



# THE UNIVERSITY *of* EDINBURGH

## Edinburgh Research Explorer

### How do we start? Sate and directions of learning analyics adoption

**Citation for published version:**

Gasevic, D, Dawson, S & Pardo, A 2016, How do we start? Sate and directions of learning analyics adoption. International Council for Open and Distance Education, Oslo, Norway.

**Link:**

[Link to publication record in Edinburgh Research Explorer](#)

**Document Version:**

Publisher's PDF, also known as Version of record

**General rights**

Copyright for the publications made accessible via the Edinburgh Research Explorer is retained by the author(s) and / or other copyright owners and it is a condition of accessing these publications that users recognise and abide by the legal requirements associated with these rights.

**Take down policy**

The University of Edinburgh has made every reasonable effort to ensure that Edinburgh Research Explorer content complies with UK legislation. If you believe that the public display of this file breaches copyright please contact [openaccess@ed.ac.uk](mailto:openaccess@ed.ac.uk) providing details, and we will remove access to the work immediately and investigate your claim.





INTERNATIONAL  
COUNCIL FOR OPEN AND  
DISTANCE EDUCATION



**How do we start?**

State and Directions of  
Learning Analytics Adoption



## How do we start?

# State and Directions of Learning Analytics Adoption

### Abstract:

The analysis of data collected from user interactions with educational and information technology has attracted much attention as a promising approach to advancing our understanding of the learning process. This promise motivated the emergence of the field of learning analytics and pushed the education sector towards increased application of data for strategic decision-making.

This paper addresses a commonly posed question asked by educators, managers, and administrators embarking on learning analytics in higher education – how do we start institutional learning analytics adoption? The paper first defines learning analytics and touches on lessons learned from some well-known case studies. The paper then reviews the current state of institutional adoption of learning analytics by examining evidence produced in several studies conducted worldwide.

The paper next outlines directions for learning analytics adoption that should enable for a system-wide institutional transformation. The paper concludes with a summary of critical challenges that require attention in order for learning analytics to make a long-term impact on research and practice of learning and teaching. The paper emphasizes that learning analytics cannot be reduced to a simplistic rhetoric of quick technological fixes. Rather, learning analytics advocates for holistic approaches that account for and support complexities associated with specific characteristics of different educational systems and institutions.

Dragan Gašević<sup>1</sup>

Shane Dawson<sup>2</sup>

Abelardo Pardo<sup>3</sup>

<sup>1</sup>Moray House School of Education and  
School of Informatics,  
The University of Edinburgh,  
United Kingdom

<sup>2</sup>Teaching Innovation Unit,  
University of South Australia, Australia

<sup>3</sup>School of Electrical and Information  
Engineering, The University of Sydney,  
Australia

ISBN: 978-82-93172-37-6

## 1. Introduction:

The modern landscape in higher education is shaped by several critical drivers.

First, several reports cite the changing population of students with a rapidly growing number of non-traditional students. Non-traditional students are characterized as financially independent, have their own dependents, and work at least part-time, and more frequently, in a full-time capacity (Davis, 2012; Jarrett, 2013).

Second, higher education institutions are trying to redefine the role they play in societies. Traditionally, universities had an endpoint in their relationship with a student. For example, students would spend a set number of years completing their degrees and then move on to start their professional careers (Siemens, Gašević, & Dawson, 2015).

However, more recently this relationship has undergone dramatic changes. The relationship between a University and student has quickly transitioned from 4 to 40 years. This has been highlighted by the increasing societal requirement for lifelong learning.

The widespread adoption of massive open online courses and demographics of their completers (usually those with university degrees) (Hansen & Reich, 2015) has surfaced a need for life-long engagements with higher education institutions with students pursuing new opportunities for upskilling and career changes.

The demand for post-university learning has forced universities to recognize the importance of scaling up their educational opportunities and seek novel models of education delivery (Siemens et al., 2015).

Third, higher education institutions are aiming to enhance the student learning experience through active learning approaches (Freeman et al., 2014) and flipped classrooms (O'Flaherty, Phillips, Karanicolas, Snelling, & Winning, 2015).

Finally, the well documented decreases in higher education funding lies in stark contrast to national goals and aspirations to increase the number of higher education graduates (Johnson, 2012).



Higher education institutions aiming to either scale up their educational opportunities or personalize the student learning experience in flipped classrooms typically turn to technologies as a solution. Learning management systems (LMS) and student information systems containing socio-demographic and student enrollment data can be considered now as “foundation” technologies for higher education institutions.

These technologies typically form the core of a broader suite or a loosely connected ecosystem of technologies. Institutions are increasingly encouraging staff to undertake further learning and teaching innovation by integrating technologies such as social networking software, blogs, video annotation, lecture capture, interactive media, and slide sharing software.

Although these technologies can aid the design of active learning pedagogies, they also inadvertently weaken the feedback loops that exist between students and educators (Ali, Hatala, Gašević, & Jovanović, 2012). Institutions are now required to broaden their conception of student learning and to observe more nuanced consideration of part-whole relationships among the elements of these new learning environments (Ellis & Goodyear, 2013).



For instance, in conventional face-to-face instructional settings many social cues about a student's engagement are easily picked up by instructors. However, through the use of online technologies such social cues are significantly reduced – if not fully eliminated (Shane Dawson, Bakharia, & Heathcote, 2010). Methods that can restore and even enhance such existing feedback loops are necessary steps.

Digital “footprints” (or trace data) about user interactions with technology have been recorded since the very introduction of the Internet and web-based software systems. Such “footprints” were introduced to assist software developers to track whether web-based software systems worked as originally designed and if not, to ease the process of software debugging. Over time, the value of such digital traces has been recognized as a promising source of data about student learning (Gašević, Dawson, & Siemens, 2015).

The application of such data and data mining methods in education settings helped inform the development of the field of learning analytics (Siemens, 2013). The analysis of user interaction data derived from educational technologies underpins much of the learning analytics research. Furthermore, student trace data are often combined with additional data sets collected through various educational research approaches such as surveys and course evaluations as well as socio-demographic and academic data recorded by student information systems.

To analyze these linked data sources, learning analytics borrows methods from a diverse set of disciplines such as statistics, machine learning, and social networks analysis. The results of such analysis are presented to the users by drawing from research and practice of disciplines such as educational psychology, user interface design, and information visualization.

The Society for Learning Analytics Research (SoLAR) defined learning analytics 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” (Long, Siemens, Conole, & Gašević, 2011). (Long, Siemens, Conole, & Gašević, 2011).

It is the second portion of the definition that emphasizes the actionable nature of learning analytics. Although educational research has traditionally used data, the critical difference in learning analytics research is that the data are often used in real-time to inform decisions for a diverse set of educational stakeholders (e.g., learners, instructors, and administrators). The prolific use of technology in higher education has driven an unprecedented collection of data about learning. Higher education institutions are now recognizing the potential this data provides in informing teaching and learning practice, developing new areas of educational research, and optimizing institutional performance (including finances) (Dawson, Gašević, Siemens, & Joksimovic, 2014).

Despite the potential of learning analytics to address various educational challenges, many institutions are yet to fully exploit the full use of learner and organizational data. This paper addresses a commonly voiced question among educators, and senior managers in higher education – How do we start the process for institutional learning analytics adoption? To address this question, the paper commences with a brief description of the current state of learning analytics adoption including an outline of well-known cases studies involving analytics adoption.

The paper then poses examples and directions for systemic institutional adoption of learning analytics. The paper draws on a) a well-established approach in business analytics; and b) evidence documented in the learning analytics literature. The paper concludes with several remarks that reinforce the critical points for future work related to the adoption of learning analytics.



## 2.State of Learning Analytics Adoption

This section gives an overview of themes commonly explored in learning analytics. Then, to illustrate the state of learning analytics, this section provides a description of two well-known large scale applications of analytics in higher education. This is followed by a review of several reports that investigated the current state of learning analytics adoption.

