SimCoL: A Simulation Tool for Computer-Supported Collaborative Learning

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SimCoL: A Simulation Tool for Computer-Supported Collaborative Learning

Nobel Khandaker and Leen-Kiat Soh

Abstract—Researchers designing the multiagent tools and techniques for computer-supported collaborative learning (CSCL) environments are often faced with high cost, time, and effort required to investigate the effectiveness of their tools and techniques in large scale and longitudinal studies in a real-world environment containing human users. Here, we propose SimCoL, a multiagent environment that simulates collaborative learning among students and agents providing support to the teacher and the students. Our goal with SimCoL is to provide a comprehensive test bed for multiagent researchers to investigate 1) theoretical multiagent research issues, e.g., coalition formation, multiagent learning, and communication, where humans are involved and 2) the impact and effectiveness of the design and implementation of various multiagent-based tools and techniques (e.g., multiagent-based human coalition formation) in a real world, distributed environment containing human users. Our results show that SimCoL 1) closely captures the individual and collective learning behaviors of the students in a CSCL environment; 2) identify the impact of various key elements of the CSCL environment (e.g., student attributes and group formation algorithm) on the collaborative learning of students; 3) compare and contrast the impact of agent-based versus nonagent-based group formation algorithms; and 4) provide insights into the effectiveness of agent-based instructor support for the students in a CSCL environment.

Index Terms—Collaborative work, cooperative systems, educational technology, simulation.

I. INTRODUCTION

COMPUTER-SUPPORTED collaborative learning (CSCL) environments facilitate student learning by enhancing their collaborative learning using computer and Internet technologies. Today, CSCL environments contain agents and agent-based services to improve the collaborative learning of students from two different aspects. First, the agents act as assistants to the students by monitoring the difficulties they face and helping them with customized support. Second, the agents act as assistants to the teacher providing decision support and helping him or her with tasks like group formation. To design agents, agent-based services, and agent-based algorithms for a CSCL environment, it is essential to: 1) understand how these various elements of the CSCL environment work together to produce the learning outcome of the students and 2) investigate how these services impact the students’ interactions and learning outcomes. Furthermore, without testing their algorithm on a large group of students for a sufficiently long time, it is difficult for the researchers to: 1) fully understand the impact of their designs and 2) evaluate their designs and algorithms against the state-of-the-art. Albeit considered the most authentic way of validating the results, it is often difficult to conduct experiments with human users for various reasons: 1) it is difficult to acquire enough students for long enough time to do the experiments; 2) replication of experiments is often not possible; and 3) experiments may yield unwanted consequences (e.g., student apathy toward the use of CSCL environment) if the agents or agent-based services do not work as expected. These issues can be alleviated by using agent-based simulation.

However, the existing tools designed to simulate the CSCL environment has yet to consider the role of agents in supporting (or scaffolding) the activities. When designed based on the individual and collaborative learning theories, the students, and their interactions with each other in the simulation would closely represent the collaborative learning in the real-world CSCL classroom. Existing tools, such as [5] only simulate the student behavior using agents and do not include agents that act as the assistant agents or any agent-based services or algorithms. As a result, the decision-making process of the CSCL module that provides scaffolding to help both the teacher and the students, as well as the appropriateness and costs of such a module, have not been studied comprehensively.

In this paper, we describe SimCoL—a multiagent application for simulating the collaborative learning of a set of students in the CSCL environment. The inspiration source of our paper is CSCL environments that combine research ideas from psychology (especially educational psychology), education, and computer science to create an online collaborative learning environment for students. This simulator would improve the CSCL and collaborative learning, in general, in the following ways. First, SimCoL would allow researchers to gain insights into the collaborative learning process by carrying out what-if simulations that reveals the emergent outcome for a given environment setting (e.g., students with specified knowledge and ability). Second, SimCoL would allow the researchers and teachers to better understand the impacts of the administrative decisions like 1) group formation scheme; 2) group size; and 3) agent-based support [28] on the student learning outcome.

To show the validity of SimCoL and to illustrate the various scenarios that SimCoL could be used to investigate the sensitivity of the CSCL environment design impacting various aspects of student models, we have run several large simulations. Our
results show that the SimCoL environment is able to capture
the change in the knowledge gain of the students due to: 1) the
changes in the attributes (e.g., ability and motivation) of
the participating students and 2) the various techniques (e.g.,
group formation method) used in CSCL. Further, the individual
and collective learning behavior patterns of the students in Sim-
Col. closely represent the learning behavior patterns reported
by the CSCL researchers. These results suggest the usefulness
of SimCoL as a simulation tool.

