Idiographic Learning Analytics: A Within-Person Ethical Perspective

Sonsoles López-Pernas
Universidad Politécnica de Madrid
sonsoles.lopez.pernas@upm.es

Mohammed Saqr
KTH Royal Institute of Technology, University of Eastern Finland
mmas3@kth.se

ABSTRACT: One of the main obstacles impeding the widespread use and adoption of learning analytics is the threat that it poses to students' data privacy. In this article, we present a proposal for generating person-centered insights for learners by combining data from multiple sources while preserving students' privacy. The basis of our approach is idiographic learning analytics, in which data are collected and insights are generated for each student individually. On the one hand, all the data collection and processing are performed locally on the student's device, thus preserving student privacy. On the other hand, being based on person-based methods, the idiographic approach helps deliver personalized insights.

Keywords: Ethics, Learning Analytics, Idiographic, Privacy.

1 INTRODUCTION AND BACKGROUND

Inspired by the encouraging industrial models that succeeded in converting data insights into competitive advantage, Learning Analytics (LA) were convened in 2011. LA can be defined as the "measurement, collection, analysis, and reporting of data about learners and their contexts, for the purposes of understanding and optimizing learning and the environments in which it occurs" (Siemens, 2013). Research in the field of LA started as an exploration of the potentials of using data generated by learning management systems (LMSs) to predict student performance. Nowadays, the range of applications has grown tremendously to include a wide range of methods, data sources, tools, and diverse threads of research across different fields (Saqr, 2015; Siemens, 2013). Such growth has been associated with wide-ranging interests from countries, universities, and many institutions to harness the benefits of data in education, and is expected to increase with the spike on online education with COVID-19 (Saqr & Wasson, 2020). Yet, the progress in learning analytics is closer to the research laboratories rather than real classrooms.

One of the main obstacles hampering the widespread use and adoption of LA is the threat that it poses to students' data privacy (Saqr, 2017). Indeed, the growth in LA research has not been matched by research in ethics and privacy, nor has there been enough policies developed or enacted across institutions that provide a healthy and safe ground for LA (Viberg et al., 2018). As ethics, privacy, and learners' protection lagged behind applications, so did the adoption of LA (Tsai et al., 2020). The scale of applications of LA, and the prospective future growth in such applications with ever-expanding technologies, is making it difficult for policymakers to match such pace with appropriate policies that can adapt to the vastly changing field of technology and its applications. What is more, research in LA has been more focused on institutional goals and perspectives rather than the needs and aspirations of learners themselves. Common objectives like decreasing dropout rates, and improving success rates are commonly cited as reasons for deploying LA applications (Bergdahl et al., 2020). In summary, although technology has shaped our learning and teaching, problems remain looking for a solution. LA has contributed to our understanding of learning; yet, efforts are impeded by a vastly growing field and lagging ethical policies. Therefore, a shift is needed where students are involved in the creation, understanding, and sense-making of their own data for their own sake.

As Winne has argued, the current approach of collecting large amounts of data from a group of learners (i.e., nomothetic LA) to derive insights about their behavior can hardly be generalizable (Winne, 2017). In other words, what applies to a group as an average behavior does not apply to the individual learners as each is a unique case (Molenaar & Campbell, 2009). In turn, the availability of high-resolution data generated by students enables another type of analytics where students can get just-in-time person-centered advice and support (Winne et al., 2017). This type of analytics is known as idiographic LA. This person-based approach has been gaining momentum in psychology research during the past decade. The move was kindled by increasing interest in delivering precisely personalized scientific interventions. Other fields have already benefited from idiographic approaches, e.g., precision medicine which has started to attract many researchers (Cook et al., 2018; Epskamp et al., 2018). Only recently the power of idiographic LA has been recognized as essential in uncovering the rich dynamics of cognitive development (Hofman et al., 2018).

