

Formation and Scaffolding Human Coalitions in I-MINDS – A Computer-Supported Collaborative Learning Environment

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Abstract: Computer-Supported Collaborative Learning environments (CSCL) are used today as a platform for delivering distance education and as a tool to improve student understanding using collaborative learning methods. The success of a CSCL environment in improving the knowledge of a student depends on the quality of group work of its participants. However, forming human user groups that allow all the users work productively is difficult because of the dynamic nature of the human users and the complex interplay of human factors (e.g., comfort level, proficiency, etc.). Furthermore, human user behavior changes over time due to the learning and other various external stimuli. So, to make the coalitions productive for the students, the framework need to take into account how humans learn from working in a team, accommodate that *change* (i.e., provide support to the coalition), and use it to improve the quality of the coalitions. *iHUCOFS* is a multiagent framework that aims to form and support human coalitions. VALCAM is an implementation of the *iHUCOFS* framework that forms and supports the learner coalitions in I-MINDS – a CSCL environment. Though not conclusive, the preliminary results of using VALCAM in I-MINDS indicate that VALCAM can make an impact on the learner coalitions formed in I-MINDS.

Keywords: Computer-supported collaborative learning, multiagent system, human coalition formation, scaffolding.

1. Introduction

Computer-supported collaborative learning (CSCL) environments are now becoming a popular platform for delivering distance education. A typical CSCL environment consists of a set of tools to facilitate communication and collaboration of the students. However, a better equipped CSCL tool could also contain provisions for the instructor to form and support student coalitions. However, forming human coalitions in a CSCL environment poses a variety of challenges. The lack of familiarity among the users, their decreased social presence, their varying level of knowledge and expertise all add to the difficulty of formation and support of human learner coalitions. Furthermore, because individual human behaviors change and inter-person relationships grow over time, a group of peers who didn't work well together initially could end up working well together in the end due to increased familiarity and comfort level. Therefore, due to the dynamic nature of the human users, a fixed scripted coalition forma-

tion algorithm may not provide the best solution. This also implies that it is possible for a coalition formation algorithm to form a group of lesser expected utility for the current task with the hope of a better reward in the future as the group members improve the quality of their group work over time. Thus, a human coalition formation framework that forms human coalitions in general should also facilitate the betterment of individual human users, i.e., support the formed coalitions, over time as group members work in those coalitions. However, this support could be *explicit* or *implicit*. In the case of explicit support, the framework would help the coalition members directly by providing hints, clues, advices, etc. In the case of implicit support, the framework would create a working environment for the group members. That environment would then improve the behavior of the human users in future coalitions. We denote this implicit and explicit coalition support provided by the framework as *scaffolding*.

In our research, we have developed an interactive multiagent framework for delivering CSCL called I-MINDS [17, 18]. I-MINDS, which stands for Intelligence Multiagent Infrastructure for Distributed Systems in Education, provides a computer-supported collaborative learning environment for learners in synchronous learning and classroom management applications for instructors, for large classroom or distance education situations. Besides being a platform for delivering distance education in the CSCL environment, I-MINDS also implements the VALCAM algorithm [16, 17], an implementation of *iHUCOFS* [16] – a multiagent framework for forming and scaffolding human coalitions.

The details of our *iHUCOFS* framework and partial results have been published before. The basic outline of the *iHUCOFS* framework has been published in [16], and the description of I-MINDS has been published in [17, 19]. Partial results of our two-semester long experiments have been published in [9, 17, and 18]. In this paper, we present structure and implementation of the improved version of I-MINDS (version 2.0) and extend the details of the *iHUCOFS* framework to explain the various types of human learning that occurs in the collaborative work environment. Furthermore, in this paper, we also present the complete results of using the *iHUCOFS* framework to form and scaffold human coalitions. This paper is organized as follows: Section 2 describes the *iHUCOFS* framework: axioms, learning types, problem characteristics, and design principles. Section 3 briefly presents the VALCAM algorithm, an implementation of the *iHU-*

COFS framework. Section 4 describes the basic architecture of I-MINDS. Section 5 outlines our implementation details. Section 6 mentions the results of our two-semester long experiment of using VALCAM. Section 7 presents the research work related to the collaborative learning systems and research work related to human coalition formations in collaborative learning scenarios. Finally, Section 8 presents the conclusion and outlines our future work.

2. iHUCOFS Framework

As alluded to in the introduction, a multiagent system supporting human coalitions has to consider both coalition formation and coalition scaffolding. Furthermore, scaffolding coalitions involve guiding human users for short terms gains and facilitating changes in human users for long terms gains. Such a system also deals with agents that each acts as a *representative for* and as an *advisor to* its human user. To address the problem, we propose the Integrated Human Coalition Formation and Scaffolding (iHUCOFS) framework. In the following, we first propose a set of axioms to support the integrated treatment of formation and scaffolding and then describe a set of design principles addressing specific characteristics of the problem.

Here we propose a set of axioms. These axioms serve as the underlying assumptions about the problem and the iHUCOFS framework. In this framework, each *human user* has a dedicated *user agent*, and they communicate or work together through the user agents. This is akin to computer-supported collaborative problem solving. The user agents live in a multiagent system, sharing a common environment.

2.1 Axioms

Axiom 1: Coalition Formation. Forming a human coalition is to identify a group of humans so that they work together to solve a problem. An *effective* coalition is one that solves the problem for which it is formed. A *good* or *efficient* human coalition is one that is capable of generating a high-utility solution.

Axiom 2: Coalition Scaffolding. Scaffolding a human coalition is to support a group of humans to help them work together when solving a problem. There are two types of scaffolding: **I.** Each human user is supported by a dedicated agent *explicitly* to deal with the present coalition and problem for short-term gains; and **II.** The human coalitions are formed to both incorporate and facilitate changes in human behavior for long-term gains. In Type I scaffolding, the objective is to increase the utility of the solution to the present problem. An example of this type of scaffolding would be for a user agent to prompt its human user to respond to a question from one of the coalition members as the human user is profiled to be knowledgeable in that question. Another example would be to discourage a human user from dominating the coalition's brainstorming sessions. In Type II scaffolding, the objective is to increase the *potential* utility of problem solving in the future. An example of this type of scaffolding is to exploit human learning: putting people of different knowledge backgrounds or capabilities in the same coalition with the intention that co-workers can learn from each other, and can learn about how to work with each other. In this manner, the system implicitly scaffolds *future* coalitions. However, human

learning in a collaborative setting can come in various shapes and forms [7]. Next, we discuss the different types of learning and explain how the scaffolding process can be used to provide a setting for the human users to go through that learning.