The rest of the paper is organized as follows. Section II
presents a set of learning theories and observations based on
the individual and collaborative human learning process and
define the scaffolding of students in a collaborative learning
environment. In Section III, we use the observations in Section II
to design the agent that represents the teacher, the agents that
represent the students, and the tasks in the SimCoL environment.
Then, we describe how the SimCoL environment was realized
using Repast—a multiagent simulation tool, in Section IV. Sec-
tion V describes our experiment setup and results. Finally, in
Section VI, we present some related work and in Section VII
discuss the conclusions.

Note that we use the following terminologies in this paper.
An agent that simulates the teacher’s behavior in SimCoL is a
simulated teacher, while one that simulates a student’s behavior
is a simulated student. An agent that assists the students in form-
group is a student-assistant agent, while one that assists the
teacher a teacher-assistant agent.

II. LEARNING

In this section, we discuss definitions, theories, and empiri-
cal observations regarding three different aspects of students’
learning processes: 1) individual learning; 2) peer-based learn-
ing; and 3) collaborative learning in student groups. Using these
learning theories, we derive a set of observations that are used in
Section III to build agents to simulate the student collaborative
learning behavior in a CSCL classroom.

A. Individual Learning

We use “learning” to refer to the improvement in a student’s
knowledge or expertise on a topic or skill, which could be topic-
specific, e.g., learning how to solve differential equation, or
topic-independent, e.g., teamwork or communication skills. Ac-
cording to learning theories [1], [7], the four main elements that
affect how a person learns are: 1) what the student already knows
(knowledge); 2) how able/intelligent the student is (ability); 3)
how motivated the student is (motivation); and 4) the emotional
state of that student (emotion). The cognitive components that
represent these factors are: 1) the crystallized intelligence as
accumulated knowledge stored in long-term memory; 2) fluid
intelligence as represented by working memory capacity; and
3) motivation as represented by working memory allocation [1];
and 4) emotional state [7]. Next, we define these elements in
greater detail.

Shell and Brooks [1] use the term knowledge to refer to the
accumulated knowledge in a student’s long-term memory. The
ultimate result of learning would occur as the improvement of
the knowledge of the students. Brooks and Shell [1] use ability
to represent the cognitive ability or intelligence of a person.
They suggest that there are two different parts of ability: fluid
intelligence and crystallized intelligence. The fluid intelligence
is a fixed entity that deals with general cognitive capacity and
crystallized intelligence represents the accumulated knowledge
of the student. Furthermore, the fluid intelligence is basically the
working memory of a student [1]. However, there is a difference
between the absolute working memory capacity a person has
and the amount of working memory capacity he or she has
available at a particular time for a particular task. The behavior
of a person while working on a task and the improvement in
his or her knowledge due to learning by working on that task
depend upon the amount of working memory that person has
available at that time. Further, the amount of working memory
available any person at a time is determined by: 1) his or her existing knowledge for that task; 2) his or her motivation to
work on that task; and 3) emotion [1]. Motivation determines
why we do and what we do [1]. In other words, motivation is
the process whereby goal directed behavior is instigated and
sustained. Finally, the emotion of a student determines whether
the students are feeling happy or sad. So, we write our first
observations as follows.

Observation 1: A student’s improvement of knowledge of a
topic is mainly affected by: 1) his or her existing knowledge; 2)
ability; 3) motivation; and 4) emotion.

Observation 2: The amount of working memory available to
a student determines how much he or she can learn.

Observation 3: The working memory of a student interacts
with his or her prior knowledge and new information (regarding
a task) to produce learning and behavior.

Observation 4: A student’s available working memory for
a task can be described as his or her ability for that
task.

Although the aforementioned four components that affect
learning are cognitively distinct from one another, there are com-
bbinatorial effects [1]: 1) the prior knowledge stored in the long-
term memory interacts with the working memory to produce
learning; 2) available amount of working memory limits how
much prior knowledge and information can be used/activated at
any time; 3) the amount of working memory is determined by
motivation, extent of prior knowledge, and emotion; and 4) as
knowledge increases, it increases the effective working memory
capacity allowing acceleration of future learning processes. Fi-
nally, according to the recent research work on perceptual and
motor acquisitions [26], [27], the pace of skill acquisition for a
learner accelerates in the beginning and slows down to a stable
state and leads as follows.

Observation 5: A student’s available working memory for a
topic is proportional to his or her: 1) knowledge on that topic
and 2) motivation to learn that topic. Furthermore, this available
working memory is inversely proportional to the emotional state
of that student.

