Math, Equity, Data, Analytics, Learning Science (MEDALS)

Purpose: to create a synthesis that addresses what has been learned around analytics for equitable math education and to identify guidance from existing literature that can practically be applied to design and development of data tools for math education.

Keywords used in literature search:

- Math Education
- Equity
- Data OR Analytics
- Data Science for Learning
- Dashboards OR Reports

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TOPIC: Math Education

Exploring Issues of Implementation, Equity, and Student Achievement in the DC Public Schools

We analyze a unique data set that combines student-level information from the district with data of student usage of a mathematics game platform: First in Math (FIM). These data offer a window into long-standing issues in the educational technology literature around implementation, equity, and student achievement. We show that time spent in FIM was correlated with improved future performance on standardized math assessments for students in Grades 4–8. However, student time spent using FIM was highly related to factors such as race, gender, and prior achievement.

Citation: June Ahn, Austin Beck, John Rice, & Michelle Foster. (August 01, 2016). Exploring Issues of Implementation, Equity, and Student Achievement with Educational Software in the DC Public Schools. Aera Open, 2.

Identity research in mathematics education

"I find it useful to think about identity as action, specifically performance, and in this way it is distinct from a psychological view. I see identity as the performance and the recognition of the self. It exists in the moment of the performance and as it is recognized. We perform our selves—be it by telling stories, joining groups, acting in a particular way at a particular time, positioning ourselves and others within wider societal discourses. In these ways, our identities are performative, we act them into being (Butler, 1988) and past acts influence those in the future. Furthermore, identity is a result of the process of identifying, whether this is self-identification or identification by others. This view of identity keeps in mind the audience at all times as the ultimate identifier and enables us to consider the ways in which power is exerted in this recognition. Perceiving identity as an act, a performance that may or may not be recognized as desired, is a useful future direction for research. It is in this direction that the study of identity has much to offer."

Citation: Darragh, L., & SpringerLink (Online service). (2016). Identity research in mathematics education. Educ Stud Math (2016) 93:19–33.

Reaping the benefits of assessment for learning: achievement, identity, and equity

In many parts of the world, there is an increased demand for effectiveness and equity in education and for the development of students who see themselves as lifelong learners to meet economic and social challenges. The purpose of assessment for learning (A*f*L) is to inform learning, not to measure it or sum it up; it is assessment that focuses on learning as it is taking place, not at the end of a sequence of learning; and it is intended to move learning forward from its current status. There is ample evidence that when effectively implemented A*f*L can improve learning for all students. A*f*L involves students in metacognitive strategies such as goal setting, monitoring and self-reflection, which give them the opportunity to steer their own learning and become more committed and effective learners (Black and Jones 2006), contributing to the development of positive mathematical identities.

Citation: Heritage, M., & Wylie, C. (August 01, 2018). Reaping the benefits of assessment for learning: achievement, identity, and equity. Zdm : Mathematics Education, 50, 4, 729-741.

TOPIC: Equity

Learning analytics: At the nexus of big data, digital innovation, and social justice in education.

We are still designing educational experiences for the *average* student, and have room to improve. Learning analytics provides a way forward. In so doing, learning analytics has the potential to contribute to more equitable and socially just educational outcomes for students who might otherwise be seen through the lens of the average student. Utilizing big data, good design, and the input of the stakeholders, learning analytics techniques aim to develop applications for the sole purpose of reducing the classroom size to 1.

Citation: Aguilar, S. J. (2018). Learning analytics: At the nexus of big data, digital innovation, and social justice in education. *TechTrends, 62*(1), 37-45.

Speaking the unspoken in learning analytics: troubling the defaults

Much of the critique around learning analytics has been about the tension between the inhumanity of the algorithm and the very human journey of student success. It is crucial that we critically engage with not only the patterns and trends of what is happening but also dedicate resources and expertise to understand the 'why'. Without understanding the 'why' of student success or failure, our assumptions and default positions may go unchecked.

Citation: Archer, E., & Prinsloo, P. (2019). Speaking the unspoken in learning analytics: troubling the defaults. *Assessment & Evaluation in Higher Education, 45*(6), 888-900.

Early warning systems and indicators of dropping out of upper secondary school

The EWS and EWI domain is a growing research area that identifies at-risk students and positively intervenes to support student persistence, using the most recent data mining techniques. A central concern of the EWS and EWI is the accuracy of indicators used to predict the probability of a student dropping out. Applications of pattern analytics and data science include dropout vs discharge (known as pushout)- a well-known issue in general dropout literature. The "Chicago on-track" indicator was identified as an accurate cross-sectional (data from a single year) dropout predictor. Growth Mixture Models (GMM) is a pattern analysis framework that identifies significantly different student data patterns over time. It provides a useful means to analyze long-term over-time data and demonstrates much higher accuracy dropout predictors for long-term longitudinal data.

