Learning Analytics – Annotated Bibliography

What are learning analytics?

The term *analytics (s., pl.)* means "the science of logical analysis" (analytics, n.d.). In practice, analytics encompasses the processes, techniques, and tools used to produce and communicate 'actionable intelligence' from large data sets (Campbell, DeBlois & Oblinger, 2007). It is an overarching concept that van Barneveld, Arnold, and Campbell (2012) have defined simply as "data-driven decision making" (p. 8) but which may be more appropriately described as data-*informed* decision-making given the fundamental role human judgment plays in analytics (Cooper, 2012). (In fact, the emphasis on human interpretation over automation is one of the primary distinctions between learning analytics and educational data mining [Siemens & Baker, 2012; US Department of Education, DOE, 2012]). Cooper (2012) insists that analytics is not just about making decisions, however; it is inclusive of exploration and problem identification. EDUCAUSE's working definition, which we will adopt for the purposes of this annotated bibliography, is thus more complete: *"Analytics is the use of data, statistical analysis, and explanatory and predictive models to gain insights and act on complex issues*" (Bichsel, 2012, p. 6).

When applied to the education sector, analytics is frequently divided into two distinct but related categories: *learning analytics (LA)* and *academic analytics (AA)*. The term academic analytics was first described by Goldstein and Katz (2005). Learning analytics, according to the US Department of Education (2012) came into use slightly later, in 2009. The Society for Learning Analytics Research (SoLAR, 2011) defines LA 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*" (p. 4). LA is more specific than AA, focusing only on the learning process (Long & Siemens, 2011). At academic institutions, LA concentrates on data relevant to students and instructors at the level of the individual learner or course and on using analytic techniques to improve student learning outcomes by better targeting instructional, curricular and support resources and interventions (Elias, 2011; van Barneveld, et al., 2012).

Whereas LA is primarily concerned with increasing learner success and the achievement of specific learning goals (van Barneveld, et al., 2012), AA's aim is analogous to that of business analytics in the corporate sector: increasing organizational effectiveness (Long & Siemens, 2011). SoLAR (2011) defines AA as "*the improvement of organizational processes, workflows, resource allocation, and institutional measurement through the use of learner, academic, and institutional data*" (p. 4). The focus is not on individual learners or courses; rather AA is employed at the level of the institution, region or nation. (SoLAR, 2011, Table 1).

In the context of professional training and development, however, the differences between LA and AA are somewhat less pronounced. "From a training industry perspective," van Barneveld, et al. (2012) explain, LA "focuses on two areas—learning effectiveness and operational excellence—with the latter referring to the metrics that provide evidence of how the training/ learning organization is aligning with and meeting the goals of the broader organization" (p. 6).

This bibliography provides some resources for consideration and further exploration of learning analytics in higher education. It is not intended to be a comprehensive review of the literature; however a list of additional recommended articles and resources has been included at the end of this document.

Overall Discussion

Just as big data has become big business in industries from marketing to medicine, so too has it found a place in higher education. Companies use the “data exhaust” we leave in our wake as we traverse the World Wide Web to generate advice and ads, recommend music and movies, and connect us to friends and colleagues on social networks. As higher education continues to shift in the direction of blended and distance learning and more services move online, a growing number of colleges and universities are also employing analytics to support teaching and learning. Learning analytics software packages that leverage advanced methods of mining, modeling, analyzing, and visualizing large sets of data enable institutions to harness the accumulated ‘bits’ of information about students’ activities, interactions and transactions within learning management and student information systems. Such software tools can inform instructional practice and decision-making by identifying, in real/near-real time, hidden patterns and relationships in the learning process and the factors that impact student success (Swan, 2012).

Despite its potential, the implementation and use of LA is not a risk-free proposition; in addition to logistical challenges, it poses legal, ethical and political obstacles. Effective learning analytics initiatives require postsecondary educators to tackle challenges pertaining to student privacy, data ownership, IT infrastructure and tools, and campus culture, amongst others (Arnold, 2010; Stiles, 2012).

Bearing in mind both the promise and the peril associated with learning analytics, a limited review of the literature provides us with several insights into this important and still-emerging area of research and practice in higher education:

- ***LA is a “hot topic” right now.*** There is no mistaking that learning analytics is a “hot topic” among researchers and practitioners alike. The *Journal of Asynchronous Learning Networks* published a special issue on learning analytics in June 2012. Other journals and magazines, including the *Journal of Educational Technology and Society* and *EDUCAUSE Review*, have also dedicated issues or published a series on the topic within the past 12 months. Still others (*British Journal for Educational Technology* and the *Journal of Technology Instruction, Cognition and Learning*) have recently put forth calls for papers on the subject to be considered for publication in upcoming special issues. The New Media Consortium’s *Horizon Project* Higher Education Advisory Board has once again named learning analytics a top technology trend in education. Their 2013 report (Johnson, et al., 2013) includes LA as a technology they expect will be widely implemented at colleges and universities within the next three to four years.
- ***LA is more than a passing trend.*** Learning analytics is becoming (or has already become) a distinct field of study in its own right. The Society for Learning Analytics Research was founded in 2011 as a professional organization devoted to advancing the field of learning analytics (SoLAR, n.d.). In April 2013, the third annual International Learning Analytics & Knowledge Conference was held in Leuven, Belgium. The newly established, peer-reviewed *Journal of Learning Analytics* will publish its inaugural issue later this year.
- ***LA is representative of a “sea change” in higher education and educational technology***. Although ‘big data’ analytics are transforming sectors across the whole of society, prominent advocates regard them as a “game changer” (Baer & Campbell, 2012; Johnson, et al., 2013), even calling them “the most dramatic factor shaping the future of higher education” (Long & Siemens, 2011, p. 31). Colleges and universities are under pressure to increase efficiency and

