EDUC 6123: Big Data, Education, and Society
Spring 2025
Professor Ryan S. Baker

SYLLABUS

Instructor Info
Email: rybaker@upenn.edu
Office: GSE 439
In-Person office hours for Ryan: Thursdays, 3pm-4pm, Location 3700 Walnut Street, Room 439
Virtual office hours for Ryan (both sections welcome): Mondays 6a-7a, Fridays 4p-5p, Location https://upenn.zoom.us/j/93923377036
In-person section time: Thursdays 930am-1130am, Location TBD
Link for in-person section simulcast: https://upenn.zoom.us/j/98421857018
Virtual section time: Thursdays 615pm-805pm
Link for virtual section: https://upenn.zoom.us/j/99858903156
Class discussion forum: https://educ6123-s25.jeepyta.net/

Required Texts:

- None

Information on how to obtain course readings will be provided in class.

Course Goals: The growth of learning analytics and educational data mining has been met with both optimism and concern. Excitement about the possibilities of individualized, personalized, adaptive learning have emerged. But concerns that student privacy will be jeopardized, and that student futures will be forever shaped by data from long ago – or warped by an errant prediction about the student years into the future – have emerged as well.

In this class, we will discuss what learning analytics can do, what it has the potential to do for good, and what the potential is for harm. We will discuss multiple uses and applications of analytics, where simple steps can mitigate risk, the relationship between validity and risk, and where risk mitigation will do more harm than good. We will do so in the context of real-world educational systems, challenges, problems, and with reference to original sources as much as possible.

Course Pre-requisites: None, but some prior experience with statistics or data mining recommended.

Assignments:

This class will have one primary assignment with multiple sub-assignments.

In this project, students will propose a learning analytics application in a group. In the first sub-project "Project Proposal", due week 5, you will propose the application and discuss past related work (in both research and practice). In the second sub-project "Needs Assessment", due week 8, you will perform a needs assessment targeted towards articulating what societal or educational need the application addresses. In the third sub-project "Risks and Challenges", due week 11, you will discuss the risks and challenges inherent in their solution and how they can be mitigated. In the fourth sub-project "Final Presentation", due in the last week of the semester, you will present your project as if they were submitting it to a potential funder. Part of your grade on each of these sub-projects will be commenting on other groups' submissions.

Extensions for the assignments will only be available in case of instructor error or extreme circumstances (assignments in other classes, research studies, work deadlines, and so on do not count as extreme circumstances; serious injury, political instability or lockdowns, illness, or death in the family do count as extreme circumstances). Outside of these circumstances, late hand-ins will not be accepted (e.g. zero credit will be given).

No examinations will be given in this class.

Class participation involves both attendance and active (and constructive) participation in classroom discussions, and on the discussion forum (beyond participation as required for the assignments). However, for students who prefer one modality over the other, intense participation in one modality can substitute for less participation in the other modality.

It does not include participation in Vivi-SD, which is graded separately. While it is not expected that you will memorize every paper assigned for the class, it is expected that you will have studied the readings to the degree that you can participate actively in discussions.

Grading

- Project Proposal 17%
- Needs Assessment 17%
- Risks and Challenges 17%
- Final Project 17%
- Class/Discussion Forum Participation 11%
- Synchronous Discussions in Vivi-SD 21%

Foundation model policy: Within this class, you are welcome to use foundation models (ChatGPT, GPT, Claude, Bing Chat, DALL-E, Stable Diffusion, Midjourney, GitHub Copilot, and anything after) in a totally unrestricted fashion, for any purpose, at no penalty. However, you should note that all large language models still have a tendency to make up incorrect facts and fake and image generation models can occasionally come up with highly offensive products. You will be responsible for any inaccurate, biased, offensive, or otherwise unethical content you submit regardless of whether it originally comes from you or a foundation model. If you use a foundation model, its contribution must be acknowledged in the handin; you will be penalized for using a foundation model without acknowledgement. Having said all these disclaimers, the use of foundation models is encouraged, as it may make it possible for you to submit assignments with higher quality, in less time.

Plagiarism policy: The university's policy on plagiarism still applies to any uncited or improperly cited use of work by other human beings, or submission of work by other human beings as your own. If you are not sure whether some action counts as plagiarism, ask before doing it. The university’s policy on plagiarism will be strictly followed.

