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Best Practices of Learning Analytics Implementations in Higher Education

CAPSTONE REPORT

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Abstract

As the use of learning analytics garners significant interest from higher education institutions, complex challenges have surfaced in the implementation of this tool. A successful implementation requires strategic and thoughtful planning and execution. This study examines the challenges and best practices for a successful learning analytics implementation. Institutions that are interested in initiating a learning analytics project and are in the process of implementation will benefit from the findings of this study.

Keywords: learning analytics, analytics, higher education, best practices, implementation

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Introduction to the Annotated Bibliography

Problem

With political pressure to increase educational attainment among the population, educational institutions are increasingly expected to measure, demonstrate and improve performance (Ferguson, 2012). Clow (2013) notes that in higher education “there is a pressure towards performance management, metrics and quantification” (p. 685). One challenge has been the sheer amount of data that is generated in a higher education institution (Ferguson, 2012). Every learning activity such as page visits and clicks are being stored as data as more learning takes place online (Clow, 2013).

Higher education institutions have joined other organizations in generating *big data*, defined as “data sets whose size is beyond the ability of typical database software tools to capture, store, manage, and analyze” (Norris & Baer, 2012, p. 10). One cause of big data in higher education is the widespread use of learning management systems (LMSs), which has generated increasingly large datasets (Ferguson, 2012). Because online courses require the use of a learning management system, the widespread adoption of online learning has added to the proliferation of big data in higher education (Ferguson, 2012).

In addition to generating large datasets of student information, online learning courses have also posed learning challenges (Ferguson, 2012). Ferguson (2012) notes that students may feel isolated, become disoriented in the online environment, experience glitches with online technology, or simply lose their motivation. Postsecondary teachers who teach online courses may be overwhelmed with the amount of data the courses and LMSs generate and face challenges attempting to “interpret and evaluate the learning and quality of participation of individuals when this is buried within hundreds of student contributions to discussions that have lasted several weeks" (Ferguson, 2012, p. 306-307).

One area that holds promise for addressing the challenges posed by the generation of big data in higher education and the increasing use of online learning is analytics (Ferguson, 2012). EDUCAUSE, "a nonprofit association that helps higher education elevate the impact of IT" (EDUCAUSE, 2019, para. 1) defines *analytics* as "the use of data, statistical analysis, and explanatory and predictive models to gain insights and act on complex issues" (Bichsel, 2012, p. 6). The use of analytics holds promise in a number of areas in higher education (van Barneveld, Arnold, & Campbell, 2012). "Like business, higher education is adopting practices to ensure organizational success at all levels by addressing questions about retention, admissions, fund raising, and operational efficiency" (van Barneveld et al., 2012, p. 2). Analytics is seen as a possible catalyst tool "for college and university leaders to improve teaching, learning, organizational efficiency, and decision making and, as a consequence, serve as a foundation for systemic change" (Long & Siemens, 2011, p. 32). Clow (2013) notes that postsecondary institutions are now able to more effectively analyze the data across the institution: "statistical and computational tools to manage large data-sets and to facilitate interpretation have become available as a result of the Big Data activity" (p. 685).

As the field of analytics in higher education has evolved, focus areas in the application of analytics have emerged that address different sets of challenges (Ferguson, 2012). Analytics tools in education can be categorized into two broad applications: *academic analytics* and *learning analytics* (Long & Siemens, 2011). Long and Siemens (2011) note that academic analytics "is the application of business intelligence in education and emphasizes analytics at institutional, regional, and international levels" (Long & Siemens, 2011, p. 34) to improve operations and services (Arroway, Morgan, O'Keefe, & Yanosky, 2016), while learning analytics refers to analytics specifically designed to enhance student performance and success (Arroway et al., 2016). Learning analytics can provide insights into student learning and performance and inform data-driven decision making and feedback to improve student success (Lester, Klein, Rangwala, & Johri, 2017). The outcomes and benefits that can be generated by learning analytics are promising (Clow, 2013).

Long and Siemens (2011) assert that learning analytics can create value for institutions by identifying at-risk students and enabling timely interventions to assist them in achieving success, or by directly providing students with feedback and recommendations for improvement on their learning behaviors. The Course Signals tool at Purdue University is a prominent example of an application of learning analytics that uses predictive analytics to generate signals predicting students' chances of success in a course and provide interventions according to the signal levels (Clow, 2013). With the targeted interventions, Clow (2013) reports that "Overwhelmingly, students' signals tend to improve over a course, rather than worsen" (p. 687).

Norris and Baer (2013) noted that learning analytics can improve student success and eliminate retention impediments by "assessing and eliminating academic bottlenecks, enhancing gateway courses, focusing on the first-year experience, and undertaking other measures shown to improve students success for all students, but especially at-risk students" (p. 23). Learning analytics can also be applied to develop personalized learning that provides more effective and collaborative learning experiences and accelerated competence development among students at a lower delivery cost (Greller & Drachsler, 2012).

While the potential to enhance or transform student performance and success with learning analytics is great, the implementation at a university is complex and requires a significant investment (Arnold, Lonn, & Pistilli, 2014). The key constituents in learning analytics include senior leadership, information technology professionals, institutional research staff (Bichsel, 2012), as well as faculty, department heads, program directors, and learning support and student affairs staff (Elouazizi, 2014). Because learning analytics has implications for various areas of an institution, “numerous campus partners must collaborate to implement a successful learning analytics project” (Zilvinskis, Willis, & Borden, 2017). The need to gain concurrence from so many different stakeholders poses challenges because they may not share the same level of awareness, urgency or competency toward learning analytics (West, Heath, & Huijser, 2016).

Tsai and Gasevic (2017) identified six primary challenges to the successful implementation of learning analytics: (a) lack of strong leadership capabilities to ensure strategic planning and monitoring of the learning analytics implementation, (b) lack of adequate and equal engagement with different stakeholders at various levels, (c) inadequate pedagogy-based approaches to removing analysis-driven learning barriers, (d) insufficient training for end users, (e) limited number of empirical studies validating the analytics-driven intervention impacts, and (f) lack of policies that are specific to learning analytics to address issues of privacy, ethics, and identified challenges. Similarly, Bichsel (2012) summarized a number of concerns, barriers, and challenges in the successful implementation of learning analytics, including affordability concerns such as the high cost of analytics implementations; data concerns such as poor data quality, fragmented data ownership across an organization, limited data access, and a lack of data definition standardization across systems; culture challenges, including organizations that do not support or trust data or data-driven decision making and lack of analytics support from leadership; resource concerns such as insufficient resources for implementations and overall lack of analytics expertise and knowledge; and immature partnerships among key analytics stakeholders such as Information Technology and Institutional Research professionals.

While the potential benefits of learning analytics for higher education institutions are widespread (Clow, 2013; Greller & Drachsler, 2012; Lester, Klein, Rangwala, & Johri, 2017; Norris & Baer, 2013), universities have faced a variety of challenges in the implementation of learning analytics on their campuses (Tsai & Gasevic, 2017). These challenges may explain why adoption remains immature despite the high interest in learning analytics among institutions (Tsai & Gasevic, 2017).

Purpose

The purpose of this literature review is to present organizational best practices for a successful learning analytics implementation in a higher education setting. This annotated bibliography includes literature that provides background information on learning analytics, examples of successful analytics applications, and challenges that have emerged in learning analytics adoption.

While the use of learning analytics emerged in the past decade, several definitions have been adopted in the literature (Ferguson, 2012). For the purpose of this study, the definition provided by the Society for Learning Analytics Research, which is widely accepted in the field of learning analytics and considered comprehensive, has been adopted: *"*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 & Gasevic, 2012, p. 1)

The study will introduce the field of learning analytics and provide insights to practitioners and institutional leaders who are considering or are about to embark on a learning analytics project in a higher education setting.

Research Questions

Main question. What are best practices for a higher education institution to ensure a successful implementation of a learning analytics initiative?

Sub-questions.

- What is learning analytics?
- What are the challenges institutions face when implementing learning analytics?

Audience

This study provides insights into the best practices required for successful implementation of an institution-wide learning analytics project. This type of large-scale data initiative will require strong sponsorship from university senior administrators (Tsai & Gasevic, 2017). These senior administrators include the Provost, Chief Information Officer (CIO), University Registrar, and Director of Institutional Research, who are decision makers and sponsors of institutional data policies and initiatives.

Information technology (IT) professionals and student support professionals are key beneficiaries of this study, as they partake in the implementation and utilization of any tools developed to intervene with and provide support to students. Understanding the optimal environment that effectively incorporates a learning analytics application is critical for these stakeholders. The institutions that are considering implementing learning analytics or that have initiated a learning analytics project will benefit from this study to identify the best practices for successful implementation and adoption.

