Let’s not forget

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Let's not forget: Learning Analytics are about Learning

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Abstract

The analysis of data collected from the interaction of users with educational and information technology has attracted much attention as a promising approach for advancing our understanding of the learning process. This promise motivated the emergence of the new research field, learning analytics, and its closely related discipline, educational data mining. This paper first introduces the field of learning analytics and outlines the lessons learned from well-known case studies in the research literature. The paper then identifies the critical topics that require immediate research attention for learning analytics to make a sustainable impact on the research and practice of learning and teaching. The paper concludes by discussing a growing set of issues that if unaddressed, could impede the future maturation of the field. The paper stresses that learning analytics are about learning. As such, the computational aspects of learning analytics must be well integrated within the existing educational research.

Keywords: educational research, Learning analytics, , learning sciences, learning technology, self-regulated learning

Introduction

Over the past several years, we have witnessed a growing trend for increased student demand for participation in higher education. While previous reports demonstrated the need for higher education and contrasted this with an argument surrounding the finite capacity to support such growth (OECD, 2013), it was not until 2012 and the hype linked to the massive open online courses (MOOC) that there was intensive public debate about the future role of the university and scalable education models (Kovanović, Joksimović, Gašević, Siemens, & Hatala, 2014). In essence, the rapid advances in technology and its subsequent broad scale adoption provided the necessary infrastructure, and the necessary tipping point for public acceptance of online learning, to enable the delivery of education at such a large scale. While there is much promise amidst the proliferation of MOOCs and online and blended modes of learning more generally, these models also promulgate a new suite of education challenges. For instance, the noted poor attrition rates, and the sheer volume of students enrolled in a MOOC necessitates a more independent study model that is in stark contrast to the more accepted socio-constructivist approaches to learning (Bayne & Ross, 2014).

Despite the challenges of online delivery, the adoption of educational technologies has afforded a new opportunity to gain insight into student learning. As with most IT systems, the student's interactions with their online learning activities are captured and stored. These digital traces (log data) can then be 'mined' and analysed to identify patterns of learning behaviour that can provide insights into education practice. This process has been described as learning analytics. The study of learning analytics has been defined as the "measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs" (Siemens & Gašević, 2012). Learning analytics is a

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bricolage field drawing on research, methods, and techniques from numerous disciplines such as learning sciences, data mining, information visualization, and psychology. This paper reviews the learning analytics research to outline a few of the major topics that the learning analytics field needs to address in order to deliver its oft cited promise for transforming education practice. In so doing, we argue that learning analytics needs to build on and better connect with the existing body of research knowledge about learning and teaching. Specifically, in this paper, we suggest how learning analytics might be better integrated into existing educational research and note the implications for learning analytics research and practice.

Course Signals: Lessons Learned

Predicting student learning success and providing proactive feedback have been two of the most frequently adopted tasks associated with learning analytics (Dawson, Gašević, Siemens, & Joksimovic, 2014). In this context, the best known application of analytics in education is Course Signals developed at Purdue University (Arnold & Pistilli, 2012). Using the trace data collected by the Blackboard learning management system (LMS) and data from the institutional Student Information System (SIS), Course Signals uses a data-mining algorithm to identify students at risk of academic failure in a course. Specifically, Course Signals identifies three main outcome types – a student at a high risk, moderate risk, and not at risk of failing the course. These three outcomes are symbolically represented as traffic light where each light represents one of the three levels of risk (red, orange, and green respectively). The traffic lights serve to provide an early warning "signal" to both instructor and student. This signal is designed to prompt a form of intervention that is aimed at improving the progression of the student identified as at risk of failure. Early studies of Course Signals showed high levels of predictive accuracy and significant benefits in the retention of the students who took at least one course adopting the early alert software versus those who took a course without the Course Signals tool (Arnold & Pistilli, 2012). While Course Signals is a well-known example, there have been many other predictive algorithms aimed towards the identification of student at risk of failure or retention (Jayaprakash, Moody, Lauría, Regan, & Baron, 2014). Any predictive model is generally accompanied by a dashboard to aid sensemaking by visualizing the trace data and prediction results (Ali, Hatala, Gašević, & Jovanović, 2012).

