Fair for whom? Investigating school identity, algorithmic fairness, and educational technologies

Clara Belitz[0009−0002−1960−0914]

University of Illinois Urbana–Champaign, Champaign IL 61820, USA
cbelitz2@illinois.edu

Abstract. Algorithmically driven systems are now frequently found in educational spaces in the form of adaptive tutoring systems and online learning environments. Previous research has shown that well-integrated technologies can augment good human teaching practices. How such integration is measured, however, is an evolving debate within the field of artificial intelligence for education. Research that seeks to measure equity in these systems often assumes the social categories that are used for comparison, typically by using already existing demographic data such as race or sex. While practical, these assumptions may limit the transferability of subsequent conclusions. This work explores dimensions of algorithmic justice questions through interviews with students. This research engages middle and high school students directly, as the least powerful but arguably most impacted individuals in the algorithmic tutoring ecosystem, about their own identities, their relationship to these technologies, and the way their data are used.

Keywords: Equity · Social Identity · Qualitative Methods · Intelligent Tutoring Systems

1 Introduction

As algorithmically driven adaptive technologies have become more commonplace, it has become possible to research both the fits and misfits of these systems (e.g., [19]). Research has been done using the massive amounts of data created by users of these systems [1], but students themselves are often not included in the research directly [19]. Youth are a frequently missing critical voice in research [11]; "student voice" research specifically engages youth in school settings, identifying students as "consequential stakeholders" who "bear the burden of decisions most often made by others" [4]. Researchers may miss important concerns, weaknesses, or ethical issues that students are able to identify.

As such, this research will involve asking the users of these technologies, middle and high school students, about their experiences with intelligent tutoring systems (ITSs). ITSs seek to support learners on an individualized basis, often using machine learning models to serve students questions based on predictions of content mastery or knowledge gain [20]. Individual predictions for each student are built from information extracted from records of students' interactions with the software. The underlying models that feed these predictions need to be able to serve large, diverse populations of students to address a wide variety of learning needs [12]. While the benefits of these systems have been studied, questions remain about whether all types of students experience these benefits equally [16]. This work proposes qualitative research to further understand the relationship between social identities, educational technologies, and algorithmic equity. In this context, social identities refer to any constructed category, such as race, gender, or student identity [3]. Which social identity is chosen for comparison will therefore impact how equity is defined. This doctoral research will ask the following questions:

- RQ1. Are student perceptions of educational technologies related to their social identities, including that of their learning identity? If so, in what ways?
- RQ2. What types of information do students think are acceptable for use in predictive systems for educational outcomes?

Using semi-structured interviews and a card sorting activity, this work will explore student identities, their perceptions of educational technology, and what information they see as appropriate for use in predictive systems.

2 Background and Related Work

The field of education has a rich history of engaging with questions of equity, which has directly impacted research being done today [17,13]. Learning sciences and computer science have inherited this tradition, investing in increasing gender diversity in computing [15], asking how AI helps and hurts [18], and exploring the impact of specific predictive algorithms [22,14]. Educational technology researchers have also argued that "better data beat big data" [23], demonstrating the value of effective and accurate data. In addition, there has been a push for research to be done *with* young people, as opposed to *on* them [21].

Social identity is an important facet of power and equity, including for educational technologies. For example, math identity influences learning outcomes and is impacted by both internal (e.g., self belief) and external (e.g., teacher enthusiasm) factors [9,6]. Math identity is not, however, a protected demographic class in the way sex or race may be in some places, such as the United States. Though it is not legally protected, it is still a valuable social identity to understand in the context of ITSs and education more broadly. In addition, protected demographic categories have been critiqued for failing to capture nuance or otherwise missing information [10]. Questions of equity therefore require careful selection of the social categories across which comparisons will be made. This research specifically builds on my prior work, which has argued for the expansion of which categories are used for comparison [3] as well as demonstrated the importance of learning identity for student outcomes with an ITS [2]. As such, a section of the interview focuses on the participant's relationship to school and learning.

