The Community Builder (CoBi): Helping Students to Develop Better Small Group Collaborative Learning Skills

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ABSTRACT

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.

CCS CONCEPTS

• **Applied computing** → **Computer-assisted instruction**; **Interactive learning environments**; **Collaborative learning**; *Sociology*; • **Computing methodologies** → **Speech recognition**; **Discourse, dialogue and pragmatics**.

KEYWORDS

collaboration, artificial intelligence, reflection support, uni-party, multi-party, unimodal, multimodal, education, K-12

ACM Reference Format:
Thomas Breideband, Jeffrey Bush, Chelsea Chandler, Michael Chang, Rachel Dickler, Peter Foltz, Ananya Ganesh, Rachel Lieber, William R. Penuel, Jason G. Reitman, John Weatherley, and Sidney D'Mello. 2023. The Community Builder (CoBi): Helping Students to Develop Better Small Group Collaborative Learning Skills. In *Computer Supported Cooperative Work and Social Computing (CSCW '23 Companion), October 14–18, 2023, Minneapolis, MN, USA.* ACM, New York, NY, USA, 5 pages. https://doi.org/10.1145/3584931.3607498

1 INTRODUCTION

Artificial Intelligence (AI) is becoming increasingly popular in the field of education [9, 26]. In fact, several educational platforms and organizations have either announced or have already deployed educational services that utilize the latest advancements in Large Language Models (LLM) and promise to revolutionize the field of instruction. For example, Khan Academy has begun to deploy "Khanmigo", a next-generation intelligent tutoring system (ITS) powered by AI that can offer one-on-one tutoring for learners of all backgrounds and skill levels as well as provide guided lesson planning for educators [1]. While ITSs are not a new phenomenon—in fact, ITSs have a long and treasured history of augmenting personal

CSCW '23 Companion, October 14–18, 2023, Minneapolis, MN, USA

ACM ISBN 979-8-4007-0129-0/23/10.
https://doi.org/10.1145/3584931.3607498

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 miscategorized a given noticing, which can provide a meaningful

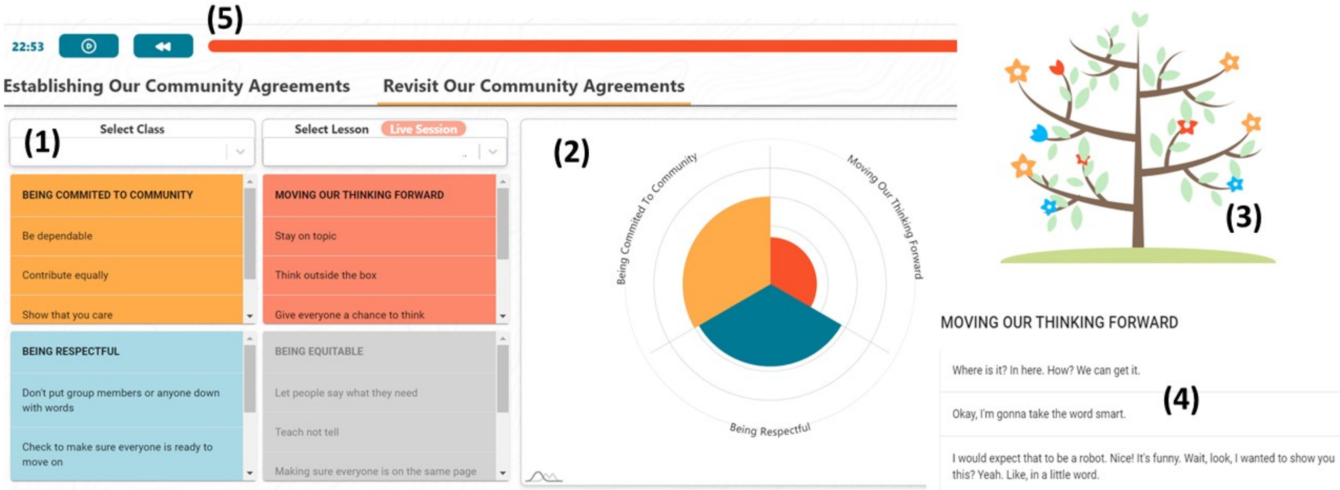

Figure 1: Left: Main elements of the CoBi interface: (1) color-coded agreement categories, (2) the radar visualization, (3) the tree version of the visualization, (4) top-ranked noticings for moving our thinking forward collected from Middle School students. The top of the page includes (5) playback buttons and a time slider that the teacher can use to show students the state of the visualization at different points in time. Note: the "being equitable" category is grayed out in this version as it is not yet included in the analysis.