Search Report

Search strategy. I started my search by looking at overall trends and topics on *learning analytics in higher education* as well as *learning analytics best practices*. I also limited my searches to literature that provided access to full-text articles through open source websites or the University of Oregon Libraries' databases.

Through the initial search, I was able to find strong resources on learning analytics implementation practices. In reviewing the abstracts, I narrowed the sources down to the articles that provided a comprehensive view of the field of learning analytics and implementation of learning analytics in higher education and eliminated sources with a narrow focus, such as data mining and modeling, data governance, and non-higher education environment such as K-12. As I discovered pertinent reference sources, my strategy was to review the references included in these articles and identify additional resources and keywords.

Search engines and databases. In my search, I extensively used Google Scholar, ERIC, and Academic Search Premier, as these databases included sources in the field of higher education. The comprehensive list of databases and websites I used in my search is provided below:

- Academic Search Premier,
- JSTOR,
- ERIC,
- Google Scholar, and
- EDUCAUSE.

Additionally, I used the Ulrichsweb to verify the authority and scholarship of the articles I identified in the process.

Keywords. In my search, I used one or a combination of the following keywords:

- predictive analytics,
- learning analytics,
- data mining,
- early alert,
- higher education,
- university,
- college,
- student success,
- students,
- retention
- persistence,
- implementation, and
- best practices.

Documentation method. I saved all resources in Zotero, which automatically saved the meta-data of each resource including the title, authors, abstract, journal details, and doi information when available. It also saved the keywords tagged in the article. I used the Notes feature in Zotero to record the database and keywords I used to locate each source and attached a copy of the full-text article to each entry. I also summarized and saved the relevant points from each article in the Notes section with an assigned reference category that I developed for the annotated bibliography. I added sub-categories such as *background, definitions, challenges, benefits, examples,* and *best practices* to highlight the main points of each source.

Reference evaluation criteria. I examined potential literature against the following criteria recommended by the Center for Public Issues Education (n.d.) for evaluating information sources:

Authority: I evaluated each article based on the authors' credentials, associated organizations, and publisher. I selected literature that was published in peer-reviewed journals or by a nonprofit or governmental organization with missions and goals that reflect a lack of bias.

Timeliness: While the literature on learning analytics spans the past twenty years, I focused on sources published in the past decade to inform the most recent environment of learning analytics in higher education. I also supplemented the findings with sources from pre-2010 to understand the historical contexts and development of the field of analytics in higher education.

Quality: I reviewed each potential source for proper grammar, clarity, and structure to verify the quality of each article. I also noted and considered extensive use of proper references and the authority of cited sources as part of my evaluation.

Relevancy: After evaluating a potential source for its authority, timeliness, and quality, I evaluated each source for its relevancy. I screened the articles to identify those that provided background on learning analytics in higher education, the use of learning analytics and best practices in its implementation.

Bias: I vetted potential sources to identify any bias concerns by reviewing the authors' positioning based on their organizational relations, their assertions and evidence of other perspectives, and whether their arguments and conclusions were supported by unbiased sources.

Annotated Bibliography

The following annotated bibliography presents the articles that examine the factors of best practices for implementing learning analytics. Institutions have faced an array of challenges in the implementation of learning analytics (Tsai & Gasevic, 2017). References provide background on the emergence of learning analytics and the challenges surfaced in the implementation to study the elements required for a successful learning analytics implementation.

The bibliography is organized into three sections: an overview of learning analytics, learning analytics applications in higher education, and best practices in implementing learning analytics in higher education. Each of the annotations includes a full reference citation, a full or abbreviated abstract published by the authors, and a summary of the literature. The ideas represented in the summaries are those of the authors and not my own.

Overview of Learning Analytics

Ferguson, R. (2012). Learning analytics: Drivers, developments and challenges. *International Journal of Technology Enhanced Learning, 4*(5/6) p. 304–317. http://dx.doi.org/doi:10.1504/IJTEL.2012.051816

Abstract. Learning analytics is a significant area of technology-enhanced learning that has emerged during the last decade. This review of the field begins with an examination of the technological, educational and political factors that have driven the development of analytics in educational settings. It goes on to chart the emergence of learning analytics, including their origins in the 20th century, the development of data-driven analytics, the rise of learning-focused perspectives and the influence of national economic concerns. It next focuses on the relationships between learning analytics, educational data mining and

academic analytics. Finally, it examines developing areas of learning analytics research, and identifies a series of future challenges.

Summary. The author examines the emergence of learning analytics through a literature review conducted from literature in education, technology, and social sciences. The author asserts that the development of learning analytics was driven by the big data revolution, online learning growth, and political pressures for institutions to measure and improve performance.

Higher education has long been engaging in institutional research and evaluation prior to the introduction of online learning or big data. Tinto's 1997 study on student persistence was conducted using a series of studies over 20 years. The introduction of the second-generation web and virtual learning environment produced and enabled the collection of a large set of data, which led to the emergence of the field of educational data mining (EDM). EDM analyzes educational data to improve students' learning and their learning environments while employing machine learning techniques to enhance learning and teaching. Since 2003, social and pedagogical approaches such as the Social Network Analysis (SNA), an analysis of networks and the relationship between them, became a popular addition to analytics. By 2007, the literature started to address educational and technological challenges in learning analytics. A paper published by EDUCAUSE stated academic analytics as a new tool to potentially address educational challenges in the United States such as college graduates lacking basic competencies. As analytics in education matured as a field, three focuses emerged; EDM focused on the technical challenges of analytics; academic analytics focused on the political or economic challenges; and learning analytics focused on the educational challenges.

The future challenges the author discusses in this paper are important to my study because it informs the elements of the best practices for learning analytic adoption as well as the areas for future study. The author discusses four challenges:

(a) *build strong connections with the learning sciences*. The research focused on cognition, metacognition, and pedagogy is not well represented in the field of learning analytics. Maximizing and improving learning through learning analytics will require an in-depth understanding of the learning process, learning support, and various factors that affect learning experiences.

(b) *develop methods of working with a wide range of datasets in order to optimize learning environments*. As learning occurs in various environments, the challenges become capturing and combining various datasets for the use of analytics. Researchers also need to understand successful learning experiences from students' perspectives.

(c) *focus on the perspectives of learners*. Shifting the focus from the needs of the institution to the perspectives of students will be critical in the successful development of learning analytics that meets learners' needs.

(d) *develop and apply a clear set of ethical guidelines*. There are no clear guidelines regarding the ownership and stewardship of data established in the field of learning analytics. The field needs to develop a detailed framework outlining the rights of learners, their responsibilities, and researchers' process for obtaining data in order to effectively address the identified challenges.

Siemens, G. (2013). Learning analytics: The emergence of a discipline. *American Behavioral Scientist, 57*(10), 1380-1400. https://doi.org/10.1177/0002764213498851

Abstract. Recently, learning analytics (LA) has drawn the attention of academics, researchers, and administrators. This interest is motivated by the need to better understand teaching, learning, "intelligent content," and personalization and adaptation. While still in the early stages of research and implementation, several organizations (Society for Learning Analytics Research and the International Educational Data Mining Society) have formed to foster a research community around the role of data analytics in education. This article considers the research fields that have contributed technologies and methodologies to the development of learning analytics, analytics models, the importance of increasing analytics capabilities in organizations, and models for deploying analytics in educational settings. The challenges facing LA as a field are also reviewed, particularly regarding the need to increase the scope of data capture so that the complexity of the learning process can be more accurately reflected in analysis. Privacy and data ownership will become increasingly important for all participants in analytics projects. The current legal system is immature in relation to privacy and ethics concerns in analytics. The article concludes by arguing that LA has sufficiently developed, through conferences, journals, summer institutes, and research labs, to be considered an emerging research field.

Summary. The author provides an overview of the development of learning analytics with tools and techniques utilized in the field and challenges in the field of learning analytics. The development of learning analytics stem from multiple disciplinary and research areas including citation analysis, social network analysis, user modeling, education/cognitive modeling, intelligent tutors, knowledge discovery in databases, adaptive hypermedia, and e-learning.

Learning analytics practitioners benefited from the tools and techniques developed in other fields. Commercial analytics tools developed by companies like SAS and IBM are well-developed and have been modified to meet the needs in education. Educational system vendors also started to include analytics in their offerings, adding values to the platforms that are widely adopted at an institutional level. The development of software such as Tableaus eases the complexity of typical analytics processes and is a reflection that analytics is being adopted by a range of users with varying levels of programming or visualization skills. In addition to the tools, the author notes that techniques and applications are equally important in advancing the field of learning analytics.

