client about task completion).

For each simulation, there is one repetition. In the first project cycle, agents learn about each other based on the available learning modes. In the second project cycle only some of these agents are retained, as determined by the level of team familiarity. Given the expertise distribution in these simulations, the minimum of messages exchanged should be 15, which is more likely in the best possible scenario where team familiarity= 100%.

Table 2. Experiment setup- simulation combinations

		Team familiarity (%)					
		17	33	50	67	75	100
Modes of learning	Personal interaction (PI)						
	PI + Task observation (TO)						
	PI+ Interaction observation (IO)						
	PI+ TO+ IO						

5. Simulation results

The number of messages required for task completion in the different simulations considered is shown in Figures 4, 5, 6 and 7. When team members learn only from personal interactions, there exists a threshold beyond which the number of messages remains fairly constant with the decrease in team familiarity, Figure 4. This suggests than when agents learn only from personal interactions, there exists a minimum threshold level of team familiarity for team familiarity to have a positive effect on team performance. In this case this threshold is observed around 66% team familiarity level.

When team members can learn from task observations in addition to personal interactions, there exists a similar threshold for team familiarity to have a positive influence on team performance, Figure 5. However in this case this threshold is reduced to 50% team familiarity level. This is expected because now agents have an additional source to obtain information about each other.

When agents learn from interaction observation, in addition to personal interaction the rate of increase in team performance with increase in level of team familiarity is more uniform, Figure 6, than task observation and personal interaction (Figure 5).

In the case where agents can learn from all modes of learning, there is a decrease in the number of messages required to perform the task as the team familiarity increases, Figure 7. The rate of increase in number of messages reduces with decrease in team familiarity. This means that as team familiarity increases, the rate of team performance increases.

The existence of a threshold in Figures 4 and 5 and lack of it in Figures 6 and 7 suggest differences in distribution of knowledge across the team members that become significant with varying level of team familiarity. This difference can be explained in terms of the type of knowledge obtained through different learning modes.

When agents learn from personal interaction, their scope of learning is limited to agents that have assigned tasks to it or that have received tasks from this agent. This interaction allows agents to identify agents that are immediately related to the role this agent has performed in the particular project. If this agent is retained in the next team and so is the other agent that knows the next related task, then the task allocation is efficient. The likelihood of this is much higher at higher levels of team familiarity, and, hence, greater rate of increase in team performance at higher levels of team familiarity. If there were only one expert per role, i.e. no two agents knew about the same role, then at 100% team-familiarity the team would have achieved optimum performance (15 messages). The optimum performance is achieved in this case because after the first run the agents identify other agents directly related to their role, and hence a critical task path is created. In the simulations, this has not been the case (18.67 messages) since there were multiple (2) agents for each role, and, hence, the critical task path (now multiple critical task paths exist) was not attained in all the simulation runs. When agents also learn from task observation in addition to personal interaction, each agent, whether it was part of the critical task path in the first project cycle or not, identifies an agent that can perform the related role. In this case, observations allow agents to identify the earlier critical task path, and optimum team performance is achieved at 100% team familiarity.

When agents learn from interaction observation in addition to personal interaction, they may not have identified the task performers. This explains why even at 100% team familiarity, the team may not have achieved optimum performance. However, the primary difference that the ability to observe and learn from third party interactions brings is the lack of a threshold for level of team familiarity to influence the rate of team performance. This can be explained in terms of the importance of knowing who does not know what. Observing third party interactions allow agents to identify failed task allocations. This knowledge of who not to allocate the tasks to reduces the number of failed task allocations. Thus, in a team environment it is also important to know who lacks what competence. For the same reasons when all modes of social learning are available to agents, the rate of increase in team performance increases uniformly with the increase in prior-acquaintance, without showing a threshold point.

