Student Learning and Team Formation in A Structured CSCL Environment

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Abstract. A computer-supported collaborative learning (CSCL) environment aims to facilitate student learning by letting them work in small teams with the support of computer technology. Two important factors that affect work in such scenario are: interaction among the students and compatibility or interactivity of the team members. I-MINDS is a tool designed to support structured Computer Supported Collaborative Learning. In I-MINDS we try to improve both the quality of student learning and the quality of student team work with the help of intelligent agents. I-MINDS facilitates student interaction through its forums and can build student teams. In our two-semester long experiment we studied the effect of the interaction environment on the learning and performance of students in face-to-face and structured CSCL scenarios. Moreover, we studied how a student's self-reported efficacy, teamwork and interaction skills affect his or her performance in face-to-face and structured CSCL settings. Our results indicate that even though students prefer face-to-face interactions; structured CSCL environment may increase their individual performance. Furthermore, we find that factors such as the difficulty of the problem or task to be solved and team member compatibility influence the quality of teamwork in structured CSCL.

Keywords: CSCL, Jigsaw, Collaboration, Team, Learning

Introduction

Computer Supported Collaborative Learning (CSCL) has been studied as a tool to increase student learning [14, 4, 9]. In a CSCL environment, students work together in small teams to solve complex problems. In *structured collaborative learning*, students are guided within a set of prescribed activities so that each activity has a set goal and measurable outcomes. The long term goal of our research is to support structured collaborative learning using an intelligent multiagent system where students and instructors may or may not have face-to-face interactions.

In a typical CSCL environment, students learn from each other by interacting with their team members and by teaching their team members [5]. However, not all student teams work well [4, 8]. In some cases the students work in teams rather than working as a team [4, 8, 11]. To work together as a team well, the students need to build a shared understanding of what they are working on as well as how they are working together [11]. Even though the team formation procedure has been investigated by researchers [6, 7, 13]—such as handling information flow during team formation and transitioning between phases of team formation, the relationship between a student's performance and his or her teamwork activities within a CSCL environment has not been addressed.

As a CSCL tool, I-MINDS [10, 14, 15, 16] provides an environment where student participants are able to interact with each other through text messaging. That is, students interact without face-to-face interactions in the same room. Furthermore, I-MINDS can automatically form student teams. The team formation algorithm in I-MINDS works by allowing students to form teams based on the performance and compatibility of the participating students. In this paper, we discuss the results of our two-semester long experiment of deploying I-MINDS in an introductory CS course. Our experiment was conducted by dividing the students in control and treatment sections. The students in the control section participated in structured collaborative learning using conventional face-to-face interaction. However, the students in the treatment section participated in structured computer-supported collaborative learning and interacted with each other through I-MINDS. During our experiment, we investigated the following issues:

- How does the teamwork in conventional structured face-to-face collaborative learning compare to the teamwork in structured computer-supported collaborative learning?
- How does the structured CSCL environment impact student learning or performance?
- How do a student's self-efficacy, perception of his or her peers, and perception of teamwork relate to his or her individual performance?

Note that we have previously reported the structure of I-MINDS [17] and our implementation of Jigsaw collaborative learning model [1, 3]. Thus, in the following, we will only focus on the experiment and results, emphasizing on how students perceived teamwork and their peers, and the impact of I-MINDS on student learning and teamwork.

1. I-MINDS

1.1 I-MINDS Structure

I-MINDS, which stands for Intelligent Multiagent Infrastructure for Distributed Systems in Education, consists of a set of intelligent agents. There are three types of agents: teacher agents, group agents (for supporting teams), and student agents. In I-MINDS, a teacher agent interacts mainly with the instructor. It helps the instructor deliver instructional content to the students and coordinates the team formation process in the virtual classroom. A teacher agent also helps the instructor answer student questions with the *question ranking* and *question grouping* modules. In addition, a teacher agent helps form student teams for structured collaborative learning, supporting the Jigsaw procedure. In an I-MINDS supported classroom, a student agent serves a unique student. It interacts with the student and exchanges information with the teacher agent and the group agents. It also maintains a dynamic profile of the student to whom it is assigned and a dynamic profile of the peers that the student has interacted with through I-MINDS. Finally, a group agent in I-MINDS is activated when there are structured collaborative learning activities. Structured collaborative learning involves specified activities that explicitly require students to cooperate. Currently, I-MINDS implements the Jigsaw model [1, 3]. The team activities monitored by the group agent include the number and type of messages sent among team members, self-reported teamwork capabilities, peer-based evaluations as a team member, and evaluation of each team. A detailed description of I-MINDS can be found in [14, 16].