- 1. Learning by Observation** – The users learn indirectly by observing other learners' learning process. This type of learning can be facilitated by the user agent by putting the human user in a group that contains users with similar level of knowledge. Then, as the group is working to solve a problem together, the user agent can provide interactive targeted learning materials so that at least some of the users can learn from it. Since, all the human users are at the same or similar knowledge level, it can be expected that, they will learn from each other by watching their learning process.
- 2. Learning by Self-Expression** – In this type of learning, human users learn by externalizing their own self-thinking process. For example, a student may learn by explaining some problem to himself or herself (e.g., while preparing a presentation for the group mates, etc.). This type of learning environment can be provided to the human users by Type II scaffolding. While a human user is working collaboratively in a group, he or she may decide to explain parts of the assigned problem's solution to the other users and that explanation may improve his or her own understanding. However, this type of learning would work better when the user expected to go through the learning process is as knowledgeable (or more knowledgeable) as the other group members about the assigned problem. A human user who is learning a topic for the first time will not be able to learn by self-explanation since he or she may not have the preliminary knowledge to begin with.
- 3. Learning by Teaching** – Learning by teaching occurs when a human user learns or refines his or her own knowledge by teaching other group members. This type of learning is particularly useful in CSCL settings where the students learn by teaching each other. Again a human coalition formation framework can provide an environment for this type of learning by putting a human user in a group that would allow him or her to learn by teaching others. However, this type of learning requires that the user teaching others is knowledgeable about the assigned problem and is able to express his or her ideas and is comfortable about teaching others.
- 4. Learning by being Taught** – This is the simplest type of learning where a human user learns when he or she is being taught by someone else. Therefore, we see that learning by teaching and learning by being taught may compliment each other. When a human user is learning by teaching other group members, those group members could learn by being taught.
- 5. Learning by Apprenticeship** – In this type of learning, the human user learns by observing someone else's behavior and then mimicking it. This type of learning can be implemented by Type I scaffolding. When a group of users are working together, the user agent may guide the group members so that when the most knowledgeable member explains or teaches something to the other group members, it can prompt some other group member to re-explain and re-do the example or problem. This way,

when that human user solves the problem again, he or she will learn by apprenticeship.

- 6. Learning by Practice** – This type of learning occurs when a human user applies his or her existing knowledge to solve an assigned problem. This type of learning is very common in situations where each human user contributes to the solution of the assigned problem by working on it. However, there may be human users who are free-riding i.e., depending on the competent and the knowledgeable users to solve the assigned problem. As a result, these users do not learn by practice. The user agent can provide reinforce the human users to learn by practice using Type II scaffolding. If the user agent detects that one of the human user is free-riding and is not contributing to the solution of the problem, it may put that human user in a group which contains human users who are not so proficient or knowledgeable about that assigned problem. Then, the free-riding human user would be forced to step up his or her effort and work on the assigned problem to avoid failing and getting penalized as a group.
- 7. Learning by Guiding** – This type of learning occurs when a human user demonstrates his or her knowledge to the other users or guides the other users. Note that *learning by guiding* improves the knowledge or skill of the human user who is guiding his or her group members. On the contrary, *learning by apprenticeship* improves the knowledge of the human user who is observing and mimicking someone else's behavior. This type of learning scenario can be established by using Type I scaffolding. For example, when a human user is working on the assigned problem, the user agent may prompt a third user to guide the person who is working on the solution. However, the user agent should intervene with care because not all human users would appreciate guidance from others.
- 8. Learning by Reflection** – This type of learning occurs when a human user rethinks his or her own solution and analyses his or her self-thinking process. This type of learning could occur when a group of users have completed a problem and are analyzing their solution process. This type of learning can also be achieved by using Type I scaffolding in combination of a structured collaborative process. For example, after each problem is solved by the human users, the collaborative process could involve a stage where each human user would discuss why his or her solution worked or did not work. If a human user is reluctant to discuss his or her solution process, the user agent may prompt him or her and engage that user to reflect on his or her own solution or thinking process.
- 9. Learning by Discussion** – This type of learning occurs when the human users discuss a topic with each other. The human users can be made involved in this type of learning by using both Type I and Type II scaffolding. Using Type II scaffolding, a human user can be put into a group which contains users who he or she is comfortable with. This higher level of comfort would increase the probability that they would discuss the assigned problem or the approach to solution. On the other hand, if the users in a group are not discussing the assigned problem with his or her group members, the user agent

can ask him or her to join the ongoing class discussion or ask leading questions that would engage that reluctant user.

On the whole, the scaffolding of a human user can be implemented to improve a human user's competence by providing a helpful environment for him or her to learn.

Axiom 3: Tradeoff between Formation and Type II Scaffolding. As indicated in Axiom 1, a good coalition is one that generates a high-utility solution to a problem. Yet, in Axiom 2, a good coalition may be one that generates a high potential utility for future problems. These two objectives may be conflicting. To illustrate, take a group of human users of diverse capabilities. To obtain the maximum-utility solution to a given problem, one may opt to selecting top n users to form a coalition. On the other hand, if one also intends the low-capability users to learn from the top human users on how to solve these problems, then one may opt to selecting a mixture of high- and low-capability users for the coalition. This means that a multiagent system implementing the iHUCOFS framework will have to consider this tradeoff between utility and potential utility.

Axiom 4: Tradeoff between Formation and Type I Scaffolding. For a human group, the importance of coalition formation and the importance of coalition scaffolding (type I) are *negatively* correlated. In other words, a MAS focusing on forming good coalitions does not have to provide as much Type I scaffolding; and a MAS with good Type I scaffolding does not need to form a very good coalition to begin with, as Axiom 2 postulates that scaffolding helps human users work together.

