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Learning analytics in higher education – Stakeholders, strategy and scale

1. Introduction

The growing prominence of digital technologies in higher education creates a futile ground for collection, analysis, and use of digital data. Higher education institutions are increasingly developing strategies for digital learning which rely on the extensive use of digital technology to transform or "flip" pedagogical practices towards more active and flexible learning. Digital technologies in education have receive much attention on different policy levels, change experience for learners, and present a rapidly growing market segment, more so than ever since the global COVID-19 crisis forced educational providers to move teaching online rapidly at scale. The evolution of education in recent years has prompted us to ask, what role does learning analytics have to play as a field that aims to harness unprecedented amounts of digital data? According to the definition adopted by the Society for Learning Analytics Research (Long, Siemens, Conole, & Gašević, D. (Eds.)., 2011), learning analytics is defined as "the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimising learning and the environments in which it occurs." The ability to collect, analyse, and use diverse datasets in a large volume and high speed makes learning analytics an attractive solution for higher education institutions that seek to improve their understanding of learning and identify opportunities for educational interventions.

Over the past decade, the field of learning analytics has demonstrated promising results in several areas, including identifying students at risk (Herodotou, Naydenova, Boroowa, Gilmour, & Rienties, 2020), personalising feedback at scale (Pardo, Jovanovic, Dawson, Gašević, & Mirriahi, 2019), enhancing student success (Lim et al., 2021), and improving learning design (Lodge, 2020; Schmitz et al., 2018; Schmitz, Scheffel, van Limbeek, Bemelmans, & Drachsler, 2018). Although many higher education institutions have made much early investment in learning analytics, there are remaining challenges that need to be resolved to demonstrate the impact of learning analytics in higher education (Guzmán-Valenzuela, Gómez-González, Rojas-Murphy Tagle, & Lorca-Vyhmeister, 2021). There has been particularly limited research on perspectives and involvement of all *stakeholder* groups in institutional planning and implementation of learning analytics. Although some pioneering work has been done on the development of learning analytics policy (Scheffel, Tsai, Gasevic, & Drachsler, 2019; Sclater, 2016; Tsai et al., 2018), there remain insufficient reports on the ways how institutions develop and enact *strategies* for the adoption of learning analytics. Finally, while several studies have demonstrated promising results of learning analytics, as mentioned earlier, there has been insufficient research on ways to *scale* the success to institution-wide adoption and impact. In response to these open challenges in learning analytics, this special issue aims to address *stakeholder perspectives and involvement*, *strategy development and enactment*, and *scalable implementations*.

2. Trends and challenges

Over the past decade, learning analytics as a field continues to see a steady growth (Guzmán-Valenzuela et al., 2021). A recent study identified that top research topics in the field are related to predictive and descriptive analytics in addition to engagement patterns and resource use (Chen, Rolim, Mello, & Gašević, 2020). Moreover, compared to the field of educational data mining, learning analytics as a field pays more attention to effects on teaching and learning practices (ibid.) These observed trends have been consistent with the three focus areas identified in the early days of the field (Brown, 2012): 1) predictors and indicators, 2) visualisations, and 3) interventions.

The first focus area is related to the analysis of data from a learning scenario, which may subsequently be used to establish a predictive model for the purpose of predicting student performance and implementing early/ timely intervention. Common sources of data used for prediction models include class performance, learning activities, and prior academic data, while popular machine learning methods are Naïve bayes, neural networks, decision trees, and clustering (Al-Tameemi, Xue, Ajit, Kanakis, & Hadi, 2020). They are applied to different aspects of data about learning, such as classifying learners for formative feedback and predicting summative learning outcomes. An emerging research topic within the first focus area is to what extent inferences based on empirical data from standardized assessments (psychometrics) can be compared with learning analytics outcomes driven by data gathered in digital learning environments (Drachsler & Goldhammer, 2020).

The second focus area is related to the *visualisation and presentation* of data analysis results for the purpose of interpretations and decision-making by key stakeholders such as administration personnel, educators, or students. This area of research and practice is representable by learning analytics dashboards (LADs). Matcha, Ahmad Uzir, Gasevic, and Pardo (2020) identified 8 themes that LADs commonly track including competency, emotions, game-based learning, learning progress, learning design, learning difficulty detection, study plan, and teamwork progress. However, despite the fact that designs of LADs mostly serve to enhance self-regulated learning skills (Jivet, Scheffel, Drachsler, & Specht, 2017), reviews have found a significant gap in grounding LAD design and the evaluation of LAD effectiveness in learning theories (Jivet, Scheffel, Specht, & Drachsler, 2018; Matcha

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et al., 2020). A pressing research topic within the second focus area is therefore how learners' goals, decision and self-regulated learning skills are related to their action on visual feedback and presentations (Jivet et al., 2021; Saint, Fan, Singh, Gasevic, & Pardo, 2021).