Observation 6: As the knowledge of a student on a particular
topic increases, his or her learning outcome for that topic would
increase at the beginning and slow down to a steady state after
a certain amount of time.
B. Peer-Based Learning

When a student is working with his or her peer to solve some assigned task, the student and the peer may learn from each other about that task. The possible learning scenarios between two interacting peers are summarized by [8], such as (see Table I): learning by observation, learning by teaching/guiding, learning by being taught, learning by reflection/self-expression, learning by apprenticeship, learning by practice, and learning by discussion. From these peer-based learning scenarios, we observe that the prior knowledge of the participating students plays an important role in deciding what type of learning scenarios may occur. For example, learning by teaching (and learning by being taught) is more common among two students, where one student with more prior knowledge teaches his or her peer, who has less prior knowledge. Furthermore, the difference between two interacting students’ prior knowledge about how to solve a certain task can hinder their learning. This effect is described in Vygotsky’s zone of proximal development (ZPD) theory [9]. For example, it may be difficult for two students to learn from each other if the amount of prior knowledge they have on a topic is vastly different from each other [9]. Therefore, we write as follows.

Observation 10: Two students may learn about a topic from their interactions (see Table I) when the content of prior knowledge they have are not too different from one another.

C. Collaborative Learning

The term “collaborative learning” is an instruction method in which students at various performance levels work together in small groups toward a common goal [10]. Derived from Stahl [11] are as follows.

Observation 11: The collaborative knowledge building is a cyclic process that feeds on itself.

Observation 12: This collaborative knowledge building cycle is a hermeneutic cycle, meaning, “one can only interpret what one already has an interpretation of.”

Observation 13: Individual knowledge of a student is gained from collaborative knowledge of his or her group members through interaction. This collaborative knowledge is, in turn, produced by individual knowledge of the interacting group members.

Kreijns [12] describe the interaction between students as the key to collaboration among group members. Furthermore, researchers [25] suggest that collaborative learning occurs from the exchange of dialogues among the students.

Observation 14: The collaboration among the members of a group of students occurs due to their interaction/discourse with each other.

Zumbach et al. [13] describe a collection of dyadic (between two students) interactions for a group of students, which were reported by researchers in the CSCL community. An example of interactions mentioned in [13] is: 1) student a proposes a solution for the assigned task and 2) student b accepts or proposes another solution to the task. Thus, we can see as follows.

Observation 15: The compilation of discourse/interaction patterns presented by Zumbach et al. [13] describes a typical dyadic (between two students) learning scenario in terms of a chain of action–reaction patterns.

The quality the discourse/interactions within a group depends on the affective state of a student [2] and his or her social relationship with other students in the group. Issroff and Jones [14] and Vass [15] report that students, who are friends, have established ways of working, which are implicitly understood rather than explicitly discussed. In addition, [12] mentions that social relationships contribute to common understanding, an orientation toward cooperation, and the desire to remain as a group. Finally, as reported in [3], the students form their view of other students due to the type and extent of collaboration they receive from their peers. Clear and Kassabova [16] further report that in collaborative learning settings, it is common to have students, whose motivation is affected by the motivation of other group members. When the other group members are motivated to learn and to collaborate, it increases the motivation of a student, who had low motivation when he or she joined the group, and vice versa. We derive from the above the following observations.

Observation 16: Good social relationship improves the quantity and quality of interactions among group members.

Observation 17: The quantity and quality (i.e., learning outcome) of interactions among a group of students vary over time due to factors internal and external to the classroom environment. Improvement in social relationship among the members of a group improves the quality of collaborations among them. On the other hand, when a student group member experiences distracting factors that experience reduces the quality of his or her collaboration with other members.

Observation 18: Motivation of the group members’ impacts the motivation of a student positively and negatively.

Observation 19: Social relationship between a student and his or her peer (as perceived by the student) change according to the frequency, extent, and quality of collaboration (e.g., how many times did my peer helped me).

D. Scaffolding

Bruner [17] and Cazden [18] define scaffolding as the act of providing assistance to a child so that he or she is able to carry out a task (e.g., solve a problem) that he or she cannot do by herself. Over time, the concept of scaffolding has been introduced into traditional classrooms to aid learners to achieve difficult learning objectives and complete difficult tasks [3], where tools and software are used to 1) offer structure and
support for completing a task and 2) promote peer interactions to enable peers to support each other’s learning. In the first type of scaffolding, the students are provided information about how to better approach to solve the task that they are having difficulty with. In the second type of scaffolding, the peer support of a student is enhanced in the hope that these peers would provide guidance and information for that student to help him or her to solve this task. Researchers in the CSCL community are now utilizing scaffolding in the form of incorporating structure of learning activities (e.g., [19]) and improving peer support (e.g., [20]). As CSCL researchers (e.g., [3], [20]), note that due to being in different ZPD, the learners benefit most when the scaffolding is targeted toward their zone of development. So, one of the recommendations provided to the CSCL practitioners is to customize the scaffolding to specific learners’ needs. Hence, we can see as following.

