THE ROLE OF LEARNING ANALYTICS IN FUTURE EDUCATION MODELS

TELSTRA

CONTENTS

EXECUTIVE SUMMARY

The use of data analysis to guide the design and deployment of learning experiences is finally reaching widespread adoption. Educational institutions at all levels are realising that, with the help of technology, they are collecting data that could be very valuable when properly analysed, aligned with learning outcomes, and integrated into a tighter feedback loop with stakeholders. But this vision is not exempt from hurdles. Educational institutions at all levels need to find the way to make the best use of data, how to integrate it into their day-to-day operations and nurture a cultural change towards institutions. In this paper we provide an overview of the current initiatives in the area of Learning Analytics, how these developments can be used in conventional learning experiences and the potential benefits.

1.0 INTRODUCTION

Data is ubiquitous and is being used in an increasing number of disciplines. Education is not an exception. On the contrary, the use of technology to mediate interactions among stakeholders allows access to detailed lists of events occurring in a learning experience. This wealth of data offers an unprecedented opportunity to achieve sustained improvements and reflection on teaching and learning practice. But there are numerous barriers to realising this potential. Leaders of educational institutions need to be aware of the complex ecosystem emerging around the notion of analytics. Institutions need to be aware of the right tools and methods, and have the know-how to apply them to detect how learning is occurring and how can it be improved. Learning analytics is opening a new space for innovation that can provide teachers, principals, parents and students with fast feedback about learning processes. This capacity is the basis for reshaping educational models, but for it to become a reality we need to identify the precise role of learning analytics and how it can influence current and future education models.

The rest of this document first describes the importance of data-informed approaches in the area of education. It then details the current state-of-the-art and emerging initiatives in the area of learning analytics. The paper concludes with a description of models and initiatives in the area of K-12 education, and the possible models that will emerge in the future.

Abelardo Pardo, Shane Dawson, Dragan Gašević and Susi Steigler-Peters

2.0 IMPORTANCE OF DATA-INFORMED APPROACHES FOR EDUCATION

The concept of data for informing teaching and learning practice is not a new phenomenon for the education sector. However, while education has long been awash with data, its strategic application for understanding the student learning process and developing scalable personalised interventions has to date been less effective. For instance, there is a mass of data related to benchmarking performance and expenditure at the international (e.g. OECD; PISA tests) and national (e.g. NAPLAN) levels. Yet the relationship between these data and findings is often far removed and loosely connected to the day-to-day teaching operations that occur within a school. These forms of data are essentially targeted towards the development, or assessment, of federal and state education policy. This is not to say that such benchmarking and standardised assessment measures do not offer broad value for individual schools. More so, that these data and forms of measurement need to be further integrated and nuanced in order to establish targeted insights that can effectively promote and guide the development of quality teaching and learning practice. As the stakeholders change so too do the types and granularity of data required to identify areas of high performance and areas requiring further support and development. Ultimately, the goal of any evaluation and quality assurance process is to improve on practice. In this case, it is demonstrating improvements in student learning or operational efficiencies. Without entering into much debate, let's assume this is important.

Over the past decade there has been a growing paradigm shift in education, from the collection of data for compliance purposes to the application of data for continuous improvement. This shift in emphasis has been promoted through the concept of data-informed or evidence-based decision-making. Data-informed decision-making in education involves the collection and analysis of data to provide actionable insights into teaching and learning practice (Mandinach, 2012; Mandinach and Jackson, 2012). As with many organisations embracing data-informed practices, the difficulty for the education sector lies not in the availability of student or school data, but how such data is made available to key stakeholders to enable decision-making for improving student learning. The diversity and volume of data and information required is largely dependent on an individual's role and responsibilities in the school.

2.0 IMPORTANCE OF DATA-INFORMED APPROACHES FOR EDUCATION

(CONT.)

For instance, school leaders will require aggregated data sets relating to standardised assessment scores commonly benchmarked against similar schools or data that assesses the impact of specific school-based strategies. Data and information on pedagogical approaches, curriculum, student assessment, remedial interventions, disciplinary actions, professional development, and level of integration of education technologies alongside the cost-effectiveness of support resources or technical infrastructure all form a subset of an education leader's arsenal of resources to help provide insight and direction for setting school policy and strategy. Similarly, teachers require data related to student performance, learning development and the effectiveness of adopted curriculum and learning strategies.

"The applied use of student learning data in this context can only further assist teachers and help improve practice."

