2018

Learning analytics from research to practice: a content analysis to assess information quality on product websites

Sandra Sarmonpal

Pepperdine University

Graduate School of Education and Psychology

LEARNING ANALYTICS FROM RESEARCH TO PRACTICE: A CONTENT ANALYSIS TO ASSESS INFORMATION QUALITY ON PRODUCT WEBSITES

A dissertation submitted in partial satisfaction

of the requirements for the degree of

Doctor of Education in Learning Technologies

by

Sandra Sarmonpal

December, 2018

Eric Hamilton, Ph.D. – Dissertation Chairperson

This dissertation, written by

Sandra Sarmonpal

under the guidance of a Faculty Committee and approved by its members, has been submitted to and accepted by the Graduate Faculty in partial fulfillment of the requirements for the degree of

DOCTOR OF EDUCATION

Doctoral Committee:

Eric Hamilton, Ph.D., Chairperson

Ebony Cain, Ph.D.

Paul Sparks, Ph.D.

TABLE OF CONTENTS

Page

LIST OF TABLES vi

LIST OF FIGURES vii

DEDICATION ix

ACKNOWLEDGEMENTS x

VITA xi

ABSTRACT xii

Chapter One: Introduction 1

- Educational Policy 1
- Research to Practice 2
- Market Influences 2
- New Data Skills for Educators 2
- Problem Statement 3
- Purpose of this Study 3
- Research Questions 3
- Significance 4
- Delimitations 5
- Definition of Terms 5
- Assumptions 6
- Conceptual Models 7
- Organization of this Study 9

Chapter Two: Literature Review 10

- Restatement of the Research Questions 10
- Overview 10
- Background 10
- Big Data's Epistemological Shifts 11
- Current State of the Field 13
- Critical Concerns 23
- Frameworks 33
- Summative Framework 54
- Summary 56

Chapter Three: Methods 57

- Restatement of the Research Questions 57

Overview ... 57
Rationale for the Study Design ... 58
Instrumentation ... 61
Data Sources and Units of Analysis ... 68
Procedures ... 69
Reliability, Validity, and Human Subjects ... 71
Chapter Summary ... 74

Chapter Four: Results ... 75

Restatement of the Study Purpose Research Questions ... 75
The Sampling Frame ... 76
Phase One Analysis ... 76
Phase Two Analysis Results ... 83
Summary ... 93

Chapter Five: Conclusions ... 94

Summary of the Study ... 94
Discussion of the Methods ... 95
Discussion of the Results with Respect to the Research Questions ... 99
Implications for Action ... 104
Conclusions ... 105
The Significance of the Findings ... 105
Limitations of the Current Work ... 106
Concluding Thoughts ... 107
Future Directions ... 110

REFERENCES ... 111

APPENDIX A: IRB Approval Letter ... 118

APPENDIX B: Study Corpus by Category ... 120

APPENDIX C: Study Corpus Content URLs ... 122

LIST OF TABLES

Page

Table 1. Shum (2012) Institutional Impact Levels 35

Table 2. Chatti et al. (2012) A Reference Model for Learning Analytics 38

Table 3. Greller and Drashler (2012) Design Framework for Learning Analytics 41

Table 4. Siemens (2013) Learning Analytics Model 42

Table 5. Knight et al. (2013) EPA Triad 43

Table 6. Pedagogies Defined and Linked to LA Indicators (Knight et al., 2014) 45

Table 7. Gummer and Mandinach (2015) Data Literacy for Teaching Constructs 47

Table 8. Bakharia et al. (2016) A Conceptual Framework Linking Learning Design with LA ... 50

Table 9. Slade and Prinsloo (2013) Ethical Framework for Learning Analytics 53

Table 10. ES Index List of Products by Category 76

Table 11. Products Remaining After Step One by Category 78

Table 12. Journal Papers Included in the Literature Corpus 82

Table 13. Top Ten Words Lists by Count in Each Corpus 84

Table 14. Study Corpus Bigrams Ranked by TF-IDF 86

Table 15. Literature Corpus Bigrams Ranked by TF-IDF 87

Table 16. Contributing Words to Sentiment Side-by-Side Listing 89

Table 17. Adapted from Bernard (1996) 96

Table 18. Overview of Analytical Techniques Mapped to Results 99

Table 19. Contribution to Sentiment Scores Side-by-Side Comparison 103

Table B1. Study Corpus by Category 120

Table C1. Study Corpus Content Extraction URLs 122

LIST OF FIGURES

Page

Figure 1. Significance model data and decision-making in education 4

Figure 2. Characteristics of ‘data personality’ to consider in LA implementations 7

Figure 3. The three main factors in LA implementations 8

Figure 4. Topics related to three central constructs in this study.. 8

Figure 5. Integrated model of the nine LA frameworks reviewed.. 55

Figure 6. Instrumentation and operationalization of the construct 64

Figure 7. Topic model representations of text at the word, document, and corpus levels........... 65

Figure 8. Product selection process overview... 77

Figure 9. Extraction path in step 1 77

Figure 10. Extraction click through path in step 1 78

Figure 11. Content extraction path... 79

Figure 12. Tf-idf measurement 85

Figure 13. Tf-idf by product type 85

Figure 14. Tf-idf by author 86

Figure 15. Study corpus sentiments scores 87

Figure 16. Literature corpus sentiments scores.. 88

Figure 17. Study corpus contributions to sentiment 88

Figure 18. Literature corpus contributions to sentiments 89

Figure 19. Topic models from the study corpus 90

Figure 20. Topic models from the literature corpus 91

Figure 21. Topic models by common words 91

Figure 22. Unmatched topic models. 92

Figure 23. Commonality cloud and comparison cloud 92

Figure 24. Words in common tags 93

Figure 25. Phase one procedure mappings 97

Figure 26. Quantitative analysis of qualitative data applied in current study 97

Figure 27. Relationship between qualitative and quantitative processes 98

Figure 28. Examples of common word comparisons. 100

Figure 29. Tf-idf by product type 102

Figure 30. Topic models generated from study corpus 102

Figure 31. Comparison cloud visualization 104

Figure 32. Preliminary framework for educational data practitioners 108

Figure 33. Preliminary learning analytics implementation framework for practitioners 109

DEDICATION

In dedication to my parents, Malee and Deacha Sarmonpal, and

In memory of my grandmother and,

my dear friend, Abraham Madrigal

ACKNOWLEDGEMENTS

This dissertation would not have been possible without the support and encouragement of my parents, sister, and family. My parents taught me the value of a good education. It is due to their sacrifice that I had the privilege to consider, pursue, and complete this level of education. I am deeply grateful for all they have provided me.

I benefited greatly from the mentoring of Eric Hamilton and comments received from Paul Sparks and Ebony Cain. I owe my desire to learn and understand through research to Eric Hamilton. Because of him, I saw how research inspired others to create and develop solutions. From his example I learned how to bring together different perspectives while honoring each. I also learned how general understandings from research related to local contexts in ways that offered meaning and value to both. I am indebted to him for generously sharing his experience, assistance and advice throughout my years as a doctoral student.

I learned much from my professors, and thank them for sharing their knowledge with me. I learned alongside others in Cadre 19, who shared ideas that helped me to refine my own. I worked most closely with Traci Garff Longmore, Jesusa Jackson, and Kim Welch. I am particularly thankful to Kim Welch for her support while writing this dissertation. Sharing the journey helped me to complete the journey.

Throughout this dissertation, I reference what I have learned from teachers, students and staff at Evanston Township High School. In particular, Franz Calixte, who I taught with for many years, and Tammie Holmes. I have been both inspired by their commitment to students and enlightened by their professional practice.

