Intelligence Augmentation for Collaborative Learning

Jeremy Roschelle[0000-0003-2219-0506]

[1] Digital Promise, San Mateo CA 94403, USA
jroschelle@digitalpromise.org

Abstract. Today's classrooms can be remarkably different from those of yesteryear. In place of individual students responding to the teacher from neat rows of desks, today's innovative schools have students working in groups on projects, with a teacher circulating among groups. AI applications in learning have been slow to catch up; most available technologies are described as personalizing or adapting instruction to needs of individual learners. Meanwhile, an established science of Computer Supported Collaborative Learning has come to prominence, with clear implications for how collaborative learning can be supported. In this contribution, I consider how intelligence augmentation could evolve to support collaborative learning. A focus on AI role in automating, adding to awareness, assisting and augmenting is suggested, extending the field's prior tendency to focus on assessing, assigning and adapting.

Keywords: Intelligence Augmentation, Collaborative Learning, Learning Sciences.

1 Introduction

Artificial Intelligence (AI) has been applied to education for 50 years. A classic early AI & education paper proposed extending computer-aided instruction systems with question-answering capabilities based on a representation of knowledge [1]. In the subsequent decades, intelligent tutoring systems (ITS) emerged as a dominant paradigm [2], in which AI was used to infer differences between the knowledge state of a student and the knowledge state of an expert, and to adjust instruction to address these differences [3]. This paradigm contemplated one student interacting with one computer. A continuation of the ITS paradigm was reflected in the most common metaphor used AI-inspired educational technology in the past decade: personalized learning [4]. By personalized, innovators most often mean an automated decision-making process that changes each student's students individual experience on their own device to better suit their learning needs. Learning engineers can continue to develop this "personalized learning" approach as they develop intelligence augmentation for learning—yet to address current educational goals it may be necessary to go beyond this metaphor toward a collaborative, social learning mindset.

1.1 Changes in Educational Goals

Over the last 50 years, the goals of education have changed. Because machines can increasingly automate routine work, it has become more important to help humans to master skills for situations that are non-routine, team-oriented, complex and all of the above. Across all sectors, including higher education, the military, and K-12 education, 21st century skills have become important and infused our understanding of subject matter [50].

For a detailed example, consider the topic of K-12 mathematics. In the United States, the National Assessment of Educational Progress (NAEP) has been used since the 1970s to measure the trend in American student's understanding of mathematics at grades 4, 8, and 12. Over the course of 50 years, NAEP has diverged into two subtests. So that we can compare scores from 1970 to those today, NAEP maintains a subtest specifically to measure the long term trend. This test focuses on knowledge of basic facts, paper and pencil computations, basic measurement formulas, and applying mathematics to everyday life situations (e.g. using money). In the 1970s, a typical mathematics classroom focused on individual students who were learning to use standard procedures to do mathematics quickly and accurately.

The main portion of NAEP today uses a framework has multiple additional dimensions (following changes in the mathematics curriculum standards that have been adopted by states in the US, based on similar international standards). *Conceptual understanding* of mathematics is understood to be a goal that is equally important to procedural problem solving [6]. Students are expected to show understanding by using tools beyond paper-and-pencil, including not only calculators but interactive geometric figures and graphs. Mathematical reasoning is important, and students are expected to make sound arguments, to identify counter-examples to false conjectures, and to use logic. Likewise, there is concern with investigating whether students can make and use mathematical models of real world situations—a much more sophisticated demand than using math in simple real-world situations with money.

Correspondingly, today's best mathematics classrooms look different than they did 50 years ago. Students are expected to work in groups to solve more challenging problems (for example, building a statistical mathematical model to make a recommendation to a soccer coach as to which players should be among the five to take end-of-game penalty kicks). They are expected to discuss and argue over concepts. They will likely make drawings, use mathematical tools (perhaps a spreadsheet or a simulation), and present their work in a broader classroom discussion. Some work is still individual (as procedural fluency in mathematics does require practicing skills), but work also occurs in groups and moves into modes where the teacher leads a discussion with student participation. A teacher, for example, may lead a discussion that compares and contrasts the mathematical strategies that different groups employed for modeling penalty-kick data, and how the different models might help or not help the soccer coach make a decision.