Axiom 5: Crossover between Formation and Scaffolding. When human users are new to each other, i.e., the user agents do not have accurate knowledge about each other, then forming a good coalition is not as viable as supporting a coalition after it is formed. Indeed, faced with lack of information and uncertainty, a system trying to improve the utility of the coalition that it is forming is akin to trying to improve the *expected* utility of the coalition based on some prior probabilities. On the other hand, when human users are familiar to each other, then having a good coalition support becomes much less important relatively to forming a good coalition. This is because (1) the system has now sufficient information to decide on a good coalition, and (2) the human users have now sufficient experience and compatibility working together and/or working in a team. So, if the set of human users stays relatively static, then the user agents (and human users) will eventually learn about each other and the emphasis on good coalition scaffolding will give way to good coalition formation as the agents will have more accurate knowledge of each other. However, if the set is dynamic in which newcomers frequently join, then the user agents might have to maintain a balanced emphasis between the two.

Axiom 6: Dual Role. A user agent is both a representative of and an advisor to its human user. Being a representative is key to coalition formation, while being an advisor is key to (Type I) scaffolding. How a human user acts is important to its user agent's modeling of the human user. This modeling, when exchanged among the user agents, allows the system to form coalitions on accurate knowledge of the users. Thus, a user agent must be able to capture an accurate representation of its human user. Actions that it performs on its own accord should be clearly separated from the actions that

it performs as instructed by its human user. As an advisor, a user agent will support human user to perform in a coalition and to also learn from working in a coalition. As discussed in Axiom 2, the human user can learn in many different ways.

Axiom 7: Tradeoff between Representative and Advisor. Analogous to Axioms 3 and 4 above, a user agent may trade-off its roles. As a mere representative, a user agent does not have autonomy; as a mere advisor, a user agent has autonomy. If one designs a user agent to pursue full autonomy, then such a user agent can forsake its human user. If one designs a user agent to only act as a representative, then it will not be able to help or scaffold its human user. On the other hand, the more a user agent helps shape its human user's decisions or actions, the more the human user lose his or her autonomy. This may not be desirable as it might reduce human users' motivation to learn.

Axiom 8: Crossover between Representative and Advisor. Analogous to axiom 5 above, depending on what a user agent knows, it may move to emphasize being a representative from being an advisor. For example, when its human user has performed consistently and has been a good or effective coalition member, then it can reduce its advisor role and act as a representative. In this case, it assumes the human user's autonomy and loses its own. When a human user is not familiar with the coalition members, the agent may need to provide information on how the observed behaviors of these members and offer tips on best to deal with these members. So over time, a user agent becomes more knowledgeable about other user agents (and their human users). Such an experienced user agent can become more effective in being an advisor. In the meantime, as its human user becomes more capable at teamwork, a user agent can become more effective in being just a representative. This evolution corresponds to the crossover between formation and scaffolding in Axiom 5.

Furthermore, the scaffolding process depends largely on the ability of the human users to learn new knowledge and new skills. However, as discussed in Axiom 2, human users learn in different ways. Thus, to facilitate all those types of learning, a human user's assigned user agent may need to switch between its role of being a representative and an advisor. For example, if the human user does not have enough expertise to work productively in a coalition, his or her user agent can act as a representative and assign that user to a coalition where that user can learn by being taught, learn by apprenticeship or learn by observation. When that human user starts working in a coalition, his or her user agent can switch to a role of advisor and monitor and engage that human user in those learning processes if he or she is not paying attention to the ongoing discussion or activities. On the other hand, if a human user is fairly knowledgeable about the assigned problem, the user agent may decide to improve his or her knowledge further by involving him or her in *learning by teaching, learning by guiding, learning by self-expression and learning by discussion* scenarios. Then the user agent could act as a representative and put that knowledgeable human user in a group that contains human users who need some training and guidance and teaching by someone who knows about the assigned topic. Once, the human user starts working in the coalition, his or her assigned user agent can assume the role of an advisor. As an advisor, the user agent

can then guide or instruct that human user so that he or she engages enough to take advantage of the learning scenario.

2.2 Problem Characteristics

In this section, we identify some characteristics of human coalitions and outline a set of design principles addressing these characteristics.

Characteristic 1: Diversity. Human users have different motivations, utility functions, and valuation of rewards.

Characteristic 2: Inconsistency/Irrationality. Human users can behave inconsistently and/or irrationally. Also, human users may learn and change their behaviors over time. This underlies the scaffolding component of the iHUCOFS framework.

Characteristic 3: Incomplete Information/Noise. It is close to impossible to completely model human reasoning and actions as there are always external factors (or noise) influencing how they behave in a coalition.

Characteristic 4: Uncertain Outcomes. Even with perfect information and accurate modeling, given the same problem, it is possible that the same coalition may not yield the same outcome.

Characteristic 5: Axioms 3-5. Human users can benefit from a well-formed coalition in the first place and good scaffolding after the coalition is formed.

Characteristic 6: Axioms 6-8. A human user can co-exist in a symbiotic relationship with its user agents. A human user can instruct how its user agent should behave and can also rely on its user agent providing timely and useful advice.

2.3 Design Principles

Design Principle 1: System and User Perspectives. There should be a system agent and a set of user agents. A system agent is needed to evaluate and make decisions regarding a coalition, while a user agent is needed to be a representative of and an advisor to its human user. Also, the goal of a system agent and the goal of the user agent can also be different. However, the system agent does not impose any specific rules on the user agent. Instead, it wants the emergent behavior the results from the user agents' own goal: forming a beneficial group for its human user and scaffolding the coalition of its human user to complete the assigned task. This design principle addresses Characteristics 5 and 6.

Design Principle 2: User Modeling. The user agents must be able to model different user motivations, behaviors, and utilities. Moreover, they should be able to consider inconsistency or irrationality in their human users' actions or reasoning. This design principle addresses Characteristics 1 and 2.

In brief, there are two main ways to model the behavior and performance of a human user. First, information about the human user can be collected from his or her interaction with the user agent, with the other human users and other group member. Since the user agent acts as a communication medium for the human users', they can closely monitor every action of him or her. The group agent can monitor the human user's actions with the other group members. With these three types of information, the entire interaction history of a human user with others can be constructed.