3 Method

Fifteen students will participate in one-hour sessions comprising a semi-structured interview and a card sorting activity. The number of participants was chosen because this is an exploratory study, and it does not seek to be representative of all young people in the United States. This sample size reflects choices made in similar studies, including a large-scale study of middle-school students' perceptions of the concept of AI which used 12 students in their initial pilot [8] and preliminary research on STEAM Teachers' perceptions of AI in education [7].

The interview questions will cover student identity, perception about technology in the classroom through an intelligent tutoring system, and opinions about teaching and learning. For example, Question 14 of the interview guide, "Are there things you like or dislike about learning math?," will help elicit students feelings towards mathematics and how they view their own math identity. The follow-up question asks whether the ITS they use makes these things better or worse. The goal of the interviews will be to expand upon findings from prior social identity surveys [3], deepen findings about the importance of student identity [2], and further investigate student opinions about educational technology. Interviews will be audio-recorded and the transcriptions will be analyzed using thematic analysis [5], allowing for both previously documented and emergent topics to be explored.

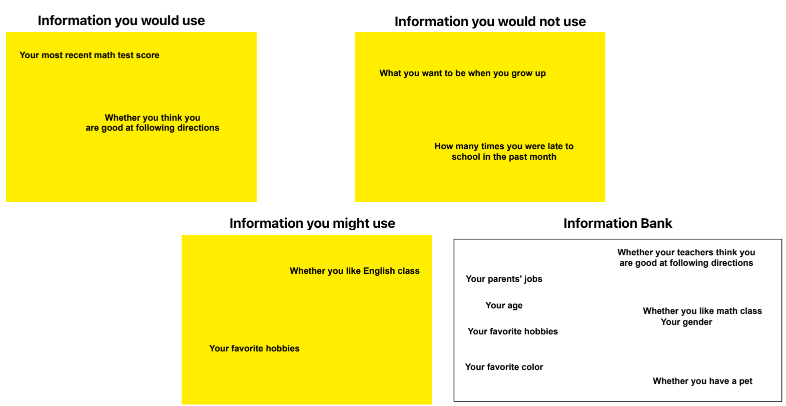

Fig. 1. A digital prototype of the card sorting activity with a subset of the features students will see. Some of the features remain in the "feature bank" while others have been distributed.

The card sorting activity will ask students about what they feel is appropriate usage of their data in educational spaces. The activity will then be repeated with a new prompt, where students will be asked to move cards when presented with new information about the predictive value of the features that they deemed unacceptable. The activity is analog, to facilitate engagement and make the experience more youth friendly. In addition, the paper and ability to move items around will help students think through the scenarios more easily.

This activity uses features that fall into one of three categories: demographic information, proxies for protected information, and proxies for behavioral or technological usage data 1. There will also be two feature of extraneous information (their favorite color and favorite animal), which can be used as a baseline for comparison. The activity will be audio recorded, allowing for thematic analysis of the transcript. At the end of each scenario, students will be asked to explain a few of their choices, with possible prompting by the interviewer. These results will be analyzed for commonalities, trends, and differences across participants.

The activity is phrased as "you" for each piece of information with the goal of prompting students to talk about themselves. Students are the experts in their own perceptions more than those of their peers, teachers, or teachers. The goal of this phrasing is to encourage students to share their opinions, rather than give answers that they think I want to hear or that they believe are generally true. The students will be reminded that there are no right or wrong answers.

4 Expected Contributions

Recruitment for this project is underway, and the first participant session has been conducted. In the card sort, the first participant indicated comfort with personalization as long as it was not "invasive" (e.g., family income) or "irrelevant" (e.g., favorite animal). The first contribution of this work is to center student perspectives on algorithmic fairness. Rather than analyzing ITSs from institutional or technical standpoints, this work prioritizes student voices. Through qualitative interviews and a card sorting activity, I hope to provide novel insights into how students perceive algorithmic decision making, what they consider fair, and how they believe their data should be used in predictive systems. Future work may be able to use the findings in the (re)design of ITSs by considering student responses to the card sorting activity about what information is acceptable for use. In addition, this work presents a methodological intervention, encouraging the field to recognize the value of qualitative, mixed–methods, and student–centered approaches.