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;

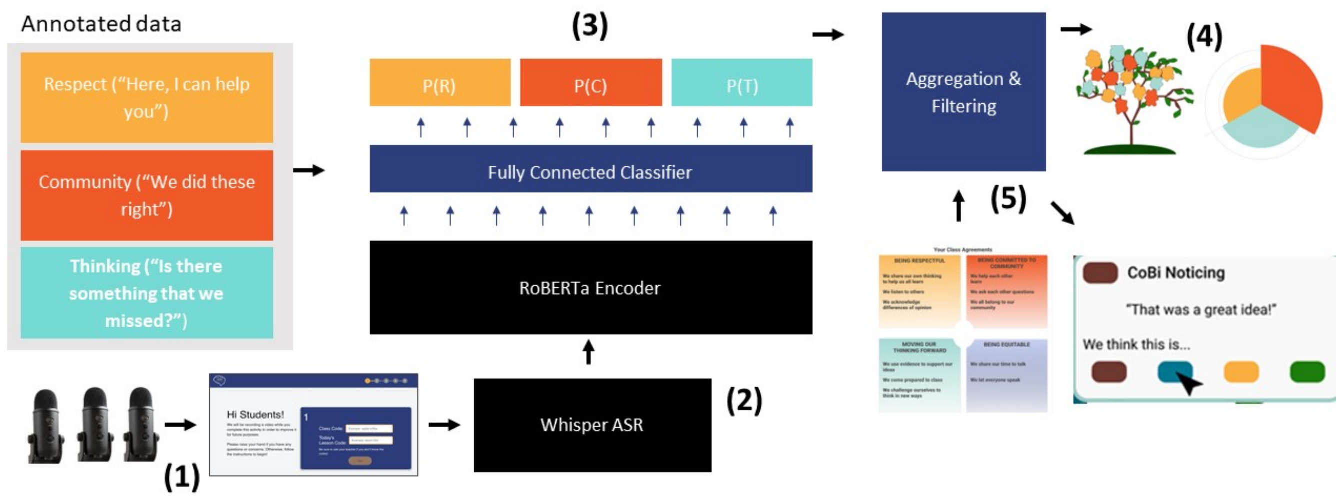

Figure 2: CoBi's technical architecture.