accountability, improve the quality of student learning, and raise retention and completion rates. LA offers a means for stakeholders to make swifter, better-informed decisions in support of these goals (Brown, 2011; Campbell, et al., 2007; Diaz & Brown, 2011; Long & Siemens, 2011; SoLAR, 2011; Swan, 2012; US DOE, 2012). Universities say it is a priority (Bichsel, 2012) and EDUCAUSE member institutions have identified "using analytics to support critical institutional outcomes" as a top ten issue in the practice of higher education IT (Grajek, 2013).

- ***LA definitions are evolving.*** There is a multitude of terms and phrases surrounding this young field and just the beginnings of agreement about their meanings and proper use (Long & Siemens, 2011; Norris & Baer, 2013; van Barneveld, et al., 2012).
- ***LA aims to inform action in the "here and now."*** In contrast to mere data analysis and conventional research methods in education, learning analytics emphasize continuous, real-time interaction. LA enables educators to move beyond post-hoc analysis to using real-time information to identify at-risk students, tailor questions to previous answers, track and monitor progress (Elias, 2011; Long & Siemens, 2011; Swan, 2012).
- ***LA relies on human judgment.*** Whether one is selecting what variables to track, determining how to visualize system activity, or determining the best course of action given the data, subjective interpretation and appraisals are unavoidable (Dziuban, et al., 2012; US DOE, 2012).
- ***LA users must avoid overly simplistic, deterministic models of student learning and success.*** While we can use data points to make inferences about complex processes and constructs such as learning, we must do so cautiously, keeping in mind that data is not knowledge. Responsible use of LA involves understanding the assumptions that an analytics system, tool or service makes about the variables that predict and indicate academic success (Contact North, 2012; Dringus, 2012; Long & Siemens, 2011).
- ***LA requires skilled data and visualization professionals.*** Analytics projects involve asking questions of data; answering these questions in a meaningful way often necessitates some expertise in data science, statistics and information visualization (Bichsel, 2012; Ellis, 2013; Norris & Baer, 2013; Olmos & Corrin, 2012).
- ***LA is about more than technology, but tools matter.*** Customization and visualization is key. Visualizations can be valuable aids in this process by helping decision-makers (be they instructors, students or other stakeholders) "see" the patterns and trends in the data (Ali, et al., 2013; Macfadyen & Dawson, 2010; Fournier, Kop, & Sitlia, 2011).
- ***LA raises questions about data ownership and ethical use of PII.*** Even among those who recognize the potential of LA to bolster online student learning and success, there are areas of controversy and debate and numerous unanswered questions about privacy, an obligation to act on information, and over reliance on quantitative information in assessment and evaluation, amongst others (Contact North, 2012; Dringus, 2012; Grajek, 2013; Long & Siemens, 2011).
- ***LA should extend beyond the LMS.*** To be most effective, institutions need to consider data beyond what is logged within the LMS and work toward greater integration of data systems (Dawson, Heathcote, & Poole, 2010; Long & Siemens, 2011).
- ***LA has a variety of promising applications.*** Evidence suggests LA may be particularly useful for developing early-warning systems and interventions, visualizing learner interactions and increasing social learning, and developing more personalized, adaptive learning experiences (Arnold & Pistilli, 2012; Black, Dawson, & Priem, 2008; Buckingham Shum & Ferguson, 2012; Fritz, 2011; Macfadyen & Dawson, 2010; Tanes, Arnold, King, & Remnet, 2011).

Annotated bibliography

Ali, L., Asadi, M., Gaševic, D., Jovanovic, J., & Hatala, M. (2013). Factors influencing beliefs for adoption of a learning analytics tool: An empirical study. *Computers & Education, 62*, 130-148. doi:10.1016/j.compedu.2012.10.023

Recognizing a lack of empirical research into the factors that influence the adoption of learning analytics tools, Ali, Asadi, Gaševic, Jovanovic, and Hatala present a "first draft" *Learning Analytics Acceptance Model* (LAAM)—illustrating how educators' (a) pedagogical knowledge and information design skills, as well as their perceptions of a LA tool's (b) *usefulness* and (c) *ease-of-use* affect their behavioral intention to use the tool in their courses. In this study, data were collected from a sample of 22 instructors, teaching assistants and researcher/learning analysts from three universities and a private Canada-based company that develops and offers technology and content for professional training. The participants experimented with a Learning Object Context Ontologies (LOCO)-Analyst tool, which provides context-specific analytics on students' activities and social interactions in the online environment and on the usage and comprehensibility level of learning content. (The article's appendix contains a useful overview of LOCO-Analyst.) Ali et al. used a questionnaire-based survey instrument to measure the elements of the LAAM and conducted statistical analyses of the participants' responses.