Although there is a growing emphasis on data-informed approaches in education, there is a long-held perception that teachers commonly make decisions based on their past experience and intuition. The notion is that effective teachers are watchful and empathetic. They can react quickly to the individual and class cues that may suggest understanding or misconceptions, apprehension or over-confidence. This ability is accrued through years of teaching experience. But while these perceptions may or may not fall into the category of urban myth, there is no debate regarding the impact of quality teaching on student learning. The applied use of student learning data in this context can only further assist teachers and help improve practice. The development of a quality teacher should not come at the cost of many years of experience. Knowledge of data analytics and understanding how student learning data manifests through curriculum strategies and relates to an individual's learning progression are fundamental skills for the 21st Century teacher. Teaching as a "science" through rigour and purpose can only enhance the practice of the "art".

Despite the growing need for teachers to adopt more data-driven approaches to their practice, there is evidence to suggest that the profession is not equipped to make optimal use of the full suite of data that is now available. The sub-optimal application of data-informed teaching and learning stems from several important variables. The promotion of data usage is influenced by the timeliness and perceived usefulness of the data itself to address an identified issue or question. When considering the types of data commonly collected in education there is justifiable reason as to why teachers are more reticent and reluctant in their uptake. Education data is commonly lag data. When developing long-term strategic goals for a school, a leader's access to lag data through standardised tests, attrition or enrolment rates, for example, can be considered applicable and fit for purpose. However, when considering student learning progression, such data is no longer of assistance. It is too late to identify a difficulty in student learning through the lens of a formative assessment. When promoting student self-regulated learning the immediacy, personalisation and scaffolding of feedback is critical. As such there is a need to establish more appropriate digitally-enabled processes and practices that can provide teachers and learners with more immediate data.

The growing uptake of education technologies across all facets of education, from K-12 to tertiary, affords novel opportunities to provide nuanced, contextualised data sources that can address the need for just-in-time feedback. The field of learning analytics is galvanising these ingredients into a discipline in which multidisciplinary work from the areas of pedagogy, technology and learning are combined to provide a much deeper insight into how learning occurs and how it can be better supported by all stakeholders in the ecosystem, particularly the learner.

3.0 LEARNING ANALYTICS OVERVIEW

3.1 What are learning analytics?

The rapid adoption of education technologies – such as learning management systems, education apps, social media, lecture capture, student information systems and mobile computing – has allowed for collecting unprecedented amounts of big data about learning, teaching and institutional processes (Baer and Campbell, 2012; Macfadyen and Dawson, 2010; Siemens and Long, 2011). As with any information technology, user interactions with the technology create digital traces that can be recorded and stored in databases. These traces can be about the content students accessed in the courses they took, the messages posted or viewed on discussion boards, classmates they took classes with or interacted with on discussion boards, or keywords used while searching for learning resources in institutional systems. These traces can automatically be "mined" to identify patterns in the educational technology use by learners. The patterns are then used to understand the learning processes underlying the use of technology and inform teaching practice, emerging learning models and institutional processes. This process has been described as learning analytics.

More formally, the Society for Learning Analytics Research (SoLAR) (Long, Siemens, Conole and Gašević, 2011) defines 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". This definition emphasises the nature of learning analytics as an evidence-based discipline – similar to medicine. That is, learning analytics use rigorous research methods to understand important problems for practice of education in order to produce evidence that can inform the decision-making process of the key stakeholders in the learning ecosystem – from students and parents to instructors, deans, university presidents, governments and other private and public sector organisations.

3.2 How can learning analytics help?

The use of analytics and data analysis is not new in education. In the past, this was typically driven by the needs of the education sector to support data-driven decision-making and planning (Baker and Yacef, 2009). In this process, there have been numerous reports of the use of approaches from different disciplines such as business intelligence, web analytics, data mining, predictive modelling, academic analytics and educational data mining (Romero and Ventura, 2010). More recently, with the growth of the field of learning analytics, the roots of the field are more deeply connected with the established research area (Ferguson, 2012) such as statistics, text mining, social network analysis, machine learning, human computer interaction, learning sciences and educational, cognitive and social psychology.