Advancing analytics also requires quality data sets that represent the complexity of learning. Institutional student information systems and learning management systems, which are the main data sources for the current learning analytics, offer limited data. In order to improve the depth and accuracy of the analysis, it is important to seek data beyond these two systems and ensure the reflection of the holistic and creative process of learning.

The author asserts that, in addition to expanding the range of data that goes into learning analytics, building organizational capacity for analytics is a vital step. Analytics requires a wide variety of skill sets including programming skills, statistical knowledge, understanding of data and its domain represented in the data. Institutional support is required for successful implementation because identifying appropriate support for learners requires cross-departmental collaboration. An effective learning analytics operation influences an institutional change that addresses not only the technical challenges but also the social challenges by developing a shared organizational culture.

Data privacy and ethics is another major challenge. Personal data generated online are improving learning, teaching, and student retention. The data is creating economic values while the data ownership has not been culturally or legally decided. While the legal system is lagging behind to address privacy issues in the digital age, considerations for data ownership and learner control must be reflected in analytics initiatives.

This study is significant because it provides context to the maturing field of learning analytics and the challenges surfaced in the implementation of learning analytics.

van Barneveld, A., Arnold, K. E., & Campbell, J. P. (2012). Analytics in higher education: Establishing a common language. *EDUCAUSE learning initiative*, *1*(1), l-ll. https://www.researchgate.net/profile/Angela_Van_Barneveld/publication/265582972_Analytics_in_Higher_Education_Establishing_a_Common_Language/links/575f12e108ae9a9c955fade7/Analytics-in-Higher-Education-Establishing-a-Common-Language.pdf

Abstract. The use of analytics in higher education is a relatively new area of practice and research. As with any new area of practice, a variety of terms are adopted to describe concepts and processes. Each of these terms is being integrated into the literature, but a preliminary review of the analytics in education and practitioner literature revealed similar terms with different conceptual or functional definitions, as well as different terms with similar conceptual or functional definitions. The intent of this paper is to present the different descriptions of the various types of analytics being discussed in the academic and practitioner literature. Second, we propose a conceptual framework that depicts the types of analytics and their relationship to each other. Finally, we propose a synthesized set of definitions for analytics-related terms commonly found in academia.

Summary. The authors examine the various terms used to describe analytics in education. The literature review revealed that the term *analytics* may describe the topics of interest such as health analytics, the intent of the activity such as descriptive analytics, or the object of analysis such as Twitter analytics. In education, the term *analytics* is being used inconsistently, in some cases, implying conceptual definitions, while other times implying functional definitions. The authors detailed various types of analytics definitions found in literature; there are 27 different definitions between seven types of analytics categories. The authors asserted that no uniformity exists over the family of analytics terms and their definitions.

The authors placed all types of analytics compiled from the literature in a framework, asserting that all analytics in education work as a cohesive and integrated system and serve the needs of an institution at all levels. The framework represents the variety and complexity of analytics developed in the educational setting. In addition, the authors presented another framework, illustrated in Figure 1, that integrated the Scholarship of Teaching and Learning (SoTL), a research area focusing on the enhancement of student learning.

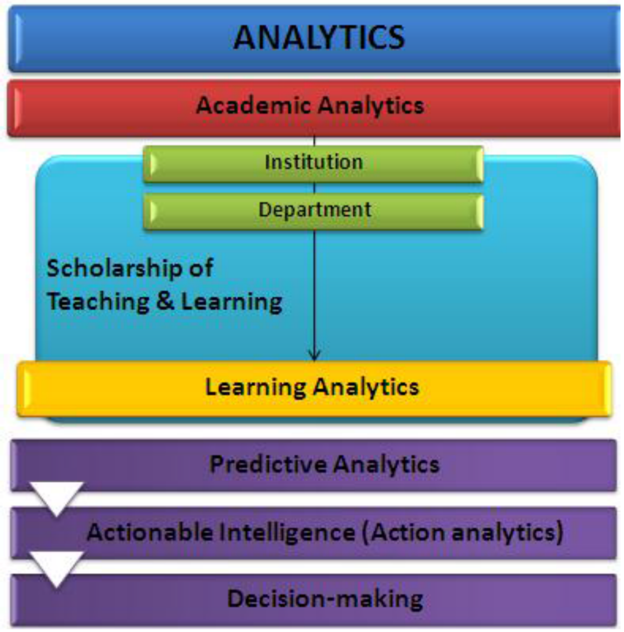

Figure 1. The Scholarship of Teaching and Learning. This figure represents the integration of teaching and learning in analytics in education.

The authors argue that SoTL and academic analytics are interdependent because learning analytics helps us understand teaching and learning while SoTL informs us about the areas on which to focus. This paper is significant to my study because it provides context to the developing field of learning analytics and confirms the lack of a unified definition found in the literature.

Learning Analytics Applications in Higher Education

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). Vancouver, British Columbia: Association for Computing Machinery. https://doi.org/10.1145/2330601.2330666

Abstract. In this paper, an early intervention solution for collegiate faculty called Course Signals is discussed. Course Signals was developed to allow instructors the opportunity to employ the power of learner analytics to provide real-time feedback to a student. Course Signals relies not only on grades to predict students' performance, but also demographic characteristics, past academic history, and students' effort as measured by interaction with Blackboard Vista, Purdue's learning management system. The outcome is delivered to the students via a personalized email from the faculty member to each student, as well as a specific color on a stoplight -- traffic signal -- to indicate how each student is doing. The system itself is explained in detail, along with retention and performance outcomes realized since its implementation. In addition, faculty and student perceptions will be shared.

Summary. This paper presents the Course Signals project executed at Purdue University. Piloted in 2007, the tool was utilized in over 100 courses with over 140 faculty, impacting more than 23,000 students. Course Signals aims to create actionable intelligence using learning analytics and to aid student persistence by facilitating their academic engagement. The tool identifies at-risk students and enables faculty to send students personalized communications about their current class performance encouraging them to seek academic support resources. The tool also integrates learning analytics that uses real-time data to predict student likelihood of success. The research revealed that the numbers of satisfactory grades increased while the numbers of unsatisfactory grades or course withdrawals decreased in the courses that incorporated Course Signals. Similarly, students who took at least one course that implemented Course Signals were retained at a significantly higher rate than those who did not enroll in any Course Signals courses. The analysis also revealed that students were retained at a higher rate if they were exposed to Course Signals earlier in their academic careers.

Students’ feedback collected through anonymous surveys and focus groups showed that an overwhelming number of students had positive experience and found the tool to be helpful and motivating. While faculty generally reported positive experiences with Course Signals, some faculty expressed concerns about a possible increase in students seeking help, more students emailing with concerns, and students developing dependencies rather than encouraging independent learning. The authors assert that increased help-seeking is one of the desired results, as Course Signals is intended for students to actively engage in a course and improve their performances.

Lastly, faculty and students both reported that best practices on how to use Course Signals were lacking. Addressing this last concern, the authors developed and made the best practices available on the Purdue website. With the strong evidence of success, the tool is supported by the senior administration in the institution; at the time of publication, Purdue planned to expand the reach of the tool to 20,000 students a semester. This paper is significant to this research because it is one of the few studies that document the significant impact of predictive analytics on a sizable population.

Clow, D. (2013). An overview of learning analytics. *Teaching in Higher Education, 18*(6), 683-695. https://doi.org/10.1080/13562517.2013.827653

Abstract: Learning analytics, the analysis and representation of data about learners in order to improve learning, is a new lens through which teachers can understand education. It is rooted in the dramatic increase in the quantity of data about learners and linked to management approaches that focus on quantitative metrics, which are sometimes antithetical to an educational sense of teaching. However, learning analytics offers new routes for teachers to understand their students and, hence, to make effective use of their limited resources. This paper explores these issues and describes a series of examples of learning analytics to illustrate the potential. It argues that teachers can and should engage with learning analytics as a way of influencing the metrics agenda towards richer conceptions of learning and to improve their teaching.

Summary: This paper provides context to the emergence of learning analytics and attributes the phenomenon to the political pressure by the federal government for institutions to improve performance management, measurements, and quantification; an increasing amount of data becoming available on learning; and the arrival of technology that can process big data. The author demonstrates the potential benefits of learning analytics by detailing examples of learning analytics applications, such as predictive modeling, social network analysis, usage tracking techniques, content and semantic analysis, and recommendation engines.

