The use of Artificial Intelligence (AI) in K-12 education is showing considerable promise to enhance student learning, yet existing tools continue to situate AI tutoring firmly within the context of one-on-one instruction and personalized learning. As HCI, learning science, and team science researchers we envision AI to help students become better collaborators—a highly valued skill for their lives after school. In this demonstration we present “CoBi”—a multi-party AI partner that focuses on the relationship dimension of collaboration. CoBi helps students to co-negotiate classroom agreements along four dimensions: respect, equity, community, and thinking. CoBi then uses state-of-the-art speech and language technologies to look for and visualize evidence of these agreements as they occur during small group student talk. Through these feedback visualizations, students can hone collaboration skills, collaboratively reflect about and identify areas for improvement, and develop critical AI literacy skills.
learning processes [19]—the incorporation of LLMs suggests a massive leap forward in making AI-driven tutoring more accessible and more personalized.

While the prospect of every student accessing their own personal AI tutor seems exciting, the single-user focus may also be its Achilles heel. In other words, an AI tutor focuses its attention (and collection of data) on a single user; its instruction does not extend to the development of relationship and collaboration skills, which are fast becoming highly desired for the future of work, especially in the context of teamwork [10, 11], and more so when AI supports cognitive work [23].

Indeed, a large body of research suggests a vastly growing importance of the interpersonal dimension in teamwork with people having the ability to rapidly develop coordination and communication mechanisms, trust, leadership, and cohesion. Multiple frameworks and policy recommendations have identified collaboration as a critical skill for the 21st century workforce [5, 6, 12, 14]. Interpersonal skills do not develop automatically; they require a lot of time and effort to master, but more importantly, they need to be practiced with others [15]. However, recent AI-driven tutoring tools seem to be keen on merely expanding the capabilities of one-on-one learning rather than leveraging AI for real-time support of student groups.

Beyond the more traditional ITS paradigm, so-called Reflection Support Tools (RSTs) provide a means of synthesizing large amounts of data to motivate reflection. For example, INEQDETECT [18] is a simple visual analytics system that analyzes audio from small group conversations to detect and represent conversational inequalities (e.g., relative talk time of group members against total talk time), which can then provide data for group members to reflect about the effectiveness of their collaborations. Additional examples include “Conversation Balance” [16], “Meeting Coach” [21], and “CPSCoach” [22], all designed to provide feedback to groups of people. However, one key limitation of these systems is that they either focus on overall production of talk (i.e., without analyzing content) or they have yet to be tested in classroom environments.

Another issue in regard to recently announced and/or deployed AI learning tools is the lack of transparency about their inner workings. This has been a persistent problem in AI development that is often referred to as a “black box” problem, meaning that AI models do not reveal their decision-making processes to the user [3]. This can be a significant handicap for the effectiveness of the system—especially in the context of education—as existing work in HCI has highlighted the role of trust in human/AI interaction [7, 13, 24, 25].

To address these gaps we present the Community Builder (“CoBi”), which is designed to help Middle school students in developing better collaborative relationships with each other, with their teacher, and even with the AI partner itself. CoBi is designed to focus on the relationship dimension of collaboration. It provides a space for students to co-negotiate “community agreements” or norms of behavior (explained in more detail in Section 2). CoBi then leverages machine learning algorithms to find evidence of community agreements in small group collaborative discourse, which is then represented to the class as a mix of feedback visualizations and exemplary pieces of the actual evidence to motivate collaborative reflection.

2 COBI CONCEPT AND DESIGN OVERVIEW

CoBi recognizes the importance of engaging youth proactively when building AI technology within the context of education. In fact, the idea for CoBi came from a series of workshops with diverse youth [8] where participants expressed a desire for AI to help them build strong communities in class. It centers on four community agreements that are derived from the Open Sci Ed [2] K-12 science materials aligned with national standards [4]; these are shared norms created by students and their teacher to guide their classroom collaboration where:

- Students brainstorm examples around four agreement categories: being respectful, being equitable, showing commitment to community, and moving the group’s thinking forward.
- Students develop a set of class-wide agreements through a consensus building discussion.
- Students revisit their agreements to reflect on agreements in action, celebrate successes, and engage with new ideas to uphold to support our learning.

CoBi’s contribution to this routine is a browser-based interface where students can input the co-negotiated examples of community agreements and then see aggregated visualizations of how these agreements manifest in student talk. CoBi can currently represent the following three agreement categories: being respectful, showing commitment to community, and moving the group’s thinking forward. However, our goal is to add the fourth category, being equitable, in the near future as well.