Second, information about the human users can also be collected from the evaluation score of the human user in various individual and group activities. While a user model can be constructed by using the raw information about the interaction of human user with others, the evaluation scores collected by administering surveys can be used to crosscheck that model. For example, if the user interaction history indicates that a human user has been a very active as a group member and that user's group members' evaluation of him or her is low, it may mean that the user is doing off topic discussions. Then the system and or group agent may provide him or her guidance and or hint to focus more on the assigned task.

Design Principle 3: Satisficing Solution. The system agent and the user agents must be able to make decisions with incomplete information or noise. Further, since outcomes are uncertain, it could be costly for the agents to devise an optimal solution only to find out that it does not lead to the expected outcome. Thus, this motivates the agents to make do with what they know, and sub-optimal but satisficing solutions may be preferable. This design principle addresses Characteristics 3 and 4.

Design Principle 4: Learning Mechanism. To overcome the noisy environment and incompleteness of the available information, the user agents should use a learning mechanism to filter out the necessary information to achieve the required level of accuracy. The learning mechanism could include typical *agent learning* (e.g., reinforcement learning) and also the *multiagent learning* where the user agents learn from each other's experience (e.g., learning by communication and learning by observing). This design principle addresses characteristics 3 and 4.

3. Implementation of iHUCOFS

With the axioms, characteristics and design principles in hand, we have designed an iterative coalition formation algorithm called VALCAM. Next, we discuss the details of designing VALCAM for I-MINDS based on the design principles described in Section 3.

1. System and User Perspectives. Based on Design Principle 1, VALCAM has two parts: VALCAM-S for the system agent and VALCAM-U for the user agent. In this implementation, we use an iterative auction to form coalitions, where each user agent bids for joining the most compatible coalition with the virtual currency that it has earned from participating in previous coalitions. The system agent acts as a coordinator and hosts an iterative auction while the user agents make bids to form coalitions. To support Type II scaffolding, VALCAM also mixes low- and high-caliber user agents (i.e., human users of varying competence) in each coalition. In the coalition formation process, the user agents and the system agent works with two different goals. For the user agents, it is very important to form the group that would improve the human user's learning and group work experience. On the other hand, the goal of the system agent is to provide an environment to maximize the number of user agents who could satisfy their goal of forming and scaffolding their assigned human users. However, due to the incomplete information and the noisy environment, it may not be possible for the system agent to find the best solution, only a satisficing solution.

2. User Modeling. Based on Design Principle 2, this algorithm relies on the modeling of user competence and their compatibility. Accurate modeling of the above two attributes allows the system to better form and scaffold coalitions. Competence defines a human user's capability in solving a particular subtask of a problem. In terms of compatibility, if the coalition members do not get along with one another, they will work in a team instead of as a team [3]. That means a group of human users who do not get along well or do not like each other's working style, discussion, etc., would work towards achieving their individual goals instead of working with others to achieve the common goal of the group. As a result, the outcome of the coalition would suffer even when the members are highly competent at what they do. Compatibility between two human users denotes their working experience with each other. Furthermore, if past behavior can predict the future, it can be expected that the human users who have worked well with each other in the past, will be able to work with each other well in the future. Therefore, by recording the working experience of a human user in a coalition, the user agent will be able to estimate the expected compatibility of this user with the members of a future coalition. Finally, using compatibility in the coalition formation process is an example of implicit scaffolding. Putting a human user in his or her favorite group would mean that he or she will be more involved in the collaborative activities. Mixing high- and low-caliber human users in a coalition can also help low-caliber human users learn to improve their performance over time.

3. Satisficing Solution Based on Design Principle 3, we use a soon-enough, good-enough strategy in VALCAM, to reduce the algorithm complexity and avoid having to obtain information that would have been needed to achieve optimality. In particular, VALCAM uses a group seed selection policy to select the first member for each coalition and forms each coalition around that first member. VALCAM also performs reinforcement learning, allowing the user agents to improve their modeling of users' competence and compatibility.

4. Learning Mechanism. VALCAM uses typical agent learning as well as multiagent learning.

Table 1: Learning Mechanism in VALCAM

Learning Topic	Mechanism
User Competence	Uses information retrieval with the evaluation history of a user to estimate the competence of a user on a topic
User Compatibility of a group of users	Uses reinforcement learning and user modeling to estimate the compatibility of a set of users for an upcoming task
User Learning	Uses a user's participation history and evaluation scores to calculate the learning rate of human user
User Inconsistency	Uses the competence, compatibility and learning to calculate the expected outcome of a user's participation and calculates the inconsistency factor by finding the difference between the <i>expected</i> performance and the <i>actual</i> performance

Table 1 summarizes the learning mechanisms used in VALCAM. In our current implementation of VALCAM, we have implemented *competence* and *compatibility* and we are working on the other parts of the learning mechanism. In brief, the VALCAM algorithm for coalition formation can be briefly described as follows:

VALCAM environment consists of a system agent, a set of user agents assigned to the human users and a group agent assigned to each user group. The system agent hosts an iterative auction to form coalitions, where each user agent bids for joining the most compatible coalition with the virtual currency that it has earned from participating in previous coalitions.

In VALCAM, virtual currency is used as a succinct representation of the users' overall performance. This performance measure denotes the performance of a human user measured from the perspective of the group agent and the user agent. Each time a user group completes a task, the individual and group performance is evaluated by the student agent and the group agent and a certain amount of virtual currency is assigned to that user. The amount of virtual currency assigned is proportional to the performance of the human user as an individual and as a group member (i.e., helpfulness in achieving the common group goal). Then, using the earned virtual currency, the user agents are able to form groups for the human users. Even though, this use of virtual currency rewards the user more who has performed well than the user who has not, the design of VALCAM prevents this assignment from becoming a *rich get richer* model by rewarding altruistic behavior during the group formation. Even though, virtual currency is used as an indicator of the users' performance, the virtual currency account balance is kept hidden from the users. Allowing the user to keep track of their virtual currency balance creates additional learning load for the human users and could also encourage them to adapt their behavior to improve their account balance.

The details of VALCAM can be found in [16]. However, a brief description is as follows: suppose that A is the set of *user agents*, m is the number of non-overlapping coalitions that will be formed, and $|A| > m$, j is the current task assigned, p is the selected auction protocol e.g., Vickrey [14].

