Artificial Intelligence and Ambitious Learning Practices

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Abstract: This symposium will provide opportunities for discussion about how Artificial Intelligence can support ambitious learning practices in CSCL. To the extent that CSCL can be a lever for educational equitable educational change, AI needs to be able to support the kinds of practices that afford agency to students and teachers. However, AI also brings to the fore the need to consider equity and ethics. This interactive session will provide opportunities to discuss these issues in the context of the examples presented here.

Introduction

Artificial Intelligence (AI) offers opportunities for supporting computer-supported collaborative learning and the kinds of ambitious learning practices associated with CSCL. We have recently argued that CSCL could be a lever for educational equity through the use of ambitious learning practices (Uttamchandani, et al., 2020). By ambitious learning practices we mean pedagogies that encourage collaboration, dialogue, inquiry, and productive disciplinary engagement (Engle & Conant 2002; Glazewski & Hmelo-Silver, 2019). We call these learning practices because they require much responsibility and agency from learners. For example, problem-based learning, knowledge building, and other forms of collaborative inquiry, often involve disciplinary practices such as explanation and modelling. These approaches abound in CSCL (Jeong et al., 2019; Hmelo-Silver & Jeong, 2022) but are resource-intensive both in terms of technology and the demands on teachers and learners. Recently, Gomez et al. (2021) have argued for the importance of considering scale to really consider diversity, equity, and inclusion in CSCL. AI offers that potential for scaling ambitious learning practices for diverse learners. In particular, the incorporation of AI into CSCL provides new opportunities. These opportunities include analyzing and providing adaptive support for collaboration, providing feedback for students engaged in complex tasks, and reducing the cognitive load for teachers as they orchestrate student learning as well as future capabilities that we are only beginning to imagine (Roschelle et al., 2021). Thus, we would like to extend this argument to the potential for AI to advance these opportunities while trying to avoid the dystopian futures that Rummel, Walker, and Aleven (2016) characterized in their depiction of students in a highly productive, yet highly mediated and prescribed, learning environment.

An important piece of the potential of AI includes attending to diversity, equity, and inclusion as well as the ethical challenges that might be posed in ways that foster meaning making and agency. Ultimately, the benefits of any innovation should be felt and experienced by everyone, which requires our design and implementation approaches to expressly leverage affordances for a diverse range of learners. Unlike dystopian visions of AI, the papers in this session have created learning environments that support agency for both students and teachers. In creating these environments, the authors have considered, at least implicitly, how power is negotiated across learners, teachers, and AI-augmented resources. These environments are designed to foster rich interactions that empower learners to engage in ambitious learning practices and concomitantly, empowering teachers with tools

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to manage the required but complex classroom orchestration (Dillenbourg et al., 2018; van Leeuwen et al., 2019). These are the tools that can enable scaling of ambitious CSCL environments but with the caution that our designs must reflect attention to equity and ethics (Roschelle et al., 2021).

This symposium will be organized with time for brief large group presentations that introduce each of the papers and smaller group discussions. Together, the papers document design, development, and empirical research efforts. Indeed in the past year, much research has been design-focused because of the COVID-19 pandemic.

Each presenter will have 5 minutes to share the major points of their paper and also address the following questions:

1) How did AI support developing learning environments that support ambitious learning practices?
2) What did AI uniquely afford?
3) How does your learning environment deal with issues of diversity, equity, and inclusion?
4) What are the ethical challenges that you have faced?

Small groups will then have 12 minutes to discuss the papers and create a slide to summarize their discussion. The discussant, Marcelo Worsley, will then comment on the themes of the session and open up for a whole group discussion, with a goal of foregrounding challenges related to issues of diversity, equity, inclusion and ethics.

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Ethical Consideration for Designing AI to Support Dynamic Learning Transitions

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Since individual and collaborative learning have different strengths, one way to leverage the benefits of both is by allowing students to dynamically switch between the two modes based on their needs at the moment. Managing dynamic transitions as students simultaneously work on different tasks is an ambitious learning practice because it entails high orchestration load for teachers and careful personalization of learning transitions (Uttamchandani et al., 2021). To support teachers, we investigated how AI and students can have a voice in deciding when these transitions occur and how (Echeverria et al., 2020). However, designing orchestration tools with shared participation requires explicit reflection on the equitable and ethical considerations regarding how these parties' agency, bias, and privacy are accounted for in the tool (Holmes et al., 2021). The contributions of our paper include findings regarding how *teachers* want to share control with students and the AI during dynamic transitions. We share challenges to consider when leveraging AI in ambitious learning practices including *navigating tensions of agency*, *considering privacy and transparency*, and *reflecting on biases*.