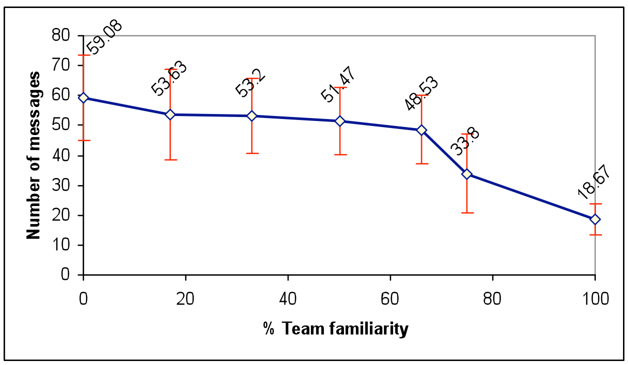

Figure 4. Number of messages needed when learning only from personal interactions

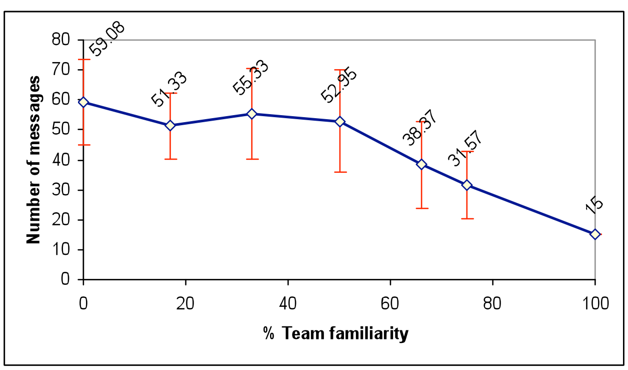

Figure 5. Number of messages needed when learning only from personal interactions and task observations

6. Discussion

These simulation results demonstrate that team performance is correlated with different modes of social learning. The simulations only consider formal task-related interactions, limiting the scope of interaction. It is hypothesized that in real world environments the greater scope of learning (about task, team, process and context), and informal interactions will increase the dependency of team performance on different modes of learning.

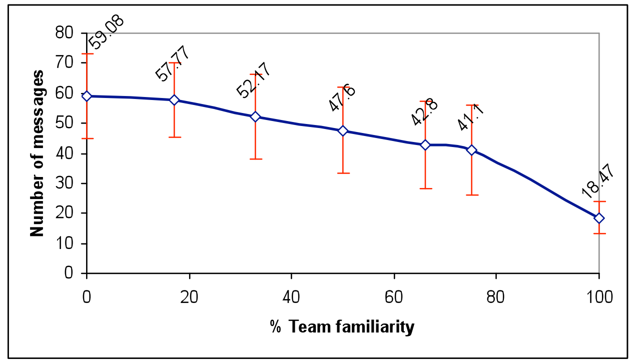

Figure 6. Number of messages needed when learning only from personal interactions and interaction observations

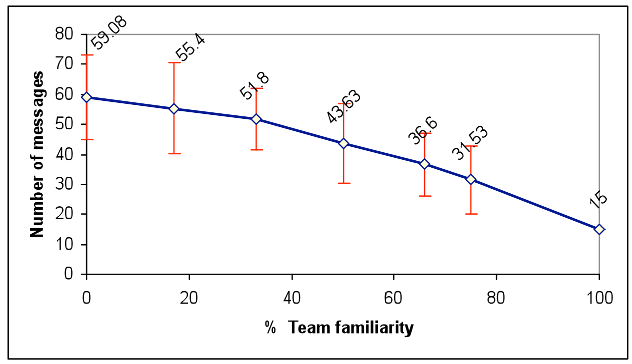

Figure 7. Number of messages needed when all modes of learning are available

In these simulations only flat teams have been used, where the team performance significantly depends on each agent knowing about other agents, since task allocation and coordination is distributed among agents. This may not be the case in hierarchical teams where team leaders coordinate task allocation and task handling. In such scenarios, performance will primarily depend upon the team leader's knowledge of expertise distribution. Even in hierarchical teams, team members learn about each other through informal interactions, which are useful in learning tacit knowledge about task, process, context and the team. It is hypothesized that while modes of learning will positively influence team performance in both flat and hierarchical teams, the rate of change in team performance with changes in modes of social learning will be higher in flat teams than hierarchical teams.

Some kinds of personal interactions such as querying an agent about another agent's competence, explicit sharing of opinion or beliefs about other agents, and instructing, have not been considered in these simulations. It would be interesting to see how the results vary once more modes of learning are included. Similarly, social factors such as trust and reputation are likely to influence the resulting TMM and team performance.