The third focus area is linked to interventions based on the analysis of data about learners and their learning progress and is meant to close feedback loops with actions taken by educators (e.g., nudging or checking on students, recommending learning resources, or adjusting the teaching delivery), students (e.g., developing or adjusting learning strategies and seeking support), or administration personnel (e.g., adjusting institutional strategic focuses, managing student enrolment, and orchestrating resources). For example, OnTask is a tool that can facilitate interventions based on learning analytics by assisting educators to personalise feedback at scale (Pardo et al., 2019). MyLA is a student-facing dashboard that is intended to help students monitor their own learning progress and make assignment planning (Kia, Teasley, Hatala, Karabenick, & Kay, 2020). LADA is a learning analytics dashboard that utilises comparative and predictive analysis to support academic advisers in study-related counselling (Gutiérrez et al., 2020). In general, learning analytics interventions aim to affect learning in three broad areas: learning environment (including the awareness and productivity of teachers in addition to learning materials), learning progress (including the awareness and productivity of learners, self-regulated learning engagement, and online activity and behaviour), and learning outcomes (including academic grades, learning gain, retention, and dropout) (Knobbout & van der Stappen, 2020). Despite success reported in a number of studies (e.g., Jovanović, Gašević, Pardo, Dawson, & Whitelock-Wainwright, 2019; Lim et al., 2021; van Leeuwen, Janssen, Erkens, & Brekelmans, 2014), reviews of the overall development of the field demand for the third focus area to improve the rigour of impact evaluations and evidence of positive influence on learning (Ferguson & Clow, 2017; Knobbout & van der Stappen, 2020; Viberg, Hatakka, Bälter, & Mavroudi, 2018; Wong & Li, 2020).

Despite the growth of research in the three focus areas, the impact of learning analytics in the real world is yet limited partly due to the continuing predominance of small-scale adoption (Dawson, Joksimovic, Poquet, & Siemens, 2019; Tsai et al., 2020; Viberg et al., 2018). This phenomenon has been attributed to issues related to the complex nature of educational systems (Dawson et al., 2018; Macfadyen, Dawson, Pardo, & Gaševic, 2014), emphasis on analytics over learning (Guzmán-Valenzuela et al., 2021; Williamson, Bayne, & Shay, 2020), high demand on technological infrastructure and resources (Klein, Lester, Rangwala, & Johri, 2019), stakeholder engagement (e.g., resistance, skills, and trust) (Alfy, Gómez, & Dani, 2019; Jones et al., 2020), and ethics and privacy (Hakimi, Eynon, & Murphy, 2021; Prinsloo & Slade, 2016). These issues have inspired a number of frameworks that aim to promote responsible, equitable, and effective use of student data in higher education.

3. Framework of learning analytics in higher education

Early work in learning analytics provides some proposals for models of learning analytics that identify dimensions of learning analytics and process phases (Table 1). A reference model of learning analytics is suggested by Chatti, Dyckhoff, Schroeder, and Thüs (2012) that identifies four key dimensions of learning analytics each one dedicated to the following four questions: what – data, environment, and context; why – objectives; how – methods; and who – stakeholders. Similarly, these four dimensions, with somewhat different names and scope, are also recognized in a generic framework for learning analytics proposed by Greller and Drachsler (2012). The Greller & Drachsler framework also includes internal limitations (i.e., competencies and acceptance) and external constraints (i.e., norms and conventions). An interactive process model of learning analytics is suggested by Steiner, Kickmeier-Rust, and Türker (2014) through a synthesis of several other process models and consist of the following phases: data selection, data capturing, data aggregation, data reporting, prediction, acting upon results, and refinement. Finally, Siemens, Dawson, and Lynch (2013) propose a model of learning analytics sophistication by distinguishing between five-levels of sophistication in higher education.

Table 1
Three focuses of learning analytics adoption frameworks.