### 2.1 Common learning analytics themes

Broadly speaking, three major emerging themes have been identified in learning analytics: predictors and indicators, visualisations, and interventions (Brown, 2012). The first category includes those solutions in which the data obtained from an initial learning scenario is processed through statistical and data mining methods to produce a model capable of predicting one of its factors (e.g., academic performance, students remaining in a course, student engagement, social network position, or self-regulated learning skills).

The model is then used in subsequent editions of the learning experience and the newly captured data is used as input to the predictive model to obtain an estimate of the factor under study. Examples of these systems are those detecting students at risk (e.g., Arnold & Pistilli, 2012), or those generically known as *Early Warning Systems* (e.g., Krumm, Waddington, Teasley, & Lonn, 2014).

Some of these systems are simply used to discover correlations between events in an online platform and academic performance (e.g., Romero-Zaldivar, Pardo, Burgos, & Delgado Kloos, 2012) and make the information available to instructors for further actions.

In recent years indicators about issues such as 21<sup>st</sup> century skills (Buckingham Shum & Deakin Crick, 2016), self-regulated learning (Roll & Winne, 2015), or learning dispositions (Buckingham Shum & Deakin Crick, 2012) by using methods coming from areas such as text analysis (Knight & Littleton, 2015), process mining (Reimann, Markauskaite, & Bannert, 2014), and social network analysis (Dawson, Tan, & McWilliam, 2011).

The *second* category of learning analytics platforms processes the data to derive visualisations that are then made available to administration personnel, instructors or even to students (Verbert, Duval, Klerkx, Govaerts, & Santos, 2013). The visualisations can offer a simpler format to explore and interpret an otherwise complex and confusing set of data and to prompt the deployment of remediation actions.

The *third* category of learning analytic approaches focuses on *interventions* or how to derive precise actions to shape the learning environment to improve the student experience. These initiatives explore how interventions can be included as an additional element in a learning design and the interaction with the rest of the design components (Lockyer, Heathcote, & Dawson, 2013; Wise, 2014).

### 2.1 Case Studies

Two cases studies are introduced. The first case study addresses the challenge of student retention, while the second is focused on improving student success and learning processes.

#### 2.2.1 Course Signals

One of the best known examples of the use of analytics in education is Course Signals (Campbell, 2007). Course Signals is essentially a predictive model that aims to provide an early warning alert for both students and instructors about the degree of risk associated with failing or succeeding in a course. Early warnings are triggered as a result of a data mining algorithm that makes use of the trace data logged by the learning management system and combines this with student prior performance and demographic data.

The algorithm is executed by the instructor at specific points during a course. The output of the algorithm is a categorical variable with the three distinct categories: i) student at high risk of failing a course; ii) student at moderate risk of failing a course; and iii) student at no risk of failing a course. These three categories are translated into the three traffic light signals – red, yellow, and green, respectively – that are incorporated into early warning dashboards designed for both students and instructors. Based on various signal presented by the traffic light, students and instructors can make informed decisions about their learning progress and teaching support.

The use of Course Signals has been noted to improve student retention. Arnold & Pistilli (2012) reported the findings of an evaluation of Course Signals in an undergraduate engineering program at Purdue University to address the challenges of student retention. In their study, they tracked a cohort of engineering students who started their program in 2007 ( $N_{2007}= 8170$ ) for four years (i.e., until their program completion) and another cohort that started in 2008 ( $N_{2008}= 9601$ ) for three years (N.B. the 2008 cohort was in their fourth year at the time the study was published).

The group of students who completed at least one or more courses that used Course Signals in each year of their studies had significantly higher results than the group of students who did not complete any course with Course Signals. The absolute percent differences in the retention rate in every given year were 13-21% higher in the Course Signals user group than in the non-user group. Although the robustness of the statistical analysis used in and interpretation of the results (implying causality) of the Arnold & Pistilli study have correctly been challenged (Caulfield, 2013), even critics acknowledge a promise of the use of Course Signals for student retention.

The impact of Course Signals on teaching quality has also been studied. Tanes, Arnold, King, & Remnet (2011) reported on the findings of a study that analyzed the quantity and quality of email messages sent by instructors to students as a consequence of the use of Course Signals.



The quality of messages was determined through content analysis of the specific messages and looking for indications of formative and summative assessment. The main finding from the study is that Course Signals was associated with an increase in the frequency of messages containing summative feedback. The messages sent to students identified as at risk significantly increased when compared to cases where Course Signals was not adopted.

The summative feedback typically communicated the simple progress indicators to the students as an attempt to motivate them to increase their engagement or level of study. However, as also noted in the research literature, the summative feedback was not associated with student academic performance (Hattie & Timperley, 2007). While, Tanes et al. did identify a significant positive association between the use of formative feedback and academic performance, the use of such feedback was in this instance poorly incorporated among the studied courses.

The study done by Tanes et al. (2011) indicates two important lessons for the adoption of learning analytics. First, learning analytics systems cannot be deployed into institutions without sufficient training of teaching staff on how to employ analytics effectively in practice. Second, learning analytics systems need to be designed to support deep insights into processes of relevance. While traffic lights are quite an intuitive metaphor for users to understand, traffic lights do not offer sufficient insight for users. For instance, insight into the actual reasons why students are identified as at risk and what kinds of support and guidance they require to mediate their learning progression.

### 2.2.2 E2Coach

The E2Coach learning analytics system shows how some of the weaknesses identified in the applications of Course Signals can be addressed (McKay, Miller, & Tritz, 2012). The E2Coach system was designed at the University of Michigan with the intention to address the needs of first year science courses with large enrollments. In those courses, it was observed that students whose major was not science (e.g., psychology) tended to have a lower success rate and more modest achievement goals than their peers with science as a home discipline.

To address this challenge and increase the success of these students in science majors, several activities were conducted. First, the learning strategies of successful students in science courses were identified via the use of a qualitative survey. These strategies were used as the foundation for developing formative feedback.

Second, operationally the concept of “better than expected” was established. Better than expected defined the major metric of success for each student. This metric was obtained by comparing students’ performance in previous courses to: i) self-reported goals for grades in currently enrolled science courses; and ii) predicted grades based on trace data and data about previous performance. Finally, the E2Coach was designed to automatically compose and send personalized messages to all students.

The messages were created by building on the principles of self-determination theory (Black & Deci, 2000) by offering a rationale as to why studying science for students from non-science majors is beneficial for their longer term careers. In the case where students self-reported goals were more modest than their actual grade point average, a motivational message was provided that aimed to increase their self-efficacy by referencing examples of other students in similar situations who managed to perform better than expected. Messages would also offer advice about study strategies recommended by their peers who previously successfully completed the course.

The findings of studies examining the use of the E2Coach showed an average increase of a half a letter grade (grades being from F to A) (Wright, McKay, Hershock, Miller, & Tritz, 2014).

The design and implementation of the E2Coach offers up several critical lessons for the adoption of learning analytics. Learning analytics systems need to be designed by building on well-established principles grounded in educational research and practice – e.g., motivational theories and literature related to the use and application of feedback.

The findings also highlight the necessity for a question-driven approach to the implementation of learning analytics. Finally, insights into the qualitative aspects of effective study strategies need to be incorporated into the design of learning analytics and offered as (in-) formative feedback to students.

## 2.2 Systemic adoption of learning analytics

In spite of the promising results noted in the above two case studies, several authors have highlighted the absence of institutional examples related to learning analytics adoption (Ferguson et al., 2014). Even the institutions involving the aforementioned two case studies do not have a systemic institution-wide adoption of learning analytics. Although the relative nascence of the field learning analytics is in part a contributing factor in the lack of institutional examples, there are clearly other substantial challenges. The adoption of analytics at an institutional level in general has been problematic. This concern is well summarized by Bichsel (2012) in noting that while interest in organizational analytics is high, many institutions are yet to make progress beyond basic reporting.



This lack of uptake is further corroborated by several studies conducted over the last decade. Goldstein & Katz (2005) investigated how higher education institutions make use of data in their decision making. In their study, they followed a five phase analytics framework. Of the 380 institutions investigated, they observed that approximately 70% were in stage one – the extraction and reporting of transaction-level data.