Predictive analytics is mathematical modeling that predicts the probability of likely outcomes and can be applied to improve student outcomes. The author cites that one of the most prominent examples of predictive modeling is the Course Signals project at Purdue University, which generated colored signals from the models for teachers to trigger appropriate interventions based on the signals.

Social network analysis tracks and examines the connections between people in the digital realm. This tool could help teachers identify patterns in students' interactions and find students who are isolated. While the author calls for additional research in its application, the author defines usage tracking as another type of learning analytics. For instance, students' online activities in a course or assignment are tracked and displayed to students to encourage increased activities.

A promising example in the area of content and semantic analysis includes a tool that tracks student development of their use of concepts through the assignments in a writing course. The author argues that an automated assessment, such as providing students feedback about their online writing skills, can also be considered learning analytics. The author describes the application of recommendation engines, seen in Amazon's customized recommendations, in education; for example, to recommend study resources to a student based on students' historical behaviors and activities. While these examples demonstrate the potential benefits of learning analytics, the author also notes areas of concern, such as the ethics of personal data. With access to various personal data, institutions could quickly start surveilling students and violating personal privacy. Lack of data protection regislation and institutional data standards create implications for the ethical application of data analytics.

This resource is useful to my study because it provides a background to the development of the field of learning analytics and context to the complicated field of analytics.

Jayaprakash, S. M., Moody, E. W., Lauría, E. J., 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. https://doi.org/10.18608/jla.2014.11.3

Abstract. The Open Academic Analytics Initiative (OAAI) is a collaborative, multi-year grant program aimed at researching issues related to the scaling up of learning analytics technologies and solutions across all of higher education. The paper describes the goals and objectives of the OAAI, depicts the process and challenges of collecting, organizing and mining student data to predict academic risk, and report results on the predictive performance of those models, their portability across pilot programs at partner institutions, and the results of interventions on at-risk students.

Summary. The authors detailed the Open Academic Analytics Initiative (OAAI), a project aimed at advancing the use of learning analytics and examined the issues preventing the technology to scale to all institutions. The intended project outcomes were to: (a) develop an open-source early alert system after examining potential challenges, solutions, and benefits of the system, (b) examine portability of predictive models from one academic context to another, and (c) study effective intervention strategies to help at-risk students. Along with the open-source predictive analytics model, OAAI provided intervention strategies and an Online Academic Support Environment (OASE) that provides an online academic support community and resources to students.

The authors state that the research findings contribute to understanding the challenges in scaling learning analytics in higher education. Some of the challenges include variability in assessment and class activity across courses or institutions, the variability of learning management system usage, and variability in the proportion of at-risk students across institutions. Findings from the research include: (a) predictive models can help faculty identify at-risk students earlier in a course, (b) initial indications that portability of predictive models from one academic context to another is possible while preserving the predictive power, and (c) alerting students that they may be academically at risk in the course can positively improve students' learning and course outcomes.

This study is relevant to my research because it demonstrates the promising benefits of predictive analytics through an open-source project and examines the issue of learning analytics scalability, which is one of the identified challenges in learning analytics.

Best Practices in Implementing Learning Analytics in Higher Education

Arnold, K. E., Lonn, S., & Pistilli, M. D. (2014). An exercise in institutional reflection: The learning analytics readiness instrument (LARI). *Proceedings of the Fourth International Conference on Learning Analytics and Knowledge* (pp. 163-167). New York, NY: Association of Computing Machinery. https://doi.org/10.1145/2567574.2567621

Abstract. While the landscape of learning analytics is relatively well defined, the extent to which institutions are ready to embark on an analytics implementation is less known. Further, while work has been done on measuring the maturity of an institution's implementation, this work fails to investigate how an institution that has not implemented analytics to date might become mature over time. To that end, the authors developed and piloted a survey, the Learning Analytics Readiness Instrument (LARI), in an attempt to help institutions successfully prepare themselves for a successful analytics implementation. The LARI is comprised of 90 items encompassing five factors related to a learning analytics implementation: (1) Ability, (2) Data, (3) Culture and Process, (4) Governance and Infrastructure, and, (5) Overall Readiness Perception. Each of the five factors has a high internal consistency, as does the overall tool. This paper discusses the need for a survey such as the LARI, the tool's psychometric properties, the authors' broad interpretations of the findings, and next steps for the LARI and the research in this field.

Summary. This article introduces the concept of institutional readiness for the implementation of learning analytics and the Learning Analytics Readiness Instrument (LARI) as a readiness assessment tool. The authors assert that the success of learning analytics initiatives is dependent on a thorough institutional review of organizational readiness and careful planning and execution. The authors note that the following LARI factors are important for a successful learning analytics implementation:

(a) Ability: the expertise and skills required for the implementation are diverse and include technical skills, analytics expertise, strategic leadership, and student support skills. Adequate and appropriate resources must be available and accessible during the implementation.

(b) Data: it is critical to understand the types of data collected at the institution, how valid and dependable the data is, where the data is stored, how it is accessed, and who owns the data.

(c) Culture and process: the introduction of learning analytics triggers institutional change, which requires cultural acceptance to be successful. The desired cultural components include awareness and acceptance of data-driven decision making, adequate stakeholder support, and a shared vision. The processes should address stakeholders' involvement, sustainability and project management, and rules, policies and practices for data use.

(d) Governance and infrastructure: sufficient readiness for the technical infrastructure, institutional governance, policies, and oversight are key for a successful implementation.

(e) Overall readiness perceptions: institutional perceptions in various areas such as adequacy of resources, support of the institutional review board (IRB), the faculty's learning analytics acceptance, and professional knowledge in the field of learning analytics must be assessed to understand the institutional positioning.

This article is relevant to the study because it provides specific factors that are required for a successful implementation of learning analytics at a higher education institution.

Arroway, P., Morgan, G., O'Keefe, M., & Yanosky, R. (2016). *Learning analytics in higher education.* Research report. Louisville, CO: EDUCAUSE Center for Analysis and Research. https://library.educause.edu/~/media/files/library/2016/2/ers1504la

Abstract. This report will explore the current state of learning analytics in higher education and identify the foundational elements of effective, efficient, and adaptable learning analytics tools. It will also identify the types of problems institutions are trying to solve with learning analytics, assess readiness to make decisions with analytics, explore the impact of learning analytics on student retention and success, and look toward the future of learning analytics in higher education.

Summary: This article discusses the important elements of a learning analytics strategy to guide the successful implementation of learning analytics. The authors used surveys, focus groups, and discussions with subject-matter experts and key analytics stakeholders including professionals and leaders in Information Technology, Institutional Research, business, and finance units. Based on their study, the authors state that a high-level learning analytics strategy that covers both academic and technical aspects is essential and should incorporate the following steps: (a) identify academic or business challenges in the institution that can be addressed by learning analytics, (b) include representatives from all stakeholder groups to develop a strategic plan and governance and lead action, (c) understand the data that is available on campus and its ownership, and ensure data cleanliness and common data definitions, (d) recognize the inhibitors to learning analytics implementation that exist in the organization and highlight the challenges in the strategic plan in order to address them, (e) recognize that a full-scale analytics implementation is likely to incorporate a suite of tools rather than a single software application, (f) work through a series of approaches that start with descriptive, diagnostics analytics and continue to predictive and prescriptive analytics, (g) examine the field of learning analytics to understand practices executed by other institutions and analytics technologies available on the market, and (h) start small before expanding the efforts in order to inform the functionality necessary for a learning analytics system. The authors recommend that the strategic plan should also cover a business case for learning analytics adaption in order to secure funding and executive support. The authors also assert that it is critical to share the strategic plan with stakeholders prior to implementation and provide continuous communication throughout the implementation process.

This source is useful for this research study because it provides the steps and guidance required for the development of a strategic plan for a learning analytics implementation.

Bichsel, J. (2012). *Analytics in higher education: Benefits, barriers, progress, and recommendations.* Research report. Louisville, CO: EDUCAUSE Center for Applied Research. https://doi.org/10.13140/RG.2.1.1064.6244

Abstract. Many colleges and universities have demonstrated that analytics can help significantly advance an institution in such strategic areas as resource allocation, student success and finance. Higher education leaders hear about these transformation occurring at other institutions and wonder how their institutions can initiate or build upon their own analytics programs. Some question whether they have the resource, infrastructure, processes, or data for analytics. Some wonder whether their institutions are on par with others in their analytics endeavors. It is within that context that this study set out to access the current state of analytics in higher education, outline the challenges and barriers to analytics and provide a basis for benchmarking progress in analytics.