The results of their research suggest that what educators value most is straight-forward information about student-student interactions and students' comprehension of course content. Participant responses indicated that the tool enabled them to gain insight into students' online interactions but was less useful in terms of identifying how to address suboptimal interactions. Although the authors had hypothesized that educators' usage beliefs (i.e., usefulness and ease-of-use perceptions) about the tool's learning analytics would positively influence their intention to adopt it in practice, analysis of the data revealed that the *usefulness* and *ease-of-use* perceptions were not significant indicators of the intention to use LOCO-Analyst. The one exception was participants' perception of whether the tool would help them identify what in the learning content needed improvement (r = 0.77, p < .01). While the LAAM model clearly needs refining and the study needs replicating with other populations and analytics tools before drawing any definitive conclusions, the article was nevertheless published in a leading journal as an early contribution to the research community's efforts to understand the acceptance and adoption of learning analytics tools—an area in which there is still much work to be done, and which has practical relevance for education practitioners.

Arnold, K. E. & Pistilli, M. D. (2012). Course Signals at Purdue: Using learning analytics to increase student success. In S. Buckingham Shum. D. Gašević, & R. Ferguson (Eds.), *LAK '12 Proceedings of the 2nd International Conference on Learning Analytics and Knowledge* (pp. 267-270). New York, NY: ACM. doi: 10.1145/2330601.2330666

In this conference proceedings paper, Arnold and Pistilli discuss the early warning student intervention system, *Course Signals* (CS). Signals uses a predictive student success algorithm (SSA) to calculate students' risk level in a class based on SIS and LMS data on their current course performance, effort compared to peers, academic history, and demographic characteristics. When the instructor runs the SSA, each student in the class is assigned a visual risk indicator (a red, yellow, or green traffic signal icon) corresponding to his or her likelihood of success.

Instructors can send accompanying written messages with student-specific feedback, information, and resources for improving performance. When Arnold and Pistilli combined the final grade distributions of all courses using Signals in a given semester, they found a 10.37% increase in A's and B's compared to the same courses before Signals was implemented. They also found a 6.41% decrease in D's, F's and withdrawals compared to pre-Signals semesters of those same courses. Additionally, first-time, full-time students who matriculated at Purdue in 2007, 2008 or 2009 and took at least one course in which Signals was used persisted in their studies at significantly higher rates than cohort peers who did not participate in a Signals-enabled course; students who took two or more Signals courses consistently persisted at higher rates than peers who took one or none. Additional analyses revealed that the earlier a student took a Signals course in their academic career, the greater the likelihood they were retained into the next semester. Perhaps most compelling are early indications that lesser-prepared students in a Signals-enabled section of a difficult course are more successful than better-prepared students in a class without Signals.

Across five semesters, Purdue has received anonymous survey feedback from 1,500 students on their experience of Signals. 89% of student respondents report that Signals provided a positive experience and 58% said they would like to have it in every course they take. Negative feedback pertained to the way faculty had used it (e.g., redundant e-mail, text, and LMS messages; not updating traffic signals after running the SSA; lack of specificity in the messages). Course instructors are also mostly positive about Course Signals but some have expressed concerns about receiving "an excess of e-mails from concerned students", "creating a dependency in newly arrived students" and "a lack of best practices for using CS" (p. 4). Purdue has assembled a list of best practice tips to address this last issue. While not without shortcomings, Purdue Course Signals is a laudable example of how analytics can have a practical and measurable impact on student success.

<u>Bichsel, J. (2012). *Analytics in higher education: Benefits, barriers, progress, and recommendations*. Louisville, CO: EDUCAUSE Center for Applied Research.</u>

The EDUCAUSE Center for Applied Research (ECAR) published this report based on survey data collected from 339 postsecondary institutions and feedback from focus groups of 41 Institutional Research (IR) and Information Technology (IT) professionals. The study and report seek to shed light on the current state of analytics in higher education and offer insights into the obstacles and opportunities confronting institutions interested in advancing their use of analytics. The research also informed the development of the *ECAR Analytics Maturity Index for Higher Education* (ECAR, 2012), formulated to help colleges and universities "gauge their progress in analytics, identify gaps that may be hindering progress in analytics, and identify strengths they might capitalize on to initiate or expand their analytics programs" (p. 24).

The results of the ECAR study demonstrate that analytics is viewed as increasingly important to institutions' strategic outcomes (e.g., 69% of participants reported that analytics is "a major priority for at least some departments, units, or programs"; 86% said that "two years from now, analytics will be more important for higher education's success," pp. 8-9). Despite the priority placed on analytics, however, the study also revealed that at most institutions data are used primarily for reporting purposes. Institutions with higher scores on the Investment, Culture/Process, Data/Reporting/Tools, Expertise/Knowledge, and Governance/Infrastructure subscales of the maturity index were more likely to be using analytics in more sophisticated ways—"to make predictions or projections or to trigger action in a variety of areas" (p. 4).