The multidisciplinary nature of learning analytics and the availability of big data in education offer numerous opportunities to answer old, difficult questions about education and offer solutions to the pressing challenges of the education sector. For example, timely feedback to learners has been proven as one of the most powerful ways to enhance learning and learners' academic success (Hattie and Timperley, 2007). However, large classes – even with "only" tens of students – could hardly allow for individualised feedback for each and every student. Much too often, learners would need to wait for the mid-term exam or first assessment points to receive any feedback about their progress. For many, mid-term is already too late and the opportunity to intervene is long gone. By tracing and analysing the data about learners' activities and visualising results through actionable dashboards (Duval, 2011), learning analytics can offer "real-time" feedback about learners' progress and give the learners hints if they are off track and tips on how to enhance their learning.

3.3 Learning analytics case studies and players

Student retention is the best established application of learning analytics, with Purdue Signals as probably the best-known showcase

3.0 LEARNING ANALYTICS OVERVIEW

(CONT.)

and success story for the new field (Pistilli, Arnold and Bethune, 2012). Purdue Signals is a software system that uses data about the interaction of learners with learning management system Blackboard. These trace data are then analysed to build predictive models about academic standing of learners, such as if they are at risk of completing the course successfully, if they are on track with course expectations, or if they need to study more or require additional instructional and/or institutional support. The system then applies the metaphor of traffic lights – green, yellow and red – to present the predicted academic standing to students and instructors. Being deployed since 2007 at Purdue University, Purdue Signals has been confirmed as a sound solution to increasing student retention (Arnold and Pistilli, 2012).

For example, students who took at least one course in year one in 2007 with Purdue Signals had a retention rate of 97%, whereas the retention rate for those that did not use Purdue Signals was 83%. This difference was much bigger in year four in 2010, when the students who took at least one course with Purdue Signals had a retention rate of 93%, whereas those who did not had a retention rate of 69%. Moreover, 89% of the students who used Purdue Signals reported an overall positive experience, while 59% of the students expressed their wish to use the system in each course they take.

Changing students' learning habits and behaviour often requires much more than just showing visual dashboards. This was well supported in Purdue Signals by notifying instructors to send personalised emails to the students who are at risk (Tanes, Arnold, King and Remnet, 2011). Similarly, the University of Michigan developed a system called E2Coach (Expert Electronic Coaching) by building on the experience of behavioural change accumulated in public health research (Wright, McKay, Hershock, Miller and Tritz, 2014). E2Coach takes data about students' grades on previous courses, survey data about the students' intentions behind the enrolment in a course and other socio-psychological factors. These data are combined with the data about the students' interaction with online learning systems and progression throughout a semester. The students then receive tailored messages with advice on how to proceed further with their learning. Unlike other solutions that focus on students at risk, E2Coach offers advice to advanced (grade A) students on how to enhance their learning. The studies show that the grades of students are improved with the increased use of E2Coach.

Learning analytics and big data go beyond assisting students within a single course. Many institutions are trying to find solutions to improve career planning of students by offering timely advice. For example, eAdvisor[1] is a system implemented at Arizona State University to offer personalised support to students in course selection and planning their degree programs. eAdvisor allows students to get insight into possible paths they may take throughout their degree majors along with the main requirements they must meet to be able to graduate. Whenever a student enrols in a particular course, eAdvisor evaluates the progression towards their degree and generates feedback about the implications of such a decision (e.g. it will take them more time to complete their degree). The results of the use of eAdvisor reportedly increased the number of students on track in their degree program from 22% in 2007 to 91% in 2010 (Jarret, 2013). Another implication of the implementation of eAdvisor was increased retention of 8% in first year.

Desire2Learn's Degree Compass[2] is another similar example to that of eAdvisor. Degree Compass recommends courses to students to take in future semesters by using predictive models obtained from the historic data about previous course completion. According to Desire2Learn, an implementation of Degree Compass at Austin Peay State University showed that Degree Compass was able to predict 92% of the total grades accurately and 90% of the passing grades (Desire2Learn, 2012, p. 2). Moreover, in the period Fall 2010 – Fall 2012, an increase in grades A, B and C of 1.4% was reported (i.e. a remarkable shift of 5.3 standard deviations).