Getting started	Maximising impacts	Involving stakeholders
Four dimensions: what, why, how, and who (Chatti et al., 2012)	Six dimensions of policy and strategy development: context, stakeholders, changes, strategy, capacity, and monitoring (Tsai et al., 2018)	Let's Talk Learning Analytics framework: prompts for dialogue with key stakeholders (West, Heath, & Huijser, 2016)
Six critial dimensions: objectives, data, instruments, stakeholders, internal limitations, and external constraints (Greller & Drachsler, 2012)	Five critical success factors: strategy and policy, information readiness, performance evaluation, skills and expertise, and data quality (Clark et al., 2020)	SHEILA framework: prompts for policy development considering key stakeholders (Tsai et al., 2018)
Seven phases: data selection, capturing, aggregation, reporting, prediction, acting upon results, and refinement (Steiner et al., 2014)	Three dimensions of learning gains: socio-communicative, cognitive, metacognitive, and affective (Blumenstein, 2020)	OrLA framework: a template for communication among teachers, developers and researchers (Prieto, Rodríguez-Triana, Martínez-Maldonado, Dimitriadis, & Gašević, 2019)
Five levels of maturity: aware, experimentation, adoption, organisational transformation, sector transformation (Siemens et al., 2013)	Value creation roadmap: building capability, moderating barriers, and establishing a value realisation process (Sheikh et al., 2021)	A CPD framework: three levels of awareness and capability raising among students, academic staff and professional services staff (Gray, Schalk, Rooney, & Lang, 2021)

With the maturity of the field over the years, recently proposed frameworks for learning analytics adoption have shifted the focus from 'how to get started with learning analytics' to 'how to implement learning analytics successfully' (Gasevic, Tsai, Dawson, & Pardo, 2019; Tsai et al., 2018) as shown in Table 1. As a response to the challenges outlined earlier, there is growing awareness to refocus on outcomes and impacts. For example, building on a Rapid Outcome Mapping Approach, the SHEILA framework emphasises the identification of desired changes and establishing monitoring processes as part of the six key dimensions that need to be considered in learning analytics policy and strategy development (Tsai et al., 2018). Taking an information system perspective, Clark, Liu, and Isaias (2020) identified five critical success factors that need to be integrated into adoption objectives, including strategy and policy at organisational level, information technological readiness, performance and impact evaluation, people's skills and expertise and data quality. Focusing on learning gains, the LALGD model draws connections between meaningful data capture and learning design approaches that enable socio-communicative, cognitive, metacognitive, and affective learning gains (Blumenstein, 2020). Finally, focusing on the creation of strategic value through the use of learning analytics, Sheikh, Bhatia, Metre, and Faqihi (2021) proposed a conceptual framework for value creation that involves building capability, moderating factors that can influence the translation of efforts into value, and establishing a value realisation process including exploring value creation mechanisms, identifying value targets, and evaluating impact.

A common element in these frameworks is the central role played by stakeholders. Stakeholder engagement is crucial to the delivery of IT products and services, and the range of stakeholders involved in a learning analytics process has brought the stakeholder element to the fore of any learning analytics related strategy. The differences among different stakeholders' needs, responsibilities, autonomy, knowledge, and skills related to learning analytics inevitably result in different expectations of and experience with learning analytics. Various models have thus been proposed by researchers to ease the process of multi-stakeholder involvement (Table 1). For example, the Let's Talk Learning Analytics framework (West et al., 2016) provides prompts for dialogue among key stakeholders especially in the context of adopting learning analytics for retention related goals. The SHEILA framework (Tsai et al., 2018) similarly provides prompts to guide the development of policies for learning analytics considering key stakeholders. The OrLA framework (Prieto et al., 2019) is a communication tool that aims to foster a common understanding among teachers, developers and researchers, thus ensuring that decisions made about learning analytics design and implementation serve the needs. Finally, a CPD framework developed by Gray et al. (2021) serves to raise the awareness and capability among students, academic staff, and professional services staff at three levels: knowing what learning analytics means to them, understanding how to use learning analytics, and identifying actions to take and implications of the actions.

4. Papers and key themes in this special issue

This special issue is a response to the emerging trends in the field with a particular focus on *stakeholders, strategy,* and *scale*. Although small-scale adoption of learning analytics based on educators' own initiatives tend to speak directly to the stakeholder's needs and can have profound network effects (through peer sharing), not only can the impact be limited due to the possible constraint of data available for greater insights (e.g., making predictions), but innovations can also lose momentum due to a lack of sustainable support in obtaining necessary resources and in addressing prominent challenges mentioned earlier. However, scaling learning analytics in higher education requires a defined strategy that engages relevant stakeholders to work together towards the desired goals. Co-design has emerged as a commonly adopted or recommended approach to achieve this goal across the articles included in this special issue. Overall, the included articles present recent initiatives and discussion around themes including *measuring stakeholder expectation and needs*, *evaluations of impact*, and *scaling adoption of learning analytics* (Table 2).

Table 2
Themes and contributions of the papers included in the special issue.