Observation 20: Scaffolding in the CSCL environment can be provided by: 1) providing structure and support for completing tasks and 2) improving of peer support.

Observation 21: Scaffolding in the CSCL environment may be used to improve the knowledge of the learners regarding the assigned task.

Observation 22: Learners in a CSCL environment benefit more when the provided scaffolding is targeted to their ZPD.

III. SimCoL Environment

The SimCoL environment $E$ represents a CSCL environment, where the teacher forms student groups and assigns a set of tasks and the students solve these tasks collaboratively to improve their knowledge about some topic. The SimCoL environment is defined as a three-tuple: $E = \langle T, I, H \rangle$, where $T$ is a set of tasks, $I$ is an agent, who simulates the teacher, and $H = \{h_1, \ldots, h_n\}$ is a set of agents, who simulates the students in a collaborative classroom environment. In this section, we first define the tasks $T$. Then, based on the observations presented in Section II, we describe the attributes and the behavior of agents $H$, who represent the students in SimCoL. Furthermore, we describe how the simulated teacher $I$ forms groups of simulated students and carries out CSCL classroom sessions in the SimCoL environment using a set of simulation steps. Finally, we describe the collaboration process of the simulated students $H$ in a group in SimCoL using a set of simulation steps and discuss how their attributes change.

A. Task

The tasks in SimCoL represent the problems and exercises that are solved by the students in a CSCL environment. The set of tasks is denoted by $T = \{T_1, \ldots, T_n\}$, where

$$T_j = \langle c_{t_j}, d_{i_j}, t_{l_j}, s_{\overline{t}_j} \rangle.$$  \hspace{1cm} (1)

Here, $c_{t_j}$ denotes the concept of the task. This concept represents the subjective knowledge required to solve the task. $d_{i_j} \in \mathbb{R}$ is the difficulty of the task as determined by the simulated teacher. $t_{l_j}$ is the time limit within which the task is to be completed. $s_{\overline{t}_j}$ is a vector representing the simulated student groups’ (who are working on the task) view of the solution quality of the task $T_j$ at time $t$.

B. Simulated Student

We represent the model $h_{m_{i,t}}$ of each simulated student $h_i \in H$ in SimCoL by a six-tuple

$$h_{m_{i,t}} = \langle K_{i,t}, AB_{i,t}, MO_{i,t}, EM_{i,t}, SR_{i,t}, TSQ_{i,t} \rangle$$  \hspace{1cm} (2)

where $K_{i,t} = \{ (ct_{j}, \text{ex}_{i,j}) \} \forall T_j \in T$ is the knowledge of simulated student $h_i$ at time $t$ with $ct_j$ representing the concept of $T_j$ and $\text{ex}_{i,j} \in \mathbb{R}$ is the expertise, i.e., the amount of knowledge the simulated student has about the concept. The goal of simulated student collaboration is to increase the value of this expertise. $AB_{i,t} \in \mathbb{R}$ is the ability of $h_i$ at time $t$ for task $T_j$. $MO_{i,t} \in \mathbb{R}$ is the motivation of $h_i$ at time $t$. $EM_{i,t} \in \mathbb{R}$ is the emotional state of simulated student $h_i$ at time $t$. $SR_{i,t} = \{sr_{i,k,t} \in \mathbb{R} | h_k \in H - h_i\}$, where $sr_{i,k,t} \in \mathbb{R}$ is the social relationship between $h_i$ and $h_k$ at time $t$ as perceived by $h_i$. $TSQ_{i,t} \in \mathbb{R}$ denotes the target solution quality of $T_j$ of $h_i$ at time $t$.