VITA

EDUCATION

2018	Ed.D Learning Technologies	Pepperdine University Malibu, CA
2003	M.Ed Education	University of Illinois Chicago
1998	B.A. Rhetoric	University of Illinois Urbana-Champaign

PROFESSIONAL EXPERIENCE

2018-Present	Associate Director, Learning & Development Doctor Evidence, Los Angeles, CA
2017-2018	Development Consultant 9 Dots, Los Angeles, CA
2015-2016	Development Director Team Prime Time, Los Angeles, CA
2013-2016	Research Assistant, Team Lead Pepperdine University, Malibu, CA
2006-2013	Teacher/Program Founder & Advisor Evanston Township High School, Evanston, IL
2003-2006	Teacher William Howard Taft High School, Chicago, IL

ABSTRACT

The purpose of this study was to examine and describe the nature of the research to practice gap in learning analytics applications in K12 educational settings. It was also the purpose of this study to characterize how learning analytics are currently implemented and understood. A secondary objective of this research was to advance a preliminary learning analytics implementation framework for practitioners. To achieve these purposes, this study applied quantitative content analysis using automated text analysis techniques to assess the quality of information provided on analytics-based product websites against learning analytics research. Because learning analytics implementations require adoption of analytical tools, characterizing content on analytics-based product websites provides insight into data practices in K12 schools and how learning analytics are practiced and understood. A major finding of this study was that learning analytics do not appear to be applied in ways that will improve learning outcomes for students as described by the research. A second finding was that policy influence expressed in the study corpus suggest competing interests within the current policy structure for K12 education settings.

Keywords: quantitative content analysis, automated text analysis, learning analytics, big data, frameworks, educational technology, website content analysis

Chapter One: Introduction

The rapid adoption of educational technologies have resulted in dramatic changes to the type and quantity of data created, collected, and stored in educational settings. Today, educational datasets evoke big data dynamics characterized by large volumes of varied data created at a high velocity and captured in real-time. Big data applications in education, called *learning analytics* (LA), impact teaching and learning practices in significant ways yet remain little understood.

Educational Policy

The 2017 National Technology Plan (U.S. Department of Education, 2017) states that "at all levels, our education system will leverage the power of technology to measure what matters and use assessment data to improve learning" (p. 55). Federal funding allocated to support analytics in K12 education settings is unprecedented, indicating a new era in educational data use that very few practitioners understand.

Policy documents indicate the purpose for a focus on data is to provide equitable access to quality education for all students (Bienkowski, Feng, & Means, 2012; U.S. Department of Education, 2014; 2017). However, studies examining data practices in K12 educational settings indicate that current practices may be worsening the problem. After observing data practices in New York public schools, Neuman (2016) warns that misunderstandings around data may lead to "a larger divide that will be more difficult to cross in the future" (p. 29). Similarly, Lonn, Aguilar, and Teasley (2015) report that LA interventions applied during a summer bridge program resulted in negative impacts to student motivation over the course of the program. The authors conclude that LA interventions and the visual tools they produce can negatively influence how students interpret their own data and their academic performance into the future.

Research to Practice

The unintended outcomes reported by Lonn et al. (2015) are emblematic of the troubling research to practice gap in LA implementations. Siemens (2012) notes that LA implementations largely occur without guidance from LA research. Similarly, a number of researchers report that available data tools do not align with relevant theories from the learning sciences (Wise & Schaffer, 2015; Knight & Shum, 2017) and the larger body of educational research (Monroy & Rangel, 2014) that are shown to be critical for effective LA implementations.

Market Influences

Freely shared methods are important to validate findings and build a knowledge base in research fields. In contrast, proprietary assets are viewed as a competitive advantage in the educational technology marketplace. The conflict means that researchers cannot test or validate the underlying algorithms driving commerical LA applications (Lazer, Kennedy, King, & Vespignani, 2014; Siemens, 2012). Further, Monroy and Rangel (2014) report that market conflicts result in analytics products that do not align with daily practices in K12 schools.

New Data Skills for Educators

A number of studies report that LA applications require a high level of data competency from end-users to effectively implement (Chatti, Dyckhoff, Schroeder, & Thüs, 2012; Papamitsiou & Economides, 2014). However, data skills are currently not a basic skill required of education practitioners. Subsequently, the lack of data competency among end-users is widely identified as a significant challenge to effective LA implementations (Greller & Drachsler, 2012; Papamitsiou & Economides, 2014; Pea, 2014).

Problem Statement

Equitable access to education for all students continues to be a national priority. Policy documents point to LA as a potential solution through applications such as personalized learning. Heightened policy support for LA implementations has resulted in a high number of analytics products entering the educational technology marketplace. The rapid implementation of LA has raised concerns from the LA research community around

- the lack of data competency among end-users,
- the implications of a widening research to practice gap, and
- market interests that conflict with the daily practices that occur around teaching and learning in schools.

This context requires additional support for educational data practitioners who are tasked with applying educational data in their daily practice. However, studies mainly focus on building knowledge for product developers and researchers and too few studies focus on knowledge building for practitioners (Wise, Vytasek, Hausknecht, & Zhao, 2016).

Purpose of this Study

The purpose of this study was to examine and describe the relationship between research and practice in analytics applications in K12 educational settings. It was also the purpose of this study to characterize how LA are currently implemented and understood. A secondary purpose for this research was to advance a preliminary LA implementation framework to support educational data practitioners effectively apply LA in their daily practice.

Research Questions

The central question of this study was: What is the quality of information provided on LA product websites?

Additionally, this research addressed the following related questions:

- What kinds of LA tools are offered?
- How are the LA tools portrayed?

Significance

Because analytics applications are designed to drive decision-making (Papamitsiou & Economides, 2014), the implications of inaccurate data practices are not trivial. Figure 1 shows how more accurate data practices improve decision-making, resulting in progress towards the goal of equitable access to quality education as identified in policy documents. The reverse is also true. Moreover, studies show that inaccurate data practices most negatively impact students who are already struggling in school. The results of this research offers insights into research and practice that can be further explored to improve practice and inform policy.

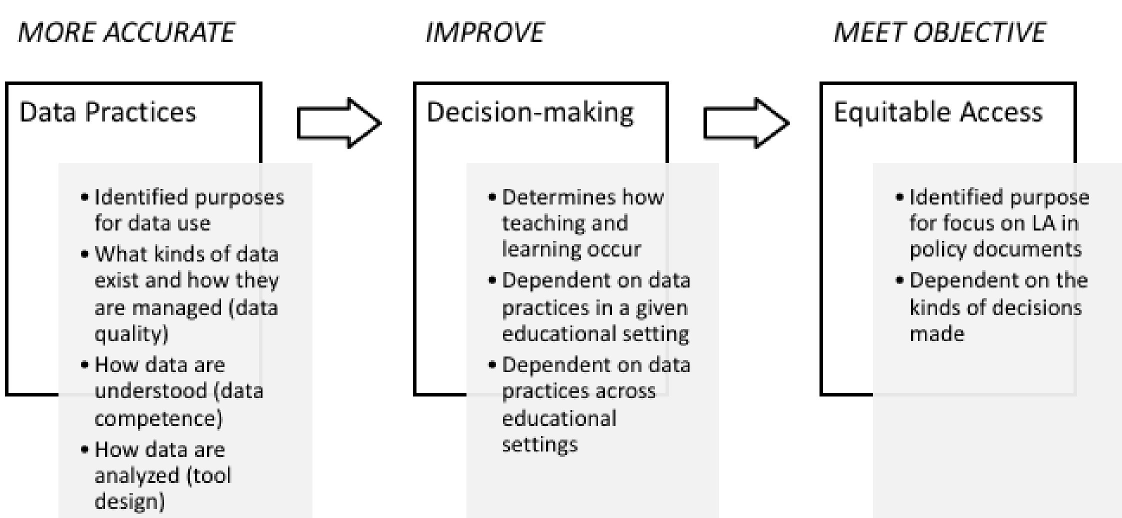

Figure 1. Significance model data and decision-making in education.

Significance of the methods. This research also offers a methodological approach that appears to be novel in education research. The widespread adoption of educational technologies make the methods particularly relevant. Because educational technologies determine how teaching and learning occur, research that characterizes content on educational technology websites will also approximate current teaching and learning practices in the contexts they are deployed. This context provides rich opportunities to examine present-day teaching and learning practices that can be used to impact practice and policy as mentioned above.

