Chapter 17: Institutional Implementation of Learning Analytics - Current State, Challenges, and Guiding Frameworks

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ABSTRACT

Since its emergence, the field of learning analytics has proposed that educational institutions can and should make better use of learner data to optimize learning and learning environments. A range of social, political and economic forces have also encouraged educational institutions to consider system-wide implementations of learning analytics. In spite of a decade of optimism and interest, however, very few examples of effective institutional LA implementation exist, and evidence of positive impact on learning is sparse. This chapter provides an updated summary of the growing body of literature exploring the challenges of making systemic change with LA in complex educational contexts. Proposed frameworks for guiding institutional LA implementations are reviewed, and work describing use of the most promising – the SHEILA framework – is outlined in more detail. The need for attention to complexity leadership and institutional logics is noted as a focus of recent work, and emerging issues are highlighted: a critical need to expand the literature documenting evidence of real impact on learning, a need for institutions to make use of reliable LA evaluation strategies, and the need for critical consideration of how and if LA can also benefit learners beyond the traditional higher education contexts of the wealthy North.

Keywords: Learning analytics, implementation, institutional, evaluation, complexity

Over the past decade, researchers, analysts and theorists have increasingly argued that higher education should harness the data exhaust from educational technologies with analytics, in order to better understand and optimize learning and learning environments across many dimensions [47]. Learning analytics (LA) is focused on the learner and on learning environments. Its many approaches make use of data from learning management and student information systems, as well as a wide range of additional tools and technologies that may be employed in teaching and learning. It explores learner choices and behaviors in a variety of learning contexts, and its measures of 'success' are educational: student success is typically represented by metrics of 'improved learning' (or improved 'achievement'). Table 1 summarizes what are believed to be the core affordances of learning analytics, illustrating the range of educational stakeholders and purposes that different approaches to learning analytics may serve.

1 BACKGROUND: THE LEARNING ANALYTICS IMPERATIVE

In principle, then, learning analytics offers institutions new approaches to understanding the activities, choices and behaviors associated with effective learning, and ideally can indicate ways of leveraging this new knowledge to optimize educational systems [6, 10].

As Ferguson [21] and others have outlined, an array of forces have coalesced in recent years that have pushed educational institutions to think about system-wide implementations of learning analytics, including pressure to 'do better' for their diverse learners (often with reduced resources), and some evidence that learning analytics may feasibly support these goals. Technological advances have made the generation, capture, storage and analysis of 'big data' faster and easier. Shifts in both educational approach and educational needs (for example, increasingly diverse learner audiences) have prompted greater integration of data-generating technologies into teaching and learning. National and regional governments are increasingly concerned about the quality of their educational systems, both in relation to their own economic development, and also to the extent that it influences their standing on the global

Table 1: Affordance of learning analytics for educational institutions (adapted and updated from [49]).

Increased formative feedback to instructors. LA can help close the instructional loop [13] by allowing instructors to identify components of their courses – online or in class – where students are struggling or failing to grasp key concepts. Realtime feedback can allow just-in-time teaching (see for example, [17]; slower reflective feedback can allow cycles of improved learning design (see for example, [46].
Empowerment of students. Giving students metrics about their own progress and their progress relative to peers can assist in development of self-directed learning skills [17] and metacognition [75], improve motivation, and help them identify areas for improvement (see for example, [24].
Illumination of curriculum connectivity. We sometimes think of courses/modules as stand-alone units. LA can help departments and committees better understand their programs and support effective learning by, for example, mapping prerequisites or common routes leading to different majors specializations [32, 58].
Improved curriculum alignment. Programs and institutions are increasingly being challenged to ensure that courses (assessments, learning outcomes) align constructively with desired graduate attributes/competencies [61]. Emerging analytics methods can map and track student progression through courses in pursuit of identified graduate attributes (see for example, [33])
Improved assessment of learning. Considerable evidence supports the argument that end-of-term summative assessments are a poor approach to measuring actual learning. LA supports a range of alternate and complementary assessment practices – practices that make better use of the rich array of educational data now available – that may well offer more effective approaches to improving learning, especially processes that reveal development of student understanding over time [51].
Improved evaluation of teaching. Garrison, Anderson, and Archer [26] identified 'teacher presence' as a critical component of high quality learning environments in their 'Community of Inquiry' model – a model of high quality learning environments now well-supported by empirical studies [27]. Clearly, teaching forms part of the 'environment in which learning occurs' [47], and yet, we have only poor metrics for evaluating teaching. LA, used sensitively and carefully, may help educational leaders understand the quality of teaching in their courses.
Evidence to inform academic planning. Which programs show potential for growth? Which appear to be in decline? Can we identify new trends and patterns revealing new areas of learner interest or new career pathways? Predictive analytics can assist with many areas of planning, from faculty recruitment and curriculum development, to student recruitment and facilities management.
Development of 'early alert' systems. Which students are at risk of failure? An increasing body of evidence indicates that predictive models developed using data from LMSs and other learning technologies, in combination with student academic history and demographic data, can indicate, earlier, which students may be in need of additional academic support [8].