Summary. This article presents the results of the EDUCAUSE Center for Applied Research (ECAR) 2012 study on analytics, which was developed to measure the state of analytics adoption maturity in higher education and to understand the barriers and challenges institutions face in implementing analytics. The study used surveys and focus groups to garner information from Information Technology and Institutional Research professionals. Because analytics can be applied to various areas of higher education, the author notes that identifying strategic questions that can be addressed with the existing data is critical for analytics implementation. The challenges in analytic adoption identified in this study are: (a) a high perceived cost of analytics, (b) concerns for data quality, silo-ed data ownership and access, and lack of data definition standardization, (c) lack of leadership that supports data-driven decision making and cultural change, (d) securing adequate staff who are experienced and knowledgeable, and (e) lack of communication and collaboration between IT, IR offices, and the key stakeholders in an analytics project.

By analyzing the data compiled from the survey and focus groups, EDUCAUSE developed a maturity index for higher education institutions to monitor progress in analytics administration. The index covers five factors: (a) culture/process, (b) data/reporting/tools, (c) investments, (d) expertise, and (f) governance/infrastructure. In the culture/process domain, an organization is more mature if the organizational culture accepts analytics and data-driven decision making. The data/reporting/tools domain looks at organizational data quality, whether appropriate types of data are being gathered for analytics and the standardization of the data. The investment factor evaluates the funding for analytics and the resources available, including technology and human resources. The last domain, *expertise,* examines the organization's analytics expertise in IT staff and end users, and available training to build staff knowledge. The author attributed the limited use of analytics in certain areas of higher education to these identified challenges. In closing, the paper presented a list of recommendations to overcome the challenges with appropriate resources, culture, and leadership; these recommendations include: (a) identify the strategic questions for the institution and build analytics capacities around those questions, (b) plan small wins to show the enhanced value brought by data-based decisions and changes instituted by the analytics, and (c) invest in people over tools as analytics is as much about people skills as it is about data and tools.

This source is useful for this study because the maturity survey discusses the key elements required for learning analytic development. The recommendations included in the paper directly translate to the best practices for a successful implementation.

Greller, W., & Drachsler, H. (2012). Translating learning into numbers: A generic framework for learning analytics. *Journal of Educational Technology & Society, 15*(3), 42-57.

Retrieved from https://www.jstor.org/stable/jeductechsoci.15.3.42?seq=1&cid=pdfreference#references_tab_contents

Abstract. With the increase in available educational data, it is expected that Learning Analytics will become a powerful means to inform and support learners, teachers and their institutions in better understanding and predicting personal learning needs and performance. However, the processes and requirements behind the beneficial application of Learning and Knowledge Analytics as well as the consequences for learning and teaching are still far from being understood. In this paper, we explore the key dimensions of Learning Analytics (LA), the critical problem zones, and some potential dangers to the beneficial exploitation of educational data. We propose and discuss a generic design framework that can act as a useful guide for setting up Learning Analytics services in support of educational practice and learner guidance, in quality assurance, curriculum development, and in improving teacher effectiveness and efficiency. Furthermore, the presented article intends to inform about soft barriers and limitations of Learning Analytics. We identify the required skills and competences that make meaningful use of Learning Analytics data possible to overcome gaps in interpretation literacy among educational stakeholders. We also discuss privacy and ethical issues and suggest ways in which these issues can be addressed through policy guidelines and best practice examples.

Summary. The authors propose a framework for a learning analytics implementation by exploring the key elements of learning analytics and critical issues in implementation. The authors state that in addition to technical issues such as data compatibility and accuracy of algorithms, the challenges that surround human or social elements such as data ownership, data access, and the ethical use of the data have a significant impact on the acceptance of learning analytics. To achieve a successful implementation of learning analytics, the authors identify a learning analytics design from discussions in the emerging learning analytics research community using a general morphological analysis. The goal of the study was to enable learning analytics designers to implement technologically and legally sound processes using the framework while considering desirable outcomes for the stakeholders and consequences for the data suppliers.

The proposed framework includes six dimensions: (a) stakeholders, (b) objectives, (c) data, (d) instruments, (e) external constraints, and (f) internal limitations. The stakeholder dimension covers data clients who are meant to be the users of the learning analytics outcomes and data subjects who are suppliers of data; this dimension is intended for learning analytics implementers to consider the impacts of the analytics processes on these stakeholders. The *objectives* dimension is divided into reflection and prediction. Reflection is meant to promote self-evaluation throughout the implementation at all levels, while prediction references both potential benefits of predictive analytics and possible ethical problems. The authors acknowledge the limitations of learning analytics data that meant to recreate an entire learning process.

The data dimension includes the availability and accessibility of data. Connecting datasets across systems would facilitate the creation of more learner-oriented services; however, because data in education is typically protected, researchers in the field have also faced challenges in effectively validating their learning analytics designs. The instruments dimension provides considerations of the technologies in the learning analytics design.

The authors identify external constraints, described as conventions and norms, as a critical factor in the learning analytics design. The constraints may limit the potential of learning analytics. *Norms* are restrictions by laws, policies, and standards that must be followed; *conventions,* such as personal ethics and privacy, require sensible and responsible judgments, while legal clarities are much needed. Lastly, internal limitations consider staff competencies and acceptance.

The authors note that the implementation of learning analytics requires a variety of skills. In addition to the technical skills to develop sound analytics, the users of learning analytics are required to interpret data and make decisions to take action to improve learning. High-level skills such as interpretative and critical evaluation skills are required competencies for the design of learning analytics. Acceptance among stakeholders and users can also impact the successful learning analytics design.

This research is important to my study because the six dimensions of the learning analytics design inform the best practices for implementing learning analytics. The authors assert that addressing all six dimensions together is critical for an optimal learning analytics design.

Lester, J., Klein, C., Rangwala, H. & Johri, A. (2017). Learning analytics in higher education. *ASHE Higher Education Report, 43*(5), 1-145. https://doi.org/10.1002/aehe.20053

Abstract. The article discusses role and importance of learning analytics in education, amidst the explosion of the big data revolution as an educational data mining tool. Topics discussed includes use of learning analytics in higher education, organizational aspects of the learning analytics in higher education model, and ethics and privacy of learning and application of analytics.

Summary. The authors present an overview of learning analytics and educational technology tools available in higher education, an examination of organizational context for the tools, how capacity and technological alignment impact the adoption of learning analytics, use of learning analytics data and tools by user types, and ethical and privacy considerations.

This paper is relevant to my study because it examines theoretical frameworks and literature findings on organizational context and capacity that have implications to a learning analytics implementation. The higher education environment in which a learning analytics framework is implemented is complex, and the complexity must be understood for effective adoption. The authors argue that the frameworks based on organizational, technological and pedagogical theories related to technology in higher education can also be applied to learning analytics in higher education.

The authors state that the organizational factors that pose challenges to learning analytics implementation and adoption are bureaucratic organizational structures, commitment, resources, readiness, capacities and a lack of incentives and rewards. Successful implementation also requires consideration of technological factors, including provisioning of data, analytics expertise, cross-organization collaboration, leadership and attention to organizational climate. The decision by faculty or advisors to adopt learning analytics may depend on their awareness, interests, time, training, disciplinary exposure, and trust of the tool. Similarly, students may base their decisions to adopt analytics on agreement with and trust, understanding, and usefulness of the data.

The authors explain that individual decision making affects the overall implementation of learning analytics. The authors state that the following factors influence if and how faculty and advisors will adopt new behaviors and tools: (a) individual variables such as the values, backgrounds, abilities and aspirations of faculty and advisors, (b) the contexts and culture of their institution, and (c) triggers such as rewards and workload. Strategically, all levels of leadership should encourage, support and reward teaching innovations in order to engage faculty with new ways of teaching and integrating technology.

The authors also acknowledge the bureaucratic nature of higher education, with units and colleges operating in silos. To enact changes within an institution of higher education, collaboration and coordination across an organization that has different structures, policies, cultures, and social norms are critical. Traditional top-down approaches do not work in fragmented organizations like higher education institutions.

The authors assert that institutional logic is a key element in promoting organizational change. Institutional logic encompasses cultural values, assumptions, and beliefs, and consists of organizing principles within an organization. Institutional logic may arise when individuals are making a decision about accepting a change introduced through institutional demands. Individuals would assess how institutions articulate the driver of the change and influence against their institutional logic. Institutional logic aligned with institutional demands can be a force to enact changes. On the other hand, the authors found that the articulation of the institutional demands is often done by the senior leadership of institution without considerations of users, which causes misalignment with the users' institutional logic.