We have included $K_{i,t}$, $AB_{i,t}$, $MO_{i,t}$, and $EM_{i,t}$ in the model according to Observation 1 and included $SR_{i,t}$ according to Observations 16 and 17. Also, combining Observations 4 and 5, we assume that the ability of a simulated student is related to his or her knowledge, motivation, and emotion in the following way:

$$AB_{i,j,t} = AB(h_{m_{i,t}}) \propto w_{abx}\text{ex}_{i,j,t} + w_{abm}MO_{i,t}$$

$$- w_{abe}[EM_{i,t}]$$  \hspace{1cm} (3)

where $w_{abx}$, $w_{abm}$, and $w_{abe}$ are weights. According to (3), the ability of a simulated student for a particular task at any time is proportional to the sum of his or her expertise on the concept of this task and motivation minus the absolute value of his or her emotional state. We also define the target solution quality of a simulated student with

$$TSQ_{i,j,t} \propto AB_{i,t}.$$  \hspace{1cm} (4)

So, a simulated student’s target of the quality of the solution of the assigned task is proportional to his or her ability for this task. According to Observations 3 and 4, the ability of a simulated student determines how much of his or her existing knowledge can be activated to produce behavior (i.e., effort to solve the task and learning). Therefore, given the same time limit $t_{l_j}$ for a task $T_j$, a simulated student with higher ability would be able to solve the assigned task better than a simulated student with lower ability. So, we assume that the simulated students have targets of the final solution quality according to their own abilities.

C. Simulated Teacher

The teacher $I$ in SimCoL acts as the coordinator of the CSCL sessions. The teacher delivers instructions, forms groups, and assigns collaborative tasks. In SimCoL, we have implemented three different group formation methods: random, Heterogeneous Algorithm (Hete-A) [21], and Vickrey Auction Based Learning Enabled Coalition Formation Algorithm for Multiagents (VALCAM) [22] group formation method. Table II shows how the teacher carries out the CSCL session.
through a set of simulation steps. First, the teacher initializes the classroom (tasks, group formation scheme, so how scaffolding should be provided, and how many groups would receive scaffolding). Then, for each initialized task, the teacher: 1) initializes a collaborative session (Step 2a), forms simulated student groups (Step 2b–d), and announces the start of the collaborative session to all simulated students (Step 2e). Then, until the collaborative session is over, the teacher periodically sorts the groups according to their current achieved solution quality of the task (Step 2f-a), and then, selects the groups, who have the lowest solution quality. Those selected groups are then provided scaffolding (Step 2f-a-2). Finally, the teacher announces the end of the collaborative session when the time limit for the current task is over (Step 2g).

### D. Assistant Agents

The student-assistant and teacher-assistant agents have been incorporated in SimCoL to implement various agent-based coalition formation algorithms. Each student-assistant agent in SimCoL is assigned to a simulated student and it monitors the change in that assigned simulated student’s: 1) expertise gain and 2) social relationship with other students. The teacher-assistant agent is assigned to the instructor to 1) assign and monitor student collaborative performances and assign them virtual currency according to this performance and (2) communicate with the student agents to form groups using VALCAM [22].

### E. Collaboration and Scaffolding

Following Observations 14 and 15 in SimCoL, we simulate the collaborative behavior (i.e., collaboration to solve the assigned task and to improve expertise) of a group of simulated students using a series of dyadic interactions among the group members. Here, we describe how these interactions occur in SimCoL. First, we define the following functions that dictate the behavior of the student agents simulating the collaborative learning in SimCoL. Here, we assume that two simulated students $h_i$ and $h_j$ with models $hm_{i,t}$ and $hm_{k,t}$ are working in a group $G_{m,t}$ to solve task $T_j$ and all variables $w_{x,y,z}$ are weights.

#### Motivation update (Observation 18):

$$\text{MSU}(MO_{i,t}, G_m) = [w_{omo}MO_{i,t} + w_{gmo} \sum_{k \in G_m} \frac{MO_{k,t}}{|G_m| - 1}].$$

#### Collaboration probability (Observation 16):

$$\text{CP}(hm_{i,t}, hm_{k,t}, T_{j,t}) = w_{copp}SR_i + w_{copp} (sq_{j,t} - TSQ_{j,t}).$$

#### Collaboration cycle (Observation 15):

$$\text{CC}_{i,k,t,j} = \{act_{i,k,t,j} \cdot \text{rect}_{i,k,t,j} \cdot \text{lect}_{i,k,t,j}\} \subseteq \text{cc}_{i,k,t,j}$$

$\text{cc}_{i,k,t,j}$ denotes a collaboration cycle completed by $h_i$ with $h_k$ at time $t$ for task $T_j$. Here, $act_{i,k,t,j}$ denotes an utterance of action, $\text{rect}_{i,k,t,j}$ denotes a collaboration object started by $h_i$, and declined by $h_k$. CY$_{i,k,t,j} = \{CC_{i,k,t,j}, CC_{i,k,t,j}, \ldots, CC_{i,k,t,j}, \ldots, CC_{i,k,t,j}\}$ is the set of all collaboration cycles between $h_i$ and $h_k$ for $T_j$.