VALCAM-S (for system agent):

1. Initialize (create a set of m groups G and assign a group agent to each group)
2. Choose first members for each group g in G (*Type II scaffolding by selecting a competent first group member*)
3. Start the auction according to p for users in A . For each group g in G ,
 - a. Accept bids from the unassigned users
 - b. Assign the highest bidder to g
4. After completing j , assign individual and group pay-offs to A based on the human user's individual and group performance (*reinforcement learning*)

VALCAM-U (for user agent):

1. Initialize (estimate and announce the human user's competence for the upcoming task) (*user modeling*)

2. For each round of bidding for group g , bid with an amount proportional to the average of *compatibility* and *competence* of the users in g . Compatibility measures the human users' view of one another, and competence measures the average individual performance of a human user.

4. I-MINDS

I-MINDS (Intelligent Multiagent Infrastructure for Distributed Systems in Education) employs a number of interacting intelligent software agents, representing individual students and the instructor to create a CSCL environment. The rationale behind using multiagent intelligence is the agent's persistence in tracking and monitoring its environment (student and instructor activities), autonomy in decision making, and responsiveness in providing services to both students and instructors. These are properties that are useful for distance learning and large classrooms. Briefly, in I-MINDS, each student has a personal agent (a student agent), each instructor has a personal agent (a teacher agent), and when students form a group, they are also assigned a group agent. Figure 1 shows the main components of a typical I-MINDS classroom.

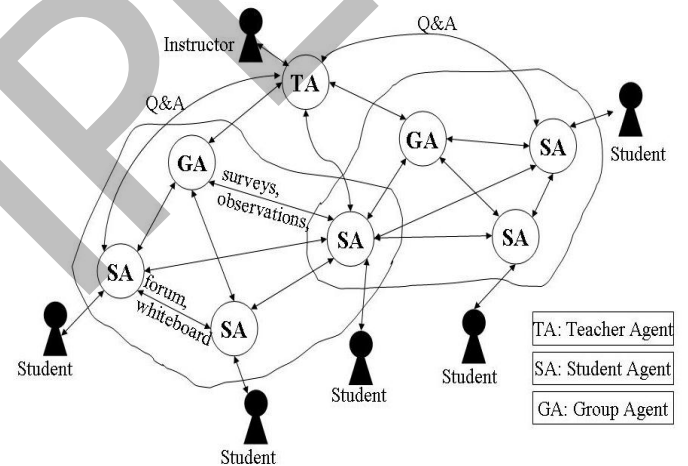


Fig. 1. I-MINDS Classroom Structure

4.1 Teacher Agent

Figure 2 shows the main modules of the teacher agent, the student agent and the group agent. In I-MINDS, a teacher agent interacts mainly with the instructor. It helps the instructor deliver instructional content to the students and coordinates the collaborative learning process. Teacher agent modules include a Slide module for exchanging slides with the students, a Question module that processes the incoming questions. This Question module has many different capabilities. For example, it uses reinforcement learning to rank the incoming questions based on their importance or relevance. The Question module can also group similar questions using the surface structure of the question. The teacher agent also contains a coalition module that forms student coalitions for group work. Finally, there is a communication module that provides a communication link to all the student agents and group agents and a repository module that handles storage of the data. In addition, a teacher agent helps form

student groups for structured cooperative learning, supporting the Jigsaw [4] procedure.

The Jigsaw procedure works as follows. First, the instructor divides the students into groups. Second, the instructor divides a problem into different parts (or sections). Third, the instructor assigns a part/section for every student such that members of the same group will have different sections to solve. The students who are responsible for the same section then work together to come up with solutions to the section to which they have been assigned and develop a strategy for teaching the solutions to their respective group members. Clarke [4] further refined the Jigsaw structure into stages. These stages are (1) **Introduction** of the topic to the class as a whole, (2) **Focused Exploration**: The focus groups explore issues pertinent to the section that they have been assigned, (3) **Reporting and Reshaping**: The students return to their original groups and instruct their teammates based on their findings from the focus groups, and (4) **Integration and Evaluation**: The team connects the various pieces generated by the individual members, address new problems posed by the instructor, or evaluates the group product.

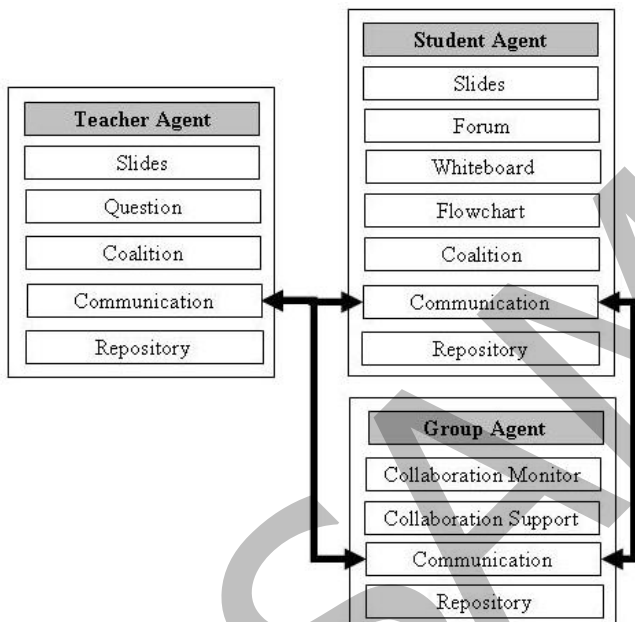


Fig. 2. I-MINDS Agent Modules

4.2 Student Agent

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. Figure 1 shows the modules of an I-MINDS student agent. Similar to the I-MINDS teacher agent, the student agent contains a Slides module to exchange slides with the instructor. The student agent also contains a forum module to communicate with the other students, a whiteboard and a flowchart module (JFlowchart) to collaboratively work on problems and a coalition module to form coalitions with other students. Finally, there is a communication module that provides a communication

link to all the agents and a repository module that handles storage of the data.