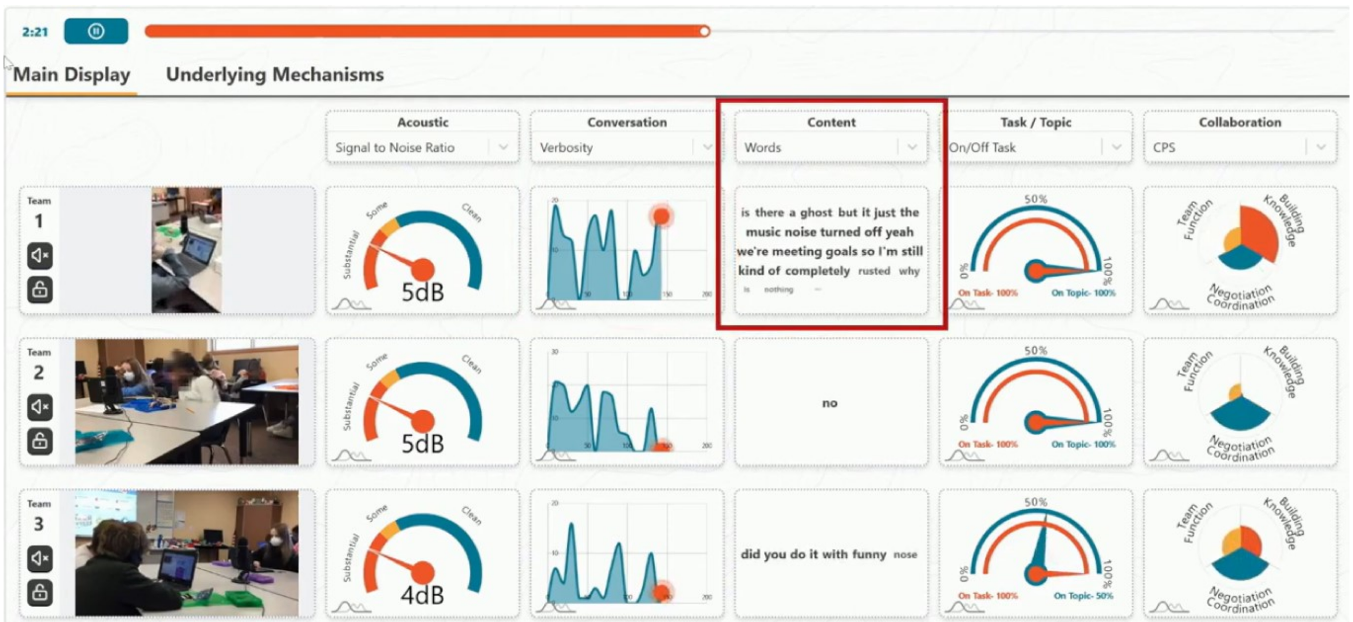

Figure 3: The Multimodal Intelligent Analyzer (MMIA) incorporates AI and analytic-based approaches to analyze components of student data.

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.

REFERENCES

[1] Accessed: 05-10-2023. *Khanmigo Education Ai Guide.* https://www.khanacademy.org/khan-labs

[2] Accessed: 05-10-2023. *OpenSciEd.* http://www.openscied.org/

[3] Amina Adadi and Mohammed Berrada. 2018. Peeking inside the black-box: a survey on explainable artificial intelligence (XAI). *IEEE access* 6 (2018), 52138–52160.

[4] Renee Affolter, Katherine L McNeill, and Gretchen Brinza. 2022. Some of You Are Smiling Now. *Science Scope* 45, 5 (2022), 26–34.

[5] Katerina Ananiadoui and Magdalean Claro. 2009. 21st century skills and competences for new millennium learners in OECD countries. (2009).

[6] Marilyn Binkley, Ola Erstad, Joan Herman, Senta Raizen, Martin Ripley, May Miller-Ricci, and Mike Rumble. 2012. Defining twenty-first century skills. *Assessment and teaching of 21st century skills* (2012), 17–66.

[7] Raymond R Bond, Maurice D Mulvenna, Hui Wan, Dewar D Finlay, Alexander Wong, Ansgar Koene, Rob Brisk, Jennifer Boger, and Tameem Adel. 2019. Human Centered Artificial Intelligence: Weaving UX into Algorithmic Decision Making.. In *RoCHI.* 2–9.

[8] Michael Alan Chang, Thomas M Philip, Arturo Cortez, Ashieda McKoy, Tamara Sumner, and William R Penuel. 2022. Engaging Youth in Envisioning Artificial Intelligence in Classrooms: Lessons Learned. (2022).

[9] Mark Chignell, Lu Wang, Atefeh Zare, and Jamy Li. 2023. The evolution of HCI and human factors: Integrating human and artificial intelligence. *ACM Transactions on Computer-Human Interaction* 30, 2 (2023), 1–30.

[10] Stephen M Fiore, Arthur Graesser, and Samuel Greiff. 2018. Collaborative problem-solving education for the twenty-first-century workforce. *Nature human behaviour* 2, 6 (2018), 367–369.

[11] Arthur C Graesser, Stephen M Fiore, Samuel Greiff, Jessica Andrews-Todd, Peter W Foltz, and Friedrich W Hesse. 2018. Advancing the science of collaborative problem solving. *psychological science in the public interest* 19, 2 (2018), 59–92.

[12] Patrick Griffin, Esther Care, and Barry McGaw. 2011. The changing role of education and schools. In *Assessment and teaching of 21st century skills.* Springer, 1–15.