1.2 Intelligence augmentation must evolve to fit educational goals

Not surprisingly, early ITS systems likewise on supporting students to do standard procedures quickly and accurately. For example, *model-tracing*, an important approach, followed a student's steps in comparison to what an expert would do, and intervened as soon as the student deviated from an expert approach [3]. AI for learning today has evolved to include many other techniques to helping individual students, often under the banner of "personalization." However, many of these techniques reference a vision of educational goals that better fits 1970s goals than the goals for today. For example, giving each student their own "playlist" of mathematical problems based on the speed and accuracy of their work in the prior playlist makes sense for the goal of learning to do mathematical procedures quickly and accurately. Having students work alone on their own personal problem set does NOT make sense when the goal is to learn to work with team-mates to build a mathematical model that solves a complex challenge. Working alone at your own pace does not make sense when the goal is to learn how to make a mathematical argument or how to explain mathematical concepts to another person.

1.3 Intelligence Augmentation and CSCL fits today's goals

As previously discussed, ITS systems beginning in the 1970s addressed 1970s educational goals. They also used 1970s information processing psychology as their theoretical framework. To address today's goals, we need a different theoretical framework. Computer-Supported Collaborative Learning (CSCL) is a body of theory, recently summarized in an international handbook [7], that is appropriate to today's educational goals and can provide a basis for conceptualizing what Intelligent Augmentation [8] for learning can look like today. CSCL fits for three reasons.

First, it contemplates students working together on more complex intellectual challenges (which may be in any academic subject, not just mathematics). It portrays students as being involved together in knowledge building [9], which can apply to the situation of building a mathematical model together, or figuring out a scientific theory, or finding a coherent framework that explains the progression in a series of historical events.

Second, it imagines a classroom where students are engaged in explaining, discussing and arguing with each other. CSCL reflects a "social turn" in learning theory [10], which sees learning not just as something that individuals do on their own, but also a human act that is profoundly social and linguistic. This image reflects what high quality instruction is expected to look like today: teachers are expected to get their students actively and socially engaged.

Third, it envisions a progression of classroom experiences that interweave individual, small group, and full-classroom modalities. The work of making a coherent progression among these modalities is termed "classroom orchestration" [11] – an imperfect analogy where the teacher leads the classroom of students just as a conductor leads an orchestra of musicians.

All three of these characteristics are hard for teachers to achieve. It is difficult to organize and support “productive struggle” among students as they try to solve complex problems. It is difficult to facilitate useful discussions among students and to shape that towards an approximation of “mathematical reasoning” or “scientific argumentation.” And it is difficult to orchestrate classrooms so that the different experiences—individual, small group, and full group—connect in meaningful and useful ways.

1.3 The Pandemic Highlighted Gaps

When teaching suddenly shifts online, as during the recent pandemic, achieving high quality collaborative learning becomes even more difficult. Although many schools and teachers have shifted to video-conference-based classrooms, interaction patterns have tended to emphasize one teacher talking to multiple students. Even though tools to support online collaboration are available and well-used in the workplace, it is difficult to find examples of schools and teachers who have shifted to been able to maintain classrooms that fulfil today’s educational goals, for example, where students work together on more complex challenges, that feature participatory discourse among students, that leverage small group work, and smoothly shift among individual, small group and community-level activities.

1.4 A New Vision for Intelligence Augmentation can build on CSCL

The difficulties that teachers and students experience in achieving today’s educational goals or in participating in what today’s instruction is expected to look like — along with the body of research on theory and design for CSCL — provide a way to specify a vision for Intelligence Automation that can meet today’s needs. The remainder of the paper elaborates how this could occur.

2 Framing computer support for collaborative learning

2.1 About CSCL

CSCL [7] is a subfield of the learning sciences that has a history dating back to the late 1980s. Broadly, the field launches from a recognition that (a) collaborative learning both increases how much students learn (b) learning to collaborate and collaborating to learn are both important (b) yet, most students require support to learn how to collaborate and to engage in effective collaborative learning. An early definition describes collaborative learning as “coordinated, synchronous activity that is the result of a continued attempt to construct and maintain a shared conception of a problem” [12]. To coordinate student activity, the field has developed a robust theory of “scripts” [13] which are supports that organize for student roles, responsibilities and shape the dynamics of collaborative learning. CSCL has led to understanding of how computer-based visualizations and representations can support constructing and maintaining a shared understanding through tools like shared concept maps [14]. More recently, CSCL has documented the supports that students need as they learn to self-regulate their own behavior and their group's work in collaborative learning [15].