5 Conclusion

Researchers, policymakers, and institutional leaders are actively engaged in lively debate about the role of technology in a variety of domains, including in United States' educational spaces. But those who are most directly impacted by these decisions are frequently left out of the conversation. This work seeks to contribute to the field by centering student perspectives on intelligent tutoring systems, offering insights into how social identity and personal experiences shape their perceptions. By using qualitative methods to explore students' views on fairness, equity, and data usage, this research contributes to ongoing discussions about ethical AI in education. The results may help inform future work on responsible integration of adaptive learning technologies and provide a foundation for more student-inclusive approaches to the use of AI for education.

Acknowledgments. Thank you to Drs. Nigel Bosch and Tobias Ley for feedback on earlier versions of this manuscript.

References

1. Ambarish, J., Fancsali, S.E., Ritter, S., Nixon, T., Berman, S.R.: Generalizing and extending a predictive model for standardized test scores based on Cognitive Tutor interactions. In: Proceedings of the 7th International Conference on Educational Data Mining. pp. 369–370. International Educational Data Mining Society (IEDMS), Online (2014)
2. Belitz, C., Lee, H., Nasiar, N., Fancsali, S.E., Stinar, F., Almoubayyed, H., Ritter, S., Baker, R.S., Ocumpaugh, J., Bosch, N.: Exploring student identity in adaptive learning systems through qualitative data. In: Artificial Intelligence in Education: 25th International Conference, AIED 2025. Springer-Verlag (2025)
3. Belitz, C., Ocumpaugh, J., Ritter, S., Baker, R.S., Fancsali, S.E., Bosch, N.: Constructing categories: Moving beyond protected classes in algorithmic fairness. Journal of the Association for Information Science and Technology **74**(6), 663–668 (2022). https://doi.org/10.1002/asi.24643
4. Brasof, M., Levitan, J.: Student Voice Research: Theory, methods, and innovations from the field. Teachers College Press, New York, NY (2022)
5. Braun, V., Clarke, V.: Using thematic analysis in psychology. Qualitative Research in Psychology **3**(2), 77–101 (2006). https://doi.org/10.1191/1478088706qp063oa
6. Cribbs, J.D., Hazari, Z., Sonnert, G., Sadler, P.M.: Establishing an explanatory model for mathematics identity. Child Development **86**(4), 1048–1062 (2015). https://doi.org/https://doi.org/10.1111/cdev.12363
7. Cruz, S., Duque, D., Carvalho, V.: STEAM teachers' perceptions of artificial intelligence in education: Preliminary research. In: Proceedings of the 16th International Conference on Computer Supported Education. pp. 278–285. SCITEPRESS - Science and Technology Publications, Angers, France (2024). https://doi.org/10.5220/0012713700003693
8. Demir, K., Güraksın, G.E.: Determining middle school students' perceptions of the concept of artificial intelligence: A metaphor analysis. Participatory Educational Research **9**(2), 297–312 (2022). https://doi.org/10.17275/per.22.41.9.2
9. Frenzel, A.C., Goetz, T., Pekrun, R., Watt, H.M.G.: Development of mathematics interest in adolescence: Influences of gender, family, and school context. Journal of Research on Adolescence **20**(2), 507–537 (2010). https://doi.org/10.1111/j.1532-7795.2010.00645.x
10. Hanna, A., Denton, E., Smart, A., Smith-Loud, J.: Towards a critical race methodology in algorithmic fairness. In: Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency. pp. 501–512. ACM, Barcelona Spain (2020). https://doi.org/10.1145/3351095.3372826
11. Hautea, S., Dasgupta, S., Hill, B.M.: Youth perspectives on critical data literacies. In: Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems. pp. 919–930. ACM, Denver Colorado USA (2017). https://doi.org/10.1145/3025453.3025823, https://dl.acm.org/doi/10.1145/3025453.3025823