Theme	Paper	Contribution
Stakeholder expectations and needs	Kollom et al. (2021)	Analysed expectations of academic staff towards learning analytics at four universities in Europe
	Whitelock-Wainwright et al. (2021)	Identified differences in student expectations of learning analytics at a fully online university in the Netherlands
	Hilliger et al. (2020)	Contrasted perspectives from teaching staff, students, and senior managers at four universities in Latin America
Evaluations of impact	Vigentini, Liu, Arthars, and Dollinger (2020)	Reports on success and lessons learnt from two cases of learning analytics adoption in Australian universities
	Antonette, Knight, and Buckingham Shum (2020)	Evaluated educators' experience in integrating a student-facing learning analytics tool into learning design at an Australian university
	Herodotou, Rienties, et al. (2020)	Analysed usage and experience of educators of a predictive learning analytics system at an open university in the UK
Scaling adoption	Munguia, Brennan, Taylor, and Lee (2020)	Discusses lessons learnt from scaling learning analytics at an Australian university
	Tsai, Kovanović, and Gašević (2021)	Analysed factors that are associated with adoption of learning analytics in 27 European universities
	Knight, Gibson, and Shibani (2020)	Proposed a model of learning analytics directed towards implementation and impact
	Selwyn (2020)	Highlights the importance of understanding political elements and inherent tensions that may surround adoption of learning analytics

Starting with *measuring stakeholder expectations and needs* for purposes such as identifying learning analytics strategy or deciding design requirements, Kollom et al. (2021) compared academic staff's expectations across four higher education institutions and identified a common interest in using learning analytics to enable early interventions among other areas. They also observed consistently low desires to act on learning analytics results obligatorily. The study based on a distance-learning university by Whitelock-Wainwright, Tsai, Drachsler, Scheffel, and Gašević (2021), on the other hand, provides a nice contrast from student perspectives. They found a consistent desire for the university to safeguard students against ethics and privacy related issues. However, when it comes to service aspects, expectations vary though mature students generally had stronger desires for learning analytics than the others. The study by Hilliger et al. (2020) based in four Latin American universities brought together perspectives from teaching staff, students, and senior managers. The teaching staff expressed a particular interest in using learning analytics to evaluate the effectiveness of their teaching practices; the students desired to get quality feedback and timely support, whereas the managers hoped to get quality information to evaluate the effectiveness of interventions.

When it comes to *evaluations of impact*, we noted more involvement of teaching staff, administrative personnel, and researchers than other stakeholders. This is somewhat in line with the previous research by Buckingham Shum, Ferguson, and Martinez-Maldonado (2019) and Tsai et al. (2020) published elsewhere indicating that educators appear to be the main end-users of learning analytics rather than students. The autoethnographic study by Vigentini et al. (2020) presents success and learnt lessons from two adoption cases, using the SHEILA framework (Tsai et al., 2018) as a reflection tool. In particular, they highlight the need for a continuous reflection on the purpose and aims of learning analytics and the need to translate values of learning analytics to different stakeholders. The study by Antonette et al. (2020) evaluated educators' experience in integrating a student-facing tool, AcaWriter, into their learning design. It became clear that the introduction of a new technology could be disruptive to teaching, and enhancing the agency of educators through a co-design process could significantly improve the design of learning analytics and support authentic learning. Finally, Herodotou, Rienties, et al. (2020) investigated the usage and educators' perspectives of a predictive learning analytics system (OUA), which was implemented on a large scale at the Open University in the UK. Although OUA was perceived as useful in supporting new students and those struggling with learning in addition to saving themselves time from checking distributed sources of information about students, the authors highlight a need for a university-wide policy to guide communications between teachers and students.

Scaling adoption of learning analytics to an enterprise-level usually takes multiple phases and continuous learning from the evaluations of each phase. The article by Munguia et al. (2020) present valuable lessons learnt in a journey of scaling learning analytics at a large Australian university. A "fail-fast strategy" was adopted to seek feedback early on a minimum viable product and to keep a "live" pilot, which served to improve the product constantly over the time based on the feedback and learnt lessons. In a similar vein, Tsai et al. (2021) highlight the importance of setting up short-term goals and regular evaluations to ensure the alignment of strategy and desired changes. Their analysis of learning analytics implementation in 27 higher education institutions shows prominent factors that influence adoption at different stages. While context factors are the most influential in the early phase of strategy development, institutions need to pay more attention people related issues as they move learning analytics into the operation phase.