4.3 Group Agent

In I-MINDS, a group agent is activated when there are structured cooperative learning activities. Structured cooperative learning involves specified activities that explicitly require students to cooperate. Currently, I-MINDS implements the Jigsaw model [4] and general group work model of collaboration. The group activities monitored by the group agent include the number and type of messages sent among group members, self-reported teamwork capabilities, peer-based evaluations as a team member, and evaluation of each team and the monitoring of JFlowchart. Figure 2 shows the modules of an I-MINDS group agent. Note that this agent works entirely behind-the-scenes and thus does not have a GUI front end.

5. Implementation of I-MINDS

All the modules of I-MINDS have been encapsulated in two different java packages: the *instructor package* and the *Student package*. The *instructor package* allows a teacher to run a virtual classroom for a set of students. On the other hand, the *student package* can be used by a student to join and participate in the virtual classroom. The latest version of I-MINDS is implemented using Java 2 and the Netbeans IDE. Due to the platform independence of Java, the *student package* can be downloaded and run on a variety of Operating Systems including Microsoft Windows (NT, 2000, XP), Linux (Suse Linux 9.0) and Mac OS X with minimal user involvement. However, the current version of *instructor package* requires a Microsoft Windows operating system. Besides Java, the *instructor package* and *student package* also uses MySQL database for data storage and retrieval.

6. Experiments and Results

6.1 Experiment Setting

To evaluate VALCAM in a real scenario, we deployed I-MINDS in CSCE 155 for two semesters, the first core course of computer science and computer engineering majors (i.e., CS1). The course has three 1-hour weekly lectures and one 2-hour weekly laboratory session. In each lab session, students were given specific lab activities to experiment with Java and practice hands-on to solve programming problems. In our experiment, there were 2-3 lab *sections* where each section had about 15-25 students. Our study utilized a control-treatment protocol. In the *control* section, students worked in cooperative learning groups without using I-MINDS. Students were allowed to move around in the room to join their groups to carry out face-to-face discussions. In the *treatment* section, students worked in cooperative learning groups using I-MINDS. 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. After the group activities, all the students filled out some surveys and took a post-test. This post-test score was graded by the instructor and used as the

measure of student performance in terms of understanding the topic of the lab.

6.2 Results

6.2.1 Feasibility Study 1

In this analysis, our objective was to see whether and how VALCAM provided Type II scaffolding. Normalized average post-test scores of the treatment and control sections (0.22 vs. 0.19) indicate that students using I-MINDS were able to obtain comparable post-test scores. We also observe that students in the treatment sections seemed to improve over time (0.21, 0.21, 0.23, 0.25), and their performance seemed to eventually overtake that of the control sections' over time—indicating that VALCAM, due to its learning mechanism, might have been effective in forming better and better coalitions over time, and *achieving the goal of Type II scaffolding*. However, more semesters of data is needed to obtain enough significance for our observations.

6.2.2 Feasibility Study 2

In this study, our objective was to measure how closely the payoff (in terms of virtual currency), a succinct representation of our user modeling, correlated with the actual performance of the students. We used the final lab (all 14 labs) and final exam scores as the actual performance indicators. In the beginning, every student started out with the same virtual currency since the agents assigned to the students had no prior background knowledge about them. Then as they formed coalitions and worked on different tasks, their virtual currency account was updated. As a result, the correlation improved (from ~0.10 to ~0.50 over four lab activities). Thus, as the students worked more with each other in the coalitions, our virtual currency model was able to capture their performance better. This is a promising observation indicating that the VALCAM design using the iHUCOFS framework is viable to learn the student models with sufficient accuracy.

6.2.3 Feasibility Study 3

In our Spring and Fall 2005 experiments using I-MINDS, the main mode of communication for the students was text messages. In this study, our objective was to check whether it is possible for the students to communicate with their group members using the limited text chat capabilities of I-MINDS.

Figure 3 and 4 show the average count length of messages exchanged during each session for Spring and Fall 2005 sessions. Even though the number of sessions in our experiments is not enough to draw any conclusions, a common trend is observed in both semesters. During both Spring and Fall 2005 semesters, the count of messages decreased and the average length of messages increased. This may indicate that as the students work in coalitions formed by VALCAM in I-MINDS, they sent fewer and lengthier (more explanatory) messages. This indicates that, as the students worked in their groups using I-MINDS, their need to explain things in detail to each other grew. Therefore, tools (e.g., whiteboard) that could aid the students to explain a concept in detail to each

other could be helpful in this scenario. However, more data and experiment is needed to validate this claim.