Although establishing lead indicators of academic performance and retention are essential steps for learning analytics, there has been a dearth of empirical studies that have sought to evaluate the impact and transferability of this initial work across domains and contexts (Dawson et al., 2014). The limited empirical research to date has revealed some significant issues that the field needs to consider and address in the future. The most significant is that learning analytics tools are generally not developed from theoretically established instructional strategies, especially those related to provision of student feedback. For instance, Tanes, Arnold, King, & Remnet (2011) undertook a content analysis of the feedback messages sent by instructors to students after receiving the Course Signals alerts. The authors noted that instructive or process feedback types were rarely observed in the instructors' messages to students. This finding is in marked contrast to the vast volume of research demonstrating that feedback is most effective when information is provided "at the process level" (for review, see Hattie & Timperley (2007)). Rather than receiving messages with detailed instructive feedback on how to address identified deficiencies in their learning, students identified at risk would exclusively receive multiple messages carrying low level summative feedback. Consistent with educational research, no effect of summative feedback on learning success was identified.

While the simplicity of the traffic light metaphor of Course Signals was clear to the target users and a simple and effective way to prompt action, the tool design did not have sufficient theoretically informed functionality to encourage adoption of effective instructional and intervention practices. This is not surprising, as Course Signals was initially designed as an academic analytics tool (Arnold & Pistilli, 2012). It is only more recently that the software has been promoted within the domain of learning analytics. However, as an academic analytics tool, Course Signals is well suited to its proposed intent and addresses the needs of the envisioned stakeholders (e.g. university administrators, government officials and funders,). That is, access to data forecasts concerning various institutional trends for resource planning.

What we learn from this case study is that learning analytics resources should be well aligned to established research on effective instructional practice. In so doing we can move from static prediction of a single academic outcome, to more sustainable and replicable insights into the learning process. This is consistent with observations from instructors who appreciated features of the LOCO-Analyst learning analytics tool that allowed for establishing links between the students activities (e.g., discussion messages posted) with “the domain topics the students were having difficulties with” (Ali et al., 2012, p. 485). That is, instructors expressed their preferences of learning analytics features that offer insights into learning processes and identify student gaps in understanding over simple performance measures. With such insights, instructors can identify weak points in the learning activities performed by their students; topics the students have struggled with, and provide instructive and process related feedback on how to improve their learning.

Direction

As noted above, it is essential that future learning analytics developments and innovations draw on, and advance educational research and practice. To do so, we posit that the field of learning analytics needs to ground data collection, measurement, analysis, reporting and interpretation processes within the existing research on learning. In this paper, we build on three *axioms* that Winne (2006) identified as commonly accepted foundations of research knowledge about learning in educational psychology: learners construct knowledge, learners are agents, and data includes randomness. We utilize these three axioms to interrogate the critical issues for the development of the learning analytics field.

The Winne and Hadwin (1998) model of self-regulated learning is based on the COPES models. That is, the model builds on *c*onditions, *o*perations, *p*roducts, *e*valuation, and *s*tandards learners adopt in order to explain how they construct knowledge. In essence, learners construct knowledge by using (cognitive, digital, and physical) tools to perform *operations* on raw information in order to create *products* of learning. For example, a student can use online discussions (as a tool) to synthesize and integrate (as operations performed) knowledge gained from different sources of information in order to develop a critical perspective (as a product of learning) to a problem under study. In this process, learners use *standards* to *evaluate* products of their learning and effectiveness of the operations performed and tools used as a part of metacognitive monitoring and control. A group of individual standards makes up a learning goal that learners set when they are working on a specific learning task. For example, a goal can be composed of the level of cohesiveness of the argument created in an online discussion message when developing their critical perspective, the number, types and trustworthiness of information sources they would consult when building their argument, or the time they decide to spend on the collection of the sources.

The notion that learners are agents implies they have “the capability to exercise choice in reference to preferences” (Winne, 2006, p. 8). The choices learners make are influenced by the (internal and external) *conditions,* which in turn can affect the standards learners use in their metacognitive monitoring and control. Examples of external conditions include course instructional designs such as, grading an online discussion and providing appropriate scaffolds to guide how students participate and use the learning tools. Examples of internal conditions are metacognitive awareness and skills (e.g., whether learners are aware that discussions can be an effective mean to develop critical thinking, and if so, how skilled they are at doing so), the level of motivation to participate in online discussions, or prior knowledge about the topic discussed online.