As mentioned earlier, recent models proposed for learning analytics adoption reflect a growing interest in impact-focused strategies as a response to previous calls for evidence of learning enhancement in the field (Ferguson & Clow, 2017; Knobbout & van der Stappen, 2020; Viberg et al., 2018; Wong & Li, 2020). A model of learning analytics directed towards implementation and impact proposed by Knight et al. (2020) exemplifies this trend. In particular, they argue that integrations of learning analytics with pedagogical practices should inform the definition of impact. Evaluations of impact should not simply focus on scale but on individual student learning and how interventions may be transferrable to different learning contexts. Despite the increasing focus on outcomes and impacts, Selwyn (2020) reminds us in this special issue that the means to the end matter. What one learner perceives as support may be control or surveillance experienced by another learner. The political elements of learning analytics are inherent to tensions that occur in negotiations over power among stakeholders, or between human and machine, and the fundamental clashes in ontological assumptions about learning and learners. Scaling learning analytics and impact may very much depend on how well we navigate these political tensions.

Overall, the ten articles included in this special issue speak about the social complexities and the importance of anchoring learning analytics to pedagogical practices. It is clear that institutional capacity for learning analytics rely on "social infrastructure and technical infrastructure in tandem", as Knight et al. (2020, p. 12) put it. This special issue invites researchers and practitioners to explore the interconnected links among stakeholders, strategy, and scale as we continue to seek opportunities to address challenges in higher education through innovations with learning analytics.

References

Alfy, S. E., Gómez, J., & Dani, A. (2019). Exploring the benefits and challenges of learning analytics in higher education institutions: A systematic literature review. *Information Discovery and Delivery, 47*(1), 25–34. https://doi.org/10.1108/IDD-06-2018-0018

Al-Tameemi, G., Xue, J., Ajit, S., Kanakis, T., & Hadi, I. (2020). Predictive learning analytics in higher education: Factors, methods and challenges. In *Proceedings of the 2020 international conference on advances in computing and communication engineering, Paper #3*. https://doi.org/10.1109/icacce49060.2020.9154946

Antonette, S., Knight, S., & Buckingham Shum, S. (2020). Educator perspectives on learning analytics in classroom practice. *The Internet and Higher Education, 46*, 100730. https://doi.org/10.1016/j.iheduc.2020.100730

Blumenstein, M. (2020). Synergies of learning analytics and learning design: A systematic review of student outcomes. *Journal of Learning Analytics, 7*(3), 13–32. https://doi.org/10.18608/jla.2020.73.3

Brown, M. (2012). *Learning analytics: Moving from concept to practice (ELI briefs, pp. 1–5)*. EDUCAUSE. https://library.educause.edu/resources/2012/7/learning-analytics-moving-from-concept-to-practice.

Buckingham Shum, S., Ferguson, R., & Martinez-Maldonado, R. (2019). Human-centred learning analytics. *Journal of Learning Analytics, 6*(2), 1–9. https://doi.org/10.18608/jla.2019.62.1

Chatti, M. A., Dyckhoff, A. L., Schroeder, U., & Thüs, H. (2012). A reference model for learning analytics. *International Journal of Technology Enhanced Learning, 4*(5/6), 318–331. https://doi.org/10.1504/IJTEL.2012.051815

Chen, G., Rolim, V., Mello, R. F., & Gašević, D. (2020). Let's shine together! A comparative study between learning analytics and educational data mining. In *Proceedings of the tenth international conference on learning analytics & knowledge* (pp. 544–553). https://doi.org/10.1145/3375462.3375500

Clark, J.-A., Liu, Y., & Isaias, P. (2020). Critical success factors for implementing learning analytics in higher education: A mixed-method inquiry. *Australasian Journal of Educational Technology, 36*(6), 89–106. https://doi.org/10.14742/ajet.6164

Dawson, S., Joksimovic, S., Poquet, O., & Siemens, G. (2019). Increasing the impact of learning analytics. In *Proceedings of the 9th international conference on learning analytics & knowledge* (pp. 446–455). https://doi.org/10.1145/3303772.3303784

Dawson, S., Poquet, O., Colvin, C., Rogers, T., Pardo, A., & Gasevic, D. (2018). Rethinking learning analytics adoption through complexity leadership theory. In *Proceedings of the 8th international conference on learning analytics and knowledge* (pp. 236–244). https://doi.org/10.1145/3170358.3170375

Drachsler, H., & Goldhammer, F. (2020). Learning analytics and eAssessment—Towards computational psychometrics by combining psychometrics with learning analytics. In D. Burgos (Ed.), *2020. Radical solutions and learning analytics* (pp. 67–80). Springer: Singapore. https://doi.org/10.1007/978-981-15-4526-9.