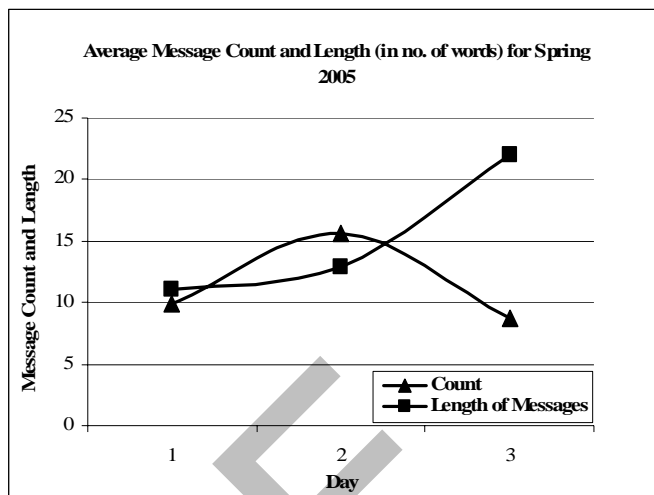


Fig. 3. Average Message Count and Length in Spring 2005

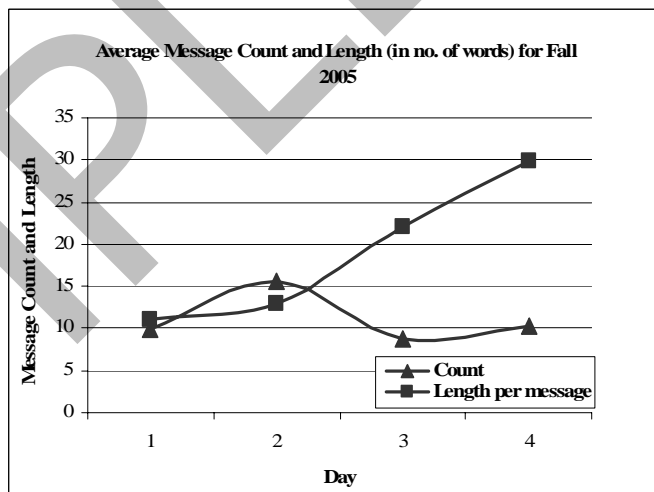


Fig. 4. Average Message Count and Length for Fall 2005

6.2.4 Impact Study 1

In this study, our objective was to measure the impact of VALCAM, through I-MINDS, on student's perception of their own competence, based on the results of the Self-Efficacy Questionnaire (SEQ) survey. The SEQ survey was conducted before the group activities started. Students entered their competency of completing a particular task. This contributes to step 2 of the VALCAM-U algorithm. We observe that for both semesters, students in the treatment sections were on average less confident than the students in the control section about their ability to solve the assigned task before the lab activities started (30.98 vs. 33.53 out of 40). This is interesting. As discussed earlier in Feasibility Study 1, the students in the treatment sections performed comparably and eventually overtook those students in the control sections in terms of their post-test scores. This indicates that even though, VALCAM seemed to be able to provide useful Type II scaffolding, it did not improve students' perception of their own competence.

6.2.5 Impact Study 2

Similar to the previous study, here we wanted to measure the impact of VALCAM, through I-MINDS, on student's perception of their peers. 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 rate the helpfulness of the group members after they have gone through the group activities. This constitutes the compatibility measure in step 2 of VALCAM-U. We find that students in the control section rated their peers better (higher means (35.95 vs. 35.78)) and more consistently (lower standard deviation values (3.54 vs. 6.42)) than the students in the treatment section. This is likely due to the fact that students of different calibers and levels of familiarities were assigned by VALCAM to the same groups, probably creating discomfort among the students. On the other hand, we see indications that students in the treatment section seemed to rate their peers better over time (from 33.71 to 35.80 to 36.37 and 37.25). This might be due to the ability of VALCAM in forming more compatible groups over time—trading off between forming and scaffolding, the key to the iHUCOFS framework.

6.2.6 Study of User Agent's Utility

The goal of VALCAM is to form and scaffold the human coalitions. However, an individual agent achieves that goal by trying to join a group that would provide the highest yield of virtual currency for the human users. That means, for an individual agent, the virtual currency earned by joining a group is a measure of its utility. Also, meaningful coalition formation and good scaffolding translates to high yield of virtual currency for the individual agents. So, to measure the utility of the whole multiagent system, the average amount of virtual currency accumulated after each day by the individual user agents was calculated. The graph in Figure 5 shows that after each classroom the student agents (i.e., the user agents) were able to increase their virtual currency account balance on average. That means, after every session, the student agents were able to earn more virtual currency than it had spent during the coalition formation session. According to our policy of rewarding virtual currency, this also means that the human users were performing well on average in the groups and were allowing their user agents to accumulate virtual currency.

On the whole, the results of our experiments are not significant enough to claim any conclusion about the effectiveness of VALCAM in forming or scaffolding human coalitions due to insufficient human subjects and short study duration. However, our results hint at the effectiveness of VALCAM in providing *Type II scaffolding* (feasibility study 1) and improving student performances over time. The results also hint at the fact that VALCAM may have been improving the quality of human coalitions over time (impact study 2).

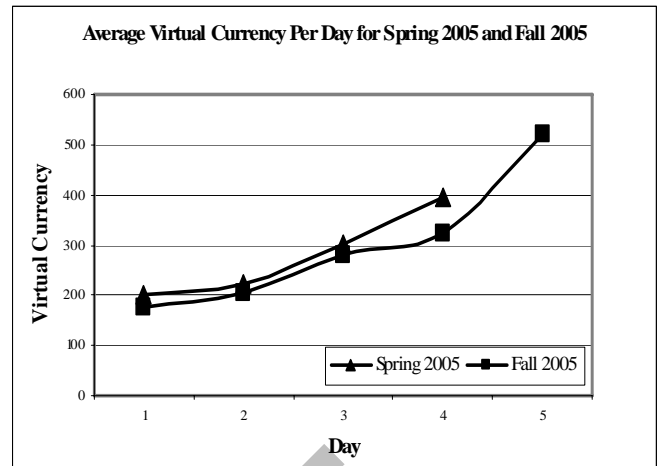


Fig. 5. Average Virtual Currency Accumulated

7. Related Work

Since the focus of this paper is on the learner coalition formation in I-MINDS using the iHUCOFS framework, we discuss research work related to collaborative learning systems for human users and we also discuss a few related research efforts that are focused on forming and scaffolding human coalitions.

Constantino-González [5] proposed a web-based environment called Collaborative Learning Environment for Entity-Relationship Modeling (COLER) in which student can solve Entity-Relationship (ER) problems while working synchronously in small groups at a distance. Their approach monitors individual work in private workspaces as well as the shared workspace to identify conflicts. COLER's coach is a personal, pedagogical agent that facilitates collaboration by encouraging students to discuss and participate during collaborative problem solving. Given personal and teammates' actions in the learning environment as input, the coach detects learning and participation opportunities, and then gives a message to the student to encourage discussion, participation, self-reflection, ER reviewing, or assign control to a teammate. For our I-MINDS framework, the student agents correspond to COLER's coaches. Currently, each student agent is only capable of monitoring a student's activities and refining the group of the student and reporting the student's profile to the teacher agent, and each is designed to work behind-the-scenes non-intrusively. As more features are added and studies are conducted, I-MINDS student agents will likely assume more responsibilities such as COLER's coaches.