stage. Meanwhile, sectors such as marketing, sports, retail, health and technology have embraced analytic methods and demonstrated their potential to enhance systems and outcomes [54]. These latter authors have argued that, "[i]n a big data world, a competitor that fails to sufficiently develop its capabilities will be left behind...Early movers that secure access to the data necessary to create value are likely to reap the most benefit" (p. 6).

The sense of urgency is palpable. LA are proposed to offer new, far-reaching and sophisticated insights into teaching, learning, the learner experience, and educational management activities that were previously unimaginable [3]. In this New (Educational) World context of increasingly constrained education budgets and increased focus on quality and accountability [50], it is perhaps not surprising that institutions are starting to see learning analytics as not just a 'nice to have' option, but, rather, a pragmatic and ethical imperative, and that some are embracing Slade and Prinsloo's [69] assertion that "[i]gnoring information that might actively help to pursue an institution's goals seems shortsighted to the extreme" (p. 1521).

1.1 INSTITUTIONAL IMPLEMENTATIONS: CURRENT STATE

Against this backdrop, every Horizon Report [1] published since 2012 - an annual publication that seeks to identify key educational technology trends and developments - has optimistically listed LA as an emerging technology on the 'mid-term time-to-adoption horizon' (3-5 years or less until adoption). And yet, education still lags behind other sectors in harnessing the power of analytics [54] or demonstrating impact. Very few well-developed examples of LA deployment at scale across educational institutions exist, and even fewer credible studies can be found in the peer-reviewed learning analytics literature of demonstrated impact on learning or student success at scale [22, 73].

Table 2 offers a selection from the small number of available case studies of institutional LA implementations in higher education, though it should be noted that their inclusion here does not necessarily indicate that empirical evidence exists to demonstrate positive impact on learning or learner success, or that the implementation is still in use.

The few examples of institutional learning analytics implementation that do exist – and the early benefits they reported (see, for example, [2, 44]) – are regularly held up as models to follow, making colleges and universities worldwide increasingly anxious to embrace the LA wave. By 2012 up to 70 percent of EDUCAUSE member institutions reported that learning analytics implementation was viewed as a major priority by at least some departments, units, or programs; 28% reported that analytics was a major priority for their entire institution [5]. However, regular surveys have found that in spite of these ambitious goals, most institutions remain mired at "Stage 1" of a five-stage implementation process: "Extraction and reporting of transaction-level data" [31]. Yanosky & Arroway's 2015 [76] analysis of 'analytics maturity' in US higher education institutions demonstrated that little had changed since 2012, and that institutions were still struggling to realize the potential of LA. And as Gasevic, Tsai, Dawson, and Pardo [28] have described, even in institutions who have reported successful LA adoption, "achievements tended to be short-term victories, such as experience-gain, cultural change, infrastructural upgrade and a better understanding of legal and ethical implications."

It appears, then, that bridging the gap between LA vision and reality is a challenge for most educational institutions. What is holding us back?