#### Solution quality update:

$$\text{SQU}(hm_{i,t}, hm_{k,t}, c_{c_{i,k,t,j}}) = 0,$$

if $p_{eq} \geq \kappa_{eq}$ and

$$ \propto (ab_{i,k,t} + ab_{k,i,t})/dj_{i,t},$$

otherwise

#### Social relationship update (based on Observation 19):

$$\text{SRU}(\text{CY}_{i,k,t,j}) \propto \left[ |CC_{i,k,t,j}| - |CI_{i,k,t,j}| \right] / \left[ |CC_{i,k,t,j}| + |CI_{i,k,t,j}| \right].$$

#### Scaffolding effect (based on Observations 20–22):

$$\text{SEU}(hm_{i,t}, ct_j, SO_j) \propto 1/(1 + |ex_{i,t} - sol_{i,t}|),$$

if $p_{ sca} \geq \kappa_{sca}$, and 0 otherwise

**Table II**

<table>
<thead>
<tr>
<th>Simulation Steps of Teacher</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Initialization: $T = {T_1, \ldots, T_n}$, $G_m = \text{group formation scheme}$, $t_{sc} = \text{scaffolding period}$, $n_{sc} =</td>
</tr>
<tr>
<td>2. For all tasks $T_j \in T$, do</td>
</tr>
<tr>
<td>a. Initialize collaborative Session $s_j$: $t = 0$, $G = {g_1, \ldots, g_m}$, $n_{sc} =</td>
</tr>
<tr>
<td>b. If $G_m = R$, form Random Group for $H$</td>
</tr>
<tr>
<td>c. Else end if $G_m = H_a$, form Hete-A [21] groups for $H$</td>
</tr>
<tr>
<td>d. Else end if $G_m = H_a$, form VALCAM [22] groups for $H$</td>
</tr>
<tr>
<td>e. Announce start of collaborative Session $s_j$ to $H$</td>
</tr>
<tr>
<td>f. While ($t &lt; t_{sc}$) true</td>
</tr>
<tr>
<td>a. If mod$(t, t_{sc}) = 0$</td>
</tr>
<tr>
<td>1. Sort (ASC) $G$ according to $tsq_{i,t}$</td>
</tr>
<tr>
<td>2. For $t \leftarrow 0$ to $n_{sc}$</td>
</tr>
<tr>
<td>Provide scaffolding to $G_i$</td>
</tr>
<tr>
<td>b. $t \leftarrow t + 1$</td>
</tr>
<tr>
<td>g. Else Announce end of collaborative Session $s_j$ to $H$</td>
</tr>
</tbody>
</table>
its group assignment and the task (Step 1) from the simulated teacher (Step 2a in Table II). Then, the simulated student updates its own motivation according to other group members’ motivations, and its ability. During the session, the simulated student tries to collaborate with its group members if the quality of the solution is less than its expected solution quality (Step 2a) or if someone else in the group wants to collaborate (Step 2b). In both of these cases, whether the collaboration is successful or not depends on the collaboration probability (Step 2b-i). During the collaborative session, if the simulated student receives scaffolding from the simulated teacher (Step 2c) in the form of a scaffolding object, it updates its expertise. When the collaborative session ends, the simulated student updates its own view of social relationships with its group members (Step 3).

IV. IMPLEMENTATION

The SimCoL environment was implemented using the Java version of the Repast [24]—a multiagent simulation toolkit. Table IV describes: 1) the categorizations and the ranges of the randomly generated values in SimCoL, i.e., the student attributes and the weights and constants used in the equations in Section III. Fig. 1 shows the deployment diagram and Fig. 2 shows the input/output/control parameters of SimCoL.

V. RESULTS

The goal of our experiment is threefold: 1) discussing how SimCoL is able to identify and reveal the complex relationship between the variables (i.e., student attributes) of a CSCL environment; 2) comparing the emergent phenomenon of student performance in SimCoL with that of the published CSCL results; and 3) providing evidence of the validity of SimCoL simulation environment. In Section V-A, we discuss how the social relationships among the students in SimCoL impact their collaborations. In Section V-B, we describe the experiment that shows the interdependence of the students’ attributes on their
TABLE V  
SKewness and Kurtosis of Distributions of Collaboration Cycles

<table>
<thead>
<tr>
<th>Social Relationship</th>
<th>0.2</th>
<th>0.4</th>
<th>0.6</th>
<th>0.8</th>
<th>1.0</th>
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</thead>
<tbody>
<tr>
<td>Skewness</td>
<td>1.2</td>
<td>1.8</td>
<td>0.2</td>
<td>-0.1</td>
<td>-0.8</td>
</tr>
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<td>Kurtosis</td>
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<td>6.4</td>
<td>2.1</td>
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<td>3.3</td>
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</tbody>
</table>