The orchestration tool we developed and discussed in this paper helps teachers identify students who may benefit from collaborative learning, pair and unpair students, and monitor their progress. The tool is positioned in the context of two AI-based tutoring systems, *Lynette*, an individual problem-solving tutoring system, and *APTA*, a collaborative tutoring system that supports mutual peer tutoring (Walker et al., 2014). We collected data from 12 middle school math teachers participating in three design phases, including constructing low-fidelity prototypes, feedback sessions, and user testing. We collected video data, observation notes, and artifacts from activities and used thematic analysis to explore what teachers needed while orchestrating dynamic transitions regarding shared control and the use of AI.

A major theme was the need to include shared control between the AI and the teachers, rather than shared control across all parties (e.g., teacher, students, and AI). Teachers rarely trusted the AI to make the decisions alone, and while some teachers thought it was good to let the students ask to be paired with someone, many found it too much to manage. They described needing the power to determine transitions between individual and collaborative learning, not students or the AI. Teachers' agency was important in facilitating learning transitions because they could use social and contextual factors from students combined with data presented in the tool. Teachers shared that data presented in the tool should be objective data, including progress, hints, and errors. They described that sensitive information including classroom dynamics and social relationships should not be embedded in the algorithm because this data is continuously changing and poses privacy issues for students. Many

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teachers felt that sharing objective data with the system was equivalent to sharing an assignment or test; therefore, was not a privacy concern. Finally, several teachers reflected on the potential for AI to hold themselves accountable. For instance, one teacher described that the orchestration tool could help create new collaborative pairs that have not worked together before by helping him reflect on his biases (e.g., not pairing students together whom he assumed would not work well).

Throughout our design process, and in preparation for initial pilot studies, we highlight three challenges that we grapple with around equity and ethics when using AI to support ambitious learning practices.

Navigating tensions of agency and user boundaries. Our project has explored how students' voices can be embedded in dynamic learning transitions (Echeverria et al., 2020), yet we found in our design process that many teachers were somewhat apprehensive about sharing control. Ignoring these concerns could cause teachers to not use our technology because it breaks their boundaries for how they run their classroom, yet not including students' voices compromises students' agency in advocating for their own learning. This tension between stakeholders is important to consider how we make decisions and whose voices we include. Our future work will explore design features that give students agency in dynamic transitions, while navigating the boundaries of teachers about holding power in the classroom.

Privacy and transparency of data. Many teachers described that sharing data about students' learning process (e.g., hints, errors) in the orchestration tool was synonymous with data they collect in their classrooms (e.g., tests, assignments), but more subjective data like classroom dynamics overstepped students' privacy. There are many issues of privacy and consent in AI education systems, wherein students should have the ability to consent, or at least have transparency, about what data is being collected and how it is used (Holmes et al., 2021). While algorithms have the potential to support ambitious learning practices, designers need to be sensitive to what data is collected and whose perspectives are prioritized regarding privacy. In the present work, we report on the needs of teachers, however, our past (Echeverria et al., 2020) and future work will continue leveraging students' voices, recognizing that even if teachers do not see privacy concerns, does not mean students feel the same about the use of their data.

Reflecting on bias. Teachers in our study had the impression that the AI was an unbiased party and could help them make more objective transitions. While we hypothesize shared control between parties has the potential to mitigate issues of bias by embedding accountability across humans and AI, it also runs the risk of exacerbating existing inequities. Our tool leverages both strengths and struggles of students to inform dynamic transitions, but we recognize the need to help teachers interpret this data and be explicit about how the AI's suggestions can be biased and could be used to harm and police children (Holmes et al., 2021). To do so, we need to evaluate our algorithms to identify and address any biases that may emerge and embed accountability and transparency across all parties.