Only 8% of the institutions involved in the study were in stage three - the ability for “what-if” decision support such as scenario building. The remaining institutions were in stage two – the analysis and monitoring of operational performance. No institutions were observed to be in stages four (predictive modeling & simulation) or five (automatic triggers, alerts, and interventions).

Similar results were reported by Yanosky (2009) who surveyed 305 institutions and found that 58% institutions were in stage one, 20% in stage two, 11.5% combined in stages three-five, while 9.5% institutions who were inactive data users. Little progress in analytics adoption had occurred despite Yanosky’s study being undertaken some 5 years after the initial work of Goldstein and Katz.

Recent studies into systemic institutional adoption of learning analytics report similar findings. For instance, Colvin et al. (2015) scanned the state of learning analytics adoption in the Australian tertiary education sector. In that process, they interviewed senior leaders responsible for the implementation of learning analytics in 32 (out of 40) Australian universities. Colvin and her colleagues identified that the Australian institutions were in either phase one (Aware) or two (Experimentation) of the five phase learning analytics sophistication model previously suggested by Siemens, Dawson, and Lynch (2014).

Moreover, the Colvin et al. study found two distinct groups of institutions identified across several dimensions such as leadership, strategy, readiness, conceptualization, and technology. The first group of institutions were focused primarily on the use of learning analytics to resolve concerns with student retention.

This group was characterized as developing a solution focused learning analytics approach. In such cases, the acquisition of technical solutions was heavily pronounced.

The conceptualization of learning analytics of the second group of institutions was more holistic. This grouping of institutions stressed the role of learning analytics to help advance understanding of learning and teaching. The second group of institutions also involved different stakeholders in the design and implementation of learning analytics and accounted for their institutional complexities.

The study of the Australian tertiary education sector emphasizes the importance of institutional leadership and the development of the institution’s strategic capability. The institution’s strategic capabilities are shaped by the analyzed dimensions (leadership, strategy, readiness, conceptualization, and technology), which can define “how an organisation sets in motion its deployment, project management, and scope of its LA [learning analytics] endeavours” (Colvin et al., 2015, p. 5).

Moreover, the recognition of the institution’s specific needs in defining a strategic vision for learning analytics to achieve long term impact is acknowledged by the international panel of experts involved in the second study reported by Colvin et al.

This observation is aligned with the argument posited by Macfadyen, Dawson, Pardo, & Gasevic (2014) suggesting that institutions need to define policies and strategies for learning analytics by embracing the complexities inherent to their organizational including cultural, and social structures and practices.

### 3. Direction for Systemic Adoption

While higher education institutions have long expressed much interest in learning analytics, there continues to be a lack of a data-informed culture in decision making such education settings (Macfadyen & Dawson, 2012; Manyika et al., 2012). It is not surprising that there are many institutions who are unclear how they should start with their process of learning analytics adoption and implementation. In this paper, we argue that the lessons learned in business analytics and organizational change can be helpful for educational institutions. Specifically, we find the approach developed and used by McKinsey and Company in engaging with their partners to achieve organizational transformation based on analytics (Barton & Court, 2012) is a promising framework for articulating the directions for learning analytics adoption.

The approach consists of three elements: data, model, and transformation. The approach is designed to ease communication with organizations (adopters of analytics) and assist senior leaders to grasp the benefits and challenges associated with adoption of analytics in organizational decision making. In the remainder of this section, we make use of this approach to offer directions necessary for systemic adoption of learning analytics by highlighting critical issues specific for education.

#### 3.1 Data

The data element of the analytics adoption approach includes two key issues: creative data sourcing and securing necessary information technology (IT) support.

##### 3.1.1 Creative data sourcing

Many institutions, aware of the opportunities for data collection afforded by learning management systems and other technologies, typically opt for the acquisition and/or development of learning analytics systems that are based on trace data about students' views of different webpages. Although there is much promise in the use of trace data, institutions need to be creative in their data sourcing that can enable them to address the questions they are interested in .

The major recommendation in the process of finding relevant sources of data is to build on existing principles established in educational research and practice (Gašević et al., 2015; Wise & Shaffer, 2015). For example, in the two cases studies already outlined in this paper, student success is one of the main concerns for many institutions. Social networks are known to play an important role students' learning process and performance (Dawson, 2008; Sparrowe, Liden, Wayne, & Kraimer, 2001), and thus can be a valuable source for understanding and predicting student success.

Although commonly used, sources for extraction of social networks do not have to be collected through social media. Social networks can be extracted even from student information systems that record information about student course enrollments. Gašević, Zouaq, & Janzen (2013) showed how centrality in such networks, called cross-class networks, can be extracted from course enrollment records from a fully online master's degree in Canada.

The network structures explained between 20% and 28% of students' grade average point. The use of more advanced methods such as exponential random graph models (ERGM) allow for testing advance characteristics in such networks like homophily – connecting with similar individuals (e.g., based on the same gender, ethnicity, or academic performance). Our unpublished study with the enrollment data from a residential master degree in Australia unveiled that homophilic relationships based on students' academic success (i.e., based on GPA) were significant.

That is, students who had high grades tended to take courses with other students with high grades.

Yet, there was no statistically significant probability of students with high to take courses with students with low grades. As argued by Gašević et al. (2013) such insights can inform institutions in developing different (counseling) supports and use different models for organizing student cohorts such as the established model of learning communities (Leigh Smith, MacGregor, Matthews, & Gabelnick, 2004).

### 3.1.2. Awareness of data limitations

Awareness of limitations and challenging assumptions related to some commonly used data types is another critical perspective for successful adoption of learning analytics at a systemic level. Time spent online interacting with resources provided in learning management systems is a commonly used type of data in learning analytics. For example, this type of data is often used for the prediction of student performance (Macfadyen & Dawson, 2010) and for understanding of learning strategies (Kovanović, Gašević, Joksimović, Hatala, & Adesope, 2015).

Although time spent online can offer some insight into the relevant activities students engaged in and how this is associated with academic performance, there remains considerable limitations in both how time is calculated and the methods deployed for analysis. Time spent online can be estimated by using trace data (especially click streams) recorded by learning management systems. Some learning management systems even offer functionality that estimates time online.

Estimation of time online is challenging and frequently inaccurate. There are internal and external (to the learning management system) threats to validity that can bias the estimation of time online. Internally, many learning management systems do not automatically log students out after some time of inactivity. In such cases, time online estimation may show that a student spent several days continually working on a task. Kovanović and colleagues (2015; 2016) looked into 15 different strategies that can be used to address overestimation of time online.

They showed that different strategies result in over 20% of absolute difference in explained variability in regression models looking at the association between variables extracted from trace data and academic performance. Yet, they could not explain which of the 15 estimation strategies was the most accurate.

Externally, there is no reliable way to know whether students were actually engaged in learning when they were online or they did some other random activity (e.g., watching TV in the same room) while visiting some of the online resources in the learning management system. There are very few studies that have investigated this limitation. A promising approach is the Baker Rodrigo Ocumpaugh Monitoring Protocol (BROMP) designed for quantitative field observations of student affect and behavior (Ocumpaugh, Baker, & Rodrigo, 2015). The BROMP has successfully been used in numerous studies that investigated off-task behavior of students (Baker et al., 2008; Baker, Corbett, Koedinger, & Wagner, 2004).

Both internal and external threats to validity of time online estimation have practical implications on learning analytics adoption. Transparency in the description of the internal method used for gauging time online is essential to help users of learning analytics understand how to implement results and take actions.

Transparency is especially critical when institutions are using learning management systems that provide estimation of time online, but do not offer any information on how this estimation is performed. A need to militate against external threats to validity calls for joint work between developers of learning analytics (technologies) and educational institutions to advance the quality of existing learning analytics solutions.