1.2 Team Formation in I-MINDS

The teacher agent forms student teams using the VALCAM algorithm [15]. In VALCAM, the teacher agent acts as a coordinator for the coalition formation process and makes global decisions, such as, what should the least number of members in a coalition be, how long should the teams last, how the performance of each coalition should be evaluated, etc. The group agents then manage the teams. Each group agent monitors the performance and activities of the members of its assigned team. After the coalition has completed their tasks, the group agent also evaluates the performance of each student agent as a team member.

The VALCAM algorithm is based on reinforcement learning of the student agents. In the beginning of every session the teacher agent chooses a few students and then initiates the team formation. During the team formation process, each student agent bids—an iterative Vickrey auction—to join its favorite team based on virtual currency earned from previous Jigsaw activities. Once the teams are formed, the group agents work with their team members to complete tasks assigned by the instructor. Finally, when the assigned task is completed, each student agent is rewarded with virtual currency based on its (student's) performance as an individual and as a team member. Students who performed well will receive more virtual currency, allowing them to more successfully bid for their favorite teams in future sessions.

Briefly, the VALCAM algorithm works as follows. Initially, the students or users are given some default amount of virtual currency to start with. In a typical coalition formation round, the auctioneer announces a task, and then the students post their self-efficacy in a blackboard. Then the auctioneer chooses the first members of the teams according to their current virtual currency balance. After the first members of the teams are chosen, the other members are assigned to each team by iterative auction. While bidding to join a team, a student agent considers how competent that team's members think they are and what its past working experience with the members already in the team was. So, student agents who join a team first influence how the team takes shape. The number of members per team is the same or greater than the number of subtasks in the task given. Over time, as the students gain experience in their interactions with other students and participate in different tasks, students accumulate varying amounts of virtual currency: students who have been in a team that produces good results, or have performed well in the post-tests, or have been rated high by their peers will be rewarded more. As a result, the student agents of these students will be able to offer higher bids in order to join teams more likely as first members, and allow their students to form teams most compatible with them. So, the student agent in VALCAM incorporates the two important aspects of successful student collaboration: the competence of the members of the team it is trying to join and its interaction history with the members of the team it is trying to join. Details of this algorithm can be found in [14, 15].

2. Experiment and Results

2.1 Experiment Setup

To investigate the issues outlined in Introduction, a two-semester long study was carried out in the closed labs of CSCE 155 at the University of Nebraska-Lincoln, in Spring and Fall semesters of 2005. CSCE 155 is the first core course required of computer science and computer engineering majors. It has three 1-hour weekly lectures and one 2-hour weekly laboratory sessions. In each lab session, students were given specific lab activities to experiment with Java and practice hands-on to solve programming problems. For each semester, there were 2-3 lab *sections* where each section had about 15-25 students.

The study utilized a control-treatment protocol. In the *control* section, students worked in Jigsaw collaborative learning teams without using I-MINDS. Students were allowed to move around in the room to join their Jigsaw teams (main group and focus groups [14]) to carry out face-to-face discussions. In the *treatment* section, students were told to stay at their computers and were *only* allowed to communicate via I-MINDS—with this setup, we essentially simulated a distance classroom environment. For each lab, the students were given a lab handout with a list of activities—thus, a lab is a task and its activities are the subtasks. The students of both the control and treatment sections were required to complete the tasks and subtasks in the four Jigsaw phases [14].

In each section, the instructor first announced the task and asked the students to fill out a Self Efficacy Questionnaire (SEQ) [14] to describe their competence in that area. Then the instructor announced the main groups. In the control section this was done by matching the strong student with the weak students (first goes with last and so on). In the treatment section, I-MINDS formed teams using the VALCAM algorithm. Once the main groups were formed, the teacher agent formed the focus groups by randomly selecting students from the main group. Then, every focus group was assigned one subtask randomly. After the subtask assignment, the focused exploration phase was started. Then the remaining Jigsaw Phases were carried out in order, during which the student agents and the group agents monitored and guided the activities of the students and the student teams, respectively. After all Jigsaw Phases were executed, all the students filled out the Peer Rating Questionnaire (PRQ) and Team-Based Efficacy Questionnaire (TEQ) [14] and took a 10-minute post-test. The post-test score was used as a measure of student individual performance in terms of understanding the lab topic.