Citation: Bowers, A. (2021). Early warning systems and indicators of dropping out of upper secondary school: The emerging role of digital technologies. In OECD Digital Education Outlook 2021: Pushing the Frontiers with Artificial Intelligence, Blockchain and Robots. Paris: OECD Publishing. OECD Digital Education Outlook 2021: Pushing the Frontiers with Artificial Intelligence, Blockchain and Robots | READ online (oecd-ilibrary.org)

Teachers interpreting data for instructional decisions: where does equity come in?

The purpose of this paper is to identify key problems with the techno-rational logic of accountability policies and reflect on the ways in which they influence teachers' data-use practices. This paper identifies three primary issues with test-based accountability policies: reducing complex constructs to quantitative variables, valuing remediation over instructional improvement, and enacting faith in instrument validity. Student learning is measured by standardized tests, which hold all students to the same metric, regardless of the educational debt owed to them and their families. At the same time, possibilities for equitable instruction were foreclosed, as teachers analyzed data in ways that gave little consideration of students' cultural identities or funds of knowledge.

Citation: Garner, B., Thorne, J. & Horn, I. (2017). Teachers interpreting data for instructional decisions: where does equity come in? Journal of Educational Administration. 55 (4), 407-426.

Ethics in Praxis: Socio-Technical Integration Research in Learning Analytics

This group of papers explores issues and principles in fairness, accountability, and transparency in education analytics.

Citation: Jones, K. & McCoy, C. (2019). Ethics in Praxis: Socio-Technical Integration Research in Learning Analytics. Companion Proceedings 9th International Conference on Learning Analytics & Knowledge (LAK19).

Accountability as a Design for Teacher Learning: Mathematics and Equity in the NCLB Era

The hope of this analysis is to highlight the unintended consequences of the current form of school accountability as they play out in educators' pedagogical reasoning. In this way, we can learn from it and design systems less fraught with contradictions to better support the development of urban students, teachers, and schools. NCLB provides a classificatory infrastructure rooted in techno-rational discourses to teaching and moves instructional decision-making away from the values of humanistic education—a phenomenon I call torque.

Citaiton: Horn, I. S. (March 01, 2018). Accountability as a Design for Teacher Learning: Sensemaking About Mathematics and Equity in the NCLB Era. Urban Education, 53, 3, 382-408.

Supporting Equity in Schools: Using Visual Learning Analytics

This chapter illustrates how user experience design methods can be applied to the design of learning analytics systems where designers must grapple with multiple interwoven concerns, such as what data should be collected, how can it be displayed to support appropriate interpretations, and how visualizations can be crafted to promote useful feedback and instructional change.

Citation: Raza, A., Penuel, W. R., Jacobs, J., & Sumner, T. (2020). Supporting Equity in Schools: Using Visual Learning Analytics to Understand Learners' Classroom Experiences. In M. Schmidt, A. A. Tawfik, I. Jahnke, & Y. Earnshaw (Eds.), Learner and User Experience Research: An Introduction for the Field of Learning Design & Technology. EdTech Books. https://edtechbooks.org/ux/supporting_school_equity

Walking the walk: using classroom analytics to address implicit bias in teaching

This manuscript explores how three university mathematics instructors reflected on and learned to address biases in their teaching while utilizing classroom observation software. EQUIP is a free, fully-customizable web app (https://equip.ninja) that automatically generates analytics and streamlines the coding of classroom video. The primary goals of our study were to understand how analytics could help instructors reflect on implicit bias in their teaching, and whether this was a productive approach for academic developers to use. The analytics helped participants recognize racialized and gendered patterns in their classrooms. We also found that instructors made a number of concrete changes to their teaching practices driven by the feedback. These changes focused on the types of questions that were asked of students, how student seating was arranged in the room, and which students were chosen to participate during discussion. Thus, this study provides evidence that technology can help generate data analytics to providing useful formative feedback to instructors.

Citation: Daniel L. Reinholz, Amelia Stone-Johnstone & Niral Shah (2020). Walking the walk: using classroom analytics to support instructors to address implicit bias in teaching, International Journal for Academic Development, 25:3, 259-272, DOI: 10.1080/1360144X.2019.1692211

Global Guidelines: Ethics in Learning Analytics

Institutions are stewards of primary and secondary level student data, subject to legislation and policy. However, institutions have broader rights and uses for adult learner data, under terms of service and regulation. In order to ensure that outputs from learning analytics applications are both valid and reliable, the institution needs to ensure that data collected and analyzed is both accurate and representative of the issue being measured. Proxy measures should be used with caution. models used to analyze, interpret and communicate learning analytics to stakeholders (support staff, advisers, faculties, students) should be sound, free from algorithmic bias; transparent where possible and clearly understood by the end users. Learning Analytics should be primarily used to support students, in student centered and inclusive ways, with student agency in mind.

Citation: Slade, S., Tait, A. (2019). Global Guidelines: Ethics in Learning Analytics**.** Retrieved July 13, 2021 from https://www.learntechlib.org/p/208251/.