### 3.1.3 Securing necessary IT support

Involvement of and support from IT units is essential for systemic institutional adoption and implementation of learning analytics. Without models specifying how existing IT processes and practices can be adopted to support learning analytics, institutions may face problems that can either postpone or even disable implementation of learning analytics processes. The first author of this paper was involved in a learning analytics project at a Canadian university that offers a good illustration of the importance of this problem. The university's Vice-President, Academic (i.e., chief academic) established a program that aimed to foster educational innovation. The program offered grants to faculty members to develop educational technology that can address some critical challenges in learning and teaching. One of these grants supported the development of a learning analytics dashboard that encourages participation in asynchronous online discussions (Beheshitha, Hatala, Gašević, & Joksimović, 2016).

The project progressed well until the point when the project team had to deploy the developed learning analytics technology to the institutional learning management system and pilot it in courses offered in the following semester. A challenge emerged in the interaction with the IT department who felt that the project would violate some of their policies for secure access to data. Specifically, the challenge was related to the process of deployment of the learning analytics software and real-time access to data from the learning management system. At the time, the IT department did not have a process and human resources allowing them to handle data needs of individual projects. Although technically the problem was easy to fix (writing a program that handles a single query), it took several weeks of negotiation until a satisfactory solution was found to enable the enactment of the planned pilots.

A critical recommendation is that institutions need to engage all relevant stakeholders in a timely manner prior to the commencement of any implementation of learning analytics projects. The involvement needs to go beyond IT units and include other key stakeholders such as students, faculty, student record representatives, security and practice protection officers, learning and teaching units, institutional ethics review boards, and senior leaders.

The embedding of learning analytics across an organization cannot be seen as the sole responsibility for an individual unit or leader. The implementation process needs to be seen as a task that requires multidisciplinary teams with active involvement from all relevant stakeholders.

## 3.2 Model

The use of machine learning methods is widespread in learning analytics. Machine learning generally involves the development of models that can best discover patterns in data, explain associations between variables, and even reveal causality relationships. To adopt learning analytics, two key aspects need to be considered: i) the analytic approach needs to be question-driven rather than data-driven; and ii) modeling needs to be based on demonstrated educational research and practice.

### 3.2.1 Question-driven, not data-driven

As noted in business analytics (Barton & Court, 2012), many educational institutions also try to outsource analytics to external consulting organizations with specialized expertise in analytics (Colvin et al., 2015). Engagement with such analytics organizations can be beneficial especially when educational institutions do not have the internal capacity and experience to meet the institution's requirements.

However, the lack of understanding in what can be achieved with analytics at a strategic level may often lead to making assumptions that providing data to external consultants is the sole input and requirement for an institution in interacting with the consultants. This (data-driven) process has been proven as ineffective in business analytics (Barton & Court, 2012). Rather, a question-driven approach is necessary.

This assumes that institutions need to define their initial questions and establish how they would like to address these challenges through the use of analytics before engaging with an analytics consultant. This approach will first help institutions understand their actual needs and second enable them to identify consultants that provide the most effective services.

The initial questions will of course be changed throughout the entire project lifecycle. They will be refined through the interactive processes of engagement and dialog with analytics consultants and data analysis, some of them possibly be even dismissed, and new questions will emerge.

The question-driven approach can be illustrated through the two case studies already outlined in the paper (Campbell, 2007; Wright et al., 2014). The institutions from the two case studies started from clear questions and institutional priorities. These questions led to the development and implementation of learning analytics solutions. According to the two institution profiles identified by Colvin et al. (2015), the formulation of questions and consequent engagement with analytics organizations for institutions focused on retention exclusively can be somewhat straightforward and clear options available on the market.

For institutions that are focused on the use of learning analytics to understand learning and teaching the question formulation requires a more complex process to identify institutional priorities and the needs of different stakeholders. However, for both institution profiles special care needs to be taken in developing processes of acting upon results based on learning analytics. This requires understanding the context and complexities of existing educational systems within and around institutions (Macfadyen et al., 2014) before new support structures and/or changes of existing processes can be instituted.

### 3.2.2 Building on existing educational research and practice

The literature argues that learning analytics need to be informed by existing education research and practice enable successful adoption and produce actionable insights (Gašević et al., 2015).

The lack of theory informed learning analytics can lead to (failed) attempts to replicate results without adequately accounting for contextual factors under which original results of analytics use were generated (Joksimović et al., 2016; Wise & Shaffer, 2015).

As education is a rich and broad discipline, relevant experience from practice and results derived from the literature needs to be first identified in order to inform the development and use of specific learning analytics. To address this challenge, several authors emphasize theory informed use of learning analytics (Rogers, Gašević, & Dawson, 2016; Wise & Shaffer, 2015).

We refer to the work of Rogers et al. (2016) as representative for theory informed learning analytics. Rogers and colleagues build on the Hadwin and Winne (1998) model of self-regulated learning to account for external (e.g., instructional design) and internal (e.g., study skills, prior knowledge, and motivation) conditions when developing, interpreting, and acting on learning analytics. Consistent with Rogers and his colleagues' proposition to account for external conditions, Lockyer, Heathcote, and Dawson (2013) posit that learning analytics needs to be first informed by documenting the pedagogical intent through detailed learning designs.

The study by Gašević, Dawson, Rogers, and Gasevic (2016) corroborated the Lockyer et al. suggestion by reporting findings from nine large enrollment undergraduate courses (n = 4,139) from an Australian university.

The study by Gašević et al. (2016) found that predictive models of student performance and retention built on trace data and generalized for all nine included courses could not offer sufficient actionable insight of relevance for practice in specific courses.

Course specific predictive models however overcame this problem and identified variables of significance for teaching practice and in accordance to course specific learning designs.

Consideration of internal conditions is of high importance for learning analytics practice. Effects of individual differences are widely recognized in the literature on academic performance (2012) and we argue that they should have an equal treatment in learning analytics. For example, there is a common assumption that time spent on learning is positively associated with academic performance (Fritz, 2011). Kovanović et al. (2015) investigated strategies that can be extracted from trace data about interaction of learners in a course designed by principles of communities of inquiry (Garrison & Arbaugh, 2007).

They found that students who spent the highest amount of time would be highly inefficient in their learning and would not have highest academic performance. Kovanović et al. interpreted that this group of learners were highly motivated, but likely had weaknesses in prior knowledge and study skills. The amount of activity and time online for the group of most successful students was mostly below the class average. These learners were interpreted as highly effective with good prior knowledge and strong study skills. The findings of the Kovanović et al. were corroborated in several studies reported by Lust et al. (Lust, Elen, & Clarebout, 2013; Lust, Vandewaetere, Ceulemans, Elen, & Clarebout, 2011).

### 3.3 Transformation

The transformation element of the analytics approach brings into dialogue the specific design of the analytics tools that will best address the stakeholders' needs. This requires tools to be designed through participatory design with the intent to support non-statistics experts. There has been much interest in the development of learning analytics tools and there are many tools – e.g., typically dashboards developed by either learning management vendors and/or educational institutions (Verbert et al., 2013). There are however no empirically validated and widely accepted principles for design and evaluation of learning analytics dashboards. This may pose a serious challenge in acceptance and performance of learning analytics by end-users. We discuss two examples of possible challenges that are emerging from the research on learning analytics dashboards.

With the discussion of these examples, we try to prompt institutions to pay attention to some key issues that need to be considered when acquiring external or developing their own learning analytics tools.

Learning analytics visualizations can be harmful if not designed and used carefully. Although the literature indicates that visualization can be valuable in general (Card, Mackinlay, & Schneiderman, 1999) and education in particular (Janssen, Erkens, & Kirschner, 2011), the visual tools need to be designed with clear benefits in mind and offer good fit for tasks they are supposed to support (Vessey, 1991). Many learning analytics dashboards use visualizations that provide students with diagrams that compare them with a class average. However, there is no clear theoretical and empirical reason to support the inclusion of diagrams for the comparison with class average. Corrin and de Barba (2014) conducted a study in which they investigated how students interpret information visualized in commonly available learning analytics dashboards.