This indicates that as the collaborative learning researchers [16] mention, social relationship among the students is a critical factor in improving the collaborations among them. Furthermore, the lack of the strong relationship between the other attributes like expertise can be explained by our formulation of collaboration probability [see (6)]. The two key factors that determine a student’s participation in a collaboration cycle is the target solution quality [see (4)] and social relationship. However, if the task solution quality is high (due to other members’ contributions), a student’s expected solution quality is then mainly determined by his or her social relationship with other group members. This result portrays a common scenario, where students often refuse to collaborate/contribute when they see other members solving the task [29].
Tables VI and VII show the skewness and kurtosis of the distributions of expertise gain for varying group sizes. According to Fig. 4, we see when the average motivation of the students is increased, the students of all categories (low, medium, and high) of expertise are able to improve their expertise gain due to better collaboration, which is also evident from the legend of Fig. 6.

In this section, we study the effect of two teacher-controlled aspects of a typical CSCL environment, i.e., 1) the group size and 2) the group formation scheme, on the average expertise gained by the students. During the simulation, the student groups in this experiment were formed using Random, Hete-A, and VALCAM group formation methods with the group size selected from the range of [2, 4]. VALCAM is an agent-based algorithm of group formation, which uses a multiagent system to form student groups that brings together experts with nonexpert students, where the members have high-social relationships. Hete-A algorithm is a nonagent-based algorithm that forms heterogeneous groups. In Hete-A, the students are first categorized by assigning them to a matrix, whose dimensions represent the attributes of a student. Once the students are categorized, the Hete-A algorithm builds heterogeneous groups by selecting students with the highest difference of attribute values according to their position in the matrix. Here, the Hete-A algorithm was used with the motivation and expertise as the two matrix dimensions. We first ran the simulation with the parameters described in Table IV for 30 students for 2000 ticks with expertise distribution mean $\mu_{ex}$ = 0.8, expertise distribution standard deviation $\sigma_{ex}$ = 0.8, and collaboration threshold $\kappa_{ch}$ = 0.5, for a set of 30 students, for ten different tasks and for 2000 simulation ticks, where the students mean expertise and social relationship was set to the mean initial values reported in [22]. Fig. 8 shows that the students in the VALCAM-formed groups performed better than the randomly formed and Hete-A formed groups.

The improvement in student performance in VALCAM-formed groups was reported in [22], so this result reproduces these observations. This improvement of student performance in VALCAM-formed groups can be explained by the way VALCAM forms student groups that contain expert and nonexperts, who have high-social relationships amongst themselves. Since, the collaboration probability [see (6)], and therefore, the collaborative learning in SimCoL is determined by the expertise difference [see (8)] and social relationship [see (6)], VALCAM-formed groups in SimCoL were able to collaborate better (i.e., higher number of successful collaborative cycles) yielding higher collaborative learning outcome. These results suggest that by setting the initial classroom conditions (e.g., student attributes) in SimCoL like a CSCL classroom, we could execute what-if scenarios by running simulations and compare the performances of group formation mechanisms.

<table>
<thead>
<tr>
<th>TABLE VI</th>
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<tbody>
<tr>
<td><strong>SKENNESS AND KURTOSIS OF DISTRIBUTIONS OF EXPERTISE GAIN (SEE FIG. 4)</strong></td>
</tr>
<tr>
<td></td>
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<tr>
<td>Skewness</td>
</tr>
<tr>
<td>Kurtosis</td>
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</table>

<table>
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<tr>
<th>TABLE VII</th>
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<tbody>
<tr>
<td><strong>SKENNESS AND KURTOSIS OF DISTRIBUTIONS OF EXPERTISE GAIN (SEE FIG. 6)</strong></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Skewness</td>
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<td>Kurtosis</td>
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</table>

Fig. 8. Average expertise gain (y-axis) for varying group sizes (x-axis).
D. Cost and Expertise Gain Through Scaffolding

In this experiment, we investigate how the individual and group scaffolding improves the expertise of the students when they are collaborating in various types of groups. To collect data, we ran the simulation with the same default set of parameters Table IV for 180 students for 2000 simulation ticks. We calculated: 1) the average improvement in the expertise gain of the students and 2) the cost incurred for providing scaffolding for individuals and groups. For a group in this experiment, one scaffolding object is used per group for group scaffolding (i.e., scaffolding cost is required for one scaffolding object) and one scaffolding object per group member (i.e., scaffolding cost is equal to the sum of all generated scaffolding objects) is used for individual scaffolding. Fig. 9(a) shows that the students in all groups are able to improve their expertise more from the group scaffolding than from the group scaffolding. This is expected, since: 1) individual scaffolding addresses individual students’ needs and 2) according to our design of scaffolding [see (11)], a student’s expertise is improved most when the scaffolding is targeted toward his or her expertise level.