Effects of Instruction Conditions

To date, learning analytics has been focused on the investigation of the effects of operations performed by using proxy measures of learning derived from trace data – i.e., counts of logs in activity or access to discrete resources and time spent online. However, far less attention has been dedicated to the other elements of COPES, such as how and to what extent the conditions affect the operations performed, the products, and the standards used for metacognitive monitoring. A lack of consideration of these elements raises significant concerns as to the validity of learning analytics results and interpretation. For example, Gašević, Dawson, Rogers and Gasevic (2014) demonstrate that the association of trace data about students’ activity in an LMS with academic performance is moderated by instructional conditions. The Gašević et al. (2014) analysis of the results of a regression model created by combining data from nine undergraduate courses in an Australian university showed that only three variables – number of logins and number of operations performed on discussion forums and resources were significant predictors of academic performance. The authors noted that these three variables explained approximately 21% of the variability in academic performance. However, in a practical sense, these predictors cannot be reasonably translated into actionable recommendations to facilitate student learning. Furthermore, there is a limited degree of feedback that can be provided to instructors without a detailed understanding of the pedagogical intent associated with their tool selection and associated learning activities. Thus, critical insights of such learning analytics could hardly be used to inform the course learning designs as previously suggested by Lockyer, Heathcote, & Dawson (2013). When regression analysis models were created for each course separately, the variables indicative of the LMS tools relevant for the learning design intention of each course emerged. For example, in the communication course with an emphasis on writing, the use of Turnitin for plagiarism detection and assignment descriptions were significant predictors of the students’ grades. This course-specific regression model explained more than 70% of the variability of the final grades of the communication students. In contrast, in the graphics course, no significant predictor was identified within the available trace data for predicting students’ grades. This finding reflects the course design and technology choices of the instructor. In this case, the course did not utilize the institutional LMS. Instead the course learning activities were performed in public social media software. As such, any counts of log-ins, tools and resources within the LMS course site, were effectively redundant for this particular course.

The reasons for the diversity observed in the findings of the Gašević et al. (2014) study may be attributed to the differing instructional models and technology choices across the courses. For instance, educational research has shown that instructors have a significant influence on a learner’s choice of tools within an LMS (McGill & Klobas, 2009) and the learning approach they follow (Trigwell, Prosser, & Waterhouse, 1999). The difference in instructional conditions is likely to shed light on the inconsistent results of the trace data-based predictors of academic success that are often reported in the literature (Jayaprakash et al., 2014; Macfadyen & Dawson, 2012). This supports the earlier proposition stressing the importance of framing future analytics studies within the existing education research.

Effects of Internal Conditions

Learners are active agents in their learning process. This simple statement has many significant implications. Learner agency implies that even when learners receive the same instructional conditions, they may choose to adopt alternate study methods. As such, we need to give greater emphasis to the importance of internal conditions for facilitating student learning. Existing studies about student choice and use of learning tools have revealed significant differences in both the quantity of tool use and how specific tools are adopted to complete a learning task. Building from the work of Winne (2006), Lust, Elen, & Clarebout (2013) posit that the use of learning tools can be considered a self-regulated learning process whereby the choices a student makes about the tool are based on (internal) conditions and individual learning goals. In their study with undergraduate students of education in a blended course, Lust et al. (2013) identified four disparate groups of students based on their use of learning tools. The groups were classified as: i) *no-users,* low level adoption of any tool in the LMS suggested to them in the course design (e.g., quizzes, web lectures, and discussion forums); ii) *intensive active learners* – used all tools suggested by the course design and used those tools actively; iii) *selective users* – only used a selected number of tools offered to them; iv) *intensive superficial users* – used all the tools and spent more time than other groups, predominantly on cognitively passive activities such as reading discussion posts in lieu of contributing to the forum. A future multivariate analysis performed by Lust et al. (2013) revealed that the differences between user groups – where groups were formed as a consequence of exercising their learner agency – was as high as the effects of instructional conditions (e.g., grade vs. non-graded tool use) on the tool use reported in other studies (Gašević, Mirriahi, & Dawson, 2014).