In this study it has been assumed that the intentions for task allocation are not biased, e.g. friendship bias, training bias etc, which means task allocation need not always be competence based as considered here.

Further experiments are planned where other situational factors such as busyness will be varied. It is hypothesized that when busyness is higher the positive effects of team familiarity on team performance will be reduced. This is because in the case of high busyness levels, even with prior acquaintance, agents do not learn as much about each other as they could have if they were not busy at all. The higher the busyness rates agents learning tends to get closer to learning only through personal interactions.

It is hypothesized that the positive correlation of team performance to modes of social learning will increase with the increase in task complexity. In these simulations we have considered routine tasks and agents with complete knowledge of the area of expertise. However, as tasks tend to become more non-routine and complex they require greater rework and greater coordination, where the scope of learning for TMM can be expected to be higher, and TMMs can be expected to have a greater role to play in affecting team performance.

7. Implications for Team management

Teams vary significantly in their scope of social interaction and dissemination of information among team members about their fellow team members. These variations in scope for social learning or learning about other team members can result from team structures, geographical distribution of team members, information protocols within teams, reports and documentations of past projects, and use of information and communication technology.

Simulation results demonstrate that, apart from knowing who knows what, it is also very useful to know who does not know what. The performance reports and documentation of past projects that team members may have an access to should be more comprehensive. Quite often summary of work done does not include the entire history of failures and reworks. Though not a form of social interaction, such information sources also facilitate social learning. How the information is documented and presented determines what assumptions the information seeker is making.

In a competitive team environment, quite often, multiple proposals for task solutions are called from within the team. Many a times the selection criteria of the proposals are not transparent and at times fluid. In such scenarios, members who have bid for the proposals or have observed others bid for the same proposal have to rely on assumptions about their own and others' competence about the related tasks. How the information protocol is designed determines what the team members perceive of each other. Thus, assumption-based mental models are particularly critical when the task involved is non-routine and the knowledge of each others preferences for solutions is important for task coordination.

Geographically distributed teams skew the opportunity for social learning. Co-located team members have multiple modes of communication channels available to them, while non-co-located team members are generally dependent on discrete set of information such as texts [21]. Social factors such as trust, reputation and confidence can be expected to have unequal influence on formation of TMM and team performance [21]. Whether these interactions are synchronous or asynchronous may be important. Asynchronous interactions are likely to provide greater control and a filter on how the information is presented, enabling team members to manipulate it to their advantage. Typically, in some of the fully virtual teams, such asynchronous interactions might be the only source of team building and team formation. Information protocols become even more critical in such team environments. Discussion forums, message blogs, and group mails are such other sources of information that team member use to impute about each others mental states.

Teams are increasingly project based, distributed across different locations. Often part of the task is outsourced to other organizations, in which case some of the team members may come from other organizations, there may be no face-to-face interactions, and one or two representatives from one organization may relocate to other geographical locations to facilitate teamwork. In such a scenario the variability in the modes of social learning are expected to play an even more important role than for co-located teams. Knowing what the implications of the different modes of learning, knowing how the information sources are organized within the team, and knowing what are the available information modes will be useful for team managers in obtaining the optimal balance of team familiarity (prior-acquaintance) for desired team performance. Knowing the relationships between modes of social learning, team familiarity and team performance in a given team environment will also be useful in achieving the right balance of team composition for the induction of trainees and new members into a team without affecting the team performance significantly.

8. Conclusion and future work

An agent-based model has been implemented to study the roles of different modes of social learning on team performance under varied team environments. The results from the simulations conducted with different modes of social learning and different levels of team familiarity imply that social interactions and observations are important determinants of team performance. In general, team performance improves with team familiarity. However, when learning from social observations and third party interactions are absent, a threshold point exists beyond which the relationship between team familiarity and team performance is more direct. These simulations have been conducted with routine tasks, flat teams with other situational factors such as busyness rates fixed. Further experiments are planned where other variables will be introduced to compare the relative contribution of modes of social learning on team performance. As with other computational studies these results indicate social behavioral patterns, and further investigations must be conducted in real world settings to determine their veridicality.