Fig. 9(b) shows that for all three types of groups, the group scaffolding yielded more expertise gain per unit cost than the individual scaffolding. The cost of scaffolding denotes the time and effort required for providing scaffolding to the students. Providing individual scaffolding requires more cost, since each individual student has to be modeled and different types of scaffolding have to be provided to the students according to their expertise level. On the other hand, group scaffolding requires less cost, since the scaffolding action is more generic and only one type of scaffolding is provided to the entire group. But unexpectedly, the group scaffolding is shown to be more economical in terms of expertise improvement per unit cost. Upon closer analysis, this can be explained by the cyclic and convergent nature of the collaborative knowledge building process (Observation 11). Due to this cyclic nature, collaborative knowledge is transferred among the group members due to their interactions throughout the collaborative session. Furthermore, our nonadaptive scaffolding process periodically provides scaffolding to a fixed number of student groups by first sorting them according to their performances. However, near the end of the collaborative cycle, due to the heterogeneous nature of groups, there are some students, who have already reached near-maximum expertise level. So, scaffolding for such group members is no longer effective. Thus, individual and group scaffolding do not yield any expertise improvement for these high-expertise group members. But, for these high-expertise group members, the individual scaffolding incurs a much higher cost than would the group scaffolding. As a result, the improvement of expertise per unit cost for individual scaffolding is smaller than the group scaffolding is shown to be more economical for group members.

E. Validity and Correlation With CSCL Results

Here, we validate SimCoL’s design by comparing its simulation results with published collaborative learning patterns.

Variance in Learning Rate: As reported in [5], high-ability students have higher learning rates than low-ability students because they are able to grasp, process, and internalize information received during the collaboration process. When we compared the learning rates of high/low-ability learners in SimCoL, we found that the high-ability students learn at a faster rate than the low-ability students (0.1 versus 0.3).

Convergence of Learning Rates: CSCL researchers [18] described the collaborative knowledge building as a cyclic process that converges to a final value. Researchers [5], [11] also described that the rate at which the students gain expertise is faster in the beginning, and then, slows down over time. The total expertise gain curve shown in Fig. 10 has two properties: 1) the total expertise gain of the students converges to a final value and 2) the rate of change of the curves is higher in the beginning and slows down at the end. Furthermore, the same convergence pattern is observed when the simulation run is repeated with Hete-A group formation method. So, the knowledge gain of the students in SimCoL follows patterns described by other CSCL researchers [28], [29].

Correlation With Observed CSCL Results: Here, we try to compare our simulation results with CSCL results published in [22]. For this comparison, we have first mimicked a simulated environment as the CSCL classroom [22] by setting the parameters of SimCoL equal to the parameters of the CSCL.
Table VIII

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Correlation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Student Expertise</td>
<td>0.83</td>
</tr>
<tr>
<td>Student Social Relationship</td>
<td>0.97</td>
</tr>
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</table>

Table IX

<table>
<thead>
<tr>
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<th></th>
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</thead>
<tbody>
<tr>
<td>Learning due to Collaborative Interactions</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Student Knowledge</td>
<td>✓</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Student Ability</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Student Motivation</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Student Emotion</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Student Social Relationship</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Group Composition</td>
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<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Group Formation Algorithm</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Agent-Based Scaffolding</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
</tbody>
</table>

* ✓ Considered, — Not considered.

The overall simulation results of the SimCoL environment are consistent with previously reported collaborative learning patterns. Furthermore, our results hint that the SimCoL environment may allow the researchers to gain better insights into the impact of: 1) individual student attributes; 2) various agent-based and nonagent-based group formation algorithms; 3) different types of scaffolding processes on the collaborative learning outcome of students; and 4) CSCL and collaborative learning on real classrooms in particular, and any human–computer environments, where online collaborative activities take place among users with diverse behaviors.

Our future work involves running a what–for simulation scenario that would allow us to gain valuable insights into the environment dynamics (e.g., which of the student attributes was the dominant factor in determining the CSCL outcome) of that CSCL setting. In future, we also plan to further investigate how the time, cost, and effort invested by the students toward their group’s impact the motivation, social relationship, and expertise gain by comparing the CSCL experiment data with SimCoL’s simulation results.

Acknowledgment

The authors would like to thank Dr. D. W. Brooks for his guidance regarding our use of Unified Learning Model in developing SimCoL.

References


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