Barros and Verdejo [1] defined a process-oriented qualitative description of a mediated group activity on three perspectives: (1) a group performance in reference to other groups, (2) each member in reference to other members of the group, and (3) the group by itself. The collaboration application is conversation-based, and thus the method to compute these attributes automatically is based on semi-structured messages. The architecture of their proposed system, Distance Environment for Group ExperiencEs (DEGREE) is organized into four levels: configuration, performance, analysis and organization. At the configuration level, once the teachers have planned an experience at the collaborative

level, they configure and install automatically the environment needed to support the activities of groups of students working together. At the performance level, a group of students can carry out collaborative activities with the support of the system. All the events related to each group and experienced are recorded. At the analysis level, the educator or instructor analyzes the user's interaction and make interventions in order to improve them, with tools for quantitative and qualitative analysis. At the organization level, the instructor gathers, selects, and stores the results of collaborative learning experiences and the processes. The information is structured and valued for searching and reusing purposes, and stored as cases forming an organizational learning memory. I-MINDS' monitoring and recording of peer-to-peer activities are very similar to DEGREE's. First, I-MINDS has both structured and unstructured cooperative learning features. When the structured cooperative learning mode is invoked, the I-MINDS teacher agent outlines the task, subtasks, and the various activity phases as configured by the instructor. When the students carry out the subtasks going through the various phases, the activities are recorded to be analyzed later. In I-MINDS, the experience and expected outcomes are not stored as cases; instead, group agents are invoked to reward or penalize the students based on several performance metrics that we see as intrinsic to collaborative activities. Further, according to resultant virtual currencies that these students earn, I-MINDS assigns roles to the students in the next round of activities.

Ogata and Yano [13] used knowledge awareness and information filtering in an open-ended collaborative learning environment. Basically, an individual user's agent, called KA-Agent, autonomously informs the learner of the up-to-the-minute activities of other learners by comparing the learner's actions with the other learners' actions. These messages are called active KA, making the learner aware of someone who has the same problem or knowledge as the learner, who has a different view about the problem or knowledge, and who has potential to assist solving the problem. The knowledge awareness filtering aims to sift out unacceptable KA messages that disturb learning, and give adequate priority and order KA messages according to individualized priority. The KA-Agent is similar to I-MINDS student agents, especially in the process of selecting buddies suitable for a particular student, and is similar to I-MINDS teacher agent in the process of forming focus groups during the Jigsaw learning procedure.

Grave et al. [6] is another interesting work where a multi-agent framework is used to build a multi-layer architecture that is able to initiate and manage student training. In this article, the authors present a multi-agent architecture allowing the implementation of a dynamic CBR for the evaluation for the potential evolution of an observed situation. This architecture design is designed on three layers of agents with a pyramidal relation. The bottom layer is used to build a representation of the target case (i.e., the current situation). The second layer is used to implement a dynamic elaboration of the target case and the upper layer implements a dynamic process of source cases recall that allows the search for past situations or cases similar to the current situation. Even though this multiagent layered approach can result in a flexible and adaptive learning or training environment, there are a few issues not addressed. The authors discuss that they are

analyzing file tracks produced by a tool of self-training to build the ontology of the domain and specify the low layer by identifying the semantic features. If such domain specific approach is used, the resulting multiagent system may not be generic enough to be used in a typical student learning scenario. Therefore, a generic framework could be more helpful. Furthermore, in their layered multiagent framework the issues relating to collaborative work among learners have not been addressed.

On the whole, these collaborative learning systems do not provide any mechanism for forming human user groups that addresses the unique characteristics of human coalitions. Furthermore, they also do not provide any scaffolding once the user groups are formed. However, there have been some approaches to form human user groups in the form of 1-to-1 peer groups.

Li et al. [10] used agent technology with fuzzy set theory to find matching peers for human users based on similar preferences or expertise. Each agent, representing a user, communicates with others and exchanges information about specific knowledge questions. The responses of these agents are then judged based on response time and the response quality. Then using Zadeh's fuzzy set theory, their framework finds the most suitable set of peers for their users.

Another such peer help system is I-HELP [2]. I-HELP combines a 1-to-1 peer help network and a discussion forum to provide offline peer help to learners. In I-HELP, each human user is assigned a user agent which builds a model for its owner and also builds partial models of all the other user agents (representing other human users) that it comes into contact. This peer help system has some similarities with how I-MINDS' coalition formation module works. For example, in both I-HELP and I-MINDS, the previous user experiences are considered when forming groups. However, in these systems, agents locate peer help for their human users, but a peer group is built based on 1-to-1 experience instead taking account how a group would work together as a team. Furthermore, noise, uncertainty and incomplete information in the environment are also not addressed.

The *scaffolding* of human coalitions has been researched in the application domain of the coalition formation after coalitions have been formed. For example, in COLER [5], students work synchronously in small groups at a distance. COLER assigns an agent to coach each learner to support and facilitate collaborative learning. The agent monitors the individual student's activities, detects the differences between the student's and his or her group's solutions, and advise the students on their collaborative skills, e.g., encouraging the students to participate, encouraging them to compare solutions with their other group members. In another research, Vizcaino et al. [19] used simulated students to detect and repair difficulties in collaborative learning among the human students in a synchronous and distributed collaborative learning environment. When a student is too passive or wandering into off-topic conversations, the simulated student intervenes to guide him or her back to productive collaborative work. These examples used only short term approaches to supporting human coalitions. However, our notion of scaffolding includes both short term and long term improvement of collaborative behavior of the users.

8. Conclusion

A computer-supported collaborative learning system called I-MINDS has been described and *iHUCOFS* a framework for forming and scaffolding human coalitions has been presented. Furthermore, the VALCAM algorithm – an implementation of the *iHUCOFS* framework in I-MINDS has been introduced. Preliminary results hint that by using *iHUCOFS* framework, I-MINDS was able to form and impact the learner coalitions in the CSCL environment.

The coalition formation and support in I-MINDS is somewhat different from the typical formation and support of learner coalitions provided by the collaborative learning environments (e.g., [1, 5, 13, and 6]). First, I-MINDS uses the *iHUCOFS* framework to address the unique characteristics of human behavior to build meaningful and helpful learner coalitions. Second, using the concept of scaffolding, I-MINDS tries to improve the quality of behavior of the learners in the future coalitions. However, more experiments are needed to obtain a better estimate of I-MINDS' capability in building and supporting learner coalitions.

Future work includes continued deployment of I-MINDS in the classroom, improvement of the GUI front-end for the teacher and student agents to better support collaborative work. We are also integrating a mathematical equation editor in I-MINDS so that, the students are able to work collaboratively on mathematical problems. Additional research includes refinement of the VALCAM algorithm to more fairly synthesize subjective peer-based evaluation and improvement of user models by estimating the learning and inconsistency in the learners using machine learning.

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