2 CHALLENGES AND BARRIERS: NUMBERS ARE NOT ENOUGH

In an early study, Macfadyen and Dawson [50] undertook a case study of LA impact in a large research-intensive university. The authors had hoped that LA provided to decision-makers would "provide compelling data that would generate the sense of urgency necessary to motivate broad scale institutional change associated with learning, teaching and technology" (p. 151). Instead, they discovered that simple provision of analytics was insufficient to inspire and motivate innovation and institutional change – a realization that prompted a deeper investigation into the challenges of systemic adoption of an innovation like LA.

Surprisingly, the challenge of moving from evidence of good educational practice to effective action is not new. As early as 1979, McIntosh bemoaned the inability of her education research unit (at the UK Open University) to have any impact on major problem areas [56], even after providing educational leaders with detailed findings drawn from research that should have usefully informed decision-making. A growing number of studies have explored this challenge in the LA era, and have examined and enumerated a wide range of barriers and challenges to the implementation of institutional analytics [15, 23, 48, 51, 68, 72]. Table 3 below summarizes barriers to learning analytics adoption identified in the literature.

3 TAKING INSTITUTIONAL CULTURE INTO ACCOUNT

As this growing list of recognized barriers makes clear, effective institution-wide adoption of LA calls for more than just increased technical and analytic capacity, and required attention to the many social and organizational elements of institutional culture in an educational institution [18]. Klein [43] quotes Thornton, Ocasio, and Lounsbury [70] to explain that institutional logics represent "the socially constructed, historical patterns of cultural symbols and material practices, including assumptions, values, beliefs, by which individuals and organizations provide meaning to their daily activity, organize time and space, and reproduce their lives and experiences" (p. 2). These logics or

[1] Educause. https://www.educause.edu/

Table 2: Selected institutional LA implementations in higher education.

Institutional LA Project	References
OU Analyse, The Open University, UK	[23, 39, 38]
Course Signals, Purdue University, USA	[2, 67]
Check My Activity (CMA), University of Baltimore, Maryland Campus	[24, 25]
Electronic Expert (E2Coach), The University of Michigan, USA	[40, 57]
Degree Compass, Austin Peay State University, USA (acquired by the Desire2Learn/Brightspace LMS software company in 2013)	[19, 74]
LATHEE, University of Cuenca, Ecuador, KU Leuven, Belgium	[9]

conceptualizations of LA shape how (and how effectively) LA are implemented and taken up by stakeholders. Recently, three significant studies undertaken in Australia [15], Europe [72] and the United States [43] have tended to confirm and extend this compilation of barriers and challenges, and highlight the significance and impact of diverging institutional contexts and logics.

In Australia, Colvin et al. [15] interviewed senior leaders from 32 of 40 universities about the implementation of LA in their institutions, and identified two distinct LA implementation profiles. Institutions clustered in the first profile, characterized as 'instrumentalist', typically identify LA as a technical solution to address a specific institutional challenge (such as student retention)and have typically employed a top-down leadership model to implement LA [18]. Their rapid LA implementations have quickly leveraged existing technical infrastructure, and made 'tools' available, but have given little or no attention to stakeholder engagement or capacity building. As a result, buy-in from learners and academic staff has been poor or non-existent. Institutions clustered under the second institutional implementation profile, characterized as 'emergent innovators', see LA as a process that may bring understanding to learning and teaching practices, and inform a continuous, iterative, dynamic and sustainable improvement of teaching and learning. Typically, institutions in this group have fostered a 'bottom-up' approach to LA adoption [18] and have sponsored more complex and localized implementations, and engagement with a greater diversity of stakeholders.

Tsai et al. [72] surveyed LA implementation in European higher education, interviewing and surveying senior managers in 83 institutions across 24 European countries. Similar to the Australian findings, these authors report two apparent 'clusters' of motivations underpinning institutional LA implementation: 'improving institutional performance or management' or 'enhancement of teaching and learning support'.