In idiographic or person-based learning analytics, students are the data collectors, the analyzers, and the sense-makers. Data are collected from individuals with high intensity to generate enough observations, so the calculated statistics are based on many observations of a single individual, and hence the resulting mean, correlations, and predictions are of the very person (Epskamp et al., 2018; Wright et al., 2019; Saqr & López-Pernas, 2021). The abundance of data about learners from multiple sources allows such intensive data methods, e.g., data from LMSs, student information systems (SIS), and library services. This information can be complemented with data that students already have on their phones (e.g., mobility, screen time, and physical activity) and other devices of their own (e.g., fitness bands, personal computers, and tablets). The wealth of such data can be collected locally on a student's own device, analyzed locally (i.e., algorithms act solely on students' own data), and the results of such analysis can be acted upon locally as well (i.e., inferences, predictions, prescriptions, etc. can be presented exclusively to the student). In other words, the whole lifecycle of learning analytics can be performed locally, eliminating the main threats related to students' privacy.

Our proposal is a bottom-up approach to learning analytics that starts from the students, in contrast to the top-down approach commonly implemented. Such an approach has been tested and proven useful in other domains. For instance, a recent large-scale meta-analysis on consumer-based wearable activity trackers has proven that access to physical fitness dashboards on their own devices has helped individuals increase in daily step count, physical and energy expenditure (Brickwood et al., 2019). Our proposal is rooted in learning theories such as self-regulated learning that views students' agency as a fundamental element where students can influence their learning, set goals, reflect on their learning activities, and take proper action.

2 AN IDIOGRAPHIC LEARNING ANALYTICS SOLUTION TO ETHICAL CONCERNS

We propose a mobile application in which students combine data from multiple sources to generate idiographic (or person-centered) learning analytics. All the data retrieved from the allowed data sources for a single student are made available within the mobile application. Then, the data analysis is performed locally, and the results from such analysis are only presented to the student himself/herself through a dashboard in the mobile application. Figure 1 shows an overview of the solution proposed.

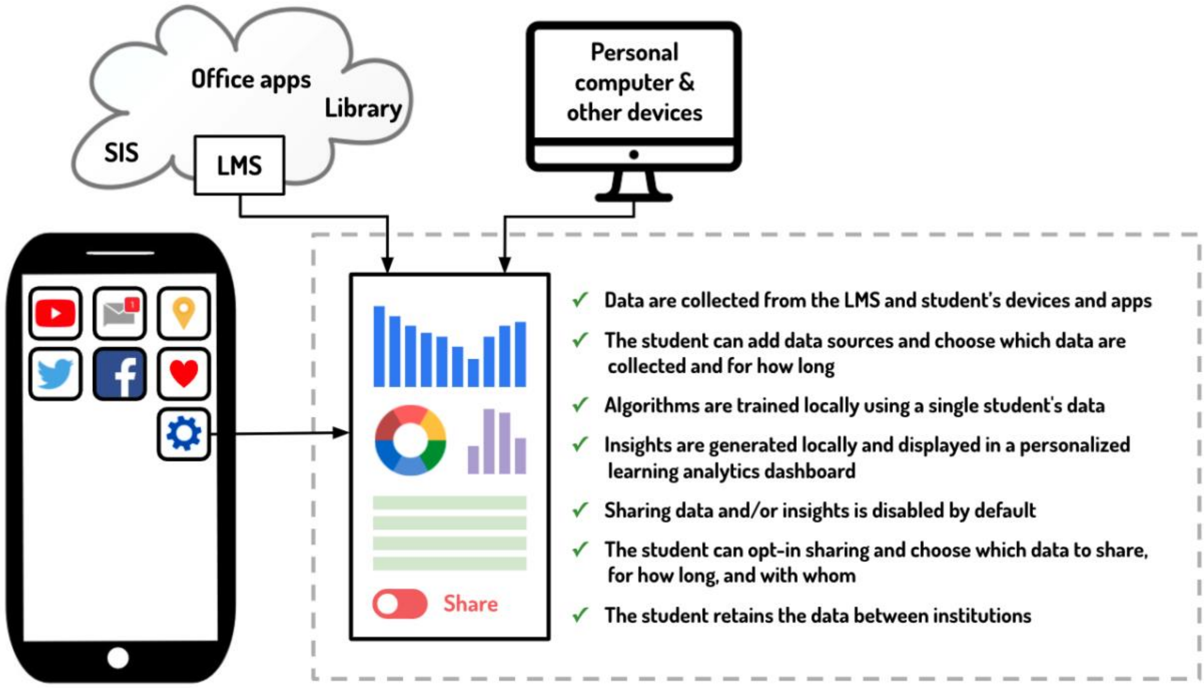

Figure 1. Proposed solution: data are collected from multiple sources and analyzed locally