Delimitations

This study included only those products that matched the selection criteria established for this study. The criteria for selection included products developed for typical K12 settings that collected, stored, or otherwise interacted with data in relationship to student performance. These criteria were applied to maintain a focus on K12 education settings and to better align the orientation of the content within the study corpus to the orientation of the framework papers used as the analytical construct in this study.

Definition of Terms

Applications. A term Siemens (2013) uses to describe how learning analytics are implemented in educational settings.

Data attributes. A term used in this study to refer to the inherent characteristics of data which must be considered in every use case.

Data environment. The types of data collected in a given setting and how the data is collected, stored, and organized.

Data quality. The suitability of a given data environment for the intended purpose of analysis. Characteristics include the types of data available, the completeness of the dataset, and how the data are stored within the database.

Data subject. Refers to data creators, as suggested by Greller and Drachsler (2012).

End-user. Refers to the target consumer for LA products.

Educational data practitioner. Refers to learners, teachers, administrators, and policymakers who are tasked with implementing data products in their daily practice.

Educational settings. Although LA applies to any environment where formal or informal learning occurs, including online, blended, and physical learning across public and private institutions at all stages of attainment. *Educational settings* in the context of this study refers to settings as those found in typical K-12 education.

Implementation. Refers to the deployment of LA tools in educational settings as used by Siemens (2012).

LA product. An educational technology that measures, collects, stores, or analyzes educational data.

Objectives. Refers to the identified purpose of LA adoption and implementation for stakeholders. This definition aligns with how the term is used by Knight, Shum and Littleton (2014)

Stakeholders. Greller and Drachsler (2012) describe stakeholders as the proposed data users (end-users) or data subjects (data creators) of LA applications. Stakeholders may include educational institutions, policy-makers, researchers, teachers, learners, and even computer agents. For example, computer agents may serve as data clients that trigger events or act on a learner's behalf once 'presented' with certain data.

Assumptions

This study assumes that

- educational technologies strongly influence how teaching and learning occur based on the instructional strategies they support,
- LA are implemented in K12 educational settings using analytics-based tools,

- commercial use of websites as a marketing tool means that communications contained there are intended to be consumer facing, and
- the sample corpus was representative of other analytics-based technologies meeting the criteria applied.

Conceptual Models

This section presents three concept models related to this research. Figure 2 and Figure 3 depict important constructs for practitioners around data practice and Figure 4 maps these constructs to the topics presented in the literature review. Brief descriptions are presented here to frame topics which appear in the next chapter.

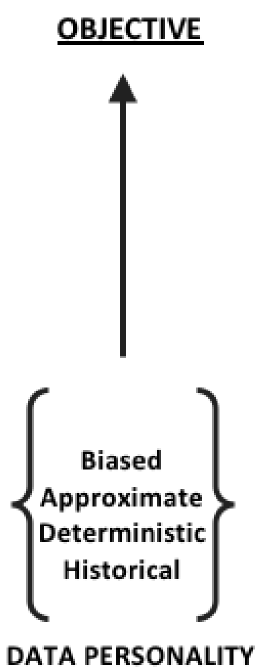

Figure 2. Characteristics of 'data personality' to consider in LA implementations.

Figure 2 describes the relationship between two of three key constructs in this study. *Objective* refers to the identified purpose for analysis of educational data and *data personality* refers to data characteristics that affect every analytics application.

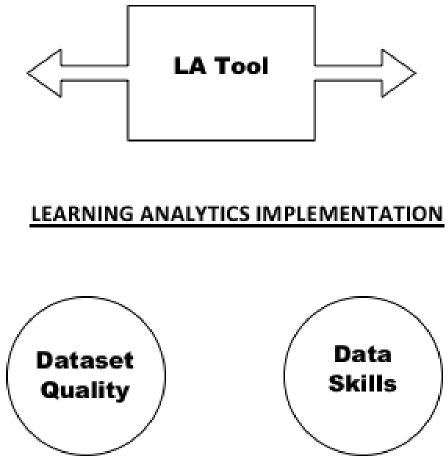

Figure 3. The three main factors in LA implementations.

Figure 3, which appears above, depicts the third key construct, *learning analytics implementation.* The term appears at the center of its three defining components. The component at the top of the figure, *LA tool*, refers to an analytics product or a combination of products. The two components that appear at the bottom of the figure are features of the education setting. *Dataset quality* refers to the kinds of data available, the completeness of the data, and the usability of the data due to how the data are stored. Finally, *data skills* refers to the end-user competencies required to accurately apply the LA tool using the available dataset. Finally, Figure 4 presents the three constructs mapped to the topics addressed in the literature review.

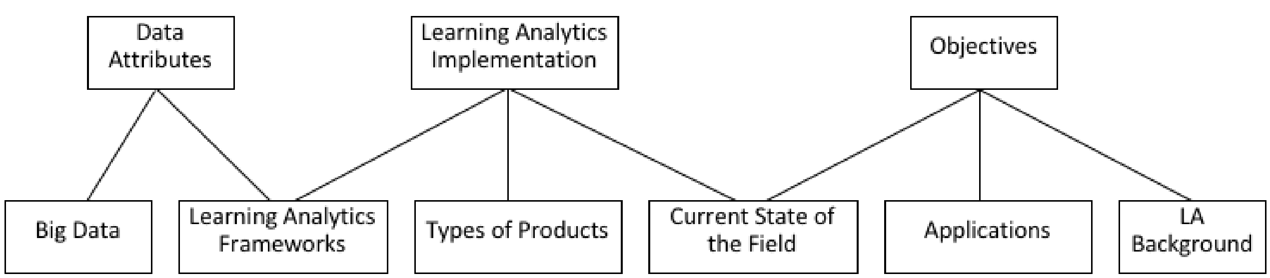

Figure 4. Topics related to three central constructs in this study.

Organization of this Study

The remainder of this study is organized into five chapters, a bibliography, and appendixes in the following manner. Chapter Two contains a review of literature relevant the topics presented in the preceding section. Chapter Three describes the methods applied in this research and the rationale for their use. Chapter Four presents the procedures and results of the analysis. Chapter Five contains a summary of this study, presents conclusions, and offers recommendations for future work as a result of the findings. The bibliography and appendixes conclude this study.

Chapter Two: Literature Review

The purpose of this study was to examine and describe the relationship between research and practice in analytics applications in K12 educational settings. It was also the purpose of this study to characterize how LA are currently implemented and understood. A secondary purpose for this research was to advance a preliminary LA implementation framework to support educational data practitioners effectively apply LA in their daily practice.

Restatement of the Research Questions

The central question of this study was: What is the quality of information provided on LA product websites?

Additionally, this research addressed the following related questions:

- What kinds of LA tools are offered?
- How are the LA tools portrayed?

Overview

The remainder of this chapter is structured in five sections as follows. Section three provides background and context for the emergence of LA as a research and practice field. Section four addresses attributes of big data that impact LA research and practice. Section five addresses the current state of LA and describes current applications, types of products, and challenges to LA implementations. Section six addresses critical concerns within the field. Finally, a review of selected LA frameworks is presented in section five followed by a summative model of the frameworks.

Background

Recent trends in big data analytics have disrupted domains and markets. Big data refers to datasets containing large volumes of varied data types created at a high velocity and captured in real-time. These data can represent minuscule events, such as tracked eye movements during engagements with digital content. This new data context, coupled with massive open datasets from education, finance, government, and health, are the components of big data.

Big data evoke epistemological changes that affect what can be known and how we come know them. Insights revealed from big data analysis encourage innovative approaches to problem solving. Big data has become difficult to ignore. Despite attempts to clearly define big data, the term is often used to describe systems that do not meet its defining criteria. This may be because the term wrongly suggests that big data's value lies in its size (Boyd & Crawford, 2012). However, massive data, such as census data, that have long existed are insufficient to elicit big data dynamics (Berman, 2013). Rather, big data's value lies in its dynamic quality, which reveals relationships within and across datasets that was not possible before (Boyd & Crawford, 2012).