Finally, in the US context, Klein's [43] preliminary work has focused on elucidating the 'institutional logic' of LA use in higher education in relation to LA, with the goal of better understanding how LA may be shaping not just student learning, but also the structures, interactions, and goals of higher education. Klein conducted 55 interviews with members of state oversight agencies, technology vendors, and higher education organizations within a single state university system. Open coding of these interviews revealed three dominant logics – 'technocratic, managerial, and success' – which appear to align meaningfully with the two broad clusters of LA motivation/conceptualization identified in the Australian and European HE contexts.

While regional and contextual details vary, then, this collection of studies should alert us to the reality that institutional cultures, contexts and logics are critical forces that will shape the scope, nature, speed, scale, uptake and effectiveness of institutional LA implementation. All three highlight the continuing "tensions between innovation and operation" [72](p. 2842) that educational institutions must manage in the current era.

4 WHERE TO START? FRAMEWORKS AND GUIDELINES FOR INSTITUTIONAL IMPLEMENTATION

Surveying the barriers listed in Table 3 and the range of possible institutional conceptualizations of LA discussed above, it is clear that successful institutional adoption of learning analytics demands comprehensive development and implementation of strategies and policies to address challenges of learning design, leadership, institutional culture, data access and security, data privacy and ethical dilemmas, technology infrastructure, and a demonstrable gap in institutional LA skills and capacity [51]. It is not surprising, then, that even educators, managers, administrators and researchers convinced by the potential of implementing learning analytics are asking "Where should we start?" [28].

In the 1st edition of the Handbook of Learning Analytics, Colvin et al. [14] usefully surveyed existing models and frameworks proposed or developed to guide institutional LA implementation efforts. Table 4 now summarizes and updates this compilation.

Colvin, Dawson, Wade, and Gašević [14] characterized most of these frameworks as either 'input' or 'output' models. They are primarily descriptive, and highlight a focus on either assessing institutional 'current state of readiness' for LA implementation, or progress through proposed states of LA 'maturity'. The dimensions and themes they introduce are largely conceptual, and not backed up by empirical research. Most critically, the majority of these models offer little pragmatic guidance for institutional leaders, and little or no evidence is available

Table 3: Challenges to Institutional learning analytics projects (adapted and updated from [49])

Pedagogical	• Weak pedagogical grounding of LA technologies and implementation design [42]. • Disagreement about or inexperience with learning design • Divergent use of learning technologies or use of technologies with limited or inaccessible data • Differing beliefs about the virtues (or not) of educational technologies • Institutional commitments to academic freedom with regards to teaching practice that preclude data gathering or 'evaluation' • Lack of standardization in relation to learner assessment and evaluation • Fundamental philosophical disputes about the virtues of quantitative vs. qualitative approaches to understanding 'learning' or 'learner success'
Technological	• Use of learning technologies with limited or inaccessible data • Institutional data sets silo-ed in mutually incompatible databases and formats • Interoperability standards not implemented • Technological challenges relating to development of integrated reporting systems or data stores • Lack of awareness of limitations of data commonly used in learning analytics [28]
Interface	• Poor data literacy at all levels of an institution [72] • Non-intuitive, highly complex, or inaccessible analytic tools • Presentation of simplistic 'dashboards' that obscure or misrepresent nuanced meaning [30, 41] • Lack of necessary contextualization and customization of data [29]
Evaluation & assessment	• Heterogeneous definitions of "student success" • Focus on 'final grade' or 'graduation' as the only available/accessible outcome measures of 'learning.' (Some researchers propose that learning analytics offers potentially new approaches to assessment and evaluation – a not uncontroversial proposition. For further discussion see, [51])
Leadership	• No established institutional data governance structure (data quality, data management, data policies, business process management, and risk management surrounding the handling of data in an institution) • A long history of educational decision-making based on anecdote and tradition • Researchers and decision-makers may speak "different languages" • Decision-makers may lack familiarity with statistical and analytic methods and interpretation • No analytics champions at the senior leadership level • A need for complexity leadership [18]