Supporting the less-adaptive student: the role of learning analytics

In this empirical study into blended learning and the role of assessment for and as learning, we investigate learning processes of students with different learning profiles. This contribution addresses the way learning analytics can facilitate underperforming students when cognitive, rather than ethnic, factors are causing underachievement: students lacking appropriate prior schooling, or lacking appropriate learning dispositions required for successful learning. Outcomes suggest that the blended design of the module with the digital environments offering many opportunities for assessment of learning, for learning and as learning together with actionable learning feedback, is used more intensively by students of the less adaptive profile.

Citation: Tempelaar, D. (2020). Supporting the less-adaptive student: the role of learning analytics, formative assessment and blended learning. *Assessment & Evaluation in Higher Education*. *45*(4), 579-593.

TOPIC: Data & Analytics

Data and education transformation A maturity model.

This report considers countries at four different levels of “maturity” in their use of education analytics–Entry Level, Emerging, Advanced, and Transformative—regarding key aspects of data collection, reporting, and analysis. At the “Transformative Level” data come from a wide range of sources including telemetry, and analysis is supported by AI and cognitive services.

Citation: Damian, H., Hosh, K., Kavuma, K., Previs, D. & Cavanaugh, C. (2019). Data and education transformation A maturity model. Microsoft Education.
https://edudownloads.azureedge.net/msdownloads/Microsoft-Education-Transformation.pdf

Working Together in Learning Analytics towards the Co-Creation of Value

It is not enough to introduce stakeholders (e.g., teachers and students) to LA technologies; they must also be a part of the LA creation and design process. This paper clarifies and compares approaches of human-centred design through an overview of participatory frameworks in LA (co-design, co-creation). It also includes a case study using an LA tool used and developed over six years as an example of how LA designers can co-create dynamic platforms with teachers. A learning-centric data lifecycle includes collate, curate, analyze, act on, evaluate, and reflect. Co-creation through this cycle built trust and usability.

Citation: Dollinger, M., Liu, D., Arthars, N., & Lodge, J. M. (January 01, 2019). Working Together in Learning Analytics towards the Co-Creation of Value**.** *Journal of Learning Analytics, 6,* 2, 10-26.

Learning Analytics for School and System Management

There is no empirical evidence that it improves the performance of educational organizations. It is useful for specialized curricula, course management and redesigning learning materials for flexible learning opportunities, complex administrative tasks, student applications and enrollment processes.

Citation: Ifenthaler, D. (2021). In OECD Digital Education Outlook 2021: Learning Analytics for School and System Management. Paris: OECD Publishing. OECD Digital Education Outlook 2021: Pushing the Frontiers with Artificial Intelligence, Blockchain and Robots | READ online (oecd-ilibrary.org)

Utilizing learning analytics to support study success

This volume offers new research in such learning analytics and demonstrates how they support students at institutions of higher education by offering personalized and adaptive support of their learning journey. It focuses on four major areas of discussion: Theoretical perspectives linking learning analytics and study success; Technological innovations for supporting student learning; and Issues and challenges for implementing learning analytics at higher education institutions.

Citation: Ifenthaler, D., Mah, D. K., & Yau, J. Y. K. (Eds.). (2019). Utilizing learning analytics to support study success. Springer.

Data science in education: Big data and learning analytics

Big data and appropriate processing techniques offer great potential for improving business in companies and provide support for more intelligent decisions. Big data are summarized as four Vs: Volume (very large volume of data), Variety (various modalities), Velocity (rapid generation), and Value (huge value but very low density). This 4 Vs definition has been widely accepted as it indicates a serious problem in big data: how to find out the values from datasets with a massive scale, diverse types, and hasty generation. Big data can address some of the key challenges in higher education practice: 1. improving learners' experience 2. improving learners' knowledge through enhanced academic studying, 3. more effective evidence-based decision making, 4. strategic response to changing global trends, 5. opportunity for converting complex, often unstructured data into actionable information.

Citation: Klašnja-Milićević, A., Ivanović, M., & Budimac, Z. (2017). Data science in education: Big data and learning analytics. *Computer Applications in Engineering Education, 25*(6), 1066-1078.

A systematic review of learning analytics intervention and student success

As the number of students enrolling in universities continues to grow, different technologies have been implemented in universities with the purpose of enhancing students' retention, engagement and motivation, and to support the provision of recommendations, and intervention. Hence, the latest research study that has been conducted regarding LA illustrates the potential for LA to support learning and teaching practice, which can ultimately improve students' engagement and retention from the generated data through to deployment of the recommendations and interventions, based on the outcome of the analysis. The ultimate goal of LA is to optimize the learning process and learning outcomes. The findings show that most of the Learning Analytics Interventions have an impact on students' success in their learning, although some of them have little impact or no significant effect, and various Learning Analytics tools and strategies are discovered. Lastly, it is suggested that further Learning Analytics Interventions should be developed in order to meet the needs of students.

Citation: Na, K. S., & Tasir, Z. (2017, April). *A systematic review of learning analytics intervention contributing to student success in online learning***.** In 2017 International conference on learning and teaching in computing and engineering (LaTICE) (pp. 62-68). IEEE.