Ferguson, R., & Clow, D. (2017). Where is the evidence?: A call to action for learning analytics. In *Proceedings of the seventh international learning analytics & knowledge conference* (pp. 56–65). https://doi.org/10.1145/3027385.3027396

Gasevic, D., Tsai, Y. S., Dawson, S., & Pardo, A. (2019). How do we start? An approach to learning analytics adoption in higher education. *International Journal of Information and Learning Technology, 36*(4), 342–353. https://doi.org/10.1108/IJILT-02-2019-0024

Gray, G., Schalk, A., Rooney, P., & Lang, C. (2021). A stakeholder informed professional development framework to support engagement with learning analytics. In *Proceedings11th international learning analytics and knowledge conference* (pp. 237–247). Association for Computing Machinery. https://doi.org/10.1145/3448139.3448162.

Greller, W., & Drachsler, H. (2012). Translating learning into numbers: A generic framework for learning analytics. *Educational Technology & Society*, 42–57.

Gutiérrez, F., Seipp, K., Ochoa, X., Chiluiza, K., De Laet, T., & Verbert, K. (2020). LADA: A learning analytics dashboard for academic advising. *Computers in Human Behavior, 107*, 105826. https://doi.org/10.1016/j.chb.2018.12.004

Guzmán-Valenzuela, C., Gómez-González, C., Rojas-Murphy Tagle, A., & Lorca-Vyhmeister, A. (2021). Learning analytics in higher education: A preponderance of analytics but very little learning? *International Journal of Educational Technology in Higher Education, 18*(1), 23. https://doi.org/10.1186/s41239-021-00258-x

Hakimi, L., Eynon, R., & Murphy, V. A. (2021). The ethics of using digital trace data in education: a thematic review of the research landscape. *Review of Educational Research.* , Article 00346543211020116. https://doi.org/10.3102/00346543211020116

Herodotou, C., Naydenova, G., Boroowa, A., Gilmour, A., & Rienties, B. (2020). How can predictive learning analytics and motivational interventions increase student retention and enhance administrative support in distance education? *Journal of Learning Analytics, 7*(2), 72–83. https://doi.org/10.18608/jla.2020.72.4

Herodotou, C., Rienties, B., Hlosta, M., Boroowa, A., Mangafa, C., & Zdrahal, Z. (2020). The scalable implementation of predictive learning analytics at a distance learning university: Insights from a longitudinal case study. *The Internet and Higher Education, 45*, 100725. https://doi.org/10.1016/j.iheduc.2020.100725

Hilliger, I., Ortiz-Rojas, M., Pesántez-Cabrera, P., Scheihing, E., Tsai, Y.-S., Muñoz-Merino, P. J., … Pérez-Sanagustín, M. (2020). Identifying needs for learning analytics adoption in Latin American universities: A mixed-methods approach. *The Internet and Higher Education, 45*, 100726. https://doi.org/10.1016/j.iheduc.2020.100726

Jivet, I., Scheffel, M., Drachsler, H., & Specht, M. (2017). Awareness is not enough: Pitfalls of learning analytics dashboards in the educational practice. In É. Lavoué, H. Drachsler, K. Verbert, J. Broisin, & M. Pérez-Sanagustín (Eds.), *Proceedings of the 12th European conference for technology-enhanced learning* (pp. 82–96). Springer International Publishing. https://doi.org/10.1007/978-3-319-66610-5_7.

Jivet, I., Scheffel, M., Specht, M., & Drachsler, H. (2018). License to evaluate: Preparing learning analytics dashboards for educational practice. In *Proceedings of the 8th international conference on learning analytics and knowledge* (pp. 31–40). https://doi.org/10.1145/3170358.3170421

Jivet, I., Wong, J., Scheffel, M., Valle Torre, M., Specht, M., & Drachsler, H. (2021). Quantum of choice: How learners' feedback monitoring decisions, goals and self-regulated learning skills are related. In *LAK21: 11th international learning analytics and knowledge conference (LAK21)* (pp. 416–427). New York, NY, USA: Association for Computing Machinery. https://doi.org/10.1145/3448139.3448179.

Jones, K. M. L., Asher, A., Goben, A., Perry, M. R., Salo, D., Briney, K. A., & Robertshaw, M. B. (2020). "We're being tracked at all times": Student perspectives of their privacy in relation to learning analytics in higher education. *Journal of the Association for Information Science and Technology, 71*(9), 1044–1059. https://doi.org/10.1002/asi.24358

Jovanović, J., Gašević, D., Pardo, A., Dawson, S., & Whitelock-Wainwright, A. (2019). Introducing meaning to clicks: Towards traced-measures of self-efficacy and cognitive load. In *Proceedings of the 9th international conference on Learning Analytics & Knowledge* (pp. 511–520). https://doi.org/10.1145/3303772.3303782

