

Setting Learning Analytics in Context: Overcoming the Barriers to Large-Scale Adoption

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ABSTRACT

Once learning analytics have been successfully developed and tested, the next step is to implement them at a larger scale – across a faculty, an institution or an educational system. This introduces a new set of challenges, because education is a stable system, resistant to change. Implementing learning analytics at scale involves working with the entire technological complex that exists around technology-enhanced learning (TEL). This includes the different groups of people involved – learners, educators, administrators and support staff – the practices of those groups, their understandings of how teaching and learning take place, the technologies they use and the specific environments within which they operate. Each element of the TEL Complex requires explicit and careful consideration during the process of implementation, in order to avoid failure and maximise the chances of success. In order for learning analytics to be implemented successfully at scale, it is crucial to provide not only the analytics and their associated tools but also appropriate forms of support, training and community building.

Categories and Subject Descriptors

K.6.0 [Management of Computing and Information Systems]: Information resource management – *project and people management, management techniques, staffing, strategic information systems planning, systems analysis and design*

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LAK '14, Mar 24-28 2014, Indianapolis, IN, USA

ACM 978-1-4503-2664-3/14/03.

<http://dx.doi.org/10.1145/2567574.2567592>

General Terms

Design, Implementation.

Keywords

Administration; change; change management; education; higher education; implementation; learning; learning analytics; teaching; technology-enhanced learning; TEL complex.

1. INTRODUCTION

Learning analytics are concerned with 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 [1]. The intention is to develop models, algorithms and processes that can be widely used. Transferability is a key factor here; the analytics that are developed need to be reliable and valid at a scale beyond the individual course or cohort.

There are currently few reports in the learning analytics literature of deployment at scale. In England and Australia, standardized testing of school children has been employed for decades, through the English SAT tests and the Australian NAPLAN tests [2, 3]. These tests are aligned with stated government aims, make use of agreed proxies for learning, provide clear and standardized visualisations of analytics and drive behaviour at every level of the education system. The data generated by these tests is collected, analysed and reported with the intention of optimizing learning and the environments in which it occurs. Despite the scale of this deployment, media reports suggest that many educators, learners and parents have not been convinced that these programmes are optimizing learning [4, 5].

On an institutional scale, the best-known example of roll-out at scale is Purdue University. By 2012, the university had applied its *Course Signals* analytics tool to over 100 courses, providing

formative grade feedback to over 23,000 students [6]. This is a significant achievement, but it has taken time. *Course Signals* is rooted in a study carried out at the university in 2005 [7]; nine years of development have not yet resulted in deployment across the entire university. In the UK, The Open University has been carrying out the learning analytics process as defined above [1] for over 40 years, but has also been identifying barriers to the implementation of that research for more than three decades [8].

2. BARRIERS TO ANALYTICS RESEARCH IMPLEMENTATION

2.1 Barriers identified in 1979

In 1979, McIntosh reported that ‘those of us in the Survey Research Department continue to be dissatisfied at our ability to have an impact on many major problem areas’ [8]. This was before the development of learning analytics. McIntosh was engaged in the related area of ‘educational evaluation’, delineating, obtaining and providing information that would be useful in judging decision alternatives. She identified seven reasons why competent research findings were never put into practice. These included an unwillingness for academics to accept and act on methods or findings from outside their own research area, individual preferences for qualitative or quantitative approaches, a tendency to base decisions on anecdote rather than on research, the different languages used by researchers and decision-makers, an unfamiliarity with statistical methods on the part of decision makers, and a tendency by researchers to hedge their conclusions.

Her recommendations focused on the need for researchers and decision-makers to work together: ‘Researchers should get clients politically, emotionally and financially committed to the outcome of the research. They are then more likely to take notice of its results’ [8]. The focus of the article was on university decision-makers as clients; the clientele for learning analytics might now be referred to as ‘stakeholders’ and would include learners, educators and administrators.

2.2 Barriers identified in 2012

In 2012, Macfadyen and Dawson reported on the non-implementation of a study relating to an institution’s use of learning analytics and its learning management system (LMS). They found that the institutional planning process was dominated by technical concerns and, because of this, ‘made little use of the intelligence revealed by the analytics process’ [9]. Indeed, after the current state analysis had been completed and noted by the institution’s standing committee on learning technologies, meeting minutes and reports showed that no references to or discussions of the findings were made in subsequent meetings.