Learning analytics in education

This book is a comprehensive introduction to learning analytics. The goal of analytics is to guide decisions and can be informed by the framework of evidence centered design. Effective learning analytics applications include important learning interventions and insights made possible by analytics, measurable impact of the interventions and insights on outcomes that matter, and scalability of the intervention. Examples include analytics that assess learner content needs to recommend content for mastery learning, analytics that assess affect and engagement to personalize a learning experience or offer insights to teachers, analytics to assess motivation to recommend interventions that increase persistence, cognitive services that assess multi-modal open-ended learning tasks to provide formative feedback. For an education system to realize the potential benefits of data, they must build capacity by creating a culture of data-informed decision making, build their data infrastructure, build human capital, and build knowledge and skill among practitioners. Data focused PLCs, wallows, and sharing are effective approaches for districts.

Citation: Niemi, D., Pea, R., Saxberg, B., & Clark, R. (2018). Learning analytics in education**.** Charlotte, NC: IAP.

Learning Analytics: fundaments, applications, and trends

This book presents the broad learning analytics landscape and in-depth studies on higher education, adaptive assessment, teaching and learning. In addition, it discusses valuable approaches to coping with personalization and huge data, as well as conceptual topics and specialized applications that have shaped the current state of the art.

Citation: Peña-Ayala, A. (2017). Learning Analytics: fundaments, applications, and trends. A view of the current state of the art to enhance e-learning. Springer.

A Systematic Review on Data Mining for Mathematics and Science Education

Data mining in mathematics and science education has been commonly used to understand students' behavior and thinking process, identify factors affecting student achievements, and provide automated assessment of students' written work. Recently, researchers have tended to use such data mining techniques as text mining to develop learning systems for supporting teachers' instruction and students' learning.

Citation: Shin, D., & Shim, J. (April 01, 2021). A Systematic Review on Data Mining for Mathematics and Science Education. International Journal of Science and Mathematics Education, 19, 4, 639-659.

Adaptive and Adaptable Learning

This book constitutes the proceedings of the 11th European Conference on Technology Enhanced Learning, EC-TEL 2016, held in Lyon, France, in September 2016. Of interest: Assessing Learner-Constructed Conceptual Models and Simulations of Dynamic Systems (p. 358); Learning Research Strategies in MOOCs (p. 60).

Citation: Verbert, K., Sharples, M., & Klobucra, T. (2016). Adaptive and Adaptable Learning. Switzerland: Springer.

TOPIC: Data Science for Learning

Classroom Analytics: Zooming Out from a Pupil to a Classroom

The overarching function of classroom analytics, classroom orchestration, is fulfilled by implementing specific functions. The following seven specific functions represent the current possibilities:

1) Monitoring and Intervention. To monitor the state of the learner is the main function of classroom dashboards. The key functionality of the system is to make visible what is invisible (e.g., how long a learner has been silent, how much a learner dominates his teammates in a group discussion). The data processes are aggregation and evaluation to trigger an alert for teachers. The use of the dashboards increased learning gains.
2) Data propagation. Workflow, the flow of data across activities, enables rich pedagogical scenarios. Team formation and debriefing are especially relevant for classroom orchestration.
3) Team formation. A specific function of classroom analytics is to process the data produced by learners in one activity in order to form dynamic teams for a subsequent activity. The data operator used this function to maximize differences within teams.
4) Debriefing. This function includes reflecting on what has been done in order to extract concepts or principles to be taught. This exploration phase followed by direct instruction can be effective.
5) Timing transitions. Future dashboards are expected to provide more instances of similar time prediction tools, thus supporting teachers to introduce short activities without wasting time.
6) Teacher self-regulation. The input of classroom analytics can be any event in the classroom including the teacher's behavior. "Reflection-on-action" enables the teachers to reflect later in order to improve their teaching over time – a powerful form of professional development.
7) Orchestration. Classroom analytics aims to facilitate the orchestration of learning activities. Empowering teachers for better orchestration of learning is about supporting them in steering rich learning scenarios.

Citation: Dillenbourg, P. (2021). Classroom Analytics: Zooming Out from a Pupil to a Classroom. In OECD Digital Education Outlook 2021: Pushing the Frontiers with Artificial Intelligence, Blockchain and Robots. Paris: OECD Publishing. [OECD Digital Education Outlook 2021: Pushing the Frontiers with Artificial Intelligence, Blockchain and Robots | READ online (oecd-ilibrary.org)]

Where is the evidence? A call to action for learning analytics

Where is the evidence for learning analytics? In particular, where is the evidence that it improves learning in practice? Can we rely on it? Learning analytics as a field is not immune from the challenges facing empirical research in other disciplines, notably medicine and psychology. To validate the field, we must have evidence about whether learning analytics does improve learning and teaching in practice. As a field with an abundance of data, learning analytics should be well placed to produce such evidence. This paper's exploration of the evidence we have to date shows clearly that there is considerable scope for improving the evidence base for learning analytics.

Citation: Ferguson, Rebecca, & Clow, Doug. (n.d.). Where is the evidence? A call to action for learning analytics. (http://oro.open.ac.uk/48992/3/Evidence%20paper%20RF%20DC.pdf.) ACM.