The report identified four major obstacles to institutions' progress in implementing successful analytics initiatives: (a) affordability, (b) data, (c) culture, and (d) expertise. That the most commonly cited challenge was the availability of resources corresponds to the finding that institutions scored lowest overall in the area of Investment. Data collected from the focus groups indicated that those who had made the most progress in this area view analytics as an investment rather than an expense. In order to move forward, Bichsel advises colleges and universities to "focus their investments on expertise, process, and policies before acquiring new tools or collecting additional data" (p. 4). She also recommends that institutions "form a partnership between IT and IR and between analysts and executive leadership that begins with better communication" (p. 26), since the study results indicate that mature, successful analytics programs exist where various constituents are working in partnership.

Black, E. W., Dawson, K., & Priem, J. (2008). Data for free: Using LMS activity logs to measure community in online courses. *Internet and Higher Education, 11*(2), 65-70.

This study investigated whether students' perception of community is associated with the number of LMS data log 'events' they generate. Black, Dawson, and Priem recruited 67 University of Florida graduate students, all of whom were enrolled in graduate-level online educational technology courses, to complete Rovai's Classroom Community Scale (CCS; Rovai, 2002). The CCS is considered a reliable and valid measure of three constructs: *learning*, *connectedness*, and *classroom community*. The results of the study indicate that student activity logs in an online graduate level course are related to both perceptions of classroom community (Adj $R^2 = .086$, $F(2, 64) = 4.090$, $p = .021$) and students' sense of connectedness (Adj $R^2 = .066$ $F(2, 64) = 3.341$, $p = .042$) (p. 67).

The researchers identify several study limitations: (a) narrow sample size; (b) lack of consideration of the course content and the variability in instructors' online teaching experience; (c) differences in students' comfort and skill using course technology; (d) the possibility that instead of responding to the CCS survey questions as intended (with just one course in mind), students who were taking multiple online courses may have answered based on their experience in the online learning program, more generally; and (e) focusing solely on the cumulative frequencies of logged course interactions and thus not accounting for the type of student activity in the LMS (e.g., reading the syllabus versus responding to a forum discussion). Despite the study limitations, Black et al. see two potential applications of activity data logged by LMSs such as Moodle: (a) "to support real-time data analysis for constructing visualizations and modeling students," (counting log entries is far easier to automate in real time than complicated data mining techniques) and (b) "to augment survey data for informing long and medium-term decision making" (or possibly even serve as an alternate, less obtrusive method of collecting affective data from students) (p. 68).

Buckingham Shum, S., & Ferguson, R. (2012). Social Learning Analytics. *Educational Technology & Society*, *15*(3), 3-26.

According to Buckingham Shum and Ferguson, *Social Learning Analytics (SLA)* is a distinctive class of learning analytics that takes a socio-cultural approach to understanding and informing online teaching and learning by focusing on data pertaining to learner interactivity.

SLA draws heavily on social constructivist pedagogical theory and research demonstrating the significant roles that interaction and collaboration play on the development and transfer and new skills and ideas. In this conceptual paper, Buckingham Shum and Ferguson discuss five major factors in the emergence of open, online social learning, which include (a) *technological drivers*, (b) *the shift to 'free' and 'open'*, (c) *the demand for knowledge-age skills*, (d) *innovation requires social learning*, and (e) *challenges to educational institutions*, and illustrate how online social learning environments differ from everyday social media platforms. They argue that these factors highlight the need for a range of analytics that can account for connected and distributed learner interaction in both formal and informal social learning contexts and which emphasize knowledge-age skills and associated learning dispositions such as resilience and creativity.

The authors identify five different types of SLA (not intended to be a complete "taxonomy"): (a) *social network analytics*; (b) *discourse analytics*; (c) *content analytics*; (d) *disposition analytics* and (e) *context analytics*. Whereas social network and discourse analytics are considered "*inherently social*" and therefore must be applied in a collective context to make sense, the latter three are categorized as "*socialized analytics*," meaning they may be used as individual learner analytics but "have important new attributes in a collective context" (p. 10). Upon explaining the relevance of each type, when and how they might be employed and some of the tools that support them, Buckingham Shum and Ferguson review some of the criticisms associated with "the balance of power in learning analytics" (p. 18) and briefly consider three important points of debate from a Social Learning Analytic perspective. They conclude by envisioning potential future scenarios in which the values, tools and practices of SLA have matured in concert with the cultural and technological factors that are driving the growth of online social learning and changing the way we think about learning.