The authors also describe organizational capacity and readiness as another area that is key for a successful implementation of learning analytics. It is important for institutions to proactively understand the resources and support available to implement learning analytics tools. The authors assert the importance of inclusion and transparency to build trust in learning analytics. The authors state that users' needs, roles, and voices must be represented throughout the process of learning analytics development and implementation.

Norris, D. & Baer, L. (2013). *Building organizational capacity for analytics.* Research report. Louisville, CO: EDUCAUSE. Retrieved from https://library.educause.edu/-/media/files/library/2013/2/pub9012-pdf.pdf

Abstract. Optimizing student success is the "killer app" for analytics in higher education. Intelligent investments in optimizing student success garner wide support and have a strong, justifiable return on investment (ROI). Moreover, improving performance, productivity, and institutional effectiveness are the new gold standards for institutional leadership in the 21st century. Enhanced analytics is critical to both optimizing student success and achieving institutional effectiveness. This report provides information about how leading institutions in higher education and vendors are building capacity in analytics to improve student success.

Summary. The authors present a preliminary report of the findings from a survey of 40 higher education institutions and 20 technology vendors about analytics capacity building for student success. The survey provides an overview of the field and the current and potential future gaps in analytics in higher education.

The authors state that one of the strategies to advance student success and institutional effectiveness is to accelerate the development of organizational capacity for analytics. While technologies and tools are necessary parts of analytics, the success of analytics depends on the institution's ability to gain the organizational capacity needed for student success in the following five factors:

(a) Technology infrastructure, tools, and applications. The basic enterprise technology environment includes analytics tools, applications, services, and solutions. Users should be able to access data for their decision making.

(b) Policies, processes, and practices. This factor covers established processes and workflows that utilize the analytics, and interventions to support at-risk students. The processes must be incorporated into the institution at all levels and be utilized by all faculty and staff.

(c) Skills of faculty, staff, students, and other stakeholders. This factor covers not only the ability to use an automated student support system but also the willingness of stakeholders to incorporate these processes into their work.

(d) Culture and behaviors. This is a critical factor in order to maintain sustainable organizational change. Institutions must transition to a culture of performance where the actions of faculty and staff related to student success are organized and measured for continuous improvements.

(e) Leadership at the institutional level. The importance of analytics must be stressed by the leadership of an organization in order to optimize student success. A resource investment plan must outline strategies for launching, resourcing, scaling, and sustaining the effort.

The authors note that learning analytics implementation is a significant change management initiative.

Tsai, Y. S., & Gasevic, D. (2017, March). Learning analytics in higher education---Challenges and policies: A review of eight learning analytics policies. In *Proceedings of the Seventh International Learning Analytics & Knowledge Conference* (pp. 233-242). Association for Computing Machinery. https://doi.org/10.1145/3027385.3027400

Abstract. This paper presents the results of a review of eight policies for learning analytics of relevance for higher education, and discusses how these policies have tried to address prominent challenges in the adoption of learning analytics, as identified in the literature. The results show that more considerations need to be given to establishing communication channels among stakeholders and adopting pedagogy-based approaches to learning analytics. It also reveals the shortage of guidance for developing data literacy among end-users and evaluating the progress and impact of learning analytics. Moreover, the review highlights the need to establish formalized guidelines to monitor the soundness, effectiveness, and legitimacy of learning analytics. As interest in learning analytics among higher education institutions continues to grow, this review will provide insights into policy and strategic planning for the adoption of learning analytics.

Summary. The authors examine the challenges faced during a learning analytics implementation, policies in place for learning analytics, and how those policies have addressed the challenges. The authors analyzed 23 empirical studies on learning analytics to glean best practices for policy makers to guide effective learning analytics implementations.

The six primary challenges the authors surfaced in their literature review are: (a) lack of leadership capabilities to drive strategic planning and monitoring of learning analytics implementations, (b) scarce examples of institutions that equally engaged all levels of stakeholders during learning analytics implementations, (c) a shortage of interventions grounded by pedagogy to address learning hurdles identified by analytics, (d) a lack of adequate training made available to prepare users to utilize learning analytics, (e) a small number of research studies that confirm the positive impacts of analytics-driven interventions, and (f) a limited number of policies specifically designed for learning analytics administration that address privacy and ethics issues and the identified challenges specific to learning analytics implementations.

Eight of the learning analytics policies identified in the literature review covered the components of strategy, including: (a) goal setting, (b) how to handle data, (c) evaluation of impact, (d) assurance of validity, including data quality and analytics comprehensiveness, (e) communication and support for usage of learning analytics, and (f) user roles that define responsibilities and expectations. All of the policies followed national and international data protection policies; considerations for privacy concerns, data handling, and access to data were also considered in the policies.

While they recognize that the findings in this paper are not comprehensive and there could be gaps between policy and practice, the authors report that the eight policies failed to effectively address the identified challenges during the implementation. The authors highlight the importance of developing policies that monitor sound and legitimate leaning analytics practices.

Tsai, Y. S., Moreno-Marcos, P. M., Tammets, K., Kollom, K., & Gašević, D. (2018). SHEILA policy framework: Informing institutional strategies and policy processes of learning analytics. In *Proceedings of the 8th International Conference on Learning Analytics and Knowledge* (pp. 320-329). Association for Computing Machinery. http://dx.doi.org/10.18608/jla.2018.53.2

Abstract. This paper introduces a learning analytics policy and strategy framework developed by a cross-European research project team -- SHEILA (Supporting Higher Education to Integrate Learning Analytics), based on interviews with 78 senior managers from 51 European higher education institutions across 16 countries. The framework was developed adapting the RAPID Outcome Mapping Approach (ROMA), which is designed to develop effective strategies and evidence-based policy in complex environments. This paper presents four case studies to illustrate the development process of the SHEILA framework and how it can be used iteratively to inform strategic planning and policy processes in real world environments, particularly for large-scale implementation in higher education contexts. To this end, the selected cases were analyzed at two stages, each a year apart, to investigate the progression of adoption approaches that were followed to solve existing challenges, and identify new challenges that could be addressed by following the SHEILA framework.

Summary. The authors present the Supporting Higher Education to Integrate Learning Analytics (SHEILA) framework that can be used in the strategic planning and systematic adoption of learning analytics. While interest in learning analytics has increased, there are often challenges to systematic and effective adoption of learning analytics. The authors state that institutions must align learning analytics under their strategic visions and goals in order to overcome barriers. The SHEILA framework was specifically developed to help institutions create policies and strategies for learning analytics adoption.

The authors identified three areas of challenge for learning analytics implementations: (a) resource challenges, (b) ethics and privacy issues, and (c) buy-in from stakeholders. Resource challenges are often related to infrastructure, financial and human resources. The implementation of learning analytics takes specialized skills and staff time. It requires an investment to strengthen data and human infrastructure. Concerns for violation of privacy and creating a sense of surveillance can become a barrier to gaining buy-in from stakeholders, as ethics and privacy issues can develop into misunderstanding and distrust in an organization. Varying degrees of understanding among stakeholders about learning analytics can also lead to disagreement and distrust. Institutional leadership must provide strategic direction for learning analytics if stakeholders are to share a common understanding of the benefits and outcomes of learning analytics.

The SHEILA framework incorporated the RAPID Outcome Mapping Approach (ROMA) that consists of six dimensions: (a) identify political context, (b) identify stakeholders, (c) articulate desired changes, (d) create engagement strategy, (e) assess capacity for creating change, and (f) develop monitoring process. The ROMA model is designed to support strategic planning and policy development and to be used iteratively. The SHEILA framework includes prompts to identify actions, challenges and policy prompts for reflection in the six ROMA dimensions. For example, the political contexts dimension includes a prompt *"Which problems are to be addressed by using Learning Analytics?"* to guide the analytics design.

This study is important to my research because it provides a practical framework that can be applied to learning analytics implementations. The SHEILA framework is valuable because it is evidence-based and can be applied to assess organizational readiness, strategy, or the progress of learning analytics adoption.

West, D., Heath, D., & Huijser, H. (2016). Let's talk learning analytics: A framework for implementation in relation to student retention. *Journal of Asynchronous Learning Network*, *20*(2). https://10.24059/olj.v20i2.792

Abstract. This paper presents a dialogical tool for the advancement of learning analytics implementation for student retention in Higher Education institutions. The framework was developed as an outcome of a project commissioned and funded by the Australian Government's Office for Learning and Teaching. The project took a mixed-method approach including a survey at the institutional level (n = 24), a survey of individual teaching staff and other academics with an interest in student retention (n = 353), and a series of interviews (n = 23). Following the collection and analysis of these data an initial version of the framework was developed and presented at a National Forum attended by 148 colleagues from 43 different institutions. Participants at the forum were invited to provide commentary on the usefulness and composition of the framework which was subsequently updated to reflect this feedback. Ultimately, it is envisaged that such a framework might offer institutions an accessible and concise tool to structure and systematize discussion about how learning analytics might be implemented for student retention in their own context.