Thinking critically about learning analytics and equity of attainment

It is unclear, from the research to date, that evidence on learning analytics' ability to helps address differential student outcomes for disadvantaged students. Learning analytics and academic analytics are primarily designed for the improvement of academic performance (although some do focus on retention); whilst learner analytics is more aligned to improving student engagement. Learning analytics research must interpret and communicate effectiveness qualitatively by including the student voice in assessments of impact. In one example, a "no engagement" alert was an effective predictor of poor outcomes and used to target intervention. Engagement time alone cannot predict outcomes. learning analytics research must interpret and communicate effectiveness qualitatively by including the student voice in assessments of impact. Learning and learner analytics should be backed by a theory of change that accounts for pedagogy.

Citation: Francis, P., Broughan, C., Foster, C., & Wilson, C. (2020). Thinking critically about learning analytics, student outcomes, and equity of attainment**.** *Assessment & Evaluation in Higher Education. 45*(6), 811-821.

Learning analytics goes to school: A collaborative approach to improving education

The book describes data-intensive approaches in research-practice partnerships to improve learning and outcomes. Data-intensive workflows are guided by research questions. Data are selected, understood, wrangled, explored, modeled and communicated in service of the questions. Data-intensive approaches may take the form of translational research, design-based implementation research, improvement science. A theory of action guides the data-intensive approach, underpinned by theory, and consisting of a description of the current state, hypothesized contributors, aligned interventions, early indicators to monitor, and a desired outcome. Collaborative data-intensive improvements (CDI) depend on trust, an explicit improvement method, sessions for collaboration and knowledge building, and shared workflows and tools. A CDI project has five phases.

Organize	Understand	Analyze	Co-develop	Test
Project team members Problems to solve Aims of the partnership	Primary data Rapid literature scan Practical improvement theory	Data analysis Wrangle, explore, model data Interpret products	High-leverage change ideas Opportunities to implement Scaffolds for implementation	Approach to testing ideas Testing Reflection on results

Citation: Krumm, A., Means, B., & Bienkowski, M. (2018). Learning analytics goes to school: A collaborative approach to improving education**.** New York: Routledge.

Demystifying learning analytics in personalized learning

This paper presents learning analytics as a mean to improve students' learning. Most learning analytics tools are developed by in-house individual educational institutions to meet the specific needs of their students. The paper concludes by highlighting framework of learning analytics in order to improve personalized learning. The paper proposes that learning analytics is dependent on personalized approach for both educators and students. From a learning perspective, students can be supported with specific learning process and reflection visualization that compares their respective performances to the overall performance of a course. Furthermore, the learners may be provided with personalized recommendations for suitable learning resources, learning paths, or peer students through recommending system.

Citation: Maseleno, A., Sabani, N., Huda, M., Ahmad, R., Jasmi, K. A., & Basiron, B. (2018). Demystifying learning analytics in personalized learning. *International Journal of Engineering & Technology, 7*(3), 1124-1129.

Teacher dashboards in practice: Usage and impact

Four stages are distinguished in this learning analytic process model. First, in the awareness stage the user becomes aware of the dashboard and the data available. Second, in the reflection stage the user interprets the data by asking questions and evaluating the relevance of these questions. In the third, sense making stage the user answers the relevant questions to further understand the value of the data. Finally, in the impact stage, the user's understanding of the data is employed to change his/her behavior. Teachers activate existing knowledge about the class and students to interpret dashboard data. The pedagogical actions teachers take after dashboard consultation are mainly providing individual feedback and additional instruction. The results show that pedagogical actions preformed at teachers' own initiative are mostly directed to low ability students, whereas actions after consulting the dashboard are more directed at middle and high ability students. Teachers, who consulted the dashboard more often, also activated more and different types of pedagogical knowledge to interpret the data. Consequently, they also engaged in more diverse pedagogical actions. In line with this development, teachers who view the dashboards more often also analyzed students' errors and progress more often. This was associated with more feedback and adjustment of students' pace and learning materials. This suggests that more diverse teaching practices are associated with awareness, reflecting and sense making of the dashboard data.

Citation: Molenaar, I., Knoop-van, C. C., & 12th European Conference on Technology Enhanced Learning, EC-TEL 2017. (January 01, 2017). Teacher dashboards in practice: Usage and impact. *Lecture Notes in Computer Science (including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics),* 125-138.

Co-designing learning analytics tools with learners

This chapter discusses a set of co-design tools and techniques that can be put into practice to increase the likelihood of successful deployment of learning analytics into classrooms, institutions and learning spaces. This chapter presents: a) an overview of how Design Thinking may help in the co-design process of learning analytics; b) a brief review of the current literature exploring co-design for education and learning analytics; and c) illustrative examples. Tools and techniques that can be used for creating understanding, defining characteristics, and building prototypes in a learning analytics project include persona profile, user journey, focus group, knowledge mapping and prototyping.