They found that students' interpretations of visualizations were inaccurate. Even the top performing students with high previous grades and high expectations in their classes perceived themselves to be doing well when they observed that they were slightly above the class average. In one sense this is an accurate interpretation. However, these students were underperforming with respect to their personal goals and past performance. This perception of excellence may stem from an individual's weak ability to interpret the meaning of average with respect to their personal goal setting. Not only does this lesson have implications for the design of dashboards, but it also sends an important message for increasing data literacy of students and teaching staff (Wasson & Hansen, 2016; Wolff, Moore, Zdrahal, Hlosta, & Kuzilek, 2016).

Students may not see learning analytics dashboards as feedback if they are not well integrated with the set learning tasks. Learning analytics dashboards are designed with the intention to provide feedback to students, instructors, and administrators with the goal to optimize learning and environments in which learning occurs (Siemens & Gasevic, 2012). There is nonetheless limited research with respect to how students react to the use of dashboards as a form of feedback for their learning. Pardo, Jovanović, Dawson, and Gašević (2016) present the findings from a study in a large enrollment computer engineering class offered in an Australian university over the period of three years. The study aimed to increase the student learning experience through the use of targeted feedback. The study introduced dashboards with similar features as common for many other contemporary analytics solutions – e.g., comparison of a student’s different activities with class average. The findings revealed that the introduction of such dashboards did not increase the perceived value of feedback by students. The perceived value of feedback significantly improved when learning analytics results were provided to instructors to construct personalized emails containing specific suggestions for students.

The findings of the study by Pardo et al. (2016) shows learning analytics can improve the quality of learning experience and increase some of the pressing challenges for institutions such as how to handle highly diverse and/or large student cohorts. The findings of the study also reiterate the importance of integrating learning analytics tools for end users with existing educational theory and practice. Analytics-based tools designed to construct feedback for students, among other key points, are more effective when they adopt a task-specific language and provide guidance while prompting dialogue between students and instructors (Boud & Molloy, 2013; O’Donovan, Rust, & Price, 2016).

### 3.4 Some ugly truths

A frequent expectation for learning analytics is that they will help advance understanding and enhancement of learning. Adoption of learning analytics may expose some issues that are not necessary consistent with and/or are contrary to some of the values and ideals educational institutions strive.

We discuss two example studies to illustrate some of these issues.

Learning analytics may show that existing educational models are not catering to the needs of different students. The study reported by Joksimović, Gašević, Loughin, Kovanović, & Hatala (2015) looked at the association of academic performance and the amount of and time spent on the three types of interactions as defined by Moore (1989) – student-student, student-instructor, and student-content. The amount of each of the three interactions was extracted from trace data logged by the institutional learning management system in a fully online master’s program in Canada for the period 2006-2012. In core courses, time spent on student-instructor interaction was negatively associated with academic performance.

This was interpreted through “increased needs of those students who struggle with the course material for an increased instructional support” (Joksimović et al., 2015, p. 212). Although this finding is consistent with the finding of a previous meta-analytic study (Lou, Bernard, & Abrami, 2006) of distance learning in higher education, it raises questions such as what policies and strategies are educational institutions and instructors will take to address this challenge? This is especially relevant in the scope of equitable teaching opportunities for all students including high performing students who receive similar instructional attention (e.g., to be challenged and exceed their personal best) as those who might be lagging behind. The trend that high performing students have little or no progression over time has already been noted in the primary and secondary education (Griffin, 2013; Masters, 2015).

Learning analytics may reveal a performance oriented culture in students' behavior. Promoting deep approaches to learning has been a long term ideal of higher education where the use of study strategies indicative of mastery learning, conceptual change, and intrinsic motivation are promoted (Trigwell & Prosser, 1991). In contrast to this, surface approaches to learning are associated with rote learning, extrinsic motivation, and a focus on grades (i.e., performance orientation).

Instructors play an essential role whether their students will follow deep or surface approaches to learning (Trigwell, Prosser, & Waterhouse, 1999). Studies making use of learning analytics methods, by examining trace data to extract learning strategies followed by students, reveal that students have a high tendency to exhibit performance-oriented behaviors – i.e., focusing on summative assessments deemed to contribute to grades (Lust et al., 2013; Pardo, Jovanović, Dawson, Gašević, & Mirriahi, 2016).

This happens even in courses with learning designs offering a plethora of opportunities promoting mastery learning and formative feedback. The systemic adoption of learning analytics will likely reveal such patterns in many educational institutions, schools, academic programs, or individual courses. The challenge for institutions striving to the ideals of modern education is to find pedagogical approaches that can systemically promote deep approaches to learning.

## 4. Concluding Remarks

This paper aimed to outline some of the current state and key directions for learning analytics. The main recommendation for systemic adoption of learning analytics is that institutions need to embrace the complexity of educational systems (Macfadyen et al., 2014) along with internal and external factors established in the literature to shape operation of and experience in educational institutions.

Adoption of learning analytics cannot be deemed as a simple fix to address the challenges of contemporary education. Rather, learning analytics must be considered in a broader context of interconnected organizational, social, and political structures that form modern educational institutions.

Effective adoption and impact of learning analytics can only be achieved only if multidisciplinary teams responsible and representative of all relevant stakeholder groups are formed and charged with implementation.

Ethics and privacy protection are key enablers for successful adoption and impact of learning analytics (Ferguson, Hoel, Scheffel, & Drachsler, 2016; Gašević, Dawson, & Jovanović, 2016). The importance of ethics and privacy, although not the focus of this paper, cannot be emphasized enough. Although early work on learning analytics identified many concerns related to ethics and privacy, there have been recently a number of frameworks, codes of practice, and other guiding documents that can be used to enable and support adoption of learning analytics. Notable examples are the Jisc code of practice for learning analytics (Sclater & Bailey, 2015), the DELICATE framework for privacy protection (Drachsler & Greller, 2016), data de-identification methods (Khalil & Ebner, 2016), and development of student agency in connection to data privacy (Prinsloo & Slade, 2016).

Several institutions already developed policies defining main principles that guide the adoption of learning analytics, including issues related to privacy and ethics. The Open University (United Kingdom) was the first organization that developed their learning analytics policy (Open University, 2014), while there are already several institutions who either have already developed or are developing their learning analytics policies.

The development of a data-informed decision making culture is probably the most profound step that educational institutions must take in order to enable institutional transformation. This process needs to recognize the limitations of data and analytics in order to make use of the benefits afforded by learning analytics and avoid possible detrimental effects of inadequate use of analytics on educational practice and stakeholders involved.



Any adoption of learning analytics should avoid simplistic measures in order to circumvent the unintended organizational consequences described by Goodhart's law (Elton, 2004). The development of data literacy, strategic capabilities, and overall institutional capacity in connection to learning analytics are key milestones for institutions on their journey of systemic learning analytics adoption.