[13] Scott S Grigsby. 2018. Artificial intelligence for advanced human-machine symbiosis. In *Augmented Cognition: Intelligent Technologies: 12th International Conference, AC 2018, Held as Part of HCI International 2018, Las Vegas, NV, USA, July 15-20, 2018, Proceedings, Part I.* Springer, 255–266.

[14] Päivi Häkkinen, Sanna Järvelä, Kati Mäkitalo-Siegl, Arto Ahonen, Piia Näykki, and Teemu Valtonen. 2017. Preparing teacher-students for twenty-first-century learning practices (PREP 21): a framework for enhancing collaborative problem-solving and strategic learning skills. *Teachers and Teaching* 23, 1 (2017), 25–41.

[15] John W Hunt and Yehuda Baruch. 2003. Developing top managers: The impact of interpersonal skills training. *Journal of Management Development* 22, 8 (2003), 729–752.

[16] Jialang Victor Li, Max Kreminski, Sean M Fernandes, Anya Osborne, Joshua McVeigh-Schultz, and Katherine Isbister. 2022. Conversation Balance: A Shared VR Visualization to Support Turn-taking in Meetings. In *CHI Conference on Human Factors in Computing Systems Extended Abstracts.* 1–4.

[17] Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019. Roberta: A robustly optimized bert pretraining approach. *arXiv preprint arXiv:1907.11692* (2019).

[18] Stephen MacNeil, Kyle Kiefer, Brian Thompson, Dev Takle, and Celine Latulipe. 2019. Ineqdetect: A visual analytics system to detect conversational inequality and support reflection during active learning. In *Proceedings of the ACM Conference on Global Computing Education.* 85–91.

[19] Elham Mousavinasab, Nahid Zarifsanaiey, Sharareh R. Niakan Kalhori, Mahnaz Rakhshan, Leila Keikha, and Marjan Ghazi Saeedi. 2021. Intelligent tutoring systems: a systematic review of characteristics, applications, and evaluation methods. *Interactive Learning Environments* 29, 1 (2021), 142–163.

[20] Alec Radford, Jong Wook Kim, Tao Xu, Greg Brockman, Christine McLeavey, and Ilya Sutskever. 2022. Robust speech recognition via large-scale weak supervision. *arXiv preprint arXiv:2212.04356* (2022).

[21] Samiha Samrose, Daniel McDuff, Robert Sim, Jina Suh, Kael Rowan, Javier Hernandez, Sean Rintel, Kevin Moynihan, and Mary Czerwinski. 2021. Meetingcoach: An intelligent dashboard for supporting effective & inclusive meetings. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems.* 1–13.

[22] Rao A. Michaels A. Sun C. Shute V. Duran N. Stewart, A. and S. K. D'Mello. In Press. CPSCoach: The Design and Implementation of Intelligent Collaborative Problem Solving Feedback. *Proceedings of the 24th International Conference on Artificial Intelligence in Education (AIED 2023)* (In Press).

[23] Chen Sun, Valerie J Shute, Angela Stewart, Jade Yonehiro, Nicholas Duran, and Sidney D'Mello. 2020. Towards a generalized competency model of collaborative problem solving. *Computers & Education* 143 (2020), 103672.

[24] Richard Tomsett, Alun Preece, Dave Braines, Federico Cerutti, Supriyo Chakraborty, Mani Srivastava, Gavin Pearson, and Lance Kaplan. 2020. Rapid trust calibration through interpretable and uncertainty-aware AI. *Patterns* 1, 4 (2020), 100049.

[25] Karel van den Bosch, Tjeerd Schoonderwoerd, Romy Blankendaal, and Mark Neerincx. 2019. Six challenges for human-AI Co-learning. In *Adaptive Instructional Systems: First International Conference, AIS 2019, Held as Part of the 21st HCI International Conference, HCII 2019, Orlando, FL, USA, July 26–31, 2019, Proceedings 21.* Springer, 572–589.

[26] Pawan Whig, Arun Velu, and Rahul Ready. 2022. Demystifying Federated Learning in Artificial Intelligence With Human-Computer Interaction. In *Demystifying Federated Learning for Blockchain and Industrial Internet of Things.* IGI Global, 94–122.