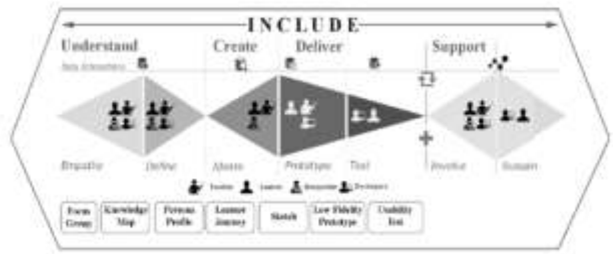

Figure 8. Tools and techniques for a co-design process used to involve MDSI learners at UTS to design learning analytics means to support the development of their graduate attributes.

Citation: Prieto-Alvarez, C, Martinez-Maldonado, R, & Anderson, T. (2019). *Co-designing learning analytics tools with learners***.** Routledge.

How to Make Data Work: A guide for Educational Leaders

How to Make Data Work provides clear strategies for getting data into workable shape and creating an environment that supports understanding, analysis, and successful use of data, no matter what data system or educational technology tools are in place in your district. This resource makes data easy to understand and use so that educators can better evaluate and maximize their systems to help their staff, students, and school succeed. For example, clear and detailed display footers and reference sheets can double or triple the accuracy with which educators use the information.

Citation: Rankin, J. G. (2016). How to Make Data Work: A guide for Educational Leaders. Taylor and Francis.

Engaging students as co-designers of learning analytics

This paper shares strategies and insights from a co-design process that involved students in the development of a LA tool, describes the participatory design workshops, and highlights three strategies for engaging students in the co-design of learning analytics tools. In design sessions with students, as a starting point for an ideation brainwriting session (where participants wrote long lists of ideas for solutions), students were presented with a set of cards (Fig. 2), which had (a) inferences that could potentially be made based on the available data (for example “which readings have you opened?”), and (b) action phrases which suggested potential uses for such information (such as “compare”; “help you understand”).

Figure 1: Structure of co-design workshops

Citation: Sarmiento, J. P., Campos, F., & Wise, A. F. (2020). Engaging students as co-designers of learning analytics. In Companion proceedings of the 10th international learning analytics and knowledge conference (pp. 29–32). Frankfurt: SoLAR.

Towards actionable learning analytics using dispositions

The impact of learning analytics on improved learning depends on interventions influenced by data, which require understanding why students act as they do. The authors studied the effects of using a combination of demographic, activity, and self-reported data of eight contemporary social-cognitive theories of education.

Citation: Tempelaar, D., Rienties, B., & Nguyen, Q. (January 01, 2017). Towards actionable learning analytics using dispositions**.** Ieee Transactions on Learning Technologies, 10, 1, 6-16.

Digital education governance: data visualization, predictive analytics, and policy

Examples of large-scale public education sets for query and analysis include the UK Education data Lab, OECD PISA. An example of a large-scale education data visualizations is the Pearson Learning Curve Databank.

Citation: Ben Williamson (2016) Digital education governance: data visualization, predictive analytics, and 'real-time' policy instruments**,** Journal of Education Policy, 31:2, 123-141, DOI: 10.1080/02680939.2015.1035758

Big Data in Education

This book is a high-level overview of data concepts, issues, and implications in education. Goals of data-driven education systems should include personalizing instruction, evidence-based learning, efficiency, continuous innovation.

Citation: Williamson, B. (2017). Big Data in Education**.** Los Angeles: Sage.

TOPIC: Dashboards & Reporting

Teaching with learning analytics

Most research on computer-based assessments suggests benefits of direct feedback on students' learning performance, but little information is available on how teachers can connect computer-based assessment data to classroom instruction. To use data for their teaching practice, teachers preferred data with detailed information about each student, task and response. Implications: The tool should be designed to provide accurate assessment information for teachers to prepare and perform their feedback in class. This means easy to-get overviews of student scores, quantitative and qualitative, and with enough details. Also, teachers desire support in more ways than providing them with relevant and accurate assessment data; they need communities of practice and professional development.

Citation: Admiraal, W., Vermeulen, J., & Bulterman-Bos, J. (2020). Teaching with learning analytics: how to connect computer-based assessment data with classroom instruction*?***.** *Technology, Pedagogy and Education, 29*(5), 577-591.

Human-Centered Learning Analytics

Learning analytics design processes need to consider a range of human factors, including why and how they will be used. In this editorial, authors introduce principles of human-centered design developed in other, related fields that can be adopted and adapted to support the development of human-centered learning analytics (HCLA). It is sensible to change the tools to suit their users, rather than changing the users to suit the tools. This perspective could shift the focus away from providing users with data to interpret, and toward providing them with answers to the questions they are asking. Involving stakeholders may be perceived as difficult, time-consuming, and expensive. Nevertheless, involving them throughout the design process can make the difference between an unsuccessful prototype and a system that is taken up successfully.

Citation: Buckingham, S. S., Ferguson, R., & Martinez-Maldonado, R. (July 22, 2019). Human-Centered Learning Analytics**.** *Journal of Learning Analytics, 6,* 2.