2.1 Data collection

The mobile application retrieves the students' data from the LMS, including grades and performance data, as well as logs from the students' interactions with the learning materials and resources within the LMS. Students can select which supplementary data sources they wish to add as an input to enrich the insights drawn from their learning data. These auxiliary data sources can be (1) institutional services (e.g., SIS, library access, productivity applications, video conferencing apps), (2) other mobile applications and utilities (e.g., screen time, fitness, social), and (3) other devices of students' own (e.g., tablets, computers, smartwatches). All data retrieval is performed through secure encrypted connections between the mobile application and the data sources. Students can enable or disable data sources for a given time period and choose which exact data provided by a certain source they wish to make use of in their learning analytics personal dashboard.

2.2 Data analysis

The main idea behind idiographic learning analytics is that only data from a single student are operationalized. Thus, there is no need to combine data from a cohort of students to extract valuable insights about a specific learner. Without this requirement to combine data from multiple students in a centralized way, the data analysis for each student can be performed locally on each student's device. This also eliminates the need to anonymize their data since all the operations are performed locally. In our proposed solution, the complete data analysis and machine learning techniques used to, e.g., suggest learning materials or recommend a learning strategy, are applied within the mobile application using the data sources of students' choice.

2.3 Presentation and action

After data collection and analysis, the results obtained are presented to the student through a learning analytics dashboard embedded within the mobile application. In this dashboard, students can gain insights from their past performance, predicted future outcomes, and prescriptions on how to improve their academic achievement and learning strategies. The dashboard accounts for data provenance, informing the students of the exact data sources used to come up with a specific result or outcome. Although complete privacy of student data and results is enforced by default, students can share —by their own choice— specific insights with their parents, teachers, and/or peers to take their advice and guidance into consideration. Moreover, students can retain the data and generate insights as they progress throughout their educational journey, even if they change to a different institution.

3 CONCLUSIONS

In this article, we have presented a proposal for a mobile application that can generate person-centered insights for learners while preserving student privacy. The basis of our approach is idiographic learning analytics, in which insights are generated from data from a single learner (N=1). On the one hand, by means of the high-resolution data generated by students, the idiographic approach becomes essential in uncovering the rich dynamics of cognitive development (Hofman et al. 2018, Winne, 2017). On the other hand, since this approach studies each learner individually, all the data collection and processing can be performed locally on the student's device. In this regard, our proposed solution meets all the technological safeguards recognized by Reidenberg and Schaub (2018) for privacy with respect to big data in education, i.e., it implements the necessary technical mechanisms to assure transparency about data collection, processing, and use; accountability for analytics algorithms and algorithmic decision making; and securing and protecting learning analytics data as sensitive data (Liu et al., 2019; Munoz-Arcentales, 2019). We believe that enabling idiographic learning analytics can offer a significant improvement on the way to responsible learning analytics. In fact, by giving the students the responsibility of their learning, idiographic analytics could be the first step towards responsible LA.

REFERENCES

Bergdahl, N., Nouri, J., Karunaratne, T., Afzaal, M., & Saqr, M. (2020). Learning Analytics for Blended Learning - A systematic review of theory, methodology, and ethical considerations.

International Journal of Learning Analytics and Artificial Intelligence for Education, *2*(2), 46–79.

Brickwood, K. J., Watson, G., O'Brien, J., & Williams, A. D. (2019). Consumer-Based Wearable Activity Trackers Increase Physical Activity Participation: Systematic Review and Meta-Analysis. *JMIR mHealth and uHealth*, 7(4), e11819. https://doi.org/10.2196/11819

Cook, C. R., Kilgus, S. P., & Burns, M. K. (2018). Advancing the science and practice of precision education to enhance student outcomes. *Journal of School Psychology*, *66*(December 2017), 4–10. https://doi.org/10.1016/j.jsp.2017.11.004

Epskamp, S., van Borkulo, C. D., van der Veen, D. C., Servaas, M. N., Isvoranu, A. M., Riese, H., & Cramer, A. O. J. (2018). Personalized Network Modeling in Psychopathology: The Importance of Contemporaneous and Temporal Connections. *Clinical Psychological Science*, *6*(3), 416–427. https://doi.org/10.1177/2167702617744325