Kia, F. S., Teasley, S. D., Hatala, M., Karabenick, S. A., & Kay, M. (2020). How patterns of students dashboard use are related to their achievement and self-regulatory engagement. In *Proceedings of the tenth international conference on Learning Analytics & Knowledge* (pp. 340–349). https://doi.org/10.1145/3375462.3375472

Klein, C., Lester, J., Rangwala, H., & Johri, A. (2019). Technological barriers and incentives to learning analytics adoption in higher education: Insights from users. *Journal of Computing in Higher Education, 31*(3), 604–625. https://doi.org/10.1007/s12528-019-09210-5

Knight, S., Gibson, A., & Shibani, A. (2020). Implementing learning analytics for learning impact: Taking tools to task. *The Internet and Higher Education, 45*, 100729. https://doi.org/10.1016/j.iheduc.2020.100729

Knobbout, J., & van der Stappen, E. (2020). Where is the learning in learning analytics? A systematic literature review on the operationalization of learning-related constructs in the evaluation of learning analytics interventions. *IEEE Transactions on Learning Technologies, 13*(3), 631–645. https://doi.org/10.1109/TLT.2020.2999970

Kollom, K., Tammets, K., Scheffel, M., Tsai, Y.-S., Jivet, I., Muñoz-Merino, P. J., … Ley, T. (2021). A four-country cross-case analysis of academic staff expectations about learning analytics in higher education. *The Internet and Higher Education, 49*, 100788. https://doi.org/10.1016/j.iheduc.2020.100788

van Leeuwen, A., Janssen, J., Erkens, G., & Brekelmans, M. (2014). Supporting teachers in guiding collaborating students: Effects of learning analytics in CSCL. *Computers & Education, 78*, 28–39. https://doi.org/10.1016/j.compedu.2014.07.007

Lim, L.-A., Gentili, S., Pardo, A., Kovanović, V., Whitelock-Wainwright, A., Gašević, D., & Dawson, S. (2021). What changes, and for whom? A study of the impact of learning analytics-based process feedback in a large course. *Learning and Instruction, 72*, 101202. https://doi.org/10.1016/j.learninstruc.2019.04.003

Lodge, J. M. (2020). Online education by design: Using evidence and course analytics to achieve best online teaching and learning practice. In S. McKenzie, F. Garivaldis, & K. R. Dyer (Eds.), *Tertiary online teaching and learning: TOTAL perspectives and resources for digital education* (pp. 3–11). Springer. https://doi.org/10.1007/978-981-15-8928-7_1.

Long, P. D., Siemens, G., Conole, G., & Gašević, D. (Eds.).. (2011). *Proceedings of the 1st international conference on learning analytics and knowledge (LAK'11)*. ACM.

Macfadyen, L., Dawson, S., Pardo, A., & Gaševic, D. (2014). Embracing big data in complex educational systems: The learning analytics imperative and the policy challenge. *Research & Practice in Assessment, 9*, 17–28.

Matcha, W., Ahmad Uzir, N., Gasevic, D., & Pardo, A. (2020). A systematic review of empirical studies on learning analytics dashboards: A self-regulated learning perspective. *IEEE Transactions on Learning Technologies, 13*(2), 226–245. https://doi.org/10.1109/TLT.2019.2916802

Munguia, P., Brennan, A., Taylor, S., & Lee, D. (2020). A learning analytics journey: Bridging the gap between technology services and the academic need. *The Internet and Higher Education, 46*, 100744. https://doi.org/10.1016/j.iheduc.2020.100744

Pardo, A., Jovanovic, J., Dawson, S., Gašević, D., & Mirriahi, N. (2019). Using learning analytics to scale the provision of personalised feedback. *British Journal of Educational Technology, 50*(1), 128–138. https://doi.org/10.1111/bjet.12592

Prieto, L. P., Rodríguez-Triana, M. J., Martínez-Maldonado, R., Dimitriadis, Y., & Gašević, D. (2019). Orchestrating learning analytics (OrLA): Supporting inter-stakeholder communication about adoption of learning analytics at the classroom level. *Australasian Journal of Educational Technology, 35*(4). https://doi.org/10.14742/ajet.4314. Article 4.

Prinsloo, P., & Slade, S. (2016). Student vulnerability, agency and learning analytics: An exploration. *Journal of Learning Analytics, 3*(1), 159–182.

Saint, J., Fan, Y., Singh, S., Gasevic, D., & Pardo, A. (2021, April). Using process mining to analyse self-regulated learning: A systematic analysis of four algorithms. In *LAK21: 11th international learning analytics and knowledge conference (LAK21)* (pp. 333–343). New York, NY, USA: Association for Computing Machinery.