The recognition of importance of data-driven decision-making and planning by the education sector

worldwide created a marketplace for learning analytics solutions. It has become a standard requirement for the vendors of learning management systems to provide some form of learning analytics. Most leading vendors of learning management systems – such Blackboard Analytics[3] and Desire2Learn Insights[4] – have their solutions that offer learning analytics based on the students' interaction with their systems. Moreover, specialised learning analytics providers – such as Civitas Learning[5] and Knewton[6] – have been founded recently. A good example of the impact of the availability of such solutions is the partnership between Arizona State University and Knewton. By using Knewton's Adaptive Learning Platform, they created a customised learning experience for about 5,000 students that were taking a remedial mathematics course (Upbin, 2012). After one semester, the effect of this solution was the reduction in the dropout rates from 13% to 6%, and the increase in the number of passing students from 66% to 75%, with half of the students successfully completing the course almost a month early.

3.4 Openness and learning analytics

There are considerable efforts to promote openness in the field of learning analytics. Open platforms for learning analytics and learning analytics solutions for open educational resources are in the centre of these efforts. The Society for Learning Analytics Research (SoLAR) published a white paper (Siemens et al., 2011), which outlined an integrated and modularised platform for open learning analytics (OLA). The primary goal of the SoLAR OLA platform is to provide a set of requirements that will guide design, implementation and evaluation of open platforms, which can integrate heterogeneous learning analytics techniques. The core components of the SoLAR OLA platform consist of a learning analytics engine, adaptive content engine, intervention engine (supports recommendations and automated feedback provisioning) and reporting (dashboards and visualisation). The platform has received considerable attention. A good example is edX Insights[7] – a learning analytics framework of edX, a leading MOOC provider – that offers an open-source solution that can easily be integrated with existing online learning systems. In this way, opportunities for adaption of learning analytics solutions are increased for institutions that either prefer open-source or cannot afford commercial solutions. Moreover, it allows institutions more flexibility in creating customised learning analytics solutions that best fit their needs.

Carnegie Mellon University's (CMU) Open Learning Initiative (OLI)[8] is a platform with numerous open courses publicly available for institutions to use in a so-called "blended learning" mode (a mix of face-to-face and online instruction) (Lovett, Meyer and Thille, 2008). The initiative contains a so-called Learning Dashboard, which is an advanced learning analytics support system built upon the cutting-edge research in the learning sciences. Learning Dashboard processes data about student activities and assessments and generates reports about students' standing for course instructors. The use of CMU OLI and learning analytics were validated through a series of randomised control trials across six public institutions. The results of the randomised control trials revealed that the students in the blended learning format are not disadvantaged "for this mode of instruction in terms of pass rates, final exam scores, and performance on a standardised assessment of statistical literacy" (Bowen, Chingos, Lack and Nygren, 2012). Moreover, in the discussion of the randomised control trials results, it was concluded that the adoption of blended models of instruction "in large introductory courses have the potential to significantly reduce instructor compensation costs in the long run".

1 https://eadvisor.asu.edu
2 http://www.desire2learn.com/products/degree-compass
3 http://www.blackboard.com/platforms/analytics/overview.aspx
4 http://www.desire2learn.com/products/insights
5 http://www.civitaslearning.com
6 http://www.knewton.com

4.0 EXAMPLES AND IMPACT OF LEARNING ANALYTICS

The examples described in the previous section show a clear advantage of using data to tackle well-known issues in the context of post-secondary education. In the context of K-12, the problem remains the same: can data be used to drive decision-making about the quality of the learning experience? The same issues of collecting and processing data to increase the knowledge of the problems are present in primary and high schools. In these environments the challenge still remains to create the right environment at different levels within institutions to increase awareness of the advantages of using data, and then foster the skills to analyse such data and transform it into actionable insight.

At the government levels, current tests are being used as a mechanism to promote this sustained improvement (e.g. the National Assessment Program – Literacy and Numerac, NAPLAN, in Australia). However, learning analytics postulates that data should be used to provide decision support with an element of immediacy. In other words, rather than deploying an assessment mechanism, process the results and then obtain actionable insights in a period of months, this procedure should aim to be almost immediate. This use of data poses a true paradigm shift for stakeholders – namely, school management, teachers, parents and students.

Moody and Dede (2008) classified the use of data depending on the derived actions in data for accountability, improvement and reflection. Currently, various assessment instruments mostly proposed by government institutions propose the use of data for accountability. School performance is now being assimilated with the results in various tests (e.g. NAPLAN). However, it is difficult for stakeholders to derive a clear vision of actionable items from the result of these tests, and therefore, its impact is not clear. Using data for improvement places the emphasis on specific changes that need to be measurable. In this type of scenario, data is analysed and immediately translated into actions that are deployed in learning scenarios seeking to improve their effectiveness. Hamilton et al (2009) have suggested the type of queries that can be answered with the help of data for administrators and teachers.