Effects of Learning Products and Strategy

Learning products and standards used for learning are essential factors that need to be captured to describe learning processes comprehensively. Although the frequency of activity and time on task are sound indicators of the extent to which learners use a tool, the high volume of these measures cannot be directly interpreted as a high quality of learning. What is of importance is the specific learning strategies that are adopted by individual students. Learning strategy can be reflective of the metacognitive monitoring and control operations, as these main metacognitive operations are based on learning standards. For example, in a study of the effects of teaching on acceptance of a video annotation software tool for self-reflection, Gašević, Mirriahi, Dawson, and Joksimovic (2014) identified that students, in performing arts, had a high level of annotations created in a course where the annotation tool used for self-reflection on video recordings of an individual's performance, was optional (i.e., not graded). The high level of the annotations created was as high as it was in a prior course where the tool was mandatory and contributed to their final course grades.

Simply counting the number of operations performed within the video annotation study (Gašević, Mirriahi, Dawson, et al., 2014) did not provide an effective measure for the quality of learning products (i.e., text of annotations) nor the adopted learning strategy. However, where counts fail the Coh-Metrix measures succeed (McNamara, Graesser, McCarthy, & Cai, 2014). The

Coh-Metrix analysis showed a significant decline in the cohesiveness and comprehensiveness of the text of self-reflections (i.e., learning products) in the learners' video annotations. Moreover, after representing learning strategies as transition graphs[1] of the activities learners performed and calculating the density of those graphs as a measure of metacognitive monitoring as suggested by Hadwin, Nesbit, Jamieson-Noel, Code, & Winne (2007), a considerable decline in metacognitive monitoring was also observed. This is in part due to the private nature of the annotation when undertaken it the absence of a graded component. For instance, notes taken without any intention for sharing with others typically do not have the same readability as notes prepared for sharing with peers or instructors. However, the decrease is a sign for concern as metacognitive monitoring is the "key SRL process" (Greene & Azevedo, 2009, p. 18) to promote understanding. This finding has much significance for learning analytics research. In essence, continued focus on event activities ignores any examination of the quality of learning products and strategy adopted.

Summary and Future Consideration

The discussion offered in the paper reflects the impetus for building the field of learning analytics upon and contributing to the existing research on learning and education. Clearly, the counting of certain types of activities that learners performed with online learning tools can be correlated with academic performance. However, the true test for learning analytics is demonstrating a longer term impact on student learning and teaching practice. In this context, the field of learning analytics can benefit from past lessons in information seeking. As a developing field in information seeking, Wilson (1999, p. 250) noted that "many things were counted, from the number of visits to libraries, to the number of personal subscriptions to journals and the number of items cited in papers. Very little of this counting revealed insights of value for the development of theory or, indeed, of practice." Significant progress in research and practice only really commenced when information seeking was framed within "robust theoretical models of human behaviour" (Wilson, 1999, p. 250). The field of learning analytics must adopt a similar approach.

While it is often perceived that education is rife with data, very little is related to capturing the conditions for learning (internal and external). For example, external conditions, such as instructional design, social context, previous learning history with the use of a particular tool, and revisions in the course content can radically change the results, interpretation of findings, and the actionable value of learning analytics. Similarly, the measurement of internal conditions such as achievement goal orientation, cognitive load, or epistemic beliefs are yet to be fully understood in relation with their collection and measurement with/from trace data. The work of Zhou and Winne (2012) could provide future research direction on how to integrate the collection of variables about internal conditions with the collection of trace data. The authors suggested that the use of a highlighting tool for reading text in an online learning tool could be framed within the achievement goal orientation framework. Essentially, each highlight (i.e., goal-orientation) can be associated with a different tag, that is easy to understand and use by learners; such as, "interesting" for mastery approach goal orientation; and "important to get a good grade" for performance approach goal-

[1] Transition graphs are constructed from a contingency matrix in which rows and columns were all events logged by the video annotation tool. The rows denoted the start and the columns the end nodes of the transition edges. To create a transition edge from event A to event B, number one was written in the matrix cell intersecting row A and column B. The number in that cell was incremented by one for any future appearance of the edge from event A to event B.

orientation. Similar instrumentation and measurement approaches could be incorporated into the existing learning tools, so that more theoretically founded trace data about internal conditions, temporally proximal to the points in them when learning activities are performed, are collected. Not only can this type of instrumentation increase the theoretically foundation of the measurement in learning analytics, but this type of measurement provides valuable contributions to educational research to overcome the well-known limitations of self-reported measures (Zhou & Winne, 2012).