Course Schedule

Big Data, Education, and Society
Professor Ryan S. Baker

Week 1: Thursday 1/16
<u>The Emerging Era of Big Data in Education</u>

Readings

- None

Week 2: Thursday 1/23
<u>Learning Analytics: The Big Picture</u>

Readings

- Baker, R., Siemens, G. (2022) Educational data mining and learning analytics. Sawyer, K. (Ed.) *Cambridge Handbook of the Learning Sciences: 3rd Edition*.
- Liu, L. T., Wang, S., Britton, T., & Abebe, R. (2023). Reimagining the machine learning life cycle to improve educational outcomes of students. *Proceedings of the National Academy of Sciences, 120* (9), e2204781120.
- Wise, A. F. (2019). Learning Analytics: Using Data-Informed Decision-Making to Improve Teaching and Learning. In *Contemporary Technologies in Education* (pp. 119-143). Palgrave Macmillan, Cham.

Week 3: Thursday 1/30
<u>At-Risk Prediction</u>

Readings

- Milliron, M. D., Malcolm, L., & Kil, D. (2014). Insight and action analytics: Three case studies to consider. *Research & Practice in Assessment*, *9.*
- Dawson, S., Jovanovic, J., Gašević, D., & Pardo, A. (2017). From prediction to impact: Evaluation of a learning analytics retention program. In *Proceedings of the Seventh International Learning Analytics & Knowledge Conference* (pp. 474-478). ACM.
- Coleman, C., Baker, R., Stephenson, S. (2019) A Better Cold-Start for Early Prediction of Student At-Risk Status in New School Districts. *Proceedings of the 12th International Conference on Educational Data Mining*, 732-737.
- Christie, S. T., Jarratt, D. C., Olson, L. A., & Taijala, T. T. (2019). Machine-Learned School Dropout Early Warning at Scale. *Proceedings of the 12th International Conference on Educational Data Mining.*

Week 4: Thursday 2/6
<u>Reports for School Personnel</u>

Readings

- Feng, M., & Heffernan, N. T. (2006). Informing teachers live about student learning: Reporting in the assistment system. *Technology Instruction Cognition and Learning*, *3*(1/2), 63
- Wise, A. F., & Jung, Y. (2019). Teaching with Analytics: Towards a Situated Model of Instructional Decision-Making. *Journal of Learning Analytics*, *6*(2), 53-69.
- Khosravi, H., Shabaninejad, S., Bakharia, A., Sadiq, S., Indulska, M., & Gasevic, D. (2021). Intelligent Learning Analytics Dashboards: Automated Drill-Down Recommendations to Support Teacher Data Exploration. *Journal of Learning Analytics*, *8*(3), 133-154.
- Kasepalu, R., Chejara, P., Prieto, L. P., & Ley, T. (2023). Studying teacher withitness in the wild: comparing a mirroring and an alerting & guiding dashboard for collaborative learning. *International Journal of Computer-Supported Collaborative Learning*, *18*(4), 575-606.

Week 5: Thursday 2/13
<u>Reports for Parents and Students</u>

Readings

- Broderick, Z., O'Connor, C., Mulcahy, Heffernan, N. & Heffernan, C. (2011). Increasing Parent Engagement in Student Learning Using an Intelligent Tutoring System. *Journal of Interactive Learning Research*, 22(4)*,* 523-550.
- Bergman, P. (2021) Parent-Child Information Frictions and Human Capital Investment: Evidence from a Field Experiment Investment. *Journal of Political Economy, 129* (1)*,* 286-322.
- Lim, L. A., Dawson, S., Gašević, D., Joksimović, S., Pardo, A., Fudge, A., & Gentili, S. (2021). Students' perceptions of, and emotional responses to, personalised learning analytics-based feedback: An exploratory study of four courses. *Assessment & Evaluation in Higher Education*, *46*(3), 339-359.
- Tomkins, S., Grossman, J., Page, L., & Goel, S. (2023). Showing high-achieving college applicants past admissions outcomes increases undermatching. *Proceedings of the National Academy of fSciences, 120*(45), e2306017120.