Contact North. (2012). *The learning analytics challenge: Culture of data or culture of evidence?* [White paper]. Ontario, CA: Contact North ǀ Contact Nord. Retrieved from http://www.contactnorth.ca/trends-directions/learning-analytics

Contact North ǀ Contact Nord, a non-profit corporation funded by the Government of Ontario, Canada, works with the province's public colleges, universities and essential skills and training providers to increase and improve online and distance learning opportunities. In this white paper, Contact North makes the case for the use of learning analytics in the post-secondary education sector. After discussing changes in the funding, regulatory and political climates in higher education and developments in information technology, the paper introduces learning analytics as the area where these changes "intersect most compellingly" (p. 2). It goes on to examine various factors that make learning analytics a challenge. The authors argue that while learning analytics may seem a natural fit for post-secondary institutions, which are by nature analytical organizations that value critical inquiry and the rigorous analysis of data, "it is precisely this culture [of evidence] that breeds skepticism of everything, including learning analytics" (p. 3). According to Contact North, factors posing a challenge to the acceptance and adoption of LA among faculty include: (a) the fundamental distinction between data and knowledge; (b) the complexity of the learning process; (c) the artisanal nature of post-secondary instruction; (d) individual student differences that impact learning but which institutions do not/cannot measure, (e) the time required of faculty to learn and use LA tools in their teaching practice; and (f) concerns about the appropriate use of data and protection of privacy. The paper then presents "The Way Forward," as a set of directives for the postsecondary education community:

(a) We need to contextualize the data.
(b) We need to Stop blaming technology or the data. The challenge is behaviour.
(c) We need to recognize the additional time that these new practices require.
(d) We need to align the goals of the instructor, department chair, dean, and provost.

We need to engage staff and students. (pp. 6-8)

Dawson, S., Heathcote, L., & Poole, G. (2010). Harnessing ICT potential: The adoption and analysis of ICT systems for enhancing the student learning experience. *International Journal of Educational Management, 24*(2), 116–128.

In this paper, Dawson, Heathcote, and Poole examine how higher education institutions capture and utilize data from their student information systems, learning management systems and communication tools to support student learning and evaluate whether institutions are using ICT data effectively for this purpose. While they discuss their research in terms of academic analytics, the scope of Dawson et al.'s investigation encompasses individual student and course level data and is thus also relevant to discussions of learner analytics. The authors present examples of automated and semi-automated IT systems that correlate quantifiable data with learning outcomes and conclude "the capacity to present individual user activity within a broader context provides a more robust analysis and pattern recognition" (p. 122). They contend that institutions need to consider data beyond what is logged within the LMS and emphasize the need for greater integration of data systems (i.e., data warehousing) in order to detect more effectively anomalies in student behaviors that "may serve to provide a catalyst for proactive instructor intervention." (p. 122) Pointing to the as yet untapped potential for integrating disparate data sources to improve student learning and success, Dawson et al. offer some possible models for harnessing information from various institutional systems.

Dringus, L. P. (2012). Learning analytics considered harmful. *Journal of Asynchronous Learning Networks, 16*(3), 87-100.

Dringus presents a critique of the strategic and tactical issues associated with applying learning analytics to online education. She points to the benefits of using learning analytics in online courses but argues that it also has the potential to be detrimental to assessment and evaluation of course quality and student progress if not used responsibly. Addressing both practitioners (e.g., instructors and administrators) and researchers, Dringus prescribes five 'MUST' statements for effective use of LA in online learning:

Effective learning analytics in online courses…

1. MUST develop from the stance of getting the right data and getting the data right.
2. MUST have transparency.
3. MUST yield from good algorithms.
4. MUST lead to responsible assessment and effective use of the data trail.
5. MUST inform process and practice. (p. 89)

"Stakeholders should be mindful," cautions Dringus: (a) The way we define 'data trail' (e.g., the variables we select as indicators of performance) may impact what we study and how we understand the online experience; (b) in order to reap the benefits of big data as the volume of data continues to increase, we must practice good learning management, reliable data warehousing and management, flexible and transparent data mining and extraction, and accurate and responsible reporting; (c) big data will influence interpretations and decisions about student progress and about the quality of online learning in general, and (d) these interpretations and decisions have the potential to affect our 'control' over the quality of the online experience (p. 97).

Dziuban, C., Moskal, P., Cavanagh, T., & Watts, A. (2012). Analytics that inform the university: Using data you already have. *Journal of Asynchronous Learning Networks, 16*(3), 21-38.

Dziuban, Moskal, Cavanaugh, and Watts of the University of Central Florida (UCF) discuss how they are using institutional data to improve course delivery and student success in online and blended learning. They describe the IT systems infrastructure utilized by UCF's Center for Distributed Learning (CDL) to maintain simultaneous "top-down" and "bottom-up" views of what is going on across the University related to distributed learning (i.e., fully online, blended, and lecture-capture courses and programs). Dziubuan et al. present scenarios that not only demonstrate how UCF has benefited from analytics but also illustrate the important role that human judgment plays in using big data effectively. The authors are emphatic that "data do not make decisions, people do" (p. 27). They identify four domains that intersect in a successful analytics program: (a) student engagement, (b) faculty engagement, (c) information value, and (d) student and faculty support. They also cite ten elements necessary for operationalizing effective analytics initiatives—adapted from Hartman, Moskal, and Dziuban's description of elements necessary for operationalizing blended learning programs: (a) Effective institutional goals and objectives; (b) Proper alignment; (c) Organizational capacity; (d) A workable vocabulary; (e) Faculty development and course development (they substitute analytics) support; (f) Support for students and faculty; (g) Robust and reliable infrastructure; (h) Institutional level on effectiveness; (i) Proactive policy development; and (j) An effective funding model (p. 27)