Overall, a strong empirical track record documenting the effectiveness of collaboration learning when the work is adequately structure and students are supported. In 2015, the well-known OECD international assessment, PISA, gave students tests of both their ability to collaborate and their skills in academic subjects. The results show a strong correlation between collaboration and learning in science, mathematics, and other subjects [16]. Empirical research has been summarized by meta-analysis (combining the weighted the results of many independent studies), and has found impressive impact of CSCL on science learning [17]. Today's teachers are also broadly supportive of collaborative learning; for example, when asked how they cognitively engage their students, the top strategies of teachers worldwide focused on giving open-ended challenges to students in small groups [18].

2.2 How CSCL frames opportunities for intelligence augmentation

Kirschner and Erkens [19] provide a useful 3x3 framework for describing the role of tools in collaborative learning. They first discuss three aspects of learning, *cognitive*, *social,* and *motivational*. Tools that support the cognitive aspect would help students with reasoning and with building their knowledge. Tools for the social aspect help students work together. Tools for the motivational aspect help to maintain student interest and engagement during collaborative learning.

A second dimension reflects the grouping of students, which may be at the *community* (or classroom) level, the *small group/team* level, or the *individual* level. A classic research-based community tool in CSCL is called "Knowledge Forum" and is a shared discussion board that has specific supports for a classroom not only to map its collective knowledge about a focal question but also to build on each other's thoughts, to work through disagreements, and to pose collective questions for further investigation.

A third dimension discusses types of pedagogical supports. *Discourse-oriented* tools may facilitate better learning in student discussions, for example, by providing prompts, organizing students into roles, and the like. *Representational* tools help students to visualize and operate on the shared state of knowledge within their group. *Process tools* can facilitate collaborations working through team work phases, such as going from a brainstorm to more focused project work.

3 Scenarios for Intelligence Augmentation for Collaborative Learning

Building on the above discussion, we now envision directions for intelligence augmentation that would specifically respond to collaborative learning goals and situations. Although thinking through each of the nine cells in the aforementioned 3x3 matrix would be productive, it would also exceed the scope available here. Instead we use the matrix to develop a few contrasting opportunities.

3.1 Actionable Awareness of Discussion Patterns

This scenario is community-level, discourse-oriented, and social.

Advances in natural language and vision processing are making it possible to automatically detect patterns in group discussions. For example, the commercially available tool called "TeachFx" provides teachers with colorful visualizations of the pattern of talk in their classrooms, based on a recording the teacher makes using an app on their smartphone. An early feature summarized how much time the teacher or students spends talking during class periods; teachers were often surprised with just how little time was devoted to student talk. Of course, an enabling condition for collaborative learning is giving students time to talk, and TeachFx has documented that teachers can improve on this metric by paying attention to simple reports.

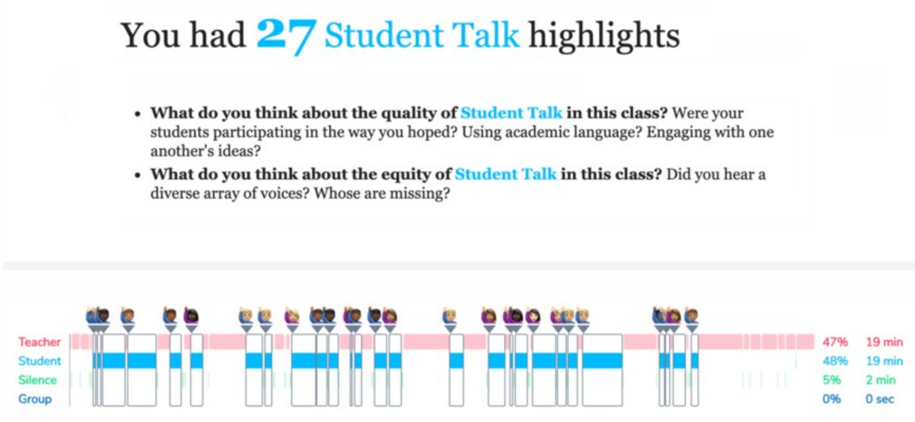

Fig. 1. Assisting a teacher by finding student talk highlights.