Week 6: Thursday 2/20
<u>Automated Intervention</u>

Readings

- Corbett, A. (2001) Cognitive computer tutors: Solving the two-sigma problem. *UM2001, User Modeling: Proceedings of the Eighth International Conference*, 137–147.
- Nye, B. D., Graesser, A. C., & Hu, X. (2014). AutoTutor and family: A review of 17 years of natural language tutoring. *International Journal of Artificial Intelligence in Education*, *24*(4), 427-469
- Li, H., Gobert, J., Dickler, R., & Moussavi, R. (2018). The impact of multiple real-time scaffolding experiences on science inquiry practices. In *International Conference on Intelligent Tutoring Systems (*pp. 99-109).

Week 7: Thursday 2/27
<u>Validity</u>

Readings

- Mislevy, R. J. (2016). How developments in psychology and technology challenge validity argumentation. *Journal of Educational Measurement*, *53*(3), 265-292.
- Fan, Y., van der Graaf, J., Lim, L., Raković, M., Singh, S., Kilgour, J., ... & Gašević, D. (2022). Towards investigating the validity of measurement of self-regulated learning based on trace data. *Metacognition and Learning*, 1-39.
- Baker, R.S. (2024) *Big Data and Education*. 8th Edition. Philadelphia, PA: University of Pennsylvania. Week 2, Video 6.

Week 8: Thursday 3/6
Generalizability

Readings

- Hawkins, D. M. (2004). The problem of overfitting. *Journal of chemical information and computer sciences*, *44*(1), 1-12.
- Levin, N., Baker, R.S., Nasiar, N., Fancsali, S., Hutt, S. (2022) Evaluating Gaming Detector Model Robustness Over Time. *Proceedings of the 15th International Conference on Educational Data Mining*.
- Baker, R.S. (2024) *Big Data and Education*. 8th Edition. Philadelphia, PA: University of Pennsylvania. Chapter 2, Video 5.

No Class Due to Spring Break: Thursday 3/13

Week 9: Thursday 3/20
Rational Modeling and Model Validity

Readings

- Muldner, K., Burleson, W., Van de Sande, B., & VanLehn, K. (2011). An analysis of students' gaming behaviors in an intelligent tutoring system: predictors and impacts. *User modeling and user-adapted interaction*, *21*(1), 99-135
- Paquette, L., de Carvalho, A.M.J.A., Baker, R.S. (2014) Towards Understanding Expert Coding of Student Disengagement in Online Learning. *Proceedings of the 36th Annual Cognitive Science Conference*, 1126-1131.

Week 10: Thursday 3/27
Discrimination and the Perpetuation of Bias

Readings

- Kizilcec, R. F. & Lee, H. (2022). Algorithmic Fairness in Education. In W. Holmes & K. Porayska-Pomsta (Eds.), *The Ethics of Artificial Intelligence in Education,* Routledge.
- Baker, R.S., Hawn, M.A. (2022) Algorithmic Bias in Education. *International Journal of Artificial Intelligence and Education, 32*, 1052-1092.
- CNN (2023) Florida elementary school principal and teacher are placed on leave after Black students are singled out at an assembly. https://www.cnn.com/2023/08/25/us/florida-flagler-county-schools-black-assembly/index.html
- Feathers, T. (2023) False Alarm: How Wisconsin Uses Race and Income to Label Students "High Risk". *The Markup*, April 27, 2023. https://themarkup.org/machine-learning/2023/04/27/false-

alarm-how-wisconsin-uses-race-and-income-to-label-students-high-risk#:~:text=The%20algorithm's%20false%20alarm%20rate,through%20a%20public%20records%20request.

- Cohausz, L., Kappenberger, J., & Stuckenschmidt, H. (2024). What fairness metrics can really tell you: A case study in the educational domain. In *Proceedings of the 14th Learning Analytics and Knowledge Conference* (pp. 792-799).

Week 11: Thursday 4/3
<u>Implementation Fidelity</u>

Readings

- Feng, M., Roschelle, J., Heffernan, N., Fairman, J., & Murphy, R. (2014). Implementation of an intelligent tutoring system for online homework support in an efficacy trial. *Proceedings of the International Conference on Intelligent Tutoring Systems* (pp. 561-566).
- Bingham, A. J., Pane, J. F., Steiner, E. D., & Hamilton, L. S. (2018). Ahead of the curve: Implementation challenges in personalized learning school models. *Educational Policy*, *32*(3), 454-489.
- Phillips, A., Pane, J. F., Reumann-Moore, R., & Shenbanjo, O. (2020). Implementing an adaptive intelligent tutoring system as an instructional supplement. *Educational Technology Research and Development*, *68*(3), 1409-1437.