Macfadyen and Dawson suggest the powerful analytic conclusions were set aside because the development and presentation of these analytics was coupled with a lack of attention to the institutional culture of higher education, a lack of awareness of the degree of resistance to change, and a lack of understanding of approaches that have been developed for motivating change within an organisation. They suggest that ‘greater attention is needed to the accessibility and presentation of analytics processes and findings so that learning analytics discoveries also have the capacity to surprise and compel, and thus motivate behavioural change’ [9].

This presents a significant challenge for learning analytics researchers, whose primary focus is on issues such as the

development and testing of algorithms and visualisations. Few analytics projects will have the capacity to undertake an ethnographic study of institutional culture or a review of recent thinking on change management, or will have team members with experience of writing a research report that both surprises and compels its audience. Yet the learning analytics community needs to investigate these issues and to engage its audience, if it is to achieve its aim of optimising learning and the environments in which it occurs.

Initial investigative work has been carried out in this area by Lonn and his colleagues [10]. They reflected on the issues encountered and lessons learned when scaling up a learning analytics intervention. The focus of their reflection was on the benefits and challenges of institutional partnership between a research team and a technology service group. They identified gaps between the two teams in areas such as usability, access, performance and calculation. In each case, they identified possible solutions, although many of these solutions were specific to the context in which they were working.

Overall, although they employ different language and describe different situations, these three studies identify some common problems [8-10]. These problems are related to different expectations around communication between researchers and those responsible for implementation, different levels of engagement with the research, and different expectations about the role and purpose of educational research. These discrepancies are found in other areas of technology-enhanced learning (TEL) research, and it is increasingly clear that significant innovation in this area is not possible without taking into account the entire TEL Technology Complex [11].

3. TEL TECHNOLOGY COMPLEX

Learning analytics, like other areas of TEL, can rarely be considered as a set of tools that can be developed, transferred and immediately adopted by practitioners. There are many associated elements that must work alongside the analytics in order to realise their full potential. These can be understood as part of a technology complex, a series of components that all need to be addressed together [12]. In the case of TEL and learning analytics, key components include pedagogy, stakeholders, communities, current practices, context, technical components and the business model [11]. When scaling up learning analytics, all these components need to be taken into account.

The introduction of learning analytics requires changes to the practices of several communities at once. Educators need to be able to evaluate them and to use them effectively. Learners need to be convinced that they are reliable and will improve their learning without intruding into their privacy. Support staff need to be trained to maintain the infrastructure and add data to the system. University administrators need to be convinced that they are both valid and cost effective. In order to convince all these stakeholders to put in the sustained effort necessary to make use of learning analytics, a clear vision of the gains to be made is required at the outset [11].

4. THE PANEL DISCUSSION

In order to consider how these changes can be carried out successfully, the panel brings together researchers who have taken on the task of implementing learning analytics at scale. They will offer insight into the processes involved, outlining different perspectives on these, identifying barriers to implementation and presenting ways of overcoming those barriers.

4.1 Rebecca Ferguson and Doug Clow

Rebecca and Doug work as ‘data wranglers’ at The Open University in the UK. In this role, they have responsibility for mediating between different university faculties and the department responsible for collecting and analyzing analytic data. They will talk about why the university decided to set up a team of data wranglers, and some of the implications of their role in bridging different communities within the university.

4.2 Leah Macfadyen

Leah is Program Director for Evaluation and Learning Analytics in the Faculty of Arts at the University of British Columbia, and has several years experience of efforts to garner institutional support for learning analytics. She will discuss a range of institutional barriers encountered, and introduce a ‘systems’ framework that may allow more careful analysis of structural and cultural blockages in institutions, and identification of points for intervention.

4.3 Alfred Essa

Alfred is Vice President, Analytics and R&D at McGraw-Hill Education and was, until August 2013, Director of Analytics Research and Strategy at Desire2Learn. There, he led product development on the Student Success System, a set of predictive analytic tools that was incorporated within the company’s cloud-base learning systems. He will talk about his experience of scaling analytics up for use across institutions and across national boundaries.

4.4 Shane Dawson

Shane is Deputy Director of Academic Learning Services at the University of South Australia and has extensive experience of developing and implementing learning analytics. He will discuss his research into problems encountered when working to implement analytic findings at institutional level, and introduce ways of overcoming the barriers to success.

4.5 Shirley Alexander

Shirley is Deputy Vice-Chancellor and Vice-President (Teaching, Learning and Equity) at the University of Technology, Sydney. Her responsibilities include enhancing the quality of the university’s teaching, creating an environment of innovation and excellence in teaching and learning. She will talk about her experience of implementing analytics across a university.

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