Intelligence augmentation can go beyond documenting overall talk-time. For example, TeachFx already automatically suggests classroom highlights. A highlight is a span of classroom talk that featured high-levels of student engagement and interaction. A teacher can quickly listen to the recording of that span of activity or review a rough transcript of what was said. This automation can greatly reduce the time it would take a teacher to review a recording of the classroom and can enable the teacher to make plans to build on successful discussions in future lesson plans.

In related research, investigators have already demonstrated the ability to detect other kinds of interactional patterns among students, for example, relating to eye-gaze, body posture, and particular features of speaking patterns [20]. One can imagine additional forms of assistance that build on this data. For example, classroom teachers seek for inclusive and equitable classroom participation; intelligence automation could help with monitoring who is participating and who has been silent, suggesting opportunities to draw students into the fray. An assistant might also help a teacher recognize which kinds of questions or activities most often lead to effective social engagement, and might suggest opportunities to use those moves in an upcoming lesson.

3.2 Maintaining student effort across a sequence of activities

This scenario is process-oriented, motivational and spans different team sizes.

In a well-established routine for peer learning, students first respond to a few challenging questions individually (for example, in a lecture that uses “clickers” to capture student responses). Then each student meets with a peer who gave a different response than their own, with the instruction to work towards agreement. This routine uses cognitive dissonance to motivate student discussion of their varied points of view.

One can imagine extrapolating from this scenario to additional forms of augmentation for classroom orchestration, in particular, for enabling the shift from one grouping size of work (individual, group, community) to another while maintaining continuity and motivation. For example, in shifting from group work to a broader discussion, an intelligent assistant might suggest an order of presentation for groups based on the work they did. Hearing about several groups that did roughly the same thing would be less interesting and evocative than discussing contrasting approaches. A full group might brainstorm conjectures that they would like to explore and an intelligent assistant might help with assigning students to conjecture teams while maintaining desired characteristics of the groups (for example, that each group should have a team lead who is good at getting the group engaged).

Motivation may also go astray in a small group for any number of reasons of personal dynamics and yet, unless a teacher is in a group, it can be quite difficult for them to know which groups are struggling. Intelligence augmentation, therefore, can add to the teacher’s awareness—for example, alerting the teacher to groups that may need attention and possible reasons to check.

3.2 Developing skill in a collaborative learning role

This scenario is individual, cognitive, and representational.

Although this may seem paradoxical, supports at the individual level may also be useful for supporting collaborative learning. In one implemented example, students are charged to give feedback to a peer about an essay. A technological support system for the feedback-giver results in better feedback and better learning [21]. One kind of cognitive support can be a tool for analyzing and representing the argument that an essay-writer is making. An appropriate tool could help students to diagram the argument and to better see addressable flaws; this kind of tool could potentially benefit from an AI assistant. Tools to support individuals as they participate in collaborations may also address neurodiversity. Some students may benefit from supports for executive function as they collaborate, for example, helping them attend to important details, strengthening short term memory, or scaffolding a multistep process. An automated system of supports could build on well-known Universal Design for Learning principles, such as providing information relevant to the collaboration in alternative representational modalities (e.g. automatic captioning or transcription of a video stream that students are watching together). Online agents can also help a child with autism to develop social skills [22].

Peer agents can also help in preparing students for a later social learning event. For example, an agent could coach a student on how to effectively communicate their question or idea in a forthcoming group or classroom discussion. A student who may be uncomfortable verbalizing their idea could be supported by a role play – or by a tool that helps them to build a graphic or other form of communication to share their idea. Another aspect of the challenge, especially for younger learners, is maintaining an awareness of alternative ideas that others in the team may have. A representational tool could help an individual team member remember that other students have ideas which are different from their own. Overall, learning to collaborate and collaborating to learn are intertwined competencies that develop over years. Tools for individuals can support the growth of these competencies.

4 Discussion: Commonalities that Deserve Attention

Looking reflectively across the scenarios suggests commonalities.

4.1 Automate, Add Awareness, Assist and Augment

Although there has been some interaction between the field of CSCL and Artificial Intelligence, this intersection is still emerging.