Hofman, A., Jansen, B., de Mooij, S., Stevenson, C., & van der Maas, H. (2018). A Solution to the Measurement Problem in the Idiographic Approach Using Computer Adaptive Practicing. *Journal of Intelligence*, *6*(1), 14. MDPI AG. Retrieved from http://dx.doi.org/10.3390/jintelligence6010014

Jacob, R., & Parkinson, J. (2015). The Potential for School-Based Interventions That Target Executive Function to Improve Academic Achievement: A Review. *Review of Educational Research*, *85*(4), 512–552. https://doi.org/10.3102/0034654314561338

Liu, S., Chai, H., Liu, Z., Pinkwart, N., Han, X., & Hu, T. (2019). Effects of Proactive Personality and Social Centrality on Learning Performance in SPOCs. *Proceedings of the 11th International Conference on Computer Supported Education*, *2*, 481–487. https://doi.org/10.5220/0007756604810487

Kirkwood, A., & Price, L. (2014). Technology-enhanced learning and teaching in higher education: what is ‘enhanced’ and how do we know? A critical literature review. *Learning, Media and Technology*, *39*(1), 6–36. https://doi.org/10.1080/17439884.2013.770404

Molenaar, P. C. M., & Campbell, C. G. (2009). The new person-specific paradigm in psychology. *Current Directions in Psychological Science*, *18*(2), 112–117. https://doi.org/10.1111/j.1467-8721.2009.01619.x

Munoz-Arcentales, A., López-Pernas, S., Pozo, A., Alonso, Á., Salvachúa, J., & Huecas, G. (2019). An Architecture for Providing Data Usage and Access Control in Data Sharing Ecosystems. *Procedia Computer Science*, 160, 590–597. https://doi.org/10.1016/j.procs.2019.11.042

Reidenberg, J. R., & Schaub, F. (2018). Achieving big data privacy in education. Theory and Research in Education, 16(3), 263–279. https://doi.org/10.1177/1477878518805308

Saqr, M. (2015). Learning analytics and medical education. *International Journal of Health Sciences*, *9*(4).

Saqr, M. (2017). Big data and the emerging ethical challenges. *International Journal of Health Sciences*, *11*(4).

Saqr, M., & Wasson, B. (2020). COVID-19: Lost opportunities and lessons for the future. *International Journal of Health Sciences*, *14*(3).

Saqr, M., & Lopez-Pernas, S. (2021). Idiographic Learning Analytics: A single student (N=1) approach using psychological networks. *Companion Proceedings 11th International Conference on Learning Analytics & Knowledge (LAK21)*, *in-press*.

Siemens, G. (2013). Learning Analytics: The Emergence of a Discipline. American Behavioral Scientist, 57(10), 1380–1400. https://doi.org/10.1177/0002764213498851

Tsai, Y. S., Whitelock-Wainwright, A., & Gašević, D. (2020). The privacy paradox and its implications for learning analytics. ACM International Conference Proceeding Series, 230–239. https://doi.org/10.1145/3375462.3375536

Viberg, O., Hatakka, M., Bälter, O., & Mavroudi, A. (2018). The current landscape of learning analytics in higher education. *Computers in Human Behavior*, 89, 98–110. https://doi.org/10.1016/j.chb.2018.07.027

Winne, P. H. (2017). Leveraging Big Data to Help Each Learner and Accelerate Learning Science. Teachers College Record, 119(3).

Wright, A. G. C., Gates, K. M., Arizmendi, C., Lane, S. T., Woods, W. C., & Edershile, E. A. (2019). Focusing Personality Assessment on the Person: Modeling General, Shared, and Person Specific Processes in Personality and Psychopathology. Psychological Assessment, 31(4), 502–515. https://doi.org/10.1037/pas0000617

Zaff, J. F., Donlan, A., Gunning, A., Anderson, S. E., McDermott, E., & Sedaca, M. (2017). Factors that Promote High School Graduation: A Review of Literature. Educational Psychology Review, 29(3), 447–476. https://doi.org/10.1007/s10648-016-9363-5