Fournier, H., Kop, R., & Sitlia, H. (2011). The value of learning analytics to networked learning on a personal learning environment. In P. Long, G. Siemens, G. Conole, & D. Gašević (Eds.), *Proceedings of the First International Conference on Learning Analytics and Knowledge (LAK '11)* (pp. 104-109). New York, NY: ACM. doi: 10.1145/2090116.2090131

In this paper, Fournier, Kop, and Sitlia describe a 2010 case study on the use of learning analytics in a free, 10-week 'connectivist' Massive Open Online Course, *Personal Learning Environments, Networks, and Knowledge (PLENK2010)*, and discuss both the benefits and concerns associated with various methodologies and tools for analyzing 'big data' collected from online networks. The research team used a mixed methods design to ensure they had robust data on the diverse participant experiences and activities in PLENK2010. Learning analytics tools "were used as a quantitative form of Social Network Analysis to clarify activity and relationships between nodes on the PLENK network" (p. 5). In addition to Moodle data mining functionality, gRSShopper aggregator statistics functionality was used to collect details on course-related use of blogs and micro-blogging tools (e.g., Twitter). The Social Networks Adapting Pedagogical Practice

(SNAPP) tool provided real-time social network visualizations of Moodle discussion forum activity, and NetDraw was used to visualize an individual's role in a discussion by creating ego networks.

The authors conclude that learning analytics "can be powerful in giving meaning to interactions and actions in a learning environment such as was used on this MOOC" (p. 9). They confirm the value of a mixed methods analytics approach and reflect on the necessity of human interpretation and analysis (or advanced artificial intelligence capacity), particularly in overcoming the limitations of the learning analytics used in the case study. Fournier et al. offer several suggestions for improving the use of LA for informing learning in a large-scale networked course, such as this C-MOOC. They remark that "the use of tags in the Moodle environment would have been helpful in linking various contents across weeks, allowing participants to search for relevant content and to see how they were connected to various content and people with similar interests" (p. 9). They also recommend exploring more powerful computational tools and intelligent and automatic data analysis, since so much data was generated that it was not feasible to conduct detailed analyses on everything using the tools in the case study.

Fritz, J. (2011). Classroom walls that talk: Using online course activity data of successful students to raise self-awareness of underperforming peers. *Internet & Higher Education, (14)*2, 89-97.

In this paper, Fritz presents a case study of the University of Maryland, Baltimore County (UMBC)'s use of learning analytics. UMBC discovered that students who earned a D or F as their final grade used the institution's CMS, Blackboard, 39% less on average than students with final grades of C or better. Fritz and his colleagues wondered whether underperforming students would be more inclined to seek, accept and sustain academic assistance if they had an objective picture of their course activity and grades compared to an anonymous summary of their fellow classmates. They developed the "Check My Activity" (CMA) tool, which includes a Grade Distribution Report (GDR) comparing students' own activity to the activity of peers who score above and below them on an assignment or exam. These comparisons are accessible to students at any time and provide them with early feedback to increase their self-awareness without creating additional work for faculty. Initially used by few students, the CMA became popular among students following a marketing campaign and usability enhancements. Fritz acknowledges there is not yet enough evidence to establish Blackboard activity as a valid and reliable predictor of UMBC student success and therefore cannot conclude that the CMA tool is actually intervening in the behavior of underperforming students; however, the high percentage of students who continue to use the tool has prompted further research to determine "what, if anything, their use can mean for changing student self-awareness, behavior and academic performance" (pp. 92-3).

Also see:

Fritz, J. (2010). Video demo of UMBC's 'Check My Activity' tool for students [Video]. *EDUCAUSE Quarterly*.

Fritz, J. (2013). *Using analytics at UMBC: Encouraging student responsibility and identifying effective course designs* (Research bulletin). Louisville, CO: EDUCAUSE Center for Applied Research.

Grajek, S. & EDUCAUSE 2012-2013 IT Issues Panel. (2013). Top-ten IT issues, 2013: Welcome to the 'Connected Age'. *EDUCAUSE Review, 48*(3), 30-57.

The 2012-13 EDUCAUSE IT Issues Panel, composed of individuals from EDUCAUSE member institutions, identified "Using analytics to support critical institutional outcomes" as one of the top ten most important issues currently confronting higher education IT practitioners. The 2013 report includes a useful set of questions to help guide institutions in strategically addressing this issue:

1. Has the institution taken the *ECAR Analytics Maturity Index* to measure its analytics maturity and identify strengths and gaps?
2. How is the institution applying analytics today?
3. Does the institution have a culture of data-driven decision making? If not, how can leadership help create this culture?
4. Is the institution viewing analytics as a strategic investment or as a new cost?
5. What strategic questions identified in the institutional strategic plan or accreditation report would benefit from analytics?
6. Has the institution performed a resource inventory to identify the campus skills and resources that could support analytics? What key skills or resources are missing that would be essential to success? Which executive is responsible for analytics services?
7. Do current data flows, definitions, and architectures need to be restructured and redefined to support institution-wide analytics? Do data owners guard their data or share it?
8. Does the institution have strategic priorities for analytics to ensure that analytics initiatives have a clear and constrained focus? What constitutes success of an analytics initiative? How will the institution evaluate success in two years, four years, and beyond? (p. 55).