In the personalized learning era, three very common verbs for the role of an intelligent agent were assessing, assigning, and adapting. Agents might assess or track what students are learning and where they need support. On this basis, they might assign new playlists of work to students (or assign specific modules to the student for their further study). Further, the agents might adapt to students' needs by providing each student with the hints, supports, or guidance they most need.

As we shift from an individualized focus to a collaborative learning focus, these verbs are not likely to suffice. Based on reviewing the scenarios, we suggest three additional verbs:

1. *Automate.* Because collaborative learning is complex, teachers and students may need help that automates more routine aspects of the work, so that they can focus their cognitive effort on building shared knowledge. For example, a computer could can efficiently score last night's individual homework, allowing a teacher and students to quickly determine which problems were difficult for students and thus deserving of further group discussion.
2. *Add awareness.* As collaborative learning situations have lots going on for participants, including both relationships and tasks, intelligence augmentation can help by adding support for awareness of key features that might otherwise go unnoticed (for example, who has not been speaking).

3. *Assist.* In a collaborative learning situation, intelligence augmentation is likely to take the form of a helpful assistant who is present during a group work. Perhaps in a lull in conversation, the assistant might suggest an activity or topic to get students' back on track. Or it might draw students to a discrepancy worthy of their shared attention.
4. *Augment.* The phrase "augmentation" in collaborative learning and teamwork has a long history dating back to Englebart's seminal work [11]. As a verb, augmentation recognizes that high-quality teamwork is not easy for students to accomplish, and thus agents might help a group accomplish more than they otherwise would. For example, augmentation could note key concepts as students discuss them verbally and suggest the concepts as nodes which need to be organized on a concept map. Or it might clean up a partial concept map to make it easier for students to work with it together.

4.2 Context-sensitive, Longitudinal and Hybrid

Looking across the scenarios, one can also observe three general challenges for the field of Intelligence Augmentation which a focus on a collaborative learning could address.

1. *Context-sensitive*. As the 3x3 matrix should make clear, collaborative learning activities occur in a rich context. Collaborations have a past, present, and future. They should reference not only the team's trajectory, but also how it connects to individual- and community-level learning activities. Learning has motivational, social, and cognitive aspects. In general, designing intelligence augmentation to be appropriately aware of context is an important challenge for AI.
2. *Longitudinal.* Supporting collaborative learning is not just about figuring out what a team of students need know right now. It is also about supporting long-term development of the ability to be a good collaborator and a good collaborative learner. For example, students should be learning how to self-regulate their emotions, cognition and participation in challenging collaborative learning situations. How intelligence augmentation could facilitate longer term development of individual and groups is an open question.
3. *Hybrid.* Collaborative learning also shifts our focus from the one-student-one-computer scenario of early ITS systems to teamwork in agency includes multiple students and multiple intelligent agents. One can readily imagine an agent serving as a "participation coach" (in reference to the first scenario) alongside an agent that may support a teacher in orchestrating a motivating sequence of activities alongside an agent that helps an individual student with their role in the collaboration Working towards a hybrid future of work with multiple forms of agency, both human and computational, is another long-term vector of growth for the field.

4.3 Responsible, Human-Centered AI

To realize a positive future of learning based on these ideas will require much attention to issues of ethics, equity, safety, privacy and related concerns. To stay within page limits, this paper deferred the thorough discussion these issues deserve.

5 Conclusion

Collaborative learning is a match to today's educational goals. These goals go beyond fast and accurate reproduction of basic and routine procedures. Driven by what is needed by future societies, educational goals more often feature teamwork, tackling complex problems, and developing the ability to work together effectively.

Further, a body of prior designs and theories can inform how innovators explore intelligence augmentation for collaborative learning. In particular, the field of CSCL has summarized its knowledge in a recent handbook of research-based knowledge. A 3x3 framework that illuminates the range of possible objectives for learning engineering. Designs may aim to address cognitive, social, or motivational aspects; they may target individual, group, or community level processes; they may offer discourse, representational, or process supports. Reflecting on potential scenarios for intelligence augmentation suggests that the field must also push for capabilities that are context-sensitive, support long-term development and that support hybrid teams of multiple human and computational agents.

As we consider both the shortfalls in learning during the pandemic and how learning may look as we move into the future, innovators and engineers who develop learning technology could create powerful new intelligence augmentations by tackling the needs of teachers and students in support of collaborative learning.

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