Boyd and Crawford (2012) comment on the misplaced and "widespread belief that large data sets offer a higher form of intelligence and knowledge that can generate insights that were previously impossible, with the aura of truth, objectivity, and accuracy" (p. 663). These views have led to what Lazer, Kennedy, King, and Vespignani (2014) characterize as *big data hubris*, the notion that big data approaches make traditional data collection, analytical methods, and their associated standards irrelevant. This perspective is a problem confronting big data applications across domains of practice and has been disputed by prominent researchers in LA and big data literature (Wise & Schaffer, 2015; Lazer et al., 2014; Siemens, 2012).

Big Data's Epistemological Shifts

Perhaps the most well-known account of the big data phenomenon is to be found in the work of Mayer-Schonberger and Cukier (2013). The authors explain how big data alters the epistemological understandings of conventional data science. They assert that big data evokes three epistemological shifts: (a) from conventional sampling based on a portion of the target population to including “all data” allows insights into more granular perspectives (i.e., clear view of subcategories within a larger phenomenon); (b) a movement from precision and accuracy to generalizable, macro-level insights; and (c) substituting knowing what is happening for understanding why it is happening.

However, Mayer-Schonberger and Cukier (2013) make it clear that big data does not replace conventional data science, rather, it extends our ability to understand phenomena from a new perspective. The authors use the phrase ‘letting the data speak for itself’ to describe the ad hoc pattern detection that challenges traditional a priori approaches, which require researchers to develop hypotheses before beginning research. While big data applications allow for more generalizable insights, it sacrifices accuracy to do so (Mayer-Schonberger & Cukier, 2013). For this reason, Mayer-Schonberger & Cukier assert that big data is primarily applicable to large scale, macro-level applications. Shum (2012b) describes macro-level analytics as district, state, or national level projects that use data collected across institutions. A macro-level analytics project drawing from education institutions at the state level may reveal unexpected relationships between variables. It may, perhaps, reveal common practices across schools with lower truancy rates, which would indicate potential best practices to accomplish the same. Results like these describe what is happening without revealing why it happens. In some cases, knowing what is happening is good enough. In micro-level settings, where analytics act upon individual learners, groups of learners, or a classroom (Shum, 2012b), inaccurate data are highly problematic. Poor data quality leads to inaccurate conclusions that may negatively impact learner engagement, motivation, and performance. Because of this, Mayer-Schonberger and Cukier point out that there are situations that still call for the precise and causal understandings offered by the carefully curated data required in conventional data science (2013).

A brief history. LA came about at the intersection of developments in educational data and advances in computing technologies. Wise and Schaffer (2015) attribute the developments in educational data to two factors: (a) the increasing number of data creators due to the rapid adoption of educational technologies; and (b) the increasing granularity of this data (i.e., the tracking of learners' eye movements as they interact with digital content). Advances in computing technologies come in the form of technical advancements in analytics, data access, and computing power (Wise & Schaffer, 2015). Together, these technical advancements allow anyone with access to a computer the ability to engage in data analysis with or without a data science background (Baker & Siemens, 2014). An analytical project no longer required prohibitive funding or a background in data science and statistics, opening the doors for non-experts to conduct analytics.

Current State of the Field

The Society for Learning Analytics Research (SoLAR) provides the most widely cited definition of learning analytics in the literature (Siemens, 2013). SoLAR's website describes learning analytics as "the measurement, collection, analysis and reporting of data about learners and their contexts, for the purposes of understanding and optimizing learning and the environments in which it occurs" (as cited in Siemens, 2012).

The learning process and the educational context are complex constructs to measure (Suthers & Verbert, 2013). Accordingly, LA emerged as a multidisciplinary field (Ferguson, Brasher, Clow, Cooper, & Hillaire, 2016; Shum, 2012b; Siemens, 2013) with foundations in other, longer established fields (Baker & Siemens, 2014; Dawson, Gasevic, & Joksimović, 2014;

Siemens, 2013) to inform the application of new developments in educational data and computing technologies (Suthers & Verbert, 2013).

Suthers and Verbert (2013) propose the term middle space as a metaphor to describe the scope and nature of the field in the opening address to the 2013 International Learning Analytics & Knowledge (LAK) Conference. The term alludes to the space between the learning sciences and data analytics where LA figuratively resides. Occupying the middle space requires researchers to maintain consistency between the underlying learning theory and the analytical techniques employed (Suthers & Verbert, 2013).

Suthers and Verbert (2013) state that "individuals, small groups, and/or larger collectives may be the agent of learning; and learning may consist of knowledge or skill acquisition, intersubjective meaning-making, or changes in identity and participation in the community, among other processes" (p. 1). They suggest that productive multivocality (the consideration of multiple, often conflicting, perspectives to inform practice) is desired between diverse practices fields, theoretical frames, and methodologies, along with the different perspectives that exist within educational settings. The value of this multidisciplinary view to informing effective LA implementations will become clear when critical perspectives are discussed later in this chapter.

Educational data mining and learning analytics. LA is most closely related to educational data mining (EDM). EDM is interested in "developing, researching, and applying computerized methods to detect patterns in large collections of educational data that would otherwise be hard or impossible to analyze due to the enormous volume of data within which they exist" (Romero & Ventura as cited in Papamitsiou & Economides, 2014, p. 49). While LA involves applying analytics to improve the learning process, EDM emphasizes the discovery of analytical techniques that are capable of deriving insight from the unique attributes in educational data.

Although LA and EDM are recognized in the literature as two distinct fields, they are often addressed side by side in the literature and educational policy documents. Baker and Siemens (2014) view EDM and LA as derivatives of the data mining and analytics fields, which are “methodologies that extract useful and actionable information from large datasets” (p. 1) applied to educational contexts. Similar to Suthers and Verbert, Papamitsiou and Economides (2014) assert that both LA and EDM communities work at the intersection of the learning sciences and data analytics, or, the middle space as coined by Suthers and Verbert (2013).

Papamitsiou and Economides’ (2014) review of LA and EDM applications noted that increases in the volume of educational data along with other improvements in the field have led to greater accuracy in LA/EDM applications. Some of the improvements the authors identify include the use of previously validated algorithmic methods, visualizations that aide data interpretation by teachers and students, more precise user models that provide better adaptive and personalization results, more accurate identification of learning events and patterns, and the ability to derive insights into learning strategies and behaviors. However, these advances are relatively modest considering the sophisticated applications demonstrated in other fields (Dawson et al., 2014).

One critical challenge is that educational datasets are currently insufficient to fully capture the complexity of the learning process (Greller & Drachsler, 2012; Siemens, 2013; Slade & Prinsloo, 2013). This shortcoming restricts the kinds of conclusions that can be drawn from results. Complicating the issue are data silos resulting from the diversity of datasets and sources, privacy concerns, and a lack of standardization that hinder access to, and use of, these educational data (Siemens, 2013). As will be discussed later in this section, these factors result in an over application of predictive analytics which may describe what is happening but fail to accurately inform educational practice (Dawson et al., 2014).

An overview of products. Siemens (2013) describes two categories to of LA products: commercial and research. He further differentiates four kinds of commercial tools: (a) analytical software companies that have adapted their products for educational use; (b) web-based analytical tools that are used for LA (but not specifically adapted for such use); (c) previously existing educational technology software that have added an analytical layer to already available software such as SISs and LMSs; and (d) products designed to integrate with existing LMSs. Shum (2012b) also distinguishes commercial products developed by educational startups as unique, explaining that they are responsible for accelerating the diversity of LA tools available for use in educational settings. Siemens (2013) states that, because research and open analytics tools are typically developed for individual use, they lack systems level support precluding adoption by organizations. However, Shum (2012b) notes that organizational adoption is possible through the combination of commercial services with open datasets and software.

Siemens (2013) identifies techniques and applications as two overlapping components of LA. Siemens notes that, while prominent techniques rely heavily on conventional analytics models, LA researchers are developing a sizable body of analytical models designed specifically to measure learning in educational settings. These models include applications that track learner behaviors to measure attributes such as persistence and attention which learning sciences research has identified to co-occur with academic achievement (Siemens, 2013).