Resource Support	• Costs associated with technological and human resources [5, 14, 72] • Missing human skills and resources across the highly interdisciplinary educational analytics domain. Demand for "deep analytical talent" may outstrip supply by 50% by the end of the decade [54] a demonstrable gap exists in institutional capacity for analytics [5]
Ethical	• No established institutional policies for ethical use of student data in the LA era • Inattention to key ethical questions and dilemmas surrounding collection and use of data about learners [69] – Purpose (and transparency) (Why is data being collected? To what end?) – Data ownership – Issues of consent, privacy, de-identification – Data handling and protection processes – The potential obligation to act on new knowledge
Institutional culture	• Institutional structures can limit progress with learning analytics as different units and teams defend their 'turf': processes, data and power • Lack of attention to institutional culture within higher education, lack of understanding of the degree to which individuals, and cultures resist innovation and change, and lack of understanding of approaches to motivating social and cultural change can seriously hinder innovation. For extended discussion see [50] • Insufficient engagement with all stakeholders, resulting in mistrust and lack of buy-in [20, 71] • Lack of recognition of the divergent institutional logics (motivations, conceptualizations) underpinning institutional LA implementation projects [15, 43]

Table 4: Frameworks and instruments designed/proposed to usefully guide institutional LA implementation

Framework	**Purpose**	**References**
Analytics Framework	Presents analytics capacity as a process of maturation from basic data querying through to predictive modelling.	[16]
Learning Analytics Framework	A generic design framework proposed to guide establishment of LA services.	[34]
ECAR Analytics Maturity Index	Allows institutions to assess maturity, readiness, and capacity for LA; Measures analytics maturity on six dimensions: process, culture, expertise, investment, governance/infrastructure, and data/reporting/tools.	[5]
Learning Analytics Sophistication Model	A five-stage model of institutional LA maturity that integrated analytic capability and systems deployment.	[68]
Organizational Capacity Analytics Framework	Maps actual institutional initiatives against a framework of seven action categories; Proposed to indicate migration paths for future practice.	[60]
Learning Analytics Readiness Instrument (LARI)	A diagnostic instrument that provides an institutional profile with readiness indicators for LA success; Can help determine strengths and weaknesses before a large-scale LA initiative is undertaken.	[1]
Model of Strategic Capability	Represents institutional dimensions as complex, dynamically interconnected and temporal. Provides empirical insights into the relationships between institutional contextual features and the outcomes of their learning analytics implementations.	[15]
ROMA Outcome Mapping Approach	Developed to support policy and strategy processes in complex contexts; A seven-step model focused on evidence-based policy change. Designed to be used iteratively, and to allow refinement and adaptation of policy goals and the resulting strategic plans over time and as contexts change.	[23, 51]
SHEILA Framework	Builds on and further elaborates the ROMA approach; Revised model can inform strategic planning and policies for LA adoption.	[71]
LALA Framework	Developed in Latin America; adapts the ROMA approach and provides detailed steps to identify the needs of different stakeholders, design, implement, and evaluate LA tools.	[64]
Barton & Court Model of Transformation	A model that builds on the pragmatic dimensions considered in earlier models, and considers actions required to develop a data-informed culture and bring about institutional transformation.	[4]

in the literature to detail their operationalization, adoption or effectiveness. The single current exception appears to be the 'process model(s)' [14] that have evolved from the ROMA model originally proposed by Ferguson et al. [23], discussed below.

5 THE SHEILA FRAMEWORK: A MODEL FOR INFORMING INSTITUTIONAL LA STRATEGIES AND POLICY PROCESSES

The SHEILA framework has emerged from the basic realization that educational institutions are complex adaptive systems [12, 35, 52, 59]. Like all complex systems, they are resilient, resistant to change, and tend to maintain their organizational structure and processes [11]. Change strategies aimed at only one or a few of their subsystems are unlikely to succeed. The wide-ranging and interconnected nature of challenges to institutional implementation of LA emphasizes that a systems perspective is critical for successful institutional implementation of LA (or indeed of any educational innovation).