Long, P., & Siemens, G. (2011). Penetrating the fog: Analytics in learning and education. *EDUCAUSE Review, 46*(5), 30-32.

According to Long and Siemens, many fields are quickly adapting and advancing through the use of large-scale data analysis and predictive modeling, but higher education, despite collecting "an astonishing array of data about its 'customers,'" (p. 32), too often fails to use data efficiently. They maintain that between the technological and social changes accompanying the Internet, mobile technologies and open education and the growing debates about what a college degree is really worth, long-standing calls for increased productivity, quality, and accountability in higher education have grown more urgent than ever. Analytics, they assert, has a big part to play in answering these calls. Long and Siemens are careful to explain what they mean by 'analytics' and attempt to clarify what distinguishes *learning* from *academic* analytics.

In their discussion of the former, they propose a model of learning analytics development:

1. *Course-level:* learning trails, social network analysis, discourse analysis
2. *Educational data-mining:* predictive modeling, clustering, pattern mining
3. *Intelligent curriculum:* the development of semantically defined curricular resources
4. *Adaptive content:* sequence based on learner behavior, recommender systems
5. *Adaptive learning:* the adaptive learning process (social interactions, learning activity, learner support, not only content) (p. 36)

The authors articulate the need for analytics that account for more than LMS activity. They remark on the potential for mobile devices and clickers to "provide additional insight into factors that contribute to learners' success" (p. 38). They also discuss the value of real-time assessment and intelligent, personalized learning, insisting, "It is not sufficient to treat big data and analytics as useful only for evaluating what learners have done and for predicting what they'll do in the future. Analytics in education must be transformative" (p. 38).

Long and Siemens are not wearing rose-colored glasses, however. They point to numerous unanswered practical and ethical questions about the use of learning analytics, the risk of a return to behaviorism as a predominant learning theory and the need to refrain from drawing conclusions about learning based on the misapplication of simplistic and deterministic models to complex issues. Yet, despite the rough road ahead, they do believe learning analytics "is essential for penetrating the fog that has settled over much of higher education" (p. 40).

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.

Macfadyen and Dawson analyzed Blackboard LMS data from five sections of a fully online undergraduate biology course at the University of British Columbia (N = 118) to determine which LMS-based activities predict student achievement. 13 (of 22) variables yielded statistically significant positive correlations with 'student final grade' ($p < .05$). Regression modeling indicated that, for this particular course, the number of forum posts, mail messages sent, and assessments completed (many being ungraded, optional quizzes) are significant predictors of final grades and account for more than 30% of grade variation among students. Their model predicted at-risk students with 70.3% accuracy. The study makes it apparent, however, that variables pertaining to instructor intent and online course website design/structure are key in generating an effective model of online student success. A different combination of variables will have a greater predictive utility depending on a course's design. Moving beyond a mere count of forum posts, Macfadyen and Dawson gained deeper insight into social interaction patterns using social network analysis (SNA) tools to visualize course discussions, thereby drawing attention to the importance of having more complex analytics available for monitoring and facilitating student engagement. While LMS-generated student tracking data do not represent a complete picture of student engagement and likelihood of success, this study provides strong evidence that LMS data can serve a meaningful role in informing pedagogical interventions by enabling instructors to identify and assist at-risk students in a more timely manner. It also points to the need for a tool that can be used to extract and visualize this information in real-time and that is also customizable enough to reflect an instructor's pedagogical goals and course site design.

Norris, D. M. & Baer, L. L. (2013) *Building organizational capacity for analytics*. Louisville, CO: EDUCAUSE. Retrieved from http://net.educause.edu/ir/library/pdf/PUB9012.pdf

This report documents preliminary research on current and projected analytics capacity in higher education, the results of which EDUCAUSE is using to develop *A Toolkit for Building Organizational Capacity in Analytics.* The paper contains an overview of the findings from in-depth interviews with 40 "leading institutions" (recommended by practitioners and thought leaders in the fields of learning analytics and higher education) and survey data collected from 20 technology vendors. Norris and Baer's high-level analysis highlights "the state of practice and gaps between needs and solutions," "the sorts of analytics innovations and practices that are possible with current and emerging tools" and "the state of analytics readiness of typical institutions" (p. 5). Institutional leaders characterize current generation analytics tools and services as "in need of enhancement" (p. 39), however cost and affordability pose significant challenges. Beyond the need to raise funds, Norris and Baer also found "substantial need for raising professional development, capacity building, and the analytics IQ of institutional leadership and practitioners, at all levels" (p. 40). The solution providers who gave their impressions of higher education's analytics readiness, reported, "Many institutional leaders overestimate their enterprise's capacity in data, information, and analytics capacity. Many do not fully appreciate the change management challenges facing their institutions if they are to fully embrace the embedded deployment of performance-focused analytics" (p. 40).

The authors discuss the development of institutions' organizational capacity as a three-stage process. Level 1, *Static Reporting*, includes the majority of institutions, where leaders are focused on data and reporting and seeking guidance on how to increase their capacity and use of student success analytics. At Level 2, *Dynamic Analysis and Intervention*, institutions are working to support evidence-based decision-making, frequently using shared or third party solutions. The third level, *Optimization*, includes approximately 30-50, mostly for-profit and majority online institutions whose "strong, committed leadership makes analytics a strategic imperative for the institution" (p. 41). Project next steps include extending the interviews and surveys to more institutions and vendors, creating FAQ and matching services for analytics solutions, developing a capacity building toolkit and certificate program, and promoting cross-institutional collaboration.