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AI-Empowered STEM Learning in Open-Ended Environments
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Our research group focuses on developing Open-Ended Learning Environments (OELEs) in STEM domains that adopt a constructivist epistemology to support the acquisition of domain knowledge along with critical thinking and problem-solving skills (Biswas, et al., 2016). Students working in these environments have a specified learning goal, e.g., construct a model of a scientific process. To facilitate ambitious learning and problem solving (Uttamchandani, et al., 2020), we have adopted AI and Machine Learning methods that provide students with tools and resources that support hypothesis generation, solution construction, and hypothesis verification and refinement in different phases of learning. Betty's Brain (Biswas, et al, 2016), C2STEM (Hutchins, et al, 2020a), and SPICE (Zhang, et al, 2019) are examples of OELEs developed by our group.

In all of our systems, we adopt AI-driven modeling representations (e.g., causal maps, block-structured programming languages) that are intuitive, visual, and executable. The ability to execute their evolving models helps students develop important reasoning, explanation, and debugging strategies (Biswas, et al, 2016; Zhang, et al, 2021). In recent work, we have exemplified the importance of AI representations in developing Domain specific modeling languages (DSMLs) to scaffold students' computational modeling of scientific phenomena (Hutchins, et al., 2020b). DSMLs play an important role in students' synergistic learning of the STEM domain and computational thinking concepts and practices (Zhang, et al., 2021).

However, OELEs can pose significant challenges, especially to novice learners who lack prior knowledge in the domain. In past studies, we have observed that students have difficulties in keeping track of the tools provided in the learning environment, and combining the use of these tools in an effective manner to accomplish their goals. These problems are further exacerbated because students' self-judgment and strategic thinking abilities may not be well developed, and they may underestimate the effort required to accomplish their tasks.

To help students understand and overcome these challenges and make progress in their learning tasks, we have developed adaptive scaffolding mechanisms in our OELEs that can monitor and interpret student difficulties, and provide adequate support to help them overcome these difficulties. To reliably interpret and respond to individual student difficulties, we have adapted model-driven learning analytics and data-driven sequence mining methods in machine learning to understand students' difficulties. With this understanding, we have also developed response mechanisms that are contextualized to match students' current task activities and be compatible with their current level of proficiency (Kinnebrew, et al., 2017). Results of studies we have run in middle school classrooms have shown that our adaptive scaffolding mechanisms led to improved student learning and use of more effective learning strategies (Basu et al, 2017, Hutchins, et al., 2021).

More recently, we have extended our approaches to provide adaptive scaffolding in collaborative learning-by-modeling environments (Snyder, et al, 2019). The focus of our scaffolds has been to help students solve problems by decomposition, and to help them develop debugging strategies to find and correct errors in their computational models. This has led to important challenges in attributing students' difficulties to their lack of knowledge of the science content, or their inability to translate their science knowledge into the correct computational forms. We have used discourse analysis to better characterize students' difficulties, by developing algorithms that facilitate automated interpretation of students' knowledge co-construction approaches and their social modes of interaction. We are currently developing deep learning based NLP techniques for automated online analysis of discourse, and designing virtual agents that can act as an additional collaborative companion in delivering these scaffolds. On the one hand, we believe that our adaptive scaffolding approaches using our AI/ML methods increase equity and diversity by providing support to a wide variety of learners in their learning and problem solving tasks. On the other, there are a number of open questions about how we may tailor these methods and our adaptive scaffolding mechanisms to account for cultural and socio-economic differences among learners.

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Combining Student and Teacher Feedback for Effective Science Writing

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In this paper, we will discuss how we are supporting students in grades 6-8 to write explanations in science. We conducted two participatory design studies with a total of 14 teachers to understand what feedback will be useful to their students, and how the information from students' writing should be presented to teachers. We will present data from these studies and also from our classroom studies using the automated feedback provided to students. Our approach to design includes working with teachers and students from a range of backgrounds and with differing levels of writing ability. Writing science explanations is challenging for students especially students who might struggle with writing in English. The examples from students with different backgrounds that we are using during our design process will provide us with information on the difficulties students experience in writing. Further, our dashboard will be available to support teachers working with students with special needs in classrooms. This provides a way to support teachers to be sensitive to students who need additional help, when a single teacher may not have the time to provide such individual support.