Week 12: Thursday 4/10
<u>Student Privacy</u>

Readings

- Sabourin, J., Kosturko, L., FitzGerald, C., & McQuiggan, S. (2015). Student Privacy and Educational Data Mining: Perspectives from Industry. *Proceedings of the International Conference on Educational Data Mining*.
- Klose, M., Desai, V., Song, Y., & Gehringer, E. (2020). EDM and Privacy: Ethics and Legalities of Data Collection, Usage, and Storage. *Proceedings of the International Conference on Educational Data Mining*.
- Baker, R.S. (2023) The Current Trade-off Between Privacy and Equity in Educational Technology. In G. Brown III, C. Makridis (Eds.) *The Economics of Equity in K-12 Education: Necessary Programming, Policy, and Systemic Changes to Improve the Economic Life Chances of American Students.* Lanham, MD: Rowman & Littlefield.
- Viberg, O., Kizilcec, R. F., Jivet, I., Monés, A. M., Oh, A., Mutimukwe, C., ... & Scheffel, M. (2024). Cultural differences in students' privacy concerns in learning analytics across Germany, South Korea, Spain, Sweden, and the United States. *Computers in human behavior reports*, *14*, 100416.

Week 13: Thursday 4/17
<u>Interpretability, Explainability, and Transparency</u>

Readings

- Liu, R., & Koedinger, K. R. (2017). Going beyond better data prediction to create explanatory models of educational data. *The Handbook of learning analytics*, 69-76.
- Zhou, T., Sheng, H., & Howley, I. (2020). Assessing Post-hoc Explainability of the BKT Algorithm. In *Proceedings of the AAAI/ACM Conference on AI, Ethics, and Society* (pp. 407-413).
- Khosravi, H., Shum, S. B., Chen, G., Conati, C., Tsai, Y. S., Kay, J., ... & Gašević, D. (2022). Explainable artificial intelligence in education. *Computers and Education: Artificial Intelligence*, *3*, 100074.
- Susnjak, T. (2023) A Prescriptive Learning Analytics Framework: Beyond Predictive Modelling and onto Explainable AI with Prescriptive Analytics and ChatGPT. Unpublished manuscript. *arXiv:2208.14582.*

Week 14: Thursday 4/24
<u>Beneficence</u>

Readings

- Prinsloo, P., & Slade, S. (2017). An elephant in the learning analytics room: the obligation to act. *Proceedings of the Seventh International Learning Analytics & Knowledge Conference.*
- Kitto, K., & Knight, S. (2019). Practical ethics for building learning analytics. *British Journal of Educational Technology*.
- Li, W., Brooks, C., & Schaub, F. (2019). The impact of student opt-out on educational predictive models. In *Proceedings of the 9th international conference on learning analytics & knowledge* (pp. 411-420).

Week 15: Thursday 5/1
<u>Big Data, Big Science, and Longitudinal Follow-up</u>

Readings

- Heffernan, N. T., & Heffernan, C. L. (2014). 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.
- Fyfe, E., de Leeuw, J., Carvalho, P., Goldstone, R., et al. (2021). ManyClasses 1: Assessing the generalizable effect of immediate versus delayed feedback across many college classes. *Advances in Methods and Practices in Psychological Science, 4*(3).
- Nasiar, N., Baker, R.S., Li, J., Gong, W. (2022) How do A/B Testing and secondary data analysis on AIED systems influence future research? *Proceedings of the 23rd International Conference on Artificial Intelligence and Education,* 115-126
- Nasiar, N., Baker, R.S., Andres, J.M.A.L., Srivastava, N. (2024) Different AIED in Different Places: Tracing the differences in Geographical Distribution of Secondary Data Analysis and A/B tests. *Proceedings of the 17th International Conference on Educational Data Mining*.

Week 16: Thursday 5/8
Synchronous Presentations of Assignment 4: Final Project