Learning analytics can also be differentiated by context. Shum & Crick (2012) describes these levels as micro-, meso-, and macro-levels which can be associated with classroom, institution, and cross-institutional levels respectively. Further, Siemens (2013) notes that these levels relate to the kinds of data that are available for analysis.

Common applications. Analytics are applied to educational environments in varied ways. Siemens (2013), refers to applications as describing how learning analytics techniques, the underlying algorithms and mathematical models, are deployed within educational settings.

In their survey of LA/EDM empirical studies from 2008-2013, Papamitsiou and Economides (2014) identify seven prevalent learning contexts: virtual learning environments (VLE) and learning management systems (LMS), massive open online courses (MOOC) and social learning environments, web-based education, cognitive tutors, computer-based education, multimodality (diverse learner data types including sensory perceptions and physical movements), and mobility (contexts where mobile devices are the primary learning delivery system). What follows is a description of some of the more prevalent LA applications found within these learning contexts.

Reflection. Greller and Drachsler (2012) describe reflection as "the critical self-evaluation of a data client as indicated by their own datasets to obtain self-knowledge" (p. 47). The authors note that self-reflection is the foundation of the quantified self, which entails using personal data logs to guide next actions. When the quantified self is applied in educational settings, the authors write that personal data logs often include performance data for another group. For example, for teachers to reflect on their instructional practices they must refer to student performance data to guide future pedagogical choices. Chatti et al. (2012) assert that student facing reflection tools are potentially valuable LA applications that lead to self-guided and self-reflective learning.

Prediction. The most common application of LA is predictive analytics (Gasevic & Dawson, 2014). Predictive analytics was also the first application to educational datasets and tied to its beginnings in big data analytics and business intelligence practices (Shum, 2012b). Prediction is the essence of big data practices and involves applying mathematical formulas to big datasets to derive probabilities (Mayer-Schonberger & Cukier, 2013). Although predictive models reveal what may happen, they do not provide insights into why it may happen (Mayer-Schonberger & Cukier, 2013). Thus, predictive analytics are descriptive and do not indicate which actions to take based on the results.

In educational settings, predictive analytics are widely viewed to provide an important opportunity to model learning activities through the development of learner profiles (Greller & Drachsler, 2012; Siemens, 2013). Learner profiles are developed based on data captured by student information systems, learning management systems, and other educational settings. It is hoped that learner profiles can be used to anticipate learner preferences and needs accurately, thereby personalizing the learning experience for individual learners (Greller & Drachsler, 2012). When applied in this way, it is believed that predictions would lead to earlier interventions and critical adaptations to curriculum or services provided to learners (Pea, 2014) and offer equitable access to quality education for every student (Freeman et al., 2017). Because predictions become more accurate with increasing volumes of data to analyze (Papamitsiou & Economides, 2014), in education, learner profiles will become increasingly accurate as educational datasets grow. Learner profiles are critical to deploying personalized learning which is an approach that aims to improve the learning experience by adapting and/or modifying activities.

Personalized learning. The 2017 National Technology Plan (U.S. Department of Education, 2017) defines personalized learning as "instruction in which the pace of learning and the instructional approach are optimized for the needs of each learner" (U.S. Department of Education, 2017, p. 9). The plan adds that adaptations are often learner initiated, and lists learning objectives, instructional approaches, sequencing, and instructional content as features of instruction that may be adapted based on learner preferences. Chatti et al. identify two adaptive approaches to deploying personalized learning - adaptivity and adaptability. The authors note that, whereas adaptivity is an approach that allows intelligent systems to modify course materials according to predetermined specifications, an adaptability-based approach to personalized learning allows learners to drive their own experience.

Systems based on adaptability are called personalized learning environments (PLE) (Chatti et al., 2012). They conclude that, because PLEs are based on adaptability, learners are not forced to follow learning pathways defined by a teacher or institution. PLEs use recommender systems to suggest potential activities for learners to pursue and are based on learner profiles (Chatti et al., 2012). Personalized learning is believed to potentially lower cost while leading to more effective learning environments (Greller & Drachsler, 2012). It is also viewed to lead to more equitable access to quality education for all students, thus, diminishing the opportunity gap prevalent in education (Pea, 2014). Pea (2014), asserts that understanding how to develop personalized learning systems is the main priority of LA research. Likewise, policy documents continue to promote personalized learning as central to educational practice. The U.S. Department of Education identified the advancement of personalized student learning and, separately, personalized professional learning, as two of the four key focus areas of effective leadership exhibited by future ready leaders (U.S. Department of Education, 2017).

Although personalized learning is a promising approach to improving learning experiences, there are, not insignificant, risks associated with the underlying techniques and the quality of existing educational datasets. These concerns are acknowledged within the LA community as well as by policy documents and are addressed later in this chapter.

Recommender systems. Chatti et al. (2012) describe recommender systems as those that collect and analyze data about a learner's use patterns to recommend well suited items. As mentioned earlier, recommender systems are one of the critical applications that are involved in personalized learning environments (PLE). Recommendations may be content based or based on the content preferred by other users with similar use patterns (Chatti et al., 2012).

LMS/VLE analytics dashboards. Visualization of data through dashboards are another very common application of LA. Dashboards are "data logs…rendered via a range of graphs, tables and other visualizations, and custom reports designed for consumption by learners, educators, administrators and data analysts" (Shum, 2012b, p. 4). Similar to predictive analytics', dashboard applications in LA are also grounded in business intelligence. In fact, Shum (2012b) describes dashboards as business intelligence deployed on learning platforms. Just like predictive analytics, dashboards do not provide direction on how to act on the information presented and require the end-user to possess data competencies to make sense of the visual displays. The level of data competency required depends on the dashboard's degree of complexity. More advanced dashboards that may, for example, access and integrate data from multiple sources, are capable of revealing more nuanced insights. However, they also require advanced data competencies as end users must be able to manipulate the data themselves to reveal relationships between variables (Shum, 2012).

Current challenges. The challenges listed here are those proposed by Pea (2014) to enable effective personalized learning environments. They are meant to be representative rather than an exhaustive examination of what is required for accurate analytics applications in general and for personalized learning environments in particular. It offers an idea of the kind of data environment required for effective LA implementations. This understanding is intended to inform the reader regarding the level of accuracy that may be expected from an LA tool. What follows is a discussion of the limitations posed by incomplete and inaccurate datasets based on Pea's three grand challenges for the LA field.

Mapping learning to standards. It is widely documented that technology adoption and regular use are a problem in educational technology adoption. Too often, educational technologies are purchased and not used or unevenly used by teachers (Monroy & Rangel, 2014). Much of this is due to misalignment between the tool and the daily context under which teachers operate (Monroy & Rangel, 2014). Tools must be calibrated against the realities impacting the professional experience of educators (Monroy & Rangel, 2014) much of which is tied to educational policies and district mandates. One of the main drivers of educational practice for teachers are state mandated standards. Tying learning progressions to their corresponding standard would both enable adoption and allow for deeper understandings of learning progressions as they relate to how learning is described in standards.

Need for systemized assessments. Pea suggests that mapping standards to corresponding summative and formative assessments would enable pedagogical recommendations based on evaluations of student mastery levels. This challenge entails identifying assessments that are valid, reliable, and engaging that may also be created by teachers or selected by teachers from a list of potentially relevant assessments.

Need for varied data. Chatti et al. assert that the main barrier to deploying personalized learning is creating a comprehensive polytextual model (2012). The authors use the term polytextual to indicate a model that integrates a diverse range of learning modalities, formal, and informal contexts. Pea (2014), like Chatti et al. also prioritizes developing the capacity to capture contextual data in learning environments. He lists examples of contextual data to include gesture, speech, spatial position, affect, and other variables that can be captured from sensors or tracked using video records.

Technical challenges. Monroy and Rangel (2014) identify a number of technical challenges associated with implementing LA in K-12 environments. In particular, they note that LA implementations are highly influenced by teacher adoption, which, in turn, is subject to time constraints that preclude teachers from learning new software and strategies that require them to implement new classroom management procedures.