Research Evidence on the Use of Learning Analytics - Implications for Education Policy

Much of the current work on learning analytics concentrates on the supply side – the development of tools, data, models and prototypes. There is considerably less work on the demand side – i.e. on how analytics connect with education and the changes that school administrators, teachers and students want these tools to make in order to support their everyday learning, teaching and assessment work. Tools seem to be focusing currently on visualizing engagement and activity developing systems that provide early alerts and eventually target interventions. These data visualizations are not necessarily 'actionable' in the way that learning analytics should be. In other words, they do not reveal what actions should be taken to improve learning and teaching. Also, efforts focus mainly on identifying students who may drop out and less on innovative pedagogical processes and practices, or on helping educational organizations to fully embrace the digital era. Analytics should empower learners and teachers to make the right decisions for their needs. There is a need to do more work on that empowerment, with a focus on building rich datasets that will enable us to support the human side of learning. If we want to encourage teachers and learners to make use of analytics, then those analytics should provide delight. The **LACE Evidence Hub** is designed as a tool to help people to make evidence–based decisions about learning analytics, whether they are teachers, managers, researchers or policymakers. The Evidence Hub gathers research evidence from around the world on learning analytics.

Citation: Ferguson, R., Brasher, A., Clow, D., Cooper, A., Hillaire, G., Mittelmeier, J., Rienties, B., Ullmann, T., Vuorikari, R. (2016). Research Evidence on the Use of Learning Analytics - Implications for Education Policy. R. Vuorikari, J. Castaño Muñoz (Eds.). Joint Research Centre Science for Policy Report; EUR 28294 EN; doi:10.2791/955210.

Awareness is not enough. Pitfalls of LAD in the educational practice

Self-regulated learning is the core theory that informs the design of LA dashboards that aim to make learners aware of their learning process by visualizing their data. However, just making learners aware is not enough. Dashboards should have a broader purpose, using awareness and reflection as means to improve cognitive, behavioral or emotional competencies. Secondly, effective support for online learners that do not have well developed SRL skills should also facilitate goal setting and planning and monitoring and self-evaluation. As dashboards mostly aim to increase awareness and trigger self-reflection, different tools should complement dashboards and be seamlessly integrated in the learning environment and the instructional design. Thirdly, there is a strong emphasis on comparison with peers as opposed to using goal achievement as reference frame. However, there is evidence in educational sciences that disproves the benefits of fostering competition in learning.

Citation: Jivet, I., Scheffel, M., Drachsler, H., & Specht, M. (2017). *Awareness is not enough. Pitfalls of learning analytics dashboards in the educational practice***.** Springer International Publishing AG.

Effects of LAD: dashboard utilization, satisfaction, and learning achievement

In an experimental study, students who received dashboard treatment presented a higher final score than those who did not.

Citation: Kim, J., Jo, I.H., Park, Y.: Effects of learning analytics dashboard: analyzing the relations among dashboard utilization, satisfaction, and learning achievement**.** Asia Pac. Educ. Rev. 17(1), 13–24 (2016).

Development of the learning analytics dashboard to support students' learning

As a result of user research, a scaffolding strategy to help students understand the meaning of the information displayed was included in each sub section of the dashboard. To mitigate students' difficulties in understanding graphs and to remind them of the goal of this dashboard, we decided to 1) include a 'help' menu as a guide on how to read the graphs, 2) consider an alternative of scatter graph to the one which was recognized as difficult to understand, and 3) provide scaffolding texts that allow students to reflect on the dashboard information and connect the information with their future learning and behavioral changes. Because users have different levels of understanding, two kinds of dashboard (advanced and simple version) were made.

Citation: Park, Y., & Jo, I.-H. (January 01, 2015). Development of the learning analytics dashboard to support students' learning performance. Journal of Universal Computer Science, 21, 1, 110-133.

Factors that affect the success of learning analytics dashboards

Dashboards were evaluated based on the framework of Kirkpatrick's four levels of evaluation using five criteria: visual attraction, usability, level of understanding, perceived usefulness, and behavioral changes. The visual attraction and usability of the dashboard significantly affected the level of understanding, and level of understanding affected perceived usefulness, which in turn significantly affected potential behavior changes. Implications from Few's design principles for dashboards are as follows: (a) the most important information should stand out from the rest in the dashboard, which usually has limited space and must ft on a single screen; (b) the information in a dashboard should support one's situational awareness and facilitate rapid perception using diverse visualization technologies; (c) the information should be deployed in a way that makes sense, and each element should support viewers' immediate and end goals for decision-making. Based on research, dashboard adaptions were made. For example, students' overall satisfaction with the LAD correlated with their understanding of the graphs, and thus, we incorporated "HELP" buttons to guide students on how to read the graphs.

Citation: Park, Y., Jo, I.-H., & SpringerLink (Online service). (2019). *Factors that affect the success of learning analytics dashboards*. (Educational technology research and development.