The analysis of learning products and strategy has received limited attention in the existing research of learning analytics, despite its demonstrated importance for educational research (Hadwin et al., 2007; McNamara et al., 2014). Although learning products can have different forms and thus, require different measurement approaches, presently, the primary emphasis in the learning analytics field has been in memory recall through the use of either scores in completing online quizzes or crude proxies such as course grades, which do not accurately measure learning products but simply academic performance at a given point in time. However, many other important learning products are available in trace data already collected by learning tools. The best example is unstructured text – e.g., created in online discussions, tags, or blogs. In order to analyze these textual products of learning, there is a need to scale up qualitative research methods. The use of text mining and natural language processing methods to conduct based content and discourse analysis is a critically important research direction (McNamara et al., 2014). Learning strategy, as discussed in this paper, can be indicative of dynamic processes activated while learning. For analysis of learning strategy and associated processes, modeling and analysis of latent variables – often not possible to detect with simple counts of certain learning operations – is required. For such dynamic processes to be understood, the process nature of learning needs to be accounted for and learning modelled as a process by building on the existing knowledge from the areas such as graph theory and process mining (Reimann, Markauskaite, & Bannert, 2014).

Although much work has been done on visualizing learning analytics results – typically in the form of dashboards (Verbert, Duval, Klerkx, Govaerts, & Santos, 2013) – their design and use is far less understood. The design of dashboards can lead to the implementation of weak and perhaps detrimental instructional practices as a result of promoting ineffective feedback types and methods (Tanes et al., 2011). For example, a common approach is to offer visualizations with the comparison of the students with the class average. Corrin and de Barba (2014) investigated the effects of such comparisons promoted by dashboards and observed that students who had strong academic standing interpreted (i.e., misinterpreted) the comparisons as if they did well in a class after seeing they were above the class average, even though they actually under-performed compared to both their previous academic performance and goals set before enrolling into the class. Likewise, the negative effect of such comparison dashboards on the students with low levels of self-efficacy is a hypothesis commonly heard in the discussions within the learning analytics community. In order to design effective learning analytics visualizations and dashboards, it is essential to consider instructional, learning and sensemaking benefits for learning. Building on the existing educational research in which the foundations in distributed cognition and self-regulated learning seem to be very promising venues for the future research (Liu, Nersessian, & Stasko, 2008; Zhou & Winne, 2012).

Finally, special attention to the development of learning analytics culture and policies around them needs to be paid. Although it may seem promising to automate many measurements and predictions about learning and teaching, the solely focus on outcomes, as the primary target of learning analytics, without consideration of learning and teaching processes can have detrimental consequences. In such cases, as suggested by Goodhart’s law (Elton, 2004), certain measures – proxies of learning and constructs associated with learning – can cease to be good measures. As a comparable analogy to teaching to the test rather than teaching to improve understanding, learning analytics that do not promote effective learning and teaching are susceptible to the use of trivial measures such as increased number of log-ins into an LMS, as a way to evaluate learning progression. In order to avoid such undesirable practices, the involvement of the relevant stakeholders – e.g., learners, instructors, instructional designers, information technology support, and institutional administrators – is necessary in all stages of the development, implementation, and evaluation of learning analytics and the culture that the extensive use of data in education carries.

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. doi: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. doi:10.1145/2330601.2330666

Bayne, S., & Ross, J. (2014). *The pedagogy of the Massive Open Online Course: the UK view*. The Higher Education Academy. Retrieved from https://www.heacademy.ac.uk/resources/detail/elt/the_pedagogy_of_the_MOOC_UK_view

Corrin, L., & de Barba, P. (2014). Exploring students’ interpretation of feedback delivered through learning analytics dashboards. In *Proceedings of the ascilite 2014 conference*. Dunedin, NZ.