Gaps in access to technology are widely acknowledged as a problem that can deepen the inequities that already exist in access to quality education (Monroy & Rangel, 2014; U.S. Department of Education, 2017). Additionally, there are logistical inconsistencies in the manner in which teachers implement educational technology. For example, Monroy and Rangel (2014) observe that teachers and students often share accounts, a practice which impacts what activities they can engage with online and how the data is recorded within the system. Greller and Drachsler (Greller & Drachsler, 2012) share a similar perspective noting that these kinds of behaviors, including the creation of test students and courses in an LMS, produce inaccurate datasets. Greller and Drachsler describe another problem with data quality pertaining to enmeshed identities, a term that describes the inability to distinguish between individual and collaborative or group activities in datasets. These are a few ways that behaviors around LA in practice are not accounted for in the analytics process, making educational datasets an unreliable source for LA applications as well as large scale pattern detection.

Critical Concerns

Big data principles are fast becoming the underlying structure driving modern life. Big data's influence is pervasive, appearing across industries and practice fields and meeting little resistance. Big data's virtually ubiquitous presence is accompanied by widespread confusion regarding what defines big data and distinguishes it from previously existing datasets (Boyd & Crawford, 2012). Along with this confusion is a false belief that data, by nature, is infallible (Boyd & Crawford, 2012). Given that education is rapidly becoming a data pervaded discipline, the lack of understanding around data has significant ramifications and may serve to further entrench the opportunity gaps that currently exist (Edwards & Fenwick, 2016).

Attempting to address these misunderstandings, Siemens (2012) emphasizes that the "hype and buzz" (p. 4) around big data should be addressed alongside clear messages that speak to the capabilities and limitations of LA applications. While the previous section spoke to some of the capabilities of LA, this section aims to address critical concerns associated with LA applications. Some of these concerns were addressed in the introduction to this study proposal. Specifically, the research to practice gap, the lack of data competency among educational data practitioners, problems associated with the proprietary nature of market-driven educational technologies, and the conflicts arising from startup and venture capital influences. While they are not re-addressed here, they should also be considered as part of the discussion below.

Data is biased. Data, inherently, is biased in two critical ways. First, it is biased because it is not fully representative. Greller and Drachsler (2012) point out that the data that is not present is as important, and may be more important, than the data that is represented. Secondly, it is biased because of the sequence of choices and interpretations that are necessary during the analytical process. While the former premise that current educational datasets are non-exhaustive is fairly evident, the second argument for bias in data may require more discussion as computational scientists have a tendency to claim objectivity due to analytics being based on mathematical models (Boyd & Crawford, 2012). Boyd and Crawford (2012) note that, despite the quantitative approach to analytics, working with data requires some level of choice and interpretation. The decisions lead to bias on some level.

Boyd and Crawford observe that, while traditional data science acknowledges and draws attention to the inherent biases in data, the rhetoric around big data applications rarely address the bias inherent in every decision made throughout the data analysis process (Boyd & Crawford, 2012). The authors posit that the categories used to differentiate data types advantage certain perspectives over others (2012). For example, the use of gender as a qualifying characteristic leads analysts to view the topic being studied from the perspective of gender. The authors state that:

> Interpretation is at the center of data analysis. Regardless of the size of a dataset, it is subject to limitation and bias. Without those biases and limitations being understood and outlined, misinterpretation is the result. Data analysis is most effective when researchers take account of the complex methodological processes that underlie the analysis of that data. (p. 668)

Human tendencies. Boyd and Crawford also point out that vast amounts of data encourage the human tendency to see patterns where they don’t exist (2012). Wise and Schaffer (2015), like Boyd and Crawford, also address this concern. The authors describe how theory can be applied to mitigate the issues that arise when working with large volumes of data. In fact, theoretical groundings are critical to effective LA implementations. However, LA tools generally demonstrate a lack of theoretical groundings, further contributing to potential inaccuracies in LA implementations.

Research to practice gap. On June 23, 2008, then Wired Magazine Editor in Chief Chris Anderson published a controversial article signaling “the end of theory” in which he asserted that the era of big data signaled an end to the need for the scientific method and the application of theory towards uncovering knowledge because “the numbers speak for themselves” (Anderson 2008 as cited in Pigliucci, 2009). Anderson’s statement, made early in the emergence of the big data phenomenon, seems to have been premature. In education, it appears that an over reliance on data alone results in what Monroy and Rangel (2014) describe as a “growing sense that many recent educational technology and big data initiatives are detached from what we know about teaching and learning” (p. 95). They argue that the detachment indicates an urgent need to apply knowledge gained in education research towards LA design and implementation (2014).

Data alone cannot improve educational practices because, like Knight, Shum, and Littleton (2014) argue, LA applications are effective to the extent that the pedagogical foundations on which they are based are already effective at improving learning outcomes for students. This is because LA tools capabilities lie in making what is currently being implemented more efficient. It currently does not address potential limitations in the applied pedagogical approach that may be problematic factors in student achievement. Furthermore, they argue that only changes to pedagogical practices can improve student performance (2014).

Likewise, Wise and Schaffer (2015) offer a compelling argument that, rather than becoming obsolete, the age of big data makes the application of theory more vital than ever before. They propose that theory is relevant to LA applications in the following ways: isolating meaningful variables, determining relevant subgroups and categories, interpreting results, informing action, and generalizing results (Wise & Schaffer, 2015). Theory's role in big data analytics is to guide meaning making throughout the analytical process.

Bias in techniques and applications. The biases inherent in data were previously addressed as a concern for LA applications. This section points to the biases contained within LA techniques and applications due to inherent data attributes, or what is called data personality in this study. Hildebrandt, notes that "invisible biases, based on...assumptions...are inevitably embodied in the algorithms that generate the patterns" (Greller & Drachsler, 2012).

Data is deterministic. Algorithmic bias is introduced by the capabilities and limitations of computational technologies alongside the kinds of data that are available in educational settings. Algorithms reduce the complexity of real world phenomena to a "manageable set of variables" (Greller & Drachsler, 2012). Applying a data lens to the learning process limits the way we think about and act within education to what can be quantified and measured (Knight et al., 2014). In turn, what can be measured is shaped by the design of the analytical tools applied. Because of the limitations of current datasets, Fenwick and Edwards (Edwards & Fenwick, 2016) observe that computers are incapable of considering ethical nuances, cultural considerations, and other complex societal structures that impact the context under analysis.

Knight and Shum (2017) propose that it is important to be cognizant of the "risks of distorting our definition of 'learning' in our desire to track it computationally" additionally, "we must unpick what is at stake when classification schemes, machine learning, recommendation algorithms, and visualizations mediate the relationships between educators, learners, policymakers, and researchers" (p. 17).

The risks Knight and Shum refer to relate to constraints presented by available technology (hardware) and the design of the technology applications (software). One such risk is that assessments will be defined by the capabilities of the technology rather than what best serves as evidence of student learning. For example, assessments will be designed according to the kinds of input that a particular tool was designed to process rather than by best practices. Because of this, Knight and Shum argue that, far from providing objective measurements, “deploying a given learning analytics tool expresses a commitment to a particular educational worldview, designed to nurture particular kinds of learners” (p. 18).

Data approximates. Predictive analytics are the drivers of personalized learning through the development of learning profiles. However, the reliability of LA-supported learner profiles have questionable applicability due to the inability for educational data to fully capture the complexity of the learning process (Greller & Drachsler, 2012; Siemens, 2012). Siemens (2013) warns that, “the learning process is essentially social and cannot be completely reduced to algorithms” (p. 1395), consequently, it is not clear how reliable LA data will be in developing learner profiles or how useful these profiles will be (Greller & Drachsler, 2012). Greller and Drachsler (2012) pose additional questions regarding the ability of data to reveal how a particular learning activity impacted the learning process for individual learners due to the diverse ways in which learners approach knowledge and skill acquisition. These critical data problems have not deterred the development of personalized learning products which depend on learner profiles to drive their algorithms.