12. Heffernan, N.T., Heffernan, C.L.: The ASSISTments ecosystem: Building a platform that brings scientists and teachers together for minimally invasive research on human learning and teaching. International Journal of Artificial Intelligence in Education **24**(4), 470–497 (2014). https://doi.org/10.1007/s40593-014-0024-x
13. Hutchinson, B., Mitchell, M.: 50 years of test (un)fairness: Lessons for machine learning. In: Proceedings of the Conference on Fairness, Accountability, and Transparency. pp. 49–58. FAT* '19, Association for Computing Machinery, New York, NY, USA (2019). https://doi.org/10.1145/3287560.3287600
14. Jiang, W., Pardos, Z.A.: Towards equity and algorithmic fairness in student grade prediction. In: Proceedings of the 2021 AAAI/ACM Conference on AI, Ethics, and Society. pp. 608–617. AIES '21, Association for Computing Machinery, New York, NY, USA (2021). https://doi.org/10.1145/3461702.3462623
15. Kim, K.A., Fann, A.J., Misa-Escalante, K.O.: Engaging women in computer science and engineering: Promising practices for promoting gender equity in undergraduate research experiences. ACM Transactions on Computing Education **11**(2), 1–19 (2011). https://doi.org/10.1145/1993069.1993072
16. Kizilcec, R.F., Piech, C., Schneider, E.: Deconstructing disengagement: Analyzing learner subpopulations in massive open online courses. In: Proceedings of the Third International Conference on Learning Analytics and Knowledge. pp. 170–179. LAK '13, Association for Computing Machinery, New York, NY, USA (2013). https://doi.org/10.1145/2460296.2460330
17. Ladson-Billings, G., Tate, W.F.: Toward a critical race theory of education. Teachers College Record **97**(1), 47–68 (1995). https://doi.org/10.1177/016146819509700104, publisher: SAGE Publications
18. Madaio, M., Blodgett, S.L., Mayfield, E., Dixon-Román, E.: Beyond "fairness:" Structural (in)justice lenses on AI for education. In: W. Holmesand, K. Porayska-Pomsta (eds.) The Ethics of Artificial Intelligence in Education: Current Challenges, Practices and Debates, p. 37. Routledge, England, UK (2022)
19. Martin, A.C., Ying, K.M., Rodríguez, F.J., Kahn, C.S., Boyer, K.E.: Intelligent support for all? A literature review of the (in)equitable design & evaluation of adaptive pedagogical systems for CS education. In: Proceedings of the 53rd ACM Technical Symposium on Computer Science Education - Volume 1. SIGCSE 2022, vol. 1, pp. 996–1002. Association for Computing Machinery, New York, NY, USA (2022). https://doi.org/10.1145/3478431.3499418
20. Nkambou, R., Bourdeau, J., Mizoguchi, R., Kacprzyk, J. (eds.): Advances in Intelligent Tutoring Systems, Studies in Computational Intelligence, vol. 308. Springer, Berlin, Heidelberg (2010), http://link.springer.com/10.1007/978-3-642-14363-2
21. Winters, N., Eynon, R., Geniets, A., Robson, J., Kahn, K.: Can we avoid digital structural violence in future learning systems? Learning, Media and Technology **45**(1), 17–30 (2020). https://doi.org/10.1080/17439884.2020.1708099
22. Wise, A.F., Sarmiento, J.P., Boothe Jr., M.: Subversive learning analytics. In: LAK21: 11th International Learning Analytics and Knowledge Conference. pp. 639–645. LAK21, Association for Computing Machinery, New York, NY, USA (2021). https://doi.org/10.1145/3448139.3448210
23. Yudelson, M.V., Fancsali, S.E., Ritter, S., Berman, S.R., Nixon, T., Joshi, A.: Better data beat big data. In: Proceedings of the 7th International Conference on Educational Data Mining. pp. 205–208. International Educational Data Mining Society, London, United Kingdom (2014)