In 2009, development scholars outlined the Rapid Outcome Mapping Approach (ROMA) [77] to help leaders bring about evidence-based change in complex contexts. Ferguson et al. [23] proposed that an adapted version of the ROMA model could act as a pragmatic, iterative and operationalizable framework to support and guide institutional LA implementation. [71] have subsequently taken up, refined and validated this framework under the auspices of a European research project: SHEILA (Supporting Higher Education to Integrate Learning Analytics) [2]. In their major study, this project team used the ROMA model to code and analyze interviews from interviews with senior managers from 51 European higher education institutions, to uncover the diverse challenges associated with each of the original 'ROMA dimensions' that institutions experienced, and to identify strategic approaches (key actions) that facilitated LA adoption. The renamed 'SHEILA Framework' (structure shown in Figure 1) now consists of "a comprehensive list of adoption actions, relevant challenges and policy prompts, framed in the six ROMA dimensions" (p. 9), and can be used to evaluate institutional readiness and initiate strategic and policy planning for early-stage adopters.

Moreover, while Ferguson et al. [23] outlined two successful case studies of institutional LA implementation that appeared to have evolved using a ROMA-like systemic approach, Tsai et al. [72] have now detailed a diverse set of European higher education case studies to illustrate the utility of the ROMA/SHEILA framework as an iterative analytic tool for examining existing LA practices, refining strategies and updating policies. At time of writing, The SHEILA Project team has developed and launched a web-based SHEILA Framework web tool [3] and associated tools and materials to allow educational institutions to build a custom framework for their own context, and a

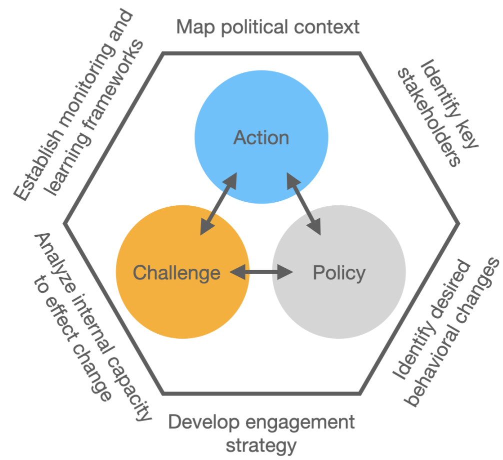

Figure 1: The SHEILA framework structure [71]

MOOC [4] has been launched to train educational leaders in its use. A number of SHEILA Framework institutional use cases describing the application or value of the framework have now appeared in the LA literature [9, 36]. And a multinational and multi-institutional team of researchers has initiated Project LALA [5] whose goal is to adapt the SHEILA Framework for use in the context of Latin American Higher Education Institutions (HEIs) [53].

At present, then, it appears that ongoing and published work emerging from the recognition of the need for a systemic approach and the development, implementation and adaptation of the ROMA/SHEILA Framework may be starting to address the lack of empirical studies of LA implementation, and helping to bridge the persistent gap between LA research and practice.

6 NEXT STEPS? PERSISTENT CHALLENGES, EMERGING THEMES

6.1 The Importance of Complexity Leadership

While earlier studies and frameworks have emphasized the need for, and importance of, committed and knowledgeable senior leadership who can champion institutional LA transitions, some more recent research has begun to explore the need for 'complexity leadership' [37] or 'distributed leadership' [7] models in such complex contexts. Recognizing the systemic complexity of educational institutions, Dawson et al. [18] and Gašević et al. [28] have explored approaches to leadership that may better support both 'instrumental/top-down' and 'emergent innovator' approaches to LA implementation. Dawson et al. [18] argue that new models of educational leadership, informed by complexity leadership theory, are needed in the LA era, to help institutions "move on from small-scale course/program levels to a more holistic and complex or-

[2] http://sheilaproject.eu
[3] https://sheilaproject.eu/sheila-framework/create-your-framework/
[4] Learning Analytics in Higher Education, https://edge.edx.org/courses/course-v1:UC3Mx+IT.2x+3T2019/about
[5] https://www.lalaproject.org/

ganizational level" (p. 236) of LA implementation. These authors argue that effective complexity leadership is critically important in supporting integrations of innovations such as LA into the social system of an organization that will lead to acceptance and action.