2.2 Results

First, we look at the average normalized post-test scores, as shown in Figure 1. Each normalized score is computed by dividing each student's post-test score for a test day by the sum of the student's post-test scores of all other lab days that did not involve the Jigsaw experiment. Therefore, this normalized score provides a measure to compare the performances of the control and treatment section students in a scale that does not depend on the individual student's abilities.

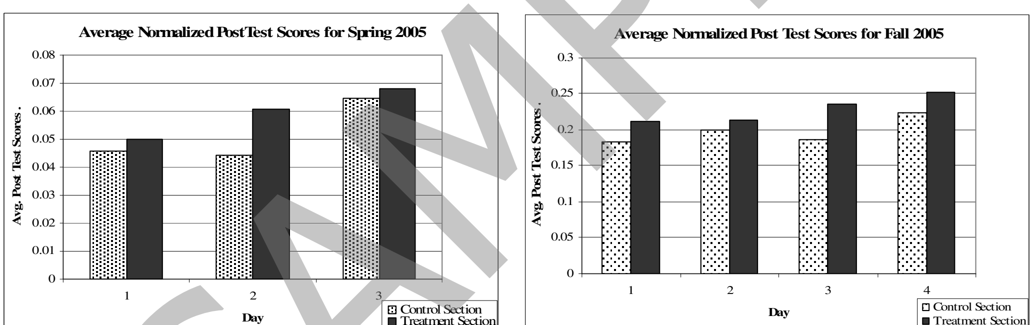

Figure 1: Control vs. Treatment: Average normalized post-test scores for (a) Spring 2005, (b) Fall 2005

For both Fall 05 and Spring 05 experiments, one tailed *t*-test reveals that the average normalized post-test score of the treatment section is significantly higher than that of the control section ($\alpha = 5\%$, p value for Spring is 6×10^{-4} and Fall is 5×10^{-5}). This indicates that I-MINDS-supported structured collaborative learning outperformed the conventional face-to-face one. This result also support those observed in [2, 12]. On average, students in the treatment section achieved better standard deviation—meaning that these students' post-test scores were more tightly clustered than those of the control section (1.67 vs. 2.36 in Spring 2005, and 1.11 vs. 1.25 in Fall 2005). We also observe that students in the treatment sections seemed to improve over time, and their performance seemed to eventually overtake that of the control sections'—indicating that VALCAM, due to its learning mechanism, might have been effective in forming better and better teams over time.

The Peer Rating Questionnaire (PRQ) surveys were conducted in both control and treatment sections *after* each lab session was completed. The PRQ is designed to quantify the compatibility of the team members after they have gone through the collaborative learning process. The average peer rating scores that each student gave to his or her team members can be used as a measurement of how well the team members were able to work with one another. Table 1 shows the results of the PRQ surveys. Students in the control section rated their peers better (higher means) and more consistently (lower standard deviation values) than those in the treatment section. This is possibly due to the convenience of face-to-face interaction since I-MINDS still lacks sufficient GUI features and multimedia capabilities to fully support real-time interactions.

	Spring 2005				Fall 2005			
Session	Control Section		Treatment Section		Control Section		Treatment Section	
	Mean	Stdev.	Mean	Stdev.	Mean	Stdev.	Mean	Stdev.
1	42.10	2.73	32.45	5.78	35.39	2.30	33.71	4.69
2	36.62	7.05	37.72	4.60	34.87	5.32	35.80	12.21
3	39.91	4.80	34.63	8.08	36.03	3.19	36.37	5.18
4	N/A	N/A	N/A	N/A	37.53	3.37	37.25	3.62
Mean	**39.54**	**4.86**	**34.93**	**6.15**	**35.95**	**3.54**	**35.78**	**6.42**

Table 1: Control vs. treatment sections: Results of the peer-rating questionnaires (PRQs)

On the other hand, there are indications that students in the treatment section for the Fall 2005 sections seemed to rate their peers better gradually as the semester progressed (from 33.71 to 35.80 to 36.37 and 37.25) and seemed to rate their peers more consistently as well. This might be due to the ability of the team formation algorithm in forming better teams over time, as indicated earlier. This evaluation in the form of PRQ then helped them choose better team members in the future sessions.