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. doi:10.1145/2567574.2567585

Elton, L. (2004). Goodhart’s Law and Performance Indicators in Higher Education. *Evaluation & Research in Education*, *18*(1-2), 120–128. doi:10.1080/09500790408668312

Gašević, D., Dawson, S., Rogers, T., & Gasevic, D. (2014). Learning analytics should not promote one size fits all: The effects of instructional conditions in predicating learning success. *Submitted to The Internet and Higher Education*.

Gašević, D., Mirriahi, N., & Dawson, S. (2014). Analytics of the Effects of Video Use and Instruction to Support Reflective Learning. In *Proceedings of the Fourth International Conference on Learning Analytics And Knowledge* (pp. 123–132). New York, NY, USA: ACM. doi:10.1145/2567574.2567590

Gašević, D., Mirriahi, N., Dawson, S., & Joksimovic, S. (2014). What is the role of teaching in adoption of a learning tool? A natural experiment of video annotation tool use. *Submitted for Publication to Computers & Education*.

Greene, J. A., & Azevedo, R. (2009). A macro-level analysis of SRL processes and their relations to the acquisition of a sophisticated mental model of a complex system. *Contemporary Educational Psychology*, *34*(1), 18–29. doi:10.1016/j.cedpsych.2008.05.006

Hadwin, A. F., Nesbit, J. C., Jamieson-Noel, D., Code, J., & Winne, P. H. (2007). Examining trace data to explore self-regulated learning. *Metacognition and Learning*, *2*(2-3), 107–124. doi:10.1007/s11409-007-9016-7

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

Jayaprakash, S. M., Moody, E. W., Lauría, E. J. M., Regan, J. R., & Baron, J. D. (2014). Early Alert of Academically At-Risk Students: An Open Source Analytics Initiative. *Journal of Learning Analytics*, *1*(1), 6–47.

Kovanović, V., Joksimović, S., Gašević, D., Siemens, G., & Hatala, M. (2014). What public media reveals about MOOCs? *Submitted for Publication to British Journal of Educational Technology*.

Liu, Z., Nersessian, N. J., & Stasko, J. T. (2008). Distributed cognition as a theoretical framework for information visualization. *IEEE Transactions on Visualization and Computer Graphics*, *14*(6), 1173–1180.

Lockyer, L., Heathcote, E., & Dawson, S. (2013). Informing Pedagogical Action Aligning Learning Analytics With Learning Design. *American Behavioral Scientist*, *57*(10), 1439–1459. doi:10.1177/0002764213479367

Lust, G., Elen, J., & Clarebout, G. (2013). Students’ tool-use within a web enhanced course: Explanatory mechanisms of students’ tool-use pattern. *Computers in Human Behavior*, *29*(5), 2013–2021. doi:10.1016/j.chb.2013.03.014

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).

McGill, T. J., & Klobas, J. E. (2009). A task–technology fit view of learning management system impact. *Computers & Education*, *52*(2), 496–508. doi:10.1016/j.compedu.2008.10.002

McNamara, D. S., Graesser, A. C., McCarthy, P. M., & Cai, Z. (2014). *Automated Evaluation of Text and Discourse with Coh-Metrix*. Cambridge, UK: Cambridge University Press.

OECD. (2013). *Education at a Glance 2013: OECD Indicators*. Retrieved from http://dx.doi.org/10.1787/eag-2013-en

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. doi:10.1111/bjet.12146

Siemens, G., & Gašević, D. (2012). Special Issue on Learning and Knowledge Analytics. *Educational Technology & Society*, *15*(3), 1–163.

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. doi:10.1016/j.compedu.2011.05.016

Trigwell, K., Prosser, M., & Waterhouse, F. (1999). Relations between teachers’ approaches to teaching and students’ approaches to learning. *Higher Education*, *37*(1), 57–70. doi: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. doi:10.1177/0002764213479363

Wilson, T. D. (1999). Models in information behaviour research. *Journal of Documentation*, *55*(3), 249–270. doi:10.1108/EUM0000000007145

Winne, P. H. (2006). How Software Technologies Can Improve Research on Learning and Bolster School Reform. *Educational Psychologist*, *41*(1), 5–17. doi:10.1207/s15326985ep4101_3

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.

Zhou, M., & Winne, P. H. (2012). Modeling academic achievement by self-reported versus traced goal orientation. *Learning and Instruction*, *22*(6), 413–419. doi:10.1016/j.learninstruc.2012.03.004