Scheffel, M., Tsai, Y., Gasevic, D., & Drachsler, H. (2019). Policy matters: Expert recommendations for learning analytics policy. In *14th European conference on technology enhanced learning, EC-TEL 2019, Delft, 16–19 September 2019, proceedings (lecture notes in computer science)*. Cham: Springer.

Schmitz, M., Scheffel, M., van Limbeek, E., Bemelmans, R., & Drachsler, H. (2018). "Make it personal!" – Gathering input from stakeholders for a learning analytics-supported learning design tool. In *, Vol. 11082. 13th European conference on technology enhanced learning, EC-TEL 2018, Leeds, UK, September 3–5, 2018, proceedings* (pp. 297–310). Cham: Springer. Lecture Notes in Computer Science.

Schmitz, M., Scheffel, M., van Limbeek, E., van Halem, N., Cornelisz, I., van Klaveren, C., … Drachsler, H. (2018). Investigating the relationships between online activity, learning strategies and grades to create learning analytics-supported learning designs. In *, Vol. 11082. 13th European conference on technology enhanced learning, EC-TEL 2018, Leeds, UK, September 3–5, 2018, proceedings* (pp. 311–325). Cham: Springer. Lecture Notes in Computer Science.

Sclater, N. (2016). Developing a code of practice for learning analytics. *Journal of Learning Analytics, 3*(1), 16–42.

Selwyn, N. (2020). Re-imagining 'learning analytics' … a case for starting again? *The Internet and Higher Education, 46*, 100745. https://doi.org/10.1016/j.iheduc.2020.100745

Sheikh, R. A., Bhatia, S., Metre, S. G., & Faqihi, A. Y. A. (2021). Strategic value realization framework from learning analytics: A practical approach. *Journal of Applied Research in Higher Education.*. https://doi.org/10.1108/JARHE-10-2020-0379 (in press)

Siemens, G., Dawson, S., & Lynch, G. (2013). *Improving the quality and productivity of the higher education sector: Policy and strategy for systems-level deployment of learning analytics* (pp. 1–35). Society for Learning Analytics Research. http://www.voced.edu.au/content/ngv%3A64739.

Steiner, C., Kickmeier-Rust, M., & Türker, M. A. (2014). *Review article about LA and EDM approaches, deliverable D3.1 – LEA's box project* (p. 83). http://css-kmi.tugraz.at/mkrwww/leas-box/downloads/D3.1.pdf.

Tsai, Y.-S., Kovanović, V., & Gašević, D. (2021). Connecting the dots: An exploratory study on learning analytics adoption factors, experience, and priorities. *The Internet and Higher Education, 50*, 100794. https://doi.org/10.1016/j.iheduc.2021.100794

Tsai, Y.-S., Moreno-Marcos, P. M., Jivet, I., Scheffel, M., Tammets, K., Kollom, K., & Gašević, D. (2018). The SHEILA framework: Informing institutional strategies and policy processes of learning analytics. *Journal of Learning Analytics, 5*(3), 5–20. https://doi.org/10.18608/jla.2018.53.2

Tsai, Y.-S., Rates, D., Moreno-Marcos, P. M., Muñoz-Merino, P. J., Jivet, I., Scheffel, M., … Gašević, D. (2020). Learning analytics in European higher education—Trends and barriers. *Computers & Education, 155*, 103933. https://doi.org/10.1016/j.compedu.2020.103933

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

Vigentini, L., Liu, D. Y. T., Arthars, N., & Dollinger, M. (2020). Evaluating the scaling of a LA tool through the lens of the SHEILA framework: A comparison of two cases from tinkerers to institutional adoption. *The Internet and Higher Education, 45*, 100728. https://doi.org/10.1016/j.iheduc.2020.100728

West, D., Heath, D., & Huijser, H. (2016). Let's talk learning analytics: A framework for implementation in relation to student retention. *Online Learning, 20*(2), 30–50. http://dx.doi.org/10.24059/olj.v20i2.792.

Whitelock-Wainwright, A., Tsai, Y.-S., Drachsler, H., Scheffel, M., & Gašević, D. (2021). An exploratory latent class analysis of student expectations towards learning analytics services. *The Internet and Higher Education, 51*, 100818. https://doi.org/10.1016/j.iheduc.2021.100818

Williamson, B., Bayne, S., & Shay, S. (2020). The datafication of teaching in higher education: Critical issues and perspectives. *Teaching in Higher Education, 25*(4), 351–365. https://doi.org/10.1080/13562517.2020.1748811

Wong, B. T., & Li, K. C. (2020). A review of learning analytics intervention in higher education (2011–2018). *Journal of Computers in Education, 7*(1), 7–28. https://doi.org/10.1007/s40692-019-00143-7

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