The Team-Based Efficacy Questionnaire (TEQ) surveys were collected after each lab based on a set of questions designed to measure how a student viewed how well his or her team had performed, as shown in Table 2.

	Spring 2005				Fall 2005			
Session	Control Section		Treatment Section		Control Section		Treatment Section	
	Mean	Stdev.	Mean	Stdev.	Mean	Stdev.	Mean	Stdev.
1	31.80	2.58	27.72	5.08	27.22	4.37	23.64	5.55
2	30.87	3.38	29.18	2.63	26.75	6.66	25.87	8.33
3	30.08	3.02	28.25	4.02	29.14	5.47	25.76	5.43
4	N/A	N/A	N/A	N/A	29.12	4.52	26.78	8.15
Mean	**30.92**	**2.99**	**28.38**	**3.91**	**28.05**	**5.25**	**25.51**	**6.86**

Table 2: Control vs. Treatment sections: Results of the team-based efficacy questionnaires (TEQs)

It is observed that students in the control section approved of their team-based activities more than the students in the treatment section. There are two possible explanations. First, the ease of face-to-face interactions gave the impression that the team was doing better, which is consistent with our earlier observation with the peer rating results. Second, how the student agents form their teams did not necessarily meet the students' preference. Note that a student did not have access to other survey results, including how his or her team members thought of him or her as a peer. However, the student agent did and perused this information in its bidding for the most useful or compatible team.

Finally, the correlation between a student's performance and the other parameters is investigated, as shown in Table 3. First, it is observed that the treatment section had higher correlation values in SEQ (0.41 vs. 0.28), PRQ (0.34 vs. 0.23), and TEQ (0.50 vs. 0.22) than did the control section. This indicates that the better students (with higher post-test scores) in I-MINDS teams rated their self-efficacies better, rated their peers better, and rated their team-based efficacies better than those in the traditional face-to-face teams. Looking more closely at how I-MINDS students interacted, we see that students who had better post-test scores were also the students who sent longer messages (with a correlation of 0.40). Thus, in this case, better students assumed a larger role in their respective teams during the treatment. Combining this observation with what has been reported earlier on the average normalized post-test scores, there are indications that better students helped other students do better in the treatment section and that resulted in better individual performances as evidenced in the post-test scores.

Spring 2005			Fall 2005	
Variable	Correlation with Post Test		Correlation with Post Test	
	Control Section	Treatment Section	Control Section	Treatment Section
SEQ	0.28	0.41	0.22	0.16
PRQ	0.23	0.34	-0.01	0.11
TEQ	0.22	0.50	0.09	0.12
Number of Messages Sent	N/A	0.11	N/A	0.27
Avg. Length of Messages	N/A	0.40	N/A	0.25

Table 3: Correlation between Post-test Score and Other Parameters

However, the above observations were not repeated in the Fall 2005 study. Comparing the two sections, how students did during the collaborative learning activities did not correlate with how they performed individually in the post-tests. Compared to Spring 2005, better-performing students in Fall 2005 tended to send more messages (0.27 vs. 0.11), but shorter messages (0.25 vs. 0.40). Does that mean that the better-performing students in Fall 2005 were less patient with their peers? Further, students in the Spring 2005 treatment section reported a 0.41 correlation between their self-efficacies and their post-test scores, compared to only 0.16 in the Fall 2005 treatment section. That means that the students in the Fall 2005 treatment section were far less accurate in their knowledge of their own ability to solve the upcoming problem set, which is very important to form effective teams: students who think they are good at a particular topic when in fact they are not as good can misguide the team activities.