Administrators may use data to detect the areas with the greatest need for improvement and the resources that can be allocated to them most effectively. They can also study how the curriculum is addressing the boundary conditions imposed by governments. Data can also be used to gain insight on the effectiveness of different teachers and the most adequate professional development opportunities that need to be provided.

Teachers, on the other hand, may use data to gain insight into how students are learning and their main strengths and weaknesses, based on fine-grained evidence such as the level of proficiency of computer assessment, engagement with activities, etc. Additionally, teaching staff may use data to monitor changes introduced into activities. Data may provide a robust framework to perform rigorous comparisons of instruction methods and detect the most adequate ones for different student profiles. However, these potential scenarios are already posing some difficulties as described in some case studies (Dauenhauer, 2014) in the context of physical education. Other recent studies document different levels of adoption of data-driven decision-making and the need to address the tensions created by the need to adopt these techniques (Hubbard, Datnow and Pruyn, 2014). Additionally, when facing comprehensive adoption in a school, there are usually issues related to the availability of data and the skills required from the staff (Rainey, 2013). The suggestion is to promote the vision of a teacher as a researcher that has the skills and interest to embrace a sustained improvement mindset. A possible strategy to alleviate this gap is to consider professional development opportunities to provide staff with the right tools and knowledge to manipulate data and create the sensibility to the benefits derived from its use (Staman, Visscher and Luyten, 2014).

The other two stakeholder groups, parents and students, together with teachers, may benefit from the third category of data use in which the main focus is reflection. In the case of teachers, reflective activities can be added systematically across the year among teams to collaboratively analyse the data and comment on the possible explanations or actions to be derived. A similar scenario is feasible for the case of parents and students. Introducing systematic reflection about the data collected and provided offers the potential of providing parents with perceptions of factors that help them participate more actively in their child's education (Bauer, 2015).

Learning analytics in the K-12 space is yet to fulfil its potential. Principals and management teams need to be aware of the possibilities of data-driven decision-making and deploy the adequate technical and non-technical resources for it to be adopted at an institutional level. They have to embrace data to drive decisions related to school performance, teaching effectiveness and resource allocation. This vision needs then to be articulated so that teachers adopt a systematic use of data for immediate feedback and potentially adjustments in their day-to-day activities. Teachers need to become data savvy to be able to orchestrate how data should be collected, analysed and turned into actionable initiatives. Parents and students should be taken into account when articulating this vision so that they get used to receiving and reflecting on the information received, as well as exploring ways to increase their engagement in a learning experience.

7 http://github.com/edx/insights
8 http://oli.cmu.edu

5.0 THE CONTEXT FOR LEARNING ANALYTICS AND FUTURE EDUCATION MODELS

There is no doubt that the trend towards delivering more personalised learning experiences for students of all ages has strengthened, both nationally and globally, over the last 10-15 years. Charles Leadbeater, in his 2008 paper *What's Next? 21 Ideas for 21st Century Learning* articulated a number of shifts in learning features including, for example, the shift away from institution-led learning to anywhere, anytime learning as well as the break from traditional teacher-as-knowledge-custodian to learner as agent and maker, contributing to their own learning. In its education thought leadership paper series, Telstra has built on the work of Leadbeater and others to postulate the elements of best practice that support personalised learning and emerging 21st-Century pedagogies. The series, commissioned by Telstra's Education Roundtable, has been written in close consultation with education stakeholders and serves as an accurate record of education issues and challenges as well as benchmarking quality examples of best practice in delivering personalised learning experiences in localised environments.

The challenge beyond the local was, and remains: how do you scale up service delivery for personalised learning?

Telstra responded to the challenge by coming up with a few ideas. These were presented and discussed with education customers, resulting in an innovative service that is able to deploy a personalised learning ecosystem to the smallest school or a university with campuses across many locations, as well as to the world of corporate learning. Moreover, the model enables a globalised approach to personalised learning.

The model is called Workspace X and is a cloud-based personalised learning ecosystem that liberates learners from the four walls of the classroom, provides access to quality learning experiences and a wide range of state-of-the-art digital tools that promote 21st-Century learning styles. It is also an affordable and effective solution for the vast numbers of disadvantaged and remote students across the globe who are still struggling to access quality learning.