Designing Data Reports that Work

The strategies in this book will help those responsible for designing education data reports—including school leaders, administrators, and educational technology vendors—to create productive data reports individualized for each school or district. *Designing Data Reports that Work* provides research-based best practices for constructing effective data systems in schools and for designing reports that are relevant, necessary, and easily understood. For example, data reports should contain only information crucial to important decisions, with uncluttered titles and footers. Reports and displays should be co-designed with users.

Citation: Rankin, J. G. (2016). Designing Data Reports that Work. Taylor and Francis.

Standards for reporting data to educators: What educational leaders should know and demand

A synthesis of research and best practices of how data should be presented to educators in order to optimize the effectiveness of data use. Synthesizing over 300 sources of peer-reviewed research, expert commentary, and best practices, Rankin develops a set of data reporting standards that education data system vendors, providers, and creators can apply to improve how data is displayed for educators.

Citation: Rankin, J. G. (2016). Standards for reporting data to educators: What educational leaders should know and demand. New York, N.Y: Routledge.

The proof of the pudding: evaluation framework for learning analytics

Learners' achievement could be increased by allowing them access to a learning analytics dashboard, i.e. a collection of visualizations. They also point out that LA visualizations should be carefully designed if interest in and usage of the dashboard and analytics is to be maintained by the main stakeholders, i.e. learners and teachers. It depended on the students' achievement goal orientation whether the effect of the visualizations on learning progress was positive or negative. For user feedback on a tool in learning analytics, use the **Evaluation Framework for Learning Analytics (EFLA)**. Using the subjective assessments by their users is a quick and simple way to get a general indication of the overall quality of a tool.

Citation: Scheffel, M., Drachsler, H., Toisoul, C., Ternier, S., Specht, M., Drachsler, H., Drachsler, H., ... 12th European Conference on Technology Enhanced Learning, EC-TEL 2017. (January 01, 2017). The proof of the pudding: Examining validity and reliability of the evaluation framework for learning analytics. *Lecture Notes in Computer Science (including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics),* 194-208.

A Systematic Literature Review of Learning Dashboard Research

In their literature review, the authors found that most studies were exploratory and proof-of-concept. Research on learning dashboards aimed to identify what data are meaningful to stakeholders (learners, instructors, and administrators) and how data can be presented to support sense-making processes. Dashboards are developed to provide visual display of the most important information needed to achieve objectives; a real-time user interface, showing a graphical presentation of the current status (snapshot) and historical trends; a container of indicators; an emerging performance management system; a display which visualizes of the results of educational data mining; visualizations of learning traces. The authors classified dashboard data into six indicator types: Learner related, Action-related, Content-related, Result-related, Context-related, and Social-related. Very few studies actually examined the impact of the dashboards on learning.

Citation: Schwendimann, B. A., Rodriguez-Triana, M. J., Vozniuk, A., Prieto, L. P., Boroujeni, M. S., Holzer, A., Gillet, D., ... Dillenbourg, P. (January 01, 2017). Perceiving Learning at a Glance: A Systematic Literature Review of Learning Dashboard Research. Ieee Transactions on Learning Technologies, 10, 1, 30-41.

A systematic literature review on learner-facing learning analytics dashboards

Experimental or quasi-experimental research designs could be adopted more often to provide stronger evidence of causality between specific components of LADs (independent variables) and an outcome of interest (eg, learning performance). Further, there is a need and an opportunity for more LAD studies to be conducted in other contexts such as K-12 and informal learning environments. This new direction would offer practitioners a broader range of designs based on the specific needs of their learners.

Citation: Valle, N., Antonenko, P., Dawson, K., & Huggins-Manley, A. C. (2021). A systematic literature review on learner-facing learning analytics dashboards**.** British Journal of Educational Technology. British Journal of Educational Technology, 00, 1-25. https://doi.org/10.1111/bjet.13089

Effects of a Teacher Dashboard for an Intelligent Tutoring System

Even though teachers generally know their classes well, a dashboard with analytics can still enhance their knowledge about their students and support their classroom practices. The teachers tended to focus primarily on dashboard information about the challenges their students were experiencing. A dashboard can affect teacher knowledge, decision-making and actions in the classroom.

Citation: Xhakaj, F., Aleven, V., & McLaren, B. M. (January 01, 2017). Effects of a Teacher Dashboard for an Intelligent Tutoring System on Teacher Knowledge, Lesson Planning, Lessons and Student Learning.

Learner Analytics; The Need for User-Centered Design in Learning Analytics

In a higher education context, the authors used HCI methods to find that learners want to be able to access an overarching view of their previous, current and future learning activity. They propose placing the learner at the center, giving them control of their own Learner Analytics. Regarding instructors, interviews showed that VLE dashboards are rarely used and do not support the questions that they would like to answer about their students' learning activity. Instructors indicated that there is no easily accessible method for seeing a student's overall level of interaction on all modules, or a way of identifying clusters of students and their usage of specific types of resource; areas that have been identified as having significant potential in identifying students at risk of failing within a module.

Citation: E,. Q., M, T., N, W., & T, K. (September 14, 2016). Learner Analytics; The Need for User-Centered Design in Learning Analytics**.** Eai Endorsed Transactions on Ambient Systems, 9, 1-4.