Using evidence to build scientific explanations and make claims is a central practice by which scientific knowledge is generated and learned (Berland & Hammer, 2012; Reiser, Berland, & Kenyon, 2012). However, students often do not understand what a scientific explanation is and frequently write incomplete, non-causal accounts of scientific phenomena (Seah, 2016), often without using data (Sandoval & Millwood, 2005). Additionally, the complex, iterative, and time-consuming nature of writing explanations limits the timeliness and quality of teachers' feedback (Berland et al., 2016; Duschl & Bybee, 2014). We address these issues by providing feedback to students both during and after they write explanations in science. Additionally, a teacher dashboard

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will provide information to teachers about students' writing, which they can use during class discussions. The teacher dashboard will give insights to teachers about how well students are understanding the material they are being taught, and give teachers the ability to address incorrect conceptions as they occur in the classroom. Our design includes providing students with feedback at two stages–during writing and after completion of writing explanations. In both stages, our focus will be on supporting students to include three key aspects of writing science explanations, i.e., description of a scientific phenomenon, (2) providing explanation of relations including causal relations; and (3) use evidence or patterns of data to support explanations which we adapted from Braaten and Windschitl (2011).

Support during the writing process: In the first stage, our focus will be on providing prompts that cover all aspects of a scientific explanation mentioned above. Students' explanations will be examined in real time for descriptions of the phenomena, connections they are making, and for use of evidence. We will utilize simple text mining techniques to ensure key ideas are mentioned in student responses, places where explanations about key ideas could be strengthened. By examining past student responses, analyzed either by an automated system or manually, we can determine how students represent ideas in their writing, and use the best responses. This general technique can be applied to both equations and data as well, so students can be alerted when they are overusing, or more likely, underusing these components to back their claims. As our project is used in more classrooms, with more students, we will continue to collect more data to allow us to provide more accurate feedback that is tailored to individual students.

Support after students complete their explanations: To provide students with feedback on their writing, we are adapting PyrEval—a wise crowd approach to content analysis (Passonneau et al., 2018; Gao et al. 2019a&b). The PyrEval software contrasts with previous work on automated writing support through its focus on identifying complete propositions, and comparing the meanings of full propositions to recognize paraphrases of the same content. In addition to quantitative scores on importance of ideas in a student passage, it also produces a qualitative assessment that identifies which phrases used by the student correspond to more or less important ideas. The original version of PyrEval constructs a model of important propositions derived from a small set of reference passages independently written to the same prompt by expert writers—the wise crowd. It implements a manual annotation method that was originally developed to assess the content of source-based summaries, e.g., reading comprehension passages. From pre-trained, high-quality vector representations of words in a large vocabulary, it creates vector representations of propositions, essentially atomic tensed clauses. The original version assigns a higher importance weight to ideas that are expressed in more of the wise crowd passages. Through reliance on meaning vectors extracted from the wise crowd samples, the method assesses similarity of meaning (content units) in a student passage to the model content units. For use in a middle-school setting with a known curriculum, we have adapted PyrEval to use a content model that is partly derived automatically from historical essays, and partly manually curated to align well with a rubric. Its ability to provide quantitative and qualitative assessment of propositions provide a foundation to develop curriculum-specific and student-specific feedback.

We will also provide teachers with feedback on students' writing. We will combine data such as the content that was covered, how the content was presented, and relate that with the strengths and deficiencies found in students' writing.

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Human-centered Automation and Deliberately Limited Labels as Design Principles of Ambitious Learning Practices

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Ambitious learning practices are a natural way for CSCL scholars to conceptualize the relationship between technology and equity. However, these practices are fundamentally a political approach to thinking about pedagogy and require deep consideration of work that is explicitly sociopolitically and ethically informed if

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they are to achieve their aims (Uttamchandani et al., 2020). Equity-oriented studies in the learning sciences, for instance, often rely on promoting heterogeneity and utilize qualitative methodologies for understanding and measuring learning (Uttamchandani, 2018). This task alone can be challenging in the CSCL context and even more so when we factor in the role of AI in education. Because of their use of learning analytics, AI projects may rely on a "normed" student model and flag those that are deviant (Aguilar, 2018). Further, AI models tend to rely on quantifying and objectifying learning in order to function effectively. Separately from this tension is the fact that AI technologies have and continue to be used with minoritized communities in dangerous ways that make people wary of AI (for example, for privacy reasons) (e.g., Noble, 2018). In this paper, we explore how we began to navigate these tensions through two principles: (1) human-centered automation and (2) deliberately limited labels.