In a single sign-on, secure environment learners can access enterprise-grade education apps that cover the public and private domains. They can also access a range of collaboration tools, digital learning content, video streaming services and communicate using their choice of social media and networking tools. Workspace X also integrates with your choice of learning management system, student information system and content management system. Workspace X users truly begin to take agency of their learning while still benefiting from interactions and guidance provided by quality teachers. The ecosystem can be accessed from any device, any time and also has plenty of space for the specially-selected digital content of your choice.

To round out the ecosystem and bring personalised learning to life, Workspace X also offers complete integration with high-order learning analytics. The learning analytics package provides a dynamic 360-degree view of learning progression displayed as an easy-to-read dashboard. Now quality mobile educational experiences are brought to learners with the rigour of benchmarked evidence of learning progress and growth.

6.0 CONCLUSIONS

The possibilities to use data to improve current educational models are here. However, the distance from simple data collection to effective data-based design support is not small. Although the number of institutions at different levels embracing learning analytics is increasing, widespread adoption still requires an effort to change the mentality towards the use of data, facilitate data integration, target analytics to the true needs of the stakeholders, and make the process robust from the point of view of ethics and privacy. In this paper we have presented a brief overview of the state of the art, and the main initiatives currently shaping the learning analytics landscape. A slow but constant shift to a culture in which data analysis is used to support decision-making at multiple levels is here. This shift has to translate into an overall more effective learning experience for students, parents, teachers, managers and governments.

This report was written by Abelardo Pardo, Shane Dawson, Dragan Gašević and Susi Steigler-Peters

7.0 REFERENCES

Arnold, K. E., and Pistilli, M. D. (2012). Course Signals at Purdue: Using Learning Analytics to Increase Student Success. In S. Buckingham Shum, D. Gašević, and R. Ferguson (Eds.), *International Conference on Learning Analytics and Knowledge* (pp. 267–270). ACM Press.

Baer, L., and Campbell, J. P. (2012). *From Metrics to Analytics, Reporting to Action: Analytics' Role in Changing the Learning Environment* (pp. 53–65). EDUCAUSE. Retrieved from http://net/educause.edu/ir/library/pdf/pub7203.pdf

Baker, R. S. J. D., and Yacef, K. (2009). The State of Educational Data Mining in 2009: A Review and Future Visions. *Journal of Educational Data Mining, 1*(1), 3–17.

Bauer, S. (2015). *Parents' Perceptions of School Accountability: A Case Study of an Urban School District.* San Diego State University.

Bowen, W. G., Chingos, M. M., Lack, K. A., and Nygren, T. I. (2012). *Interactive Learning Online at Public Universities: Evidence from Randomized Trials.* Ithaka S+R. Retrieved from http://www.sr.ithaka.org/sites/default/files/reports/sr-ithaka-interactive-learning-online-at-public-universities.pdf

Dauenhauer, B. D. (2014). *Data-driven Decision Making in Physical Education: A Case Study.* The University of Texas at Austin. Retrieved from http://repositories.lib.utexas.edu/bitstream/handle/2152/24745/DAUENHAUER-DISSERTATION-2014.pdf?sequence=1

Desire2Learn. (2012). *Desire2Learn Client Success Story: Austin Peay State University.* Retrieved from http://content.brightspace.com/wp-content/uploads/Desire2Learn_Success_Story-Degree-Compass-APSU.pdf

Duval, E. (2011). Attention please!: Learning Analytics for Visualization and Recommendation. In *International Conference on Learning Analytics* (pp. 9–17). ACM Press. Retrieved from http://dl.acm.org/citation.cfm?id=2090118

Ferguson, R. (2012). Learning Analytics: Drivers, Developments and Challenges. *International Journal of Technology Enhanced Learning, 4*(5/6), 304–317. http://doi.org/10.1504/IJTEL.2012.051816

Hamilton, L., Halverson, R., Jackson, S. S., Mandinach, E. B., Supovitz, J. A., and Wayman, J. C. (2009). *Using Student Achievement Data to Support Instructional Decision Making* (No. NCEE 2009-4067) (p. 76). Washington, D.C.: National Center for Education Evaluation and Regional Assistance, Institute of Education Sciences, U.S. Department of Education.

Hattie, J., and Timperley, H. (2007). The Power of Feedback. *Review of Educational Research, 77*(1), 81–112. http://doi.org/10.3102/003465430298487

Hubbard, L., Datnow, A., and Pruyn, L. (2014). Multiple Initiatives, Multiple Challenges: The Promise and Pitfalls of Implementing Data. *Studies in Educational Evaluation, 42*(2014), 54–62.