## 5 References

- Ali, L., Hatala, M., Gašević, D., & Jovanović, J. (2012). A qualitative evaluation of evolution of a learning analytics tool. *Computers & Education*, *58*(1), 470–489. <https://doi.org/10.1016/j.compedu.2011.08.030>
- Arnold, K. E., & Pistilli, M. D. (2012). Course signals at Purdue: using learning analytics to increase student success. In *Proceedings of the 2nd International Conference on Learning Analytics and Knowledge* (pp. 267–270). New York, NY, USA: ACM. <https://doi.org/10.1145/2330601.2330666>
- Baker, R. S., Corbett, A. T., Koedinger, K. R., & Wagner, A. Z. (2004). Off-task Behavior in the Cognitive Tutor Classroom: When Students “Game the System.” In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (pp. 383–390). New York, NY, USA: ACM. <https://doi.org/10.1145/985692.985741>
- Baker, R. S., Walonoski, J., Heffernan, N., Roll, I., Corbett, A., & Koedinger, K. (2008). Why students engage in “gaming the system” behavior in interactive learning environments. *Journal of Interactive Learning Research*, *19*(2), 185–224.
- Barton, D., & Court, D. (2012). Making advanced analytics work for you. *Harvard Business Review*, *90*(10), 78–83.
- Beheshitha, S. S., Hatala, M., Gašević, D., & Joksimović, S. (2016). The role of achievement goal orientations when studying effect of learning analytics visualizations. In *Proceedings of the Sixth International Conference on Learning Analytics & Knowledge* (pp. 54–63). ACM. <https://doi.org/10.1145/2883851.2883904>
- Bichsel, J. (2012). *Analytics in Higher Education: Benefits, Barriers, Progress, and Recommendations* (p. 31). ECAR. Retrieved from <http://net.educause.edu/ir/library/pdf/ers1207/ers1207.pdf>
- Black, A. E., & Deci, E. L. (2000). The effects of instructors’ autonomy support and students’ autonomous motivation on learning organic chemistry: A self-determination theory perspective. *Science Education*, *84*(6), 740–756. [https://doi.org/10.1002/1098-237X\(200011\)84:6<740::AID-SCE4>3.0.CO;2-3](https://doi.org/10.1002/1098-237X(200011)84:6<740::AID-SCE4>3.0.CO;2-3)
- Boud, D., & Molloy, E. (2013). Rethinking models of feedback for learning: the challenge of design. *Assessment & Evaluation in Higher Education*, *38*(6), 698–712. <https://doi.org/10.1080/02602938.2012.691462>
- Brown, M. (2012). *Learning Analytics: Moving from Concept to Practice* (EDUCAUSE Learning Initiative Briefs). Louisville, CO: EDUCAUSE. Retrieved from <http://net.educause.edu/ir/library/pdf/elib1203.pdf>
- Buckingham Shum, S., & Deakin Crick, R. (2012). Learning Dispositions and Transferable Competencies: Pedagogy, Modelling and Learning Analytics. In *Proceedings of the 2Nd International Conference on Learning Analytics and Knowledge* (pp. 92–101). New York, NY, USA: ACM. <https://doi.org/10.1145/2330601.2330629>

- Buckingham Shum, S., & Deakin Crick, R. (2016). Learning Analytics for 21st Century Competencies. *Journal of Learning Analytics*, 3(2), 6–21. <https://doi.org/10.18608/jla.2016.32.2>
- Campbell, J. P. (2007). *Utilizing student data within the course management system to determine undergraduate student academic success: An exploratory study* (Ph.D.). Purdue University, West Lafayette, IN, USA. Retrieved from <http://search.proquest.com/docview/304837810/abstract?accountid=14649>
- Card, S. K., Mackinlay, J., & Schneiderman, B. (Eds.). (1999). *Readings in Information Visualization: Using Vision to Think*. San Francisco, CA: Morgan Kaufmann Publishers In.
- Caulfield, M. (2013, November 12). What the Course Signals “Kerfuffle” is About, and What it Means to You. Retrieved from <http://www.educause.edu/blogs/mcaulfield/what-course-signals-kerfuffle-about-and-what-it-means-you>
- Colvin, C., Rogers, T., Wade, A., Dawson, S., Gašević, D., Buckingham Shum, S., ... Fisher, J. (2015). *Student retention and learning analytics: A snapshot of Australian practices and a framework for advancement* (Research Report). Canberra, Australia: Office of Learning and Teaching, Australian Government.
- Corrin, L., & de Barba, P. (2014). Exploring students’ interpretation of feedback delivered through learning analytics dashboards. In *Proceedings of the ascilite 2014 conference* (pp. 629–633). Dunedin, NZ.
- Davis, J. (2012). *School Enrollment and Work Status: 2011* (American Community Survey Briefs). United States Census Bureau. Retrieved from <http://www.census.gov/prod/2013pubs/acsbr11-14.pdf>
- Dawson, S. (2008). A study of the relationship between student social networks and sense of community. *Educational Technology and Society*, 11(3), 224–238.
- Dawson, S., Bakharia, A., & Heathcote, E. (2010). SNAPP: Realising the affordances of real-time SNA within networked learning environments. In *Proceedings of the 7th International Conference on Networked Learning* (pp. 125–133).
- Dawson, S., Gašević, D., Siemens, G., & Joksimovic, S. (2014). Current State and Future Trends: A Citation Network Analysis of the Learning Analytics Field. In *Proceedings of the Fourth International Conference on Learning Analytics And Knowledge* (pp. 231–240). New York, NY, USA: ACM. <https://doi.org/10.1145/2567574.2567585>
- Dawson, S., Tan, J. P. L., & McWilliam, E. (2011). Measuring creative potential: Using social network analysis to monitor a learners’ creative capacity. *Australasian Journal of Educational Technology*, 27(6), 924–942.
- Drachsler, H., & Greller, W. (2016). Privacy and Analytics: It’s a DELICATE Issue a Checklist for Trusted Learning Analytics. In *Proceedings of the Sixth International Conference on Learning Analytics & Knowledge* (pp. 89–98). New York, NY, USA: ACM. <https://doi.org/10.1145/2883851.2883893>
- Ellis, R., & Goodyear, P. (2013). *Students’ Experiences of e-Learning in Higher Education: The Ecology of Sustainable Innovation*. Routledge.
- Elton, L. (2004). Goodhart’s Law and Performance Indicators in Higher Education. *Evaluation & Research in Education*, 18(1-2), 120–128. <https://doi.org/10.1080/09500790408668312>
- Ferguson, R., Hoel, T., Scheffel, M., & Drachsler, H. (2016). Guest Editorial: Ethics and Privacy in Learning Analytics. *Journal of Learning Analytics*, 3(1), 5–15. <https://doi.org/10.18608/jla.2016.31.2>
- Ferguson, R., Macfadyen, L. P., Clow, D., Tynan, B., Alexander, S., & Dawson, S. (2014). Setting learning analytics in context: overcoming the barriers to large-scale adoption. *Journal of Learning Analytics*, 1(3), 120–144.

- Freeman, S., Eddy, S. L., McDonough, M., Smith, M. K., Okoroafor, N., Jordt, H., & Wenderoth, M. P. (2014). Active learning increases student performance in science, engineering, and mathematics. *Proceedings of the National Academy of Sciences*. <https://doi.org/10.1073/pnas.1319030111>
- Fritz, J. (2011). Classroom Walls that Talk: Using Online Course Activity Data of Successful Students to Raise Self-Awareness of Underperforming Peers. *The Internet and Higher Education*, *14*(2), 89–97. <https://doi.org/10.1016/j.iuheduc.2010.07.007>
- Garrison, D. R., & Arbaugh, J. B. (2007). Researching the community of inquiry framework: Review, issues, and future directions. *The Internet and Higher Education*, *10*(3), 157–172. <https://doi.org/10.1016/j.iuheduc.2007.04.001>
- Gašević, D., Dawson, S., & Jovanović, J. (2016). Ethics and Privacy as Enablers of Learning Analytics. *Journal of Learning Analytics*, *3*(1), 1–4. <https://doi.org/10.18608/jla.2016.31.1>
- Gašević, D., Dawson, S., Rogers, T., & Gasevic, D. (2016). Learning analytics should not promote one size fits all: The effects of instructional conditions in predicting learning success. *The Internet and Higher Education*, *28*, 68–84. <https://doi.org/10.1016/j.iuheduc.2015.10.002>
- Gašević, D., Dawson, S., & Siemens, G. (2015). Let's not forget: Learning analytics are about learning. *TechTrends*, *59* (1), 64–71. <https://doi.org/10.1007/s11528-014-0822-x>
- Gašević, D., Zouaq, A., & Janzen, R. (2013). “Choose Your Classmates, Your GPA Is at Stake!” The Association of Cross-Class Social Ties and Academic Performance. *American Behavioral Scientist*, *57*(10), 1460–1479. <https://doi.org/10.1177/0002764213479362>
- Goldstein, P. J., & Katz, R. N. (2005). *Academic Analytics: The Uses of Management Information and Technology in Higher Education* (p. 12). ECAR. Retrieved from <https://library.educause.edu/resources/2005/12/academic-analytics-the-uses-of-management-information-and-technology-in-higher-education>
- Griffin, P. (2013). *Submission to the effectiveness of the National Assessment Program - Literacy and Numeracy* (Inquiry and Report of the Senate Education, Employment and Workplace Relations References Committee No. 20). Canberra, ACT, Australia: Parliament of Australia. Retrieved from [http://bit.ly/Griffin\\_aph\\_2013](http://bit.ly/Griffin_aph_2013)
- Hansen, J. D., & Reich, J. (2015). Socioeconomic Status and MOOC Enrollment: Enriching Demographic Information with External Datasets. In *Proceedings of the Fifth International Conference on Learning Analytics And Knowledge* (pp. 59–63). New York, NY, USA: ACM. <https://doi.org/10.1145/2723576.2723615>
- Hattie, J., & Timperley, H. (2007). The Power of Feedback. *Review of Educational Research*, *77*(1), 81–112. <https://doi.org/10.3102/003465430298487>
- Janssen, J., Erkens, G., & Kirschner, P. A. (2011). Group awareness tools: It's what you do with it that matters. *Computers in Human Behavior*, *27*(3), 1046–1058. <https://doi.org/10.1016/j.chb.2010.06.002>
- Jarrett, J. (2013). Bigfoot, Goldilocks, and Moonshots: A Report from the Frontiers of Personalized Learning. *EDUCAUSE Review*, *48*(2). Retrieved from <http://www.educause.edu/ero/article/bigfoot-goldilocks-and-moonshots-report-frontiers-personalized-learning>
- Johnson, H. (2012). *Defunding Higher Education: What Are the Effects on College Enrollment?* (PPIC Publication). Public Policy Institute of California. Retrieved from [http://www.ppic.org/content/pubs/report/R\\_512HJR.pdf](http://www.ppic.org/content/pubs/report/R_512HJR.pdf)

