

Introduction to the Minitrack on Learning Analytics 2024

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In the digital age, education has undergone a significant transformation. With the proliferation of technology in learning environments, the education sector has witnessed a dramatic increase in the generation of digital data. Consequently, over recent decades, learning analytics (LA) and educational data mining have evolved into significant areas of research, with the purpose of enhancing education at all educational levels (Deeva et al., 2021).

LA centers around aspects of personalization, adaptive learning, predictive analysis, and user behavior profiling. Frequently, learning analytics is portrayed as having boundless potential due to the substantial volumes of data generated and collected within educational systems. This presents an opportunity to cultivate a data-driven comprehension of the processes involved in both learning and teaching (Flores et al., 2023; Nguyen et al., 2020; Siemens & Baker, 2012). Lately, the need for direct involvement of educational research in learning analytics has been acknowledged as the first fundamental pillar of learning analytics to frame the research, i.e., to determine which data to collect and analyze. The second pillar, “capturing”, refers to finding evidence of learning, by identifying and explaining useful data for analyzing and understanding teaching, learning, and developing methods that capture and model learning. Third, “understanding” is associated with how learning theory is informed by large-scale data analysis, as well as the use of data science techniques to grasp specific aspects of teaching and learning. The fourth pillar is the “impact” on learning and teaching by offering decision support and feedback based on LA. For example, through dashboards and early alert systems, and personalized and adaptive learning.

For LA to reach an impact in practice there is a need to enhance the understanding of educators' overall practice, their needs, and how to support them in making use of a data-informed process (Viberg &

Gronlund, 2021). Additionally, learning analytics prompts significant inquiries regarding students' autonomy and integrity (Pargman & McGrath, 2019) an aspect that has frequently been neglected due to the enthusiasm for exploring the potential of this approach

For this minitrack, we welcomed papers that address, reflect on, and relate to, the four pillars of learning analytics and datafication in educational settings alongside papers that reflect on changes in learning platforms, teaching and learning practices, and student profiling. We particularly welcomed papers that take a critical and ethical perspective on learning analytics. In total, two papers were accepted for the minitrack this year. In the paper written by McNett and Noteboom (2023) “Something for Every Kind of Learner: Students’ Perception of an Educational Recommender Study Tool”, the authors employ design science methodology to advocate for an educational recommender framework with a theoretical base in self-regulated learning. The paper gains insights into student perceptions to obtain design themes that can facilitate the future design of educational recommender systems. The paper written by Tiukhova et al. (2023) “Discovering Unusual Study Patterns Using Anomaly Detection and XAI” leverages anomaly detection and explainable AI techniques to distinguish between normal and abnormal study patterns and to possibly discover unexpected patterns that are not apparent from clustering alone. In summary, the contributions to the minitrack in both the current and previous years showcase a diverse range of perspectives and methodologies within the field of learning analytics.

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References

- Deeva, G., Willermark, S., Islind, A. S., & Oskarsdottir, M. (2021). Introduction to the Minitrack on Learning Analytics. Proceedings of the 54th Hawaii International Conference on System Sciences,
- Flores, N. L., Islind, A. S., & Óskarsdóttir, M. (2023). *A learning analytics-driven intervention to support students' learning activity and experiences*. Routledge.
- Nguyen, A., Gardner, L., & Sheridan, D. (2020). A design methodology for learning analytics information systems: Informing learning analytics development with learning design.
- Pargman, T. C., & McGrath, C. (2019). Be Careful What You Wish For! Learning Analytics and the Emergence of Data-Driven Practices in Higher Education. *Technology*, 50(6), 2839-2854.
- Siemens, G., & Baker, R. S. d. (2012). Learning analytics and educational data mining: towards communication and collaboration. Proceedings of the 2nd international conference on learning analytics and knowledge,
- Viberg, O., & Gronlund, A. (2021). Desperately seeking the impact of learning analytics in education at scale: Marrying data analysis with teaching and learning. *arXiv preprint arXiv:2105.06680*.