CoBi operates in four distinct phases:

1. With the help of the teacher, students work in small groups to input their examples of agreements into the CoBi interface (see Figure 1 for a list of real-world examples for each agreement category collected in a Middle school classroom);
2. As students engage in collaborative learning tasks, CoBi analyzes student discourse for evidence, or “noticings” for the three agreement categories. The results are aggregated across student groups (to protect student privacy), and then visualized at the classroom level. Teachers can see these visualizations develop in real-time to provide class-level guidance about the extent to which students are realizing their agreements. Two types of visualizations are available: a more quantitative, summative design represented as a radar chart and a more qualitative, creative, and expansive representation of noticings by way of a growing tree animation (Figure 1).
3. At the end of a collaborative learning task, teachers use CoBi to guide students to reflect on the extent to which their collaborative discourse was aligned with their co-negotiated community agreements.
4. Teachers can reveal the top-ranked noticings that CoBi identified for each agreement during the recorded session. This added level of transparency invites deeper reflection and discussion about the affordances and limitations of AI systems, thereby helping students develop critical 21st century AI literacy skills. For example, students may find that CoBi misclassified a given noticing, which can provide a meaningful
avenue for students to reflect about the error-proneness of current AI systems (which may be due to a host of reasons including poor audio quality from a very noisy classroom or missed contextual cues).

3 SYSTEM ARCHITECTURE

CoBi is developed using a scalable, modular architecture implemented to run in the Amazon Web Services (AWS) cloud. The architecture provides secure access and storage of classroom data using cloud instances, AWS lambda and fargate services, expandable containerized services, and cloud-based large file storage. CoBi’s backend architecture consists of the following components (see Figure 2): (1) Student audiovisual recorders that stream audio from table top mics (Yeti Blue) one per student group; (2) Whisper for automatic speech recognition [20]; (3) RoBERTa language models [17] trained on a data set of student conversations annotated for the community agreements; (4) User Interfaces for teachers and students; and (5) an aggregation and inference engine to populate the visualizations.

The Recorders capture audio (and video) of students in the classroom. The audio is streamed in ten second chunks, which are then analyzed via three separate pretrained RoBERTa models—one each for being respectful, being committed to community, and moving our thinking forward. Each model outputs a probability in the range [0, 1] that a student utterance during a given ten second audio snippet may be considered an example of one of the community agreements, with probabilities greater than 0.5 signaling a positive match. The results from the analysis are then securely stored in a data repository and then presented as one of the two feedback visualizations. This is done via an aggregation and inference engine, which also utilizes semantic matching so that the students’ co-negotiated agreements help to select the CoBi noticings which are displayed on its interfaces.

Beyond its direct use in the classroom, CoBi is also part of a Multimodal Intelligent Analyzer (MMIA), which is a suite of analysis modules that researchers can leverage for studying classroom interactions from various angles (see Figure 3). Alongside CoBi, modules can be Automatic Speech Recognition (ASR), Diarization, On-Topic/Off-Topic, Collaborative Problem Solving (CPS) skills, eye-gaze analysis, and person re-identification. In addition, a particular module can support multiple model versions for A/B comparison purposes. Researchers are able to integrate modules into the MMIA to process classroom data streams and evaluate output. In addition, modules are used to generate output for interactive AI Partners in real time.

4 CLASSROOM TESTING, LIMITATIONS, AND FUTURE WORK

We conducted preliminary testing with one teacher implementing it with 23 of her students. These initial tests revealed that students expressed positive sentiments about CoBi listening in on their conversations and motivating collaborative reflection; however, upon their reflection of their own results, students sought to find explanations in their own collaboration behaviors (“we need to do better next time”, etc.) rather than considering the possibility of CoBi making errors. Our team is looking forward to incorporating our findings into future versions of CoBi to make it more comprehensive and transparent.

While CoBi has already shown promise during our initial classroom testing, it still has several limitations that we need to address. First and foremost, the current version of CoBi can only analyze spoken communication. Future versions will integrate non-verbal communication (gestures, posture, eye-gaze) to account for diverse communication and collaboration styles and preferences. This should further improve the accuracy of CoBi’s mechanisms. Further, CoBi can currently monitor only three of the four agreement categories;
we are in the process of developing a computational model for the equitable category. Future versions will also include features where students can experiment with CoBi’s underlying computational models by providing hypothetical utterances, viewing CoBi’s responses, and providing suggestions.

5 CONCLUSION

Our Community Builder CoBi marks a significant step from uni-party and uni-modal to multi-party and multi-modal collection of data, which can then be used to foster rich socio-collaborative learning experiences for all students. By focusing on the social dimension of collaboration, CoBi’s feedback visualizations can help students to develop and hone critical 21st century social skills as well as AI literacy skills via teacher-led conversations about CoBi’s affordances and limitations. In so doing, CoBi presents an approach for collaborative reflection about the nature, behavior, power, and consequences of AI systems.

ACKNOWLEDGMENTS

This research was supported by the NSF National AI Institute for Student-AI Teaming (iSAT) under grant DRL 2019805. The opinions expressed are those of the authors and do not represent views of the NSF.
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