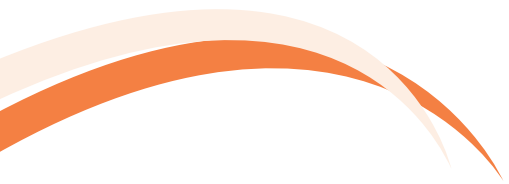
- Joksimović, S., Gašević, D., Loughin, T. M., Kovanović, V., & Hatala, M. (2015). Learning at distance: Effects of interaction traces on academic achievement. *Computers & Education*, *87*, 204–217. <https://doi.org/10.1016/j.compedu.2015.07.002>
- Joksimović, S., Manataki, A., Gašević, D., Dawson, S., Kovanović, V., & de Kereki, I. F. (2016). Translating Network Position into Performance: Importance of Centrality in Different Network Configurations. In *Proceedings of the Sixth International Conference on Learning Analytics & Knowledge* (pp. 314–323). New York, NY, USA: ACM. <https://doi.org/10.1145/2883851.2883928>
- Khalil, M., & Ebner, M. (2016). De-Identification in Learning Analytics. *Journal of Learning Analytics*, *3*(1), 129–138. <https://doi.org/10.18608/jla.2016.31.8>
- Knight, S., & Littleton, K. (2015). Discourse Centric Learning Analytics: Mapping the Terrain. *Journal of Learning Analytics*, *2*(1), 185–209.
- Kovanovic, V., Gašević, D., Dawson, S., Joksimovic, S., & Baker, R. S. (2016). Does Time-on-task Estimation Matter? Implications on Validity of Learning Analytics Findings. *Journal of Learning Analytics*, *2*(3), 81–110. <https://doi.org/10.18608/jla.2015.23.6>
- Kovanović, V., Gašević, D., Dawson, S., Joksimović, S., Baker, R. S., & Hatala, M. (2015). Penetrating the Black Box of Time-on-task Estimation. In *Proceedings of the Fifth International Conference on Learning Analytics And Knowledge* (pp. 184–193). New York, NY, USA: ACM. <https://doi.org/10.1145/2723576.2723623>
- Kovanović, V., Gašević, D., Joksimović, S., Hatala, M., & Adesope, O. (2015). Analytics of communities of inquiry: Effects of learning technology use on cognitive presence in asynchronous online discussions. *The Internet and Higher Education*, *27*, 74–89. <https://doi.org/10.1016/j.iheduc.2015.06.002>
- Krumm, A. E., Waddington, R. J., Teasley, S. D., & Lonn, S. (2014). A Learning Management System-Based Early Warning System for Academic Advising in Undergraduate Engineering. In J. A. Larusson & B. White (Eds.), *Learning Analytics* (pp. 103–119). Springer New York. Retrieved from [http://link.springer.com/chapter/10.1007/978-1-4614-3305-7\\_6](http://link.springer.com/chapter/10.1007/978-1-4614-3305-7_6)
- Leigh Smith, B., MacGregor, J., Matthews, R., & Gabelnick, F. (2004). *Learning Communities & Reforming Undergraduate Education*. San Francisco, CA: Jossey Bass.
- Lockyer, L., Heathcote, E., & Dawson, S. (2013). Informing Pedagogical Action Aligning Learning Analytics With Learning Design. *American Behavioral Scientist*, *57*(10), 1439–1459. <https://doi.org/10.1177/0002764213479367>
- Long, P. D., Siemens, G., Conole, G., & Gašević, D. (Eds.). (2011). *Proceedings of the 1st International Conference on Learning Analytics and Knowledge (LAK'11)*. New York, NY, USA: ACM.
- Lou, Y., Bernard, R. M., & Abrami, P. C. (2006). Media and Pedagogy in Undergraduate Distance Education: A Theory-Based Meta-Analysis of Empirical Literature. *Educational Technology Research and Development*, *54*(2), 141–176. <https://doi.org/10.1007/s11423-006-8252-x>
- Lust, G., Elen, J., & Clarebout, G. (2013). Regulation of tool-use within a blended course: Student differences and performance effects. *Computers & Education*, *60*(1), 385–395. <https://doi.org/10.1016/j.compedu.2012.09.001>

- Lust, G., Vandewaetere, M., Ceulemans, E., Elen, J., & Clarebout, G. (2011). Tool-use in a blended undergraduate course: In Search of user profiles. *Computers & Education*, 57(3), 2135–2144. <https://doi.org/10.1016/j.compedu.2011.05.010>
- Macfadyen, L. P., & Dawson, S. (2010). Mining LMS data to develop an “early warning system” for educators: A proof of concept. *Computers & Education*, 54(2), 588–599. <https://doi.org/10.1016/j.compedu.2009.09.008>
- Macfadyen, L. P., & Dawson, S. (2012). Numbers Are Not Enough. Why e-Learning Analytics Failed to Inform an Institutional Strategic Plan. *Educational Technology & Society*, 15(3).
- Macfadyen, L. P., Dawson, S., Pardo, A., & Gasevic, D. (2014). Embracing big data in complex educational systems: The learning analytics imperative and the policy challenge. *Research & Practice in Assessment*, 9(2), 17–28.
- Manyika, J., Chui, M., Brown, B., Bughin, J., Dobbs, R., Roxburgh, C., & Byers, A. H. (2012). *Big Data: The Next Frontier for Innovation, Competition and Productivity*. McKinsey Global Institute. Retrieved from [http://www.mckinsey.com/insights/business\\_technology/big\\_data\\_the\\_next\\_frontier\\_for\\_innovation](http://www.mckinsey.com/insights/business_technology/big_data_the_next_frontier_for_innovation)
- Masters, G. (2015). Challenging our most able students. *Teacher Magazine - Evidence + Insight + Action*. Retrieved from <https://www.teachermagazine.com.au/geoff-masters/article/challenging-our-most-able-students>
- McKay, T., Miller, K., & Tritz, J. (2012). What to do with actionable intelligence: E<sup>2</sup>Coach as an intervention engine. In *Proceedings of the 2nd International Conference on Learning Analytics and Knowledge* (pp. 88–91). New York, NY, USA: ACM. <https://doi.org/10.1145/2330601.2330627>
- Moore, M. G. (1989). Editorial: Three types of interaction. *American Journal of Distance Education*, 3(2), 1–7. <https://doi.org/10.1080/08923648909526659>
- Ocuppaugh, J., Baker, R. S., & Rodrigo, M. M. T. (2015). *Baker Rodrigo Ocuppaugh Monitoring Protocol (BROMP) 2.0 Technical and Training Manual*. Technical Report. New York, NY: Teachers College, Columbia University. Manila, Philippines: Ateneo Laboratory for the Learning Sciences.
- O’Donovan, B., Rust, C., & Price, M. (2016). A scholarly approach to solving the feedback dilemma in practice. *Assessment & Evaluation in Higher Education*, 41(6), 938–949. <https://doi.org/10.1080/02602938.2015.1052774>
- O’Flaherty, J., Phillips, C., Karanicolas, S., Snelling, C., & Winning, T. (2015). The use of flipped classrooms in higher education: A scoping review. *The Internet and Higher Education*, 25, 85–95. <https://doi.org/10.1016/j.iheduc.2015.02.002>
- Open University. (2014). Ethical use of Student Data for Learning Analytics Policy. Retrieved July 28, 2016, from <http://www.open.ac.uk/students/charter/essential-documents/ethical-use-student-data-learning-analytics-policy>
- Pardo, A., Jovanović, J., Dawson, & Gašević, D. (2016). Using Learning Analytics to Scale the Provision of Personalised Feedback. *Submitted for Publication to British Journal of Educational Technology*.
- Pardo, A., Jovanović, J., Dawson, S., Gašević, D., & Mirriahi, N. (2016). Exploring student interactions with preparation activities in a flipped learning experience. *Submitted for Publication to Computers & Education*.
- Prinsloo, P., & Slade, S. (2016). Student Vulnerability, Agency and Learning Analytics: An Exploration. *Journal of Learning Analytics*, 3(1), 159–182. <https://doi.org/10.18608/jla.2016.31.10>