Jarret, J. (2013). Bigfoot, Goldilocks, and Moonshots: A Report from the Frontiers of Personalised Learning. *EDUCAUSE Review, 48*(2).

Kaufman, T. E., Graham, C. R., Picciano, A. G., Popham, J. A., and Wiley, D. (2014). Data-Driven Decision Making in the K-12 Classroom. In J. M. Spector, M. D. Merrill, J. Elen, and M. J. Bishop (Eds.), *Handbook of Research on Educational Communications and Technology* (p. 337–). Springer.

Leadbeater, C. (2008) What's Next? 21 Ideas for 21st Century Learning.

Long, P. D., Siemens, G., Conole, G., and Gašević, D. (Eds.). (2011). *Proceedings of the first International Conference on Learning Analytics and Knowledge.* ACM Press.

Lovett, M., Meyer, O., and Thille, C. (2008). The Open Learning Initiative: Measuring the Effectiveness of the OLI Statistics Course in Accelerating Student Learning. *Journal of Interactive Media in Education, 2008*(1).

Macfadyen, L. P., and Dawson, S. (2010). Mining LMS data to develop an "early warning system" for educators: A Proof of Concept. *Computers and Education, 54*(2), 588–599. http://doi.org/10.1016/j.compedu.2009.09.008

Mandinach, E. B. (2012). A Perfect Time for Data Use: Using Data-Driven Decision Making to Inform Practice. *Educational Psychologist, 47*(2), 71–85.

Mandinach, E. B., and Jackson, S. S. (2012). *Transforming Teaching and Learning Through Data-Driven Decision Making.* Corwin.

Moody, L., and Dede, C. A. (2008). Models of Data-Based Decision Making: A Case Study of the Milwakee Public Schools. In E. B. Mandinach and M. Honey (Eds.), *Data-Driven School Improvement.* Teachers College, Columbia University.

Pistilli, M. D., Arnold, K. E., and Bethune, M. (2012). *Signals: Using Academic Analytics to Promote Student Success.* EDUCAUSE Review Online. Retrieved from http://www.educause.edu/ero/article/signals-using-academic-analytics-promote-student-success

Rainey, L. R. (2013). *What Are You Driving At?: How School Leaders Use Data When Making School Level Decisions About Instructional Improvement* (PhD Dissertation). University of Washington.

Romero, C., and Ventura, S. (2010). Educational Data Mining: A Review of the State of the Art. *IEEE Transactions on Systems, Man, and Cybernetics, Part C: Applications and Reviews, 40*(6), 601–618.

Schweer, M. and Steigler-Peters, S. (2011). Personalised Learning: Meeting the Australian Education Challenge

Siemens, G., Gašević, D., Haythornthwaite, C., Dawson, S., Buckingham Shum, S., Ferguson, R., and Baker, R. S. J. D. (2011). *Open Learning Analytics: An Integrated and Modularized Platform* (White Paper). Society for Learning Analytics Research. Retrieved from http://solaresearch.org/openlearninganalytics.pdf

Siemens, G., and Long, P. (2011). Penetrating the Fog: Analytics in Learning and Education. *Educause Review, 48*(5), 31–40.

Staman, L., Visscher, A. J., and Luyten, H. (2014). The Effects of Professional Development on the Attitudes, Knowledge and Skills for Data-Driven Decision Making. *Studies in Educational Evaluation, 42*(September 2014), 79–90.

Steigler-Peters, S. (2014) mEducation: Mobility Enabling Personalised Learning.

Tanes, Z., Arnold, K. E., King, A. S., and Remnet, M. A. (2011). Using Signals for Appropriate Feedback: Perceptions and Practices. *Computers and Education, 57*(4), 2414–2422. http://doi.org/10.1016/j.compedu.2011.05.016

Upbin, B. (2012, February 22). Knewton is Building the World's Smartest Tutor. *Forbes.* Retrieved from http://www.forbes.com/sites/bruceupbin/2012/02/22/knewton-is-building-the-worlds-smartest-tutor/

Wasson, L., and Steigler-Peters, S. (2012). Quality Teaching for Personalised Learning: Leveraging Technology for Exceptional Results.

Wright, M., McKay, T., Hershock, C., Miller, K., and 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.

TELSTRA