6.2 The Need for Evidence of Impact

Numerous authors across the decade have pointed to the persistent lack of 'evidence of impact' of LA on learning and learner success – especially at the whole-institution level; several of the large-scale studies discussed in this chapter have reported 'lack of evidence' as a critical barrier to buy-in and institutional adoption of LA (see for example, [72]). Ferguson & Clow [22] have investigated this challenge in detail and highlight that as yet little evidence of positive LA impact exists. Evidence that is available appears to be significantly skewed towards the positive, suffers from a variety of other weaknesses, and likely does not represent the full range of findings within the discipline. These authors point to the Evidence Hub [6] of the Learning Analytics Community Exchange (LACE) (now a SoLAR SIG) as a venue and project around which the LA community might organize to share evidence from countries and sectors that are under-represented, and identify gaps in the current evidence. They characterize the need for more and better empirical evidence as a moral and scientific imperative that is absolutely critical for validating the field of LA as a whole.

6.3 How Can We Evaluate LA Implementation?

At present, even institutions that self-report some adoption of LA typically have no monitoring or evaluation strategy in place [72]. The challenge of how to evaluate impact of institutional LA adoption is not insignificant in complex and diverse educational contexts and systems. Scheffel's Evaluation framework for learning analytics (EFLA) [65, 66] was developed with the goal of standardizing the evaluation of learning analytics tools. It appears to offer an approach to measurement and comparison the impact of learning analytics on educational practices, and contribute to the evidentiary literature in the field.

6.4 Integration Beyond Higher Education

The current LA research and implementation literature is overwhelmingly focused on higher education, with very limited focus on schools, workplace, informal, or other learning contexts [22]. Starting in 2018, SoLAR's annual international conference (Learning Analytics and Knowledge, LAK) has hosted an Analytics in Schools workshop [7], with the goal of building interest and community in the compulsory/K-12 education sector. Mazziotti, Kovanović, Dawson, & Siemens [55] report the launch of a new project to investigate LA implementation in schools and develop a theory-based and data-driven framework for guiding LA implementation in school contexts.

[6] https://www.lalaproject.org/

[7] See for example: https://lak20.solaresearch.org/la-for-schools

6.5 LA Implementation Beyond the Global North

As Pelánek [62] notes, most LA research currently takes place in the United States or other rich countries, placing this research in a specific context which unquestionably shapes both the research and its findings. One 2018 compilation [45] invited reflections on the potential for and value of LA implementation in 'The Global South', and included responses from scholars in South Africa, Mainland China, and developing countries in Southeast Asia and Latin America. To date, preliminary work from the LALA Project [53] appears to be the only literature available detailing efforts to implement LA for the benefit of learners in Latin American contexts. Prinsloo [63] cautions us, however, to give attention to uncritical assumptions that data use in the Global South is 'necessary for development', and the attendant risks of data colonialism, as LA providers increasingly focus their attention on 'new markets' in the South. We must as a field remain alert to the social, cultural, economic, methodological, technical, institutional, ethical and communal aspects that shape the complex educational systems of the many countries of the Global South, and expand our awareness that LA "should not promote one size fits all" [29] to acknowledge this global reality.

7 CONCLUSION

In summary, then, we might conclude that learning analytics remains a field that offers great potential to support educational development, but that the barriers to sustainable, impactful and ethical system-wide integrations are extensive and complex. Some selected examples highlight possible strategies for success: attention to institutional logics and cultures, use of effective process models to guide strategy and policy across multiple dimensions, and appointment of leaders who are demonstrably effective in complex contexts. As efforts to harness the power of LA evolve in the next decade, it will be critical to expand our literature to include rich descriptions of LA successes and failures [22], to focus more attention on investigating and documenting evidence of real impact on learning, to adopt reliable LA evaluation strategies, and to carefully and critically consider how and if LA can also support improved learning out comes beyond higher education contexts of the wealthy North

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