- Reimann, P., Markauskaite, L., & Bannert, M. (2014). e-Research and learning theory: What do sequence and process mining methods contribute? *British Journal of Educational Technology*, *45*(3), 528–540. <https://doi.org/10.1111/bjet.12146>
- Richardson, M., Abraham, C., & Bond, R. (2012). Psychological correlates of university students' academic performance: A systematic review and meta-analysis. *Psychological Bulletin*, *138*(2), 353–387. <https://doi.org/10.1037/a0026838>
- Rogers, T., Gašević, D., & Dawson, S. (2016). Learning analytics and the imperative for theory driven research. In C. Haythornthwaite, R. Andrews, J. Fransma, & E. Meyers (Eds.), *The SAGE Handbook of E-Learning Research, 2nd edition* (pp. 232–250). London, UK: SAGE Publications Ltd.
- Roll, I., & Winne, P. H. (2015). Understanding, evaluating, and supporting self-regulated learning using learning analytics. *Journal of Learning Analytics*, *2*(1), 7–12.
- Romero-Zaldivar, V.-A., Pardo, A., Burgos, D., & Delgado Kloos, C. (2012). Monitoring student progress using virtual appliances: A case study. *Computers & Education*, *58*(4), 1058–1067. <https://doi.org/10.1016/j.compedu.2011.12.003>
- Slater, N., & Bailey, P. (2015). *Code of practice for learning analytics*. Jisc. Retrieved from <https://www.jisc.ac.uk/guides/code-of-practice-for-learning-analytics>
- Siemens, G. (2013). Learning Analytics The Emergence of a Discipline. *American Behavioral Scientist*, *57*(10), 1380–1400. <https://doi.org/10.1177/0002764213498851>
- Siemens, G., Dawson, S., & Lynch, G. (2014). *Improving the Quality and Productivity of the Higher Education Sector - Policy and Strategy for Systems-Level Deployment of Learning Analytics*. Canberra, Australia: Office of Learning and Teaching, Australian Government. Retrieved from [http://solaresearch.org/Policy\\_Strategy\\_Analytics.pdf](http://solaresearch.org/Policy_Strategy_Analytics.pdf)
- Siemens, G., & Gasevic, D. (2012). Guest Editorial-Learning and Knowledge Analytics. *Educational Technology & Society*, *15*(3), 1–2.
- Siemens, G., Gašević, D., & Dawson, S. (2015). *Preparing for the digital university: a review of the history and current state of distance, blended, and online learning*. Gates Foundation through MOOC Research Initiative.
- Sparrowe, R. T., Liden, R. C., Wayne, S. J., & Kraimer, M. L. (2001). Social Networks and the Performance of Individuals and Groups. *Academy of Management Journal*, *44*(2), 316–325. <https://doi.org/10.2307/3069458>
- Tanes, Z., Arnold, K. E., King, A. S., & Remnet, M. A. (2011). Using Signals for appropriate feedback: Perceptions and practices. *Computers & Education*, *57*(4), 2414–2422. <https://doi.org/10.1016/j.compedu.2011.05.016>
- Trigwell, K., & Prosser, M. (1991). Improving the quality of student learning: the influence of learning context and student approaches to learning on learning outcomes. *Higher Education*, *22*(3), 251–266. <https://doi.org/10.1007/BF00132290>
- Trigwell, K., Prosser, M., & Waterhouse, F. (1999). Relations between teachers' approaches to teaching and students' approaches to learning. *Higher Education*, *37*(1), 57–70. <https://doi.org/10.1023/A:1003548313194>
- Verbert, K., Duval, E., Klerkx, J., Govaerts, S., & Santos, J. L. (2013). Learning Analytics Dashboard Applications. *American Behavioral Scientist*, *57*(10), 1500–1509. <https://doi.org/10.1177/0002764213479363>

- Vessey, I. (1991). Cognitive Fit: A Theory-Based Analysis of the Graphs Versus Tables Literature\*. *Decision Sciences*, 22 (2), 219–240. <https://doi.org/10.1111/j.1540-5915.1991.tb00344.x>
- Wasson, B., & Hansen, C. (2016). Data literacy and use for teaching. In P. Reimann, S. Bull, M. Kickmeier-Rust, R. Vatrappu, & B. Wasson (Eds.), *Measuring and Visualizing Learning in the Information-Rich Classroom* (pp. 56–73). New York: Routledge.
- Winne, P. H., & Hadwin, A. F. (1998). Studying as self-regulated learning. In D. J. Hacker, J. Dunlosky, & A. C. Graesser (Eds.), *Metacognition in educational theory and practice* (pp. 277–304). Mahwah, NJ, US: Lawrence Erlbaum Associates Publishers.
- Wise, A. F. (2014). Designing Pedagogical Interventions to Support Student Use of Learning Analytics. In *Proceedings of the Fourth International Conference on Learning Analytics And Knowledge* (pp. 203–211). New York, NY, USA: ACM. <https://doi.org/10.1145/2567574.2567588>
- Wise, A. F., & Shaffer, D. W. (2015). Why Theory Matters More than Ever in the Age of Big Data. *Journal of Learning Analytics*, 2(2), 5–13. <https://doi.org/10.18608/jla.2015.22.2>
- Wolff, A., Moore, J., Zdrahal, Z., Hlosta, M., & Kuzilek, J. (2016). Data Literacy for Learning Analytics. In *Proceedings of the Sixth International Conference on Learning Analytics & Knowledge* (pp. 500–501). New York, NY, USA: ACM. <https://doi.org/10.1145/2883851.2883864>
- Wright, M. C., McKay, T., Hershock, C., Miller, K., & Tritz, J. (2014). Better Than Expected: Using Learning Analytics to Promote Student Success in Gateway Science. *Change: The Magazine of Higher Learning*, 46(1), 28–34. <https://doi.org/10.1080/00091383.2014.867209>
- Yanosky, R. (2009). *Institutional Data Management in Higher Education* (p. 180). ECAR. Retrieved from <https://library.educause.edu/resources/2009/12/institutional-data-management-in-higher-education>

## NOTES





ICDE - International Council For Open And Distance Education  
Lilleakerveien 23, Oslo 0283, Norway

[www.icde.org](http://www.icde.org)

[icde@icde.org](mailto:icde@icde.org)

Creative Commons Attribution  
ShareAlike 4.0 International license  
(CC BY-SA 4.0)