We explore these tensions in the process of designing an orchestration assistant (OA) to support middle school teachers and students to collaboratively investigate phenomena in complex ecosystems while engaging with a problem-based learning scenario in a game-based learning environment, CRYSTAL ISLAND: ECOJOURNEYS. Because such environments require demanding facilitation approaches, the OA leverages a teacher dashboard, and extends the dashboard in ways that aim to support teachers in more successful classroom orchestration (Dillenbourg et al., 2018; van Leeuwen et al., 2019). The OA will provide teachers with real-time information about groups' participation, progress, and nature of their scientific discussion. It will have *prospective* tools to support teachers in lesson planning before class, *concurrent* tools to support real time classroom orchestration, and *retrospective* guidance to support teachers in reflecting on how class went.

AI technologies play a significant role in the design of the orchestration assistant. Machine learning techniques are deployed to create models of how students engage with the learning environment, and are the basis for understanding what information should be presented to a teacher (for example, because student activity is somehow unusual). In addition, recommender systems can help discover teacher preferences and patterns of use regarding group prompts or individual assistance. This in turn, can support teachers with varying teacher expertise and instructional background. Computer vision techniques are deployed to process students' gaze, facial expression, and body posture to further ascertain and triangulate information about students' engagement or participation. AI techniques provide a way for teachers to monitor multiple students at the same time, and support teachers in understanding their instructional practices by learning about their preferences and facilitation strategies.

In designing an orchestration assistant to support ambitious learning practices, several design considerations at the intersection of ethics, equity and AI emerged. We consistently reminded ourselves that the orchestration assistant is a *human-in-the-loop* technology, where human decision-makers are ultimately responsible for taking consequential pedagogical actions. We were animated by a *principle of human-centered automation.* Although dramatic, we use this term to intentionally move against dominant discourses that envision the primary role of AI in the classroom as to automate things like giving feedback. While some automation is part of our design, a principle of human-centered automation allowed us to focus on what is not being automated: the decisions teachers make about what to say, to which groups of students, and when. Then, AI technology is designed to help support those decisions through giving teachers a comprehensive, yet tightly-focused and actionable amount of information about learners. The role of the AI, then, is truly to support a teacher but never to replace one, and any automated features should be about "freeing up" the teacher to make the kinds of consequential pedagogical decisions that only a teacher can given their professional vision (van Leeuwen et al., 2019), and that are necessary for successful ambitious learning practices. For example, the orchestration assistant provides the teacher with student information, but does not evaluate teachers' performance or reaction to that information. Instead, it provides teachers information about their facilitation strategies in relation to specific group profiles and requests that the teachers evaluate the effectiveness of these strategies.

We were also guided by a *principle of deliberately limited labels* to enable teachers to think and act expansively. While AI is often useful to sort and categorize students, we are cautious of how these groupings are typically labeled and how they frame and sometimes even diagnose learners. We are especially cautious about deficit framings that are routinely applied to students with disabilities, students of color, and other minoritized students. For example, while groups progress through the game at different rates, it was crucial to us that we did not label groups as "slow." Similar framings to avoid were labeling students as "bad collaborators" or "off-task." Instead, we considered the information teachers needed to know because they could contextualize that information, placing emphasis on descriptive but not diagnostic information. For example, teachers are given information about where each group is in the game, without interpretation from the AI labeling a group "behind." Rather, we focused on the extent that student participation in groups are relatively similar to one another. Then, the teacher is empowered to re-specify what is "normal" in their classroom, or even abandon this idea. This also has the advantage of helping balance between giving teachers too much raw data to be interpretable vs. over-interpreting such data.

The principles of human-centered automation and deliberately limited labels provide a path to continue thinking at the intersection of critical perspectives and AI technologies to design for ambitious learning practices.

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