9. ACKNOWLEDGMENTS

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10. REFERENCES

[1] Badke-Schaub, P., Neumann, A., Lauche, K. and Mohammed, S., Mental models in design teams: a valid approach to performance in design collaboration? CoDesign, **3**(1), 5 – 20, 2007.

[2] Klimoski, R., and Mohammed, S., Team mental model: Construct or metaphor? Journal of Management, **20**; 403-437, 1994.

[3] Candy, L. and Edmonds, E., Collaborative expertise for creative technology design, 2004, URL: http://research.it.uts.edu.au/creative/design/papers/42CandyDTRS6.pdf., accessed on 15/03/06.

[4] Grecu, D.L. and Brown, D.C., Dimensions of Learning in Design, Artificial Intelligence for Engineering Design, Analysis and Manufacturing, (in) Duffy, AHB, Brown, DC and Goel, AK (eds.) Special issue on Machine Learning in Design **12**; 117-122, 1998.

[5] Tomasello, M., The cultural origins of human cognition. Cambridge, MA: Harvard University Press, 1999.

[6] Salas, E. Dickinson, T. L., Converse, S. A., and Tannenbaum, S. I., Towards an understanding of team performance and training. In R. W. Swezey & E. Salas (Eds.), *Teams: Their training and performance* , 3-29, Norwood, NJ: Ablex, 1992.

[7] Beng-Chong, L. and Katherine, J.K., Team mental models and team performance: A field study of the effects of team mental model similarity and accuracy, Journal of Organizational Behavior, **27**, 403-418, 2006.

[8] Rouse, W. B. and J. A. S. Cannon-Bowers, Eduardo, The Role of Mental Models in Team Performance in Complex Systems, IEEE Transactions on Systems, Man and Cybernetics **22**(6): 1296-1308, 1992.

[9] Huckman, R.S., Staats, B.R. and Upton, D.M., Team Familiarity, Role Experience, and Performance: Evidence from Indian Software Services, HBS Technology & Operations Mgt. Unit Research Paper No. 08-019, Available at SSRN: http://ssrn.com/abstract=1015569

[10] Wegner, D. M., Transactive memory: A contemporary analysis of the group mind. In B. Mullen & G. R. Goethals (Eds.), Theories of group behavior (pp. 185-208). New York: Springer-Verlag, 1986.

[11] Mori, T. and Cutksoky, M.R., Agent based collaborative design of parts in assembly, Proceedings of DETC'98, ASME Design Engineering Technical Conferences, September 13-16, Atlanta, Georgia, USA, 1998.

[12] Carley, K., V. Hill . Structural change and learning within organizations. In: Lomi, A. and Larsen, E.R., (Eds.) Dynamics of Organizational Computational Modeling and Organization Theories, Cambridge, MA, MIT Press, 2001.

[13] Garland, A. and Alterman, R., Autonomous agents that learn to better coordinate, Autonomous Agents and Multi-Agent Sytems, **8**, Kluwer Academic Publishers, 267–301, 2004.

[14] Wu Zhichao and Duffy, A.H.B, Modeling collective learning in design, Artificial Intelligence for Engineering Design, Analysis and Manufacturing **18**; 289-313, 2004.

[15] Paniat, L. and Luke, S. Cooperative Multi-Agent Learning: The State of the Art, Autonomous Agents and Multi-Agent Systems, **11**, 387–434, 2005.

[16] FIPA, Foundation for Intelligent Physical Agents, FIPA ACL Message Structure Specification, 2002. URL: http://www.fipa.org/specs/fipa00061/SC00061G.pdf, accessed on 03/06/06.

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

[18] Carley, K.M., Validating computational models. Working Paper: Social and Decision Sciences, Carnegie Mellon University, Pittsburgh, PA, 1997.

[19] Levitt, R.E., Orr, R.J. and Nissen M.E., Validation of the Virtual Design Team (VDT) computational modelling environment, CRGP working paper series#25, 2005.

[20] Singh, V., Dong, A. and Gero J.S., Exploring the role of social learning on team mental models (submitted), ICORD09, Bangalore, 2009.

[21] McDonough III, E. F., Kahn, K. B., and Barczak, G., An investigation of the use of global, virtual, and colocated new product development teams, Journal of Product Innovation Management **18**(2): 110-120, 2001.