This indicates that even though a student is doing very well individually, he or she may not be helpful to other team members. Therefore, when forming teams of learners, the individual competence is not the only factor, the compatibility and the history of the members working together should also be considered. Indeed, I-MINDS' team formation algorithm—VALCAM—does consider the PRQ values while forming teams. However, since this algorithm uses reinforcement learning, it needs some training before it could form effective cooperating teams. The quality of interaction between the teammates depends on various things, their likings of each other, their expertise in the problem and the difficulty of the assigned problem. This last factor is vital because if the problem is too easy, interaction among team members becomes a liability instead of being an asset. From our close observation of the students, it was observed that more students in Fall 2005, on average, found the assigned problems to be easy, than those in Spring 2005—as they also achieved better course grades. Therefore, this could be a very possible reason for the lack of impact of structured collaborative learning (both control and treatment) in Fall 2005. This hints that a learner team in a CSCL environment could work better only when the problem is too difficult for one team member to solve by himself or herself. This could then also motivate students to exchange messages to help each other obtain a solution. As a whole, the findings of our experiment can be summarized in the following way:

- From the user's perspective, the conventional structured face-to-face collaborative learning is more preferable than the structured computer-supported collaborative learning. The higher TEQ and PRQ values of the control group point to that. However, the students' perspective of teamwork is affected by various factors like ease of use of the communication tool, variety of communication methods, etc. I-MINDS only allowed students to communicate with each other using text messages. However, in face-to-face interaction, the students worked with each other in person. So, it is not fair to compare face-to-face interaction with simple text messaging. Considering this, we are now working on an advanced whiteboard in I-MINDS that would let the students work with their team members more closely and through more intuitive ways than text messages such as equations, flowcharts and handwriting/hand-drawing.

- Our results indicate that structured computer-supported collaborative learning helps students learn better than conventional structured face-to-face collaborative learning. The higher normalized post test score of the treatment section point to that. Since both the control and treatment groups followed the Jigsaw process, this observation may be attributed to the fact that the restricted mode of I-MINDS' communication forced the students of the treatment section to be more explicit and articulate in expressing their ideas. So, they were able to gain a deeper understanding of the subject matter than the control section students. To gain further understanding, we are working on a message classification system that would allow us to understand how a student's understanding or expertise in the given problem changes over time during a session.
- Our results indicate that a student's self-efficacy assessment does not correlate with his or her performance in either setup. Since the students are solving problems in an area which is new to them, it is reasonable that they may not be able to judge their own performance accurately. However, our team formation algorithm uses the self-efficacy assessment of a student while forming teams as a measure of that student's potential ability. So, we will look into lowering the weight or importance of this measure in the team formation algorithm (VALCAM), thus giving more importance to tractable measure (such as the quality of questions asked) that we use for computing a student's competence. Further, we will also include past individual performance (e.g., post-test scores) of a student to help refine the self-efficacy measurement.
- According to our results, individual performance of a student is not correlated to his or her impression about the usefulness of his or her team. In some situations, the good students view the teamwork as not useful and the not-so-good students view the teamwork as useful and vice versa. The low correlation between a student's performance and his or her TEQ values point to that. In general, if a strong student can solve the assigned problems without the help of the team members, he or she may perceive teamwork as unnecessary. As a result, cooperation or interaction between both parties suffers, resulting in low valuation of the teamwork (TEQ). So, students rate their teams lowly regardless of their own performance, generating low correlation values. To gain further insight into this correlation, our future experiments will involve challenging tasks or problems that can only be (better) solved through effective teamwork.
- Finally, our results indicate that, individual performance value of a student is not correlated with the peer review received by that student. A good student can receive a low review from his or her peers and vice versa. This happens because in teamwork, a student's helpfulness is very important in determining how his or her peers perceive him or her as a team member, regardless of the student's individual capabilities. The team members' perception of each other contributes to their compatibility. The team formation algorithm (VALCAM) used PRQ values to measure the compatibility of the team members; it was not very successful because of two reasons. First, VALCAM uses reinforcement learning and thus requires more than three or four iterations to form compatible teams, whereas our experiments had only three or four iterations. Second, PRQ value alone may not be a sufficient measure of compatibility. For our future experiments, we will build a more precise and accurate compatibility measure that would model student dialogues, and semi-structured activities on digital whiteboards. This revised compatibility measure would help VALCAM build better teams.

3. Conclusions and Future Work

In this paper, we have presented the results of our two-semester long experiment with I-MINDS, a structured CSCL delivery tool. Our results indicate that even though students prefer conventional structured face-to-face collaborative learning over computer-supported structured collaborative learning, working in the latter may improve their performance or learning. Furthermore, the results indicate that in both conventional face-to-face and computer-supported structured collaborative learning, a variety of factors affect the performance of a learner team. These factors include difficulty of the assigned problem and compatibility of team members. Therefore, these factors should be taken into account to build successful teams in structured collaborative learning environment.

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