Datasets are historical by nature. Greller and Drachsler (2012) caution against the use of predictive analytics to infer judgments about learners because it may limit the learner’s potential. As Fenwick and Edwards (2016) note, algorithms privilege information that have already occurred and have been previously recorded. Consequently, the authors argue, they are incapable of predicting occurrences that have not been previously accounted for (2016). Likewise, Siemens (2013) notes that analytics "is about identifying what already exists" (p. 1395). In other words, they will never suggest an event that is not already represented in the data. This has negative implications for educational applications, such as planning future courses for students (Edwards & Fenwick, 2016). If the data that exists includes demographics such as race, gender, and socio-economic status, then these applications "can be self-reinforcing and reproductive, augmenting path dependency and entrenching existing inequities" (Edwards & Fenwick, 2016, p. 71).

Data is biased. Knight, Shum, and Littleton (2014) argue that LA applications privilege particular pedagogical and epistemological perspectives due to the kinds of assessments they contain. LA products, by design, are assessment orientated tools (Knight et al., 2014). As such, the authors conclude that the type of assessment employed by a particular tool necessarily evokes a particular pedagogical practice and, consequently, the underlying epistemological understanding.

Over-reliance on quantitative methods. As described in the previous section, common LA applications fall under predictive analytics and dashboard applications. Both applications are quantitative approaches that lead to descriptive results and fall short of providing insights that lead to informed practice (Baker & Siemens, 2013). Descriptive reports do little to support decision making. Therefore, they require educators to have well developed data competency to interpret results accurately (Papamitsiou & Economides, 2014). The reliance on human judgment combined with a general lack of data competency among educational data practitioners easily leads to misinterpretation of the data (Papamitsiou & Economides, 2014).

The prevalence of quantitative approaches to LA is not surprising given LA's roots in big data analytics. Yet the lack of methodological diversity is one of the current shortcomings of big data analytics practices (Edwards & Fenwick, 2016). In fact, Mayer-Schonberger and Cukier (2013) assert that "big data is about predictions" (p. 19). As previously mentioned, the authors also note that big data offers descriptive results without indicating causality. So, although big data results in patterns and correlations that reveal what is happening, it does not provide insight into why something is happening (Mayer-Schonberger & Cukier, 2013).

It is exactly this characteristic of big data analytics that lead many authors to point out that LA, to date, has fallen short of the critical challenge in education which is to move beyond diagnosing a condition to informing educational practice (Baker & Siemens, 2014; Dawson et al., 2014; Papamitsiou & Economides, 2014). As mentioned in this study's introduction, big data applied to small scale analytics results in inaccuracies and are less suitable for micro-level applications, which need to be accurate to be useful (Mayer-Schonberger & Cukier, 2013).

Prevalence of quantitative analysis related to data access and use. Siemens and Baker (Baker & Siemens, 2014) attribute the reliance on predictive analytics in LA in part to the complexity of the educational landscape. Likewise, Dawson, Gasevic, Siemens, and Joksimović (2014) also point to the "social, technical and cultural problems that pervade the education sector" (p. 231) as a main reason for the lack of advancement in big data applications in education compared to more sophisticated approaches used in other fields.

Barriers to advancements in LA include, but are not limited to, factors such as data silos and privacy concerns. The complexity of the landscape results in research that utilizes readily available data found in LMSs and SISs in combination with basic demographical traits (Dawson et al., 2014). These kinds of studies tend to be the easiest to perform with most research questions associated with identifying key factors leading to student retention and academic performance (Dawson et al., 2014). In other words, these LA applications are largely focused on identifying students ‘at risk’ of a particular undesirable academic event. While predictive applications can indicate that an intervention is required, it does not reveal what kinds of interventions may be helpful. This is because variables that indicate the need for particular interventions are yet to be defined. Indeed, Siemens (2013) asserts that the biggest challenges in LA are not technical ones. The most significant concerns involve the quality and completeness of educational datasets to capture the learning experience, privacy, and ethics (as cited in Siemens, 2013; Slade & Prinsloo, 2013).

Changes to professional responsibilities. Fenwick and Edwards (Edwards & Fenwick, 2016) assert that big data analytics raises new questions about professional agency and accountability. The authors posit that while big data applications may provide benefits such as creating efficiencies and improving services, they appear alongside potentially troubling concerns that change the nature of daily professional practices and responsibilities in ways that are not yet understood (2016).

As mentioned earlier in this chapter, algorithmic reduction of knowledge and reliance on comparison and prediction are potentially problematic characteristics of big data applications. Fenwick and Edwards argue that these characteristics elicit fundamental shifts in professional accountability (2016). Big data relies on automated processes that occur without the supervision of professional practitioners. These processes are meant to drive decision making and inform action, functions that were previously dependent upon professional judgment based on experience and expertise (Mcafee & Brynjolfsson, 2012; Siemens & Long, 2011). Fenwick and Edwards assert that this shift confuses how accountability is measured in the workplace creating fundamental changes to professional practices, professional learning, and the nature of work (2016).

However, Papamitsiou and Economides (2014) report that LA/EDM applications are not yet fully automated. Therefore, they rely on human judgment identify human judgment as a decisive factor leading to misinterpretation of data in schools. They state that, currently, only those teachers with a high level of data competency could interpret LA results accurately.

The points raised by Fenwick and Edwards are echoed by the 2017 NMC/CoSN Horizons Report for K-12 (Freeman et al., 2017). The report lists re-conceptualizing the role of teachers as one of the significant challenges impeding technology adoption with no current solutions. The report asserts that "educators are moving beyond dispensing information and assessing students' knowledge, which are tasks that can be increasingly outsourced to machines" (2017, p. 30) and list data competencies as one of the skillsets that must be addressed by pre-service teacher training programs.

Data-driven instruction in practice. The theoretically derived concerns listed in this section do, indeed, play out in real world practice. In a study conducted across nine New York public schools, Neuman (2016) found that data-driven instructional practices negatively affect students who require the most support. She argues that in data-driven instructional contexts, "vulnerable students are measured, examined, rubricated, labeled — and denied the meaningful instruction they need" (p. 24).

Neuman (2016) observes that instruction is based on pedagogical practices that Knight et al. (2014) list as transactional or instructionalist approaches. She argues that the instructional practices she observed were insufficient to provide meaningful learning experiences. As Knight et al. propose, only changes to pedagogical practices can improve learning outcomes. Neuman also observes that the data-driven practices privilege an “instructional regime that’s bereft of content and meaningful instruction” (p. 25). Likewise, Knight et al. conclude that “the types of analytic we chose to deploy, and the ways in which we deploy them implicate particular approaches to learning and assessment” (p. 29).

Neuman (2016) reports that data-driven instruction, in practice, has not realized the promise of greater efficiencies or improved outcomes for students. Rather, she writes that one of the schools she observed saw a decrease in student English language arts scores from the 13th to the 8th percentile in the year since data-driven instructional practices were implemented. On a national level, she points out that, although it’s been over a decade since data-driven practices have been mandated in education, reading achievement scores have not improved and have declined for struggling readers. Finally, Neuman offers recommendations for correcting the problems appearing in the schools she observed. They address many of the concerns listed above including, data quality, detaching instruction from standardized testing, and reorienting how teachers engage with and use student data in their daily practice.

Neuman’s (2016) study makes it clear that misunderstandings about data due to a lack of data competency is most harmful to the most vulnerable students. Given these outcomes, policymakers and district leaders have relinquished their focus on standardized testing. Every Student Succeeds Act (ESSA), for instance, allows state boards to submit their own custom evaluation plans that consider diverse metrics.

Section summary. This section provided a review of some of the main concerns associated with LA implementations in educational settings. As mentioned in the introduction, data use in schools is not a new phenomenon. However, the rapid adoption of learning analytics requires caution. The implications for students of being “defined by numbers, compared to others, collected, classified, and sorted into categories" (Smith, 2016, p. 10) is unclear. The current context requires a clear understanding of the dynamics of educational datasets alongside knowledge around the capabilities and limitations of computing technologies. The consequences of failing in this task are substantial. Rather than solving the challenges faced in education settings, these challenges may become more deeply entrenched within educational systems. Inequities may be extended rather than reduced, resulting in a widening of the opportunity gap (Neuman, 2016). Finally, a unique opportunity to develop a more inclusive model for educating diverse learners may be lost.