Olmos, M., & Corrin, L. (2012). Learning analytics: A case study of the process of design of visualizations. *Journal of Asynchronous Learning Networks, 16*(3), 39-49.

Olmos and Corrin argue that although visualizations can support human interpretation of complex student engagement and experience data and provide opportunities for improving learning support and curriculum design, creating clear and useful visualizations is itself a challenging process that requires human interpretation. Data can be represented in many different ways, and determining the most effective visualization method necessitates advanced analytical and information visualization skills. In a case study that involved visualizing students' patient care experiences in a medical degree program, they explored the iterative design process by which a visualization was developed and refined. This paper describes their findings and includes lessons learned that may be applicable to other analytics projects and visualizations:

- A clear understanding of the questions to be answered and data available is critical
- The process of representing the available data in a way that provides insight into the analytical questions is one of visual analysis and design that requires specific skills.
- It is helpful to develop a clear mockup of a visualization. This enables early feedback from the target audience, before development time and effort are wasted. It also provides a clear ideal to aim for, even if it cannot yet be implemented.
- Designing a visualization involves navigating through tradeoffs. It is critical to identify these and make choices based on clear goals. One such example is the decision to use an existing and standard chart type that isn't ideal but can be readily used versus developing a new one that would be better but costlier. (p. 47)

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.

This paper discusses two studies examining the content and nature of instructor feedback provided via Purdue University's *Course Signals* (also see Arnold & Pistilli, 2012). In the first study, Tanes et al. interviewed eight instructors to learn how they defined the content and nature of feedback sent via the tool. Analyses of the interview transcripts suggested instructors conceive of the technology primarily as a means of transmitting summative feedback during the semester. Given that formative feedback leads to better learning experiences and outcomes (Chen, 2001; Higgins et al., 2002, as cited in Tanes et al., 2011, p. 2148), the focus on summative feedback led the researchers to question whether the system's feedback capabilities were being used to their full potential. Tanes et al. also concluded there is "a great need" to examine the frequency, timing and proportion of positive and negative feedback sent using *Signals* (p. 2418).

The second study focused on the message, themselves. The researchers coded the content and nature of feedback sent by the participants using the same categories from the first study and assessed the success of these feedback interventions. (Success was defined as a 5% increase in the number of A, B, or C grades compared to the previous cohort with the same instructor.) Quantitative analyses revealed statistically significant associations between student success and instructional (rather than motivational) feedback. The type of summative and formative feedback students received was also found to be more important than the frequency. Successful cases tended to provide explicit rather than implicit feedback, compared students to others in the class in summative feedback messages (rather than comparing students to standards) and were succinct and focused on outcomes (rather than existing performance) in formative feedback messages. The study did not consider some feedback elements, such as message personalization.

van Barneveld, A., Arnold, K. E. & Campbell, J. P. (2012). *Analytics in Higher Education: Establishing a Common Language* (ELI Paper 1: January 2012). Boulder, CO: EDUCAUSE Learning Initiative. Retrieved from http://net.educause.edu/ir/library/pdf/ELI3026.pdf

Aware of discontinuities in the terminology being adopted to describe concepts and processes associated with analytics in higher education, van Barneveld, et al. conducted a preliminary review of the academic and practitioner literature and found that similar vocabularies were being used in disparate conceptual and functional capacities. Likewise, different terms were defined in much the same way. Upon presenting the array of discrepant terms discussed in the literature as well as the varied and overlapping definitions applied to them, the authors propose a conceptual framework and a lexicon that depict, delineate, define and relate the various types and levels of analytics used in higher education. They do acknowledge, however, that while conceptually distinct, the different analytics are, from a functional perspective, "intended to work as a cohesive whole that serves the needs of the academy at a variety of levels" (i.e., at the levels of the (a) institution, (b) department, (c) instructor, and (d) learner) (p. 5).

In addition to clarifying the relationships between the different kinds of analytics, van Barneveld, et al. also situate analytics higher education in relation to business analytics and to the scholarships of teaching and learning (SoTL) (See Appendix A). In their proposed framework, the SoTL encompasses the institutional, departmental, and learner levels. The authors regard this research domain as "the key transformative piece" (p. 6), being "at the heart of academic analytics" (p. 6) and having, "at [its] very core…a symbiotic relationship" with learning analytics (p. 8). Each field has the opportunity to inform the other. van Barneveld, et al. argue that, as a relatively new field, analytics in higher education must confront challenges of (a) credibility, (b) transformation, (c) open and accessible scholarship, and (d) scale. They explain that these issues are in fact the very same ones that the SoTL had faced when it was still emerging as a field

(Hutchings & Shulman, 1999, as cited in van Barneveld, et al., 2012). The authors believe that establishing a common language and a framework constitute a major step forward for higher education practitioners of analytics, helping to ease the difficulty of institutional collaboration and setting an agenda for the larger teaching and learning community.

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