Summary. The authors present the framework developed for learning analytics implementation from the "Learning Analytics: Assisting Universities with Student

Retention" project commissioned by an Australian Government Office for Learning and Teaching. The authors conducted a brief literature review, which revealed that continuous refinement of the process and improvement through reflection are critical to the development of successful learning analytics. The authors also state that the development and implementation of learning analytics is a complicated and dynamic effort that involves various stakeholders. The authors reported that the literature cites technical infrastructure, policy and governance, skills, support, and culture most frequently as the key elements to consider when developing learning analytics. The literature stressed that the development must be executed in accordance with institutional contexts and environment, as the structural and cultural elements are unique to every institution.

The authors detail the elements of the framework for implementation of learning analytics focused on student retention. The framework was initially drafted based on the data collected from the institutional-level and academic-level surveys and interviews with senior leaders and academic staff. The framework was then piloted among the project partners and refined based on the additional feedback compiled. The framework titled *Let's Talk Learning Analytics Framework* consists of a set of discussion questions that guide the use of the framework. The framework includes six domains for organizations to consider when developing learning analytics for retention: (a) institutional context; (b) transitional institutional elements, which are parameters of learning analytics implementation such as culture and level of sponsorship; (c) learning analytics infrastructure; (d) transitional retention elements, which are parameters to improve deployment of learning analytics for retention such as retention strategy and implementation; (e) learning analytics for retention; and (f) intervention and reflection.

The framework promotes collaboration in learning analytics implementations by prompting dialogues between stakeholders. It is complementary to other frameworks published in prior literature, which often focus on measuring progress.

The source is useful to this study because it describes the key elements for successful learning analytics development. The collaborative approach highlighted in the framework also supplements the successful implementation process.

Conclusion

While interest in developing learning analytics has grown among higher education institutions (Tsai et al., 2018), a small number of institutions are making the implementation of learning analytics a priority (Arroway et al., 2016, p. 8). Investing in learning analytics is a complex endeavor (Greller & Drachsler, 2012; Lester et al., 2017; West et al., 2016), with numerous challenges to an effective and systematic adoption of learning analytics (Bichsel, 2012; Lester et al., 2017; Siemens, 2013; Tsai & Gasevic, 2017; Tsai et al., 2018). Successful implementation of learning analytics requires careful planning and a complex array of resources (Arnold, Lonn & Pistilli, 2014).

This annotated bibliography discusses the benefits and challenges of learning analytics and provides key factors in successfully implementing this tool. The findings are presented in three categories: (a) overview of learning analytics, (b) learning analytics applications in higher education, and (c) best practices in implementing learning analytics in higher education.

Overview of Learning Analytics

Learning analytics is a recently developed interdisciplinary field that combines various research categories (Siemens, 2013). The development of learning analytics was driven in part by an increase in available educational data (Clow, 2013). The introduction of learning management systems (LMSs) and an increase in online learning caused universities to accumulate a large amount of educational data (Ferguson, 2012).

Ferguson (2012) states that another driver of learning analytics is attributed to a new set of challenges created by online learning environments, noting that it is harder for instructors to identify students who are struggling in online courses due to the lack of visual cues teachers may have had in a traditional classroom setting (Ferguson, 2012). Instructors may also struggle to evaluate learning and the quality of participation from vast amounts of participation threads in online discussion boards (Ferguson, 2012). Increased economic and political pressures on institutions to educate more students and to measure and improve their performance is another driver of the recent development of learning analytics (Clow, 2013; Ferguson, 2012). Learning analytics is seen as a promising tool to provide insights into complex learning environments (Ferguson, 2012).

As an emerging field, van Barneveld et al. (2012) found that there were no consistent definitions of terms describing analytics that are used in higher education. Van Barneveld et al. (2012) assert that all types of analytics in higher education work as a cohesive and integrated system and serve different needs of an institution at various levels of the organization. As the field of educational analytics developed, three types of analytics have emerged as the main focus areas: (a) educational data mining (EDM) that focuses on addressing the technical challenges of data mining to improve learning and the learning environment, (b) academic analytics that focus on the political or economic challenges education institutions face by analyzing at the organizational level, and (c) learning analytics that focus on the educational challenges at a learner level (Ferguson, 2012).

Learning Analytics Applications in Higher Education

Learning analytics tools have been developed by private companies and educational technology vendors, making the analytics more accessible to users (Siemens, 2013). The benefits of learning analytics can be explained through examples of applications.

Predictive analytics, applied to improve student learning, is mathematical modeling that predicts the probability of likely outcomes (Clow, 2013). One of the most prominent predictive analytics projects is Course Signals at Purdue University (Clow, 2013). Arnold and Pistilli

(2012) documented the Course Signals predictive analytics pilot with more than 23,000 students. Course Signals creates actionable intelligence using real-time data by generating colored signals and enables faculty to intervene with at-risk students based on their current class performances (Arnold & Pistilli, 2012). According to Arnold and Pistilli (2012), the aim of Course Signals is to predict the likelihood of students' success and encourage students to seek academic support resources. The impact of the analytics was encouraging: the proportion of satisfactory grades increased while unsatisfactory grades and course withdrawals decreased in the courses that piloted Course Signals (Arnold & Pistilli, 2012). In addition, students who took at least one course that used Course Signals were retained at a significantly higher rate than those who did not enroll in any Course Signals courses (Arnold & Pistilli, 2012).

Social network analysis is another example of learning analytics that shows promise (Clow, 2013). It tracks the connections between people in a digital space, which could be applied to help teachers identify students who are isolated from interactions with their peers (Clow, 2013). While they require additional research, content analysis and semantic analysis enable the analysis of qualitative, textual data (Clow, 2013). Clow (2013) provided an example of a tool developed by Lárusson and White (2012) that was intended to monitor how students develop originality when using key concepts over multiple writing assignments. The students' writing was analyzing against an advanced English database and returned colored markers to indicate more or less original use of key words; Clow (2013) asserts that these types of automated assessments can be categorized under learning analytics.

Recommendation engines, similar to Amazon's engine that provides customized recommendations, are another analytics tool that can be used in an educational context (Clow, 2013). Based upon the results of an analysis using historical student data, a recommendation engine may be utilized to suggest study resources for a student based on information about the student and data on resources that other students found helpful (Clow, 2013).

Due to the complexity of institutions and educational settings that are unique to each institution (West, Heath & Huijser, 2016), the field is struggling to scale a learning analytics model from one institution to another to promote sharing within a wider community (Jayaprakash, Moody, Lauría, Regan, & Baron, 2014). The Open Academic Analytics Initiative (OAAI) is a project aimed at advancing the use of learning analytics by examining issues preventing the scaling of the technology to various institutions (Jayaprakash et al., 2014). Some of the challenges in scaling learning analytics in higher education include variability in the use of learning management systems, the proportion of at-risk students across institutions, and student behavior across courses or institutions (Jayaprakash et al., 2014). Jayaprakash et al. (2014) found that the initial indications from the research are promising and that the portability of predictive models is viable while preserving their predictive power.

The use of learning analytics to enable timely interventions is also promising (Jayaprakash et al., 2014). Jayaprakash et al. (2014) note that alerting students that they may be academically at-risk in a course can positively improve the students' learning and course outcomes. Jayaprakash et al. (2014) assert that "Predictive models do not influence course completion and retention rates without being combined with effective intervention strategies aimed at helping at-risk students succeed" (p. 7). There are various initiatives that have been introduced in this area, but a limited number of research studies with documented longitude outcomes are available due to the significant time lag between intervention and student persistence or graduation (Jayaprakash et al., 2014).

Best Practices in Implementing Learning Analytics in Higher Education

A common theme of challenges related to the implementation and use of learning analytics in higher education has surfaced in this literature review, including data issues (Bichsel, 2012; Greller & Drachsler, 2012; Tsai & Gasevic, 2017; Tsai et al., 2018), lack of leadership (Bichsel, 2012; Lester et al., 2017 Tsai & Gasevic, 2017), resource challenges (Greller & Drachsler, 2012; Lester et al., 2017; Tsai & Gasevic, 2017; Tsai et al., 2018), and lack of communication and collaboration (Bichsel, 2012; Greller & Drachsler, 2012; Lester et al., 2017; Tsai & Gasevic, 2017).

Data issues. Academic analytics implementations often experience issues with data quality, siloed data ownership and access, and lack of data definition standardization (Bichsel, 2012). Since education data is generally protected, researchers have also faced challenges in effectively validating their designs across institutions (Greller & Drachsler, 2012). Personal ethics and privacy concerns are high, while legal and policy clarity is lacking (Greller & Drachsler, 2012; Tsai & Gasevic, 2017). Concerns for the violation of privacy or the unethical use of data could result in distrust in an institution (Tsai et al., 2018).

Lack of leadership. Lack of leadership capacity may result in the failure to drive strategic planning and monitor the progress of learning analytics implementations (Tsai & Gasevic, 2017). Leadership that does not support data-driven decision making and cultural change is also not helpful during these implementations (Bichsel, 2012). A lack of incentives and rewards for the use of learning analytics also impacts end users and their motivation to adopt the new tool (Lester et al., 2017).

Resource challenges. Resource challenges related to infrastructure, financial or human resources may arise during academic analytics implementation (Tsai et al., 2018). Lack of appropriate staffing, especially adequate human resources who are skilled and knowledgeable in academic analytics, poses a potential limit to a learning analytics initiative (Greller & Drachsler, 2012; Lester et al., 2017). Additionally, users are often not well equipped with training to gain the skills necessary to successfully utilize learning analytics (Tsai & Gasevic, 2017).

Lack of communication and collaboration. A lack of collaboration between key stakeholders is a common challenge in an analytics project (Bichsel, 2012), especially due to the bureaucratic organizational structures of higher education (Lester et al., 2017). Tsai and Gasevic (2017) state that there are a limited number of institutional examples available that successfully engaged all levels of stakeholders during the implementation of academic analytics. Lack of buy-in also becomes a hurdle when implementing learning analytics (Greller & Drachsler, 2012).

While various challenges have been identified in the implementation of learning analytics, organizational readiness and capacity can build a strong foundation for learning analytics to thrive (Bichsel, 2012; Lester et al., 2017). Arnold et al. (2014) state that sufficient readiness for the technical infrastructure, institutional governance, policies and oversight of learning analytics are key for a successful implementation. The following recommendations are compiled from the literature as best practices for a successful learning analytics implementation:

Leadership and strategic vision. Strong leadership that supports learning analytics is critical for a successful learning analytics implementation (Arnold et al., 2014; Norris & Baer, 2013). An organization's leaders must support data-driven decision making (Bichsel, 2012), provide strategic vision, and identify academic challenges in the organization that can be addressed using the existing data through learning analytics (Arroway et al., 2016; Bichsel, 2012; Tsai et al., 2018). Different levels of understanding among stakeholders about the benefits of learning analytics can lead to disagreements and distrust (Tsai et al., 2018). Institutional leadership should provide strategic direction for the use of learning analytics so stakeholders share a common understanding of the expected benefits and outcomes (Tsai et al., 2018).

Arroway et al. (2016) state that effective leaders also recognize and address the barriers that may impact the implementation in the strategic plan. Strategies for launching, resourcing, scaling, and sustaining the effort should be clearly identified (Norris & Baer, 2013). In addition, the strategic plan should include a business case for learning analytics adoption in order to secure funding and executive support (Arroway et al., 2016).

Workflows that utilize analytics and interventions must be adopted at all levels of an institution to be effective (Norris & Baer, 2013). Leaders should encourage, support and reward teaching innovations in order to engage faculty and advisors with new ways of teaching and integrating technology into their work (Lester et al., 2017).

Resources and expertise. It is important to evaluate and understand the funding, technology, and human resources available for an analytics initiative (Bichsel, 2012; Lester et al., 2017). Adequate and appropriate resources must be available and accessible during the implementation (Arnold et al., 2014). The successful application of analytics relies on people skills as much as data and tools (Bichsel, 2012). The expertise and skills required for learning analytics implementations are diverse and include technical skills, analytics expertise, strategic leadership, and student support skills (Arnold et al., 2014). Advanced skills such as interpretative and critical evaluation skills are essential competencies for the design of learning analytics (Greller & Drachsler, 2012). Likewise, the users of learning analytics are expected to interpret data, make decisions and take action to improve learning (Greller & Drachsler, 2012). Bichsel (2012) asserts that training to build staff skills should be considered.

Data. Learning analytics requires quality data sets that represent the complexity of learning (Siemens, 2013). It is important to understand the types of data available at the institution; the cleanliness, validity, and dependability of the data; where the data is stored and how it is accessed; and data ownership (Arnold et al., 2014; Arroway et al., 2016). While Greller and Drachsler (2012) acknowledge the limitations of learning analytics data that is meant to recreate the complex learning process, they assert that connecting divided datasets across systems would facilitate the creation of more learner-oriented analytics.

Stakeholder engagement, communication, and collaboration. Learning analytics implementations involve various stakeholders in an organization (West et al., 2016). The acceptance of learning analytics by stakeholders and users is key to a successful learning analytics design (Greller & Drachsler, 2012). When developing a strategic plan and governance structure, including all stakeholder groups has been proven to be most effective (Arroway et al., 2016). End users' needs, roles, and voices should be represented throughout the process of learning analytics development and implementation (Lester et al., 2017). The impacts on stakeholders' processes should also be considered during learning analytics implementations (Greller & Drachsler, 2012). Inclusion and transparency are important to build trust in learning analytics (Lester et al., 2017).

According to Arroway et al. (2016), the strategic plan for learning analytics should be shared with stakeholders prior to its implementation, and continuous communication should be provided to stakeholders throughout the implementation process. Consideration needs to be given to establishing communication channels among stakeholders (Tsai & Gasevic, 2017). Engaging stakeholders by planning small wins will show the enhanced value brought by data-based decisions and changes instituted through the use of learning analytics (Bichsel, 2012).

Greller and Drachsler (2012) state that learning analytics becomes more valuable to the stakeholders if they can be shown that the tool benefits them and supports their objectives.

Universities are bureaucratic organizations with units and colleges operating in silos (Lester et al., 2017). Creating changes in such a fragmented environment with different structures, policies, cultures, and social norms is generally difficult (Lester et al., 2017). Lester et al. (2017) state that top-down approaches do not work in fragmented organizations like higher education institutions. To implement change, close collaboration and coordination across an organization are critical (Lester et al., 2017).

Change management. Arnold et al. (2014) state that the introduction of learning analytics triggers institutional change. When implementing learning analytics, institutions are forced to transition to a culture of performance where the actions of faculty and staff are organized and measured for continuous improvements (Norris & Baer, 2013). Strong leadership that can monitor and manage the change process is critical for successful learning analytics implementations (Tsai & Gasevic, 2017).

Change requires cultural acceptance to be successful (Arnold et al., 2014). Institutional logic, which encompasses organizing principles and cultural values, assumptions, and beliefs within an organization, plays a key role when people are making a decision about accepting a change introduced through institutional demands (Lester et al., 2017). The desired cultural elements that support change to implement learning analytics include support for data-driven decision making, adequate stakeholder buy-in, and a shared vision (Arnold et al., 2014).

Lester et al. (2017) assert that institutional logic that is in line with institutional demands has a positive impact on the creation of change. Unfortunately, institutional demands are often created by the senior leadership of an institution without consideration for end users and result in a mismatch with users' institutional logic (Lester et al., 2017). Strategic leadership should consider the ability of the project to maintain sustainable organizational change (Arnold et al., 2014).

Greller and Drachsler (2012) also recommend reflection throughout the process at all levels to promote self-evaluation of the learning analytics implementation progress. Formal guidelines and policies to track the dependability and effectiveness of learning analytics are needed (Tsai & Gasevic, 2017). Frameworks should be utilized to assess organizational readiness and measure progress during a learning analytics project (Tsai et al, 2018).

Final Thoughts

It is clear from the literature that the implementation of learning analytics is an involved process that warrants intentional planning and continuous attention (Arnold, Lonn & Pistilli, 2014). While technical components such as technologies and modeling are a large part of learning analytics implementations, the organizational aspects of learning analytics implementations are equally significant (Greller & Drachsler, 2012). The complexity of the higher education environment must be understood for the effective adoption of learning analytics (Greller & Drachsler, 2012). In addition, consideration must be given to the privacy and ethical questions that arise with the use of student data in learning analytics, and guidelines that outline the rights and responsibilities of students and researchers need to be established (Ferguson, 2012). Despite these challenges, learning analytics holds promise in helping to understand personal learning needs (Greller & Drachsler, 2012) and providing assistance in the complicated and dynamic process of learning (Ferguson, 2012).

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