Frameworks

The following frameworks describe attributes of LA from different orientations. For example, a framework may be aimed towards supporting LA tool design while another may be geared towards developing researchers' understandings around the factors affecting LA research and implementation. Some of the work included in this section do not call themselves frameworks, but were included because they present a model important for the purposes of this study. What is absent from this selection are frameworks aimed towards educational practitioners, i.e., those who are tasked with implementing LA in their daily practice (Wise et al., 2016). Wise and Vytasek note that the perspective of educational practitioners has remained largely ignored in the literature.

Shum (2012) institutional impact levels. Shum (2012b) offers a comprehensive description of the LA landscape from a high-level perspective. He divides LA into macro-, meso-, and micro-levels to provide a context for understanding how LA functions across institutional levels. Shum's model indicates that integration of datasets across these three levels are mutually beneficial. These levels are summarized in Table 1 and described in more detail below.

Macro-level analytics. Shum defines macro-level analytics as enablement of cross-institutional analytics. At this level, LA can provide insight by uncovering patterns and correlations between institutional practices and, for instance, identified success metrics. Insights gained at this level could identify beneficial practices or combinations of practices for particular environments. As mentioned in this study's Introduction, Mayer-Schonberg and Cukier (2013) suggest that big data analytics are well-suited to deriving insights at this level.

Meso-level analytics. The meso-level indicates analytics applied at the institutional layer. LA applications at the mess-level focus on building operational efficiencies within a particular educational organization.

Micro-level analytics. Micro-level analytics operate at the individual or group level. Data collected at this level are the most granular, detailed, and personal. It can include data such as clickstreams, geolocation, library activities, and interpersonal data related to social networks. Shum reports that techniques adapted from diverse fields such as serious gaming, EDM, recommender systems, computer supported collaborative learning, social network analysis, and intelligent tutoring systems function at the micro-level.

Benefits of this perspective towards conceptualizing the LA landscape. This study's introduction described critical features of big data practices and how those features impact epistemological understandings. It offered an understanding of big data as being more appropriate for certain contexts and particular purposes. Although big data can offer impact at each of the levels Shum identifies, it is important to consider how big data analytics function in different data environments and assess the risk involved in particular applications at the micro- and meso- levels.

Table 1

Shum (2012) Institutional Impact Levels

Construct	Dimension	Examples
Macro	Across institutions	District or statewide projects
Meso	Institutional	Operational and process based analysis to increase efficiencies
Micro	Classroom or individual learner	Aimed at improving the learning experience at the individual or group level

Chatti et al. (2012) a reference model for learning analytics. Chatti, Dyckhoff, Schroeder, and Thüs (2012) describe the function of the LA approach as one that moves from data to analysis to action, resulting in learning. The authors propose a reference model for LA that focuses on the following four dimensions: what, who, why, and how. The framework is summarized in Table 2 and described in more detail below.

(What) kinds of data are used in the analysis. Chatti et al. distinguish two categories of educational data by their source: centralized education systems and distributed learning environments. Centralized education systems are those that collect student data within one system. LMSs are representative of a centralized system. In contrast, distributed learning environments refer to educational data created across multiple settings and systems. Personalized learning environments (PLEs) represent this type of educational data. Educational data from distributed sources are created in both formal and informal learning activities and may be highly varied. The authors suggest that it is the data that are created from distributed sources that offer an opportunity to lead to more comprehensive data for individual learners which, in turn, results in increased accuracy for LA implementations. Datasets from distributed learning environments also may exhibit the characteristics of big data sets and can lead to real-time feedback to guide self-regulated learning.

(Who) the analysis is being performed for. Different stakeholders include students, teachers, intelligent tutors, tutors/mentors, educational institutions (i.e., administrators and other decision-makers). Tools aimed at stakeholders should offer goal-oriented feedback, opportunities for self-awareness or reflection, and support decision-making (Chatti et al., 2012). Chatti et al. describe the number and hierarchy of stakeholders as a potential conflict in the design of LA tools and advise that stakeholder involvement, particularly that of teachers and learners, as critical to tool adoption in educational settings. The authors suggest that involving and supporting all stakeholder interests as a difficult problem that needs to be solved.

(Why) the analysis is performed. The why dimension in the LA reference model corresponds to what Siemens (2013) refers to as applications in his LA model. These include monitoring, analysis, prediction, intervention, tutoring/mentoring, assessment, feedback, adaptation, personalization, recommendation, and reflection. The Why dimension varies according to Who the analysis aims to serve.

(How) the analysis is performed. The how dimension maps to what Siemens (Siemens, 2013) calls techniques, or the underlying algorithms or mathematical models applied to the analysis. Four techniques are recognized by the authors: statistics, information visualization, data mining, and social network analysis.

Statistics. Statistics refers to tracking use patterns within a system. Examples include frequency, duration, total visits, distribution of visits over time, the percentage of material read, and statistics associated with forum posts.

Information visualization. Information visualization refers to descriptive statistics presented on dashboards. These may come in the form of charts, scatterplots, 3D representations, and maps among others. Although visualizations can be a powerful way of presenting data comprehensively, the authors caution that dashboards are challenged to identify the kinds of visual representations that align with analytics objectives.

Data mining. Also referred to in this model as knowledge discovery in databases (KDD) and fall into three general categories: supervised (classification, prediction), unsupervised (clustering), and association rule mining.

Social network analysis. These are quantitative techniques that manage, visualize, and analyze relationships between individuals or organizations.

Learning analytics process. Chatti et al. (2012) describe a circular three-stage process for LA: data collection and pre-processing, analytics and action, and post-processing. The post-processing stage subsequently informs decisions made in the following cycle and so forth. The iterative process allows the classroom teacher (or the LA algorithm) to make continual improvements to their teaching practices. In this way, LA is closely aligned with the process involved in action research, a field the authors identify as being closely aligned with LA. Continual improvements to instruction are also closely aligned with personalized learning environments and are recognized as one of the more valuable outcomes for LA implementations.

Table 2

Chatti et al. (2012) A Reference Model for Learning Analytics

Construct	Dimension	Examples
Data and environments (what?)	Sources of educational data; centralized educational systems (LMS) vs. distributed learning environments (PLE diverse sources of data)	SIS, social media, web-based courses, LMS, adaptive intelligent systems (including intelligent tutors), adaptive hypermedia systems, PLEs, open datasets
Stakeholders (who?)	Orientation of LA applications	students, teachers, intelligent tutors/mentors, educational institutions, administrators, researchers, system designers, expectations from the LA exercise
Objectives (why?)	The goal of the application	monitoring and analysis, prediction and intervention, tutoring and mentoring, assessment and feedback, adaptation, personalization, and recommendation
Methods (how?)	Techniques used to achieve objectives	statistics, information visualization, data mining (classification, clustering association rule mining), social network analysis

Greller and Drachsler (2012) design framework for learning analytics. Greller and Drachsler's (2012) design framework provides a guide for designing LA applications that considers soft barriers to effective implementations. The authors characterize soft barriers as "challenges that depend on assumptions being made about humans or the society in general, e.g., competencies or ethics" (2012, p. 43). In contrast, the authors describe hard barriers as challenges that relate to data environments and analysis. The framework is summarized in Table 3 and described in more detail below.

Methods used to develop the framework. Greller and Drachsler (2012) used a general morphological analysis approach to identify six critical dimensions from discussions collected from the emerging LA research community. To further develop their framework, they collected and analyzed discussions from 2011 and 2012 Learning and Knowledge Analytics Conference (LAK) proceedings and presentations, conducted a brief literature review of abstracts from LA and EDM literature, scanned live discussions on LA google groups and the 2011 LAK MOOC presentation chats and social network posts, and reviewed RTD projects containing elements of analytics. They then applied cognitive mapping to develop a preliminary framework which was evaluated by commercial and academic experts whose feedback led to the framework presented here.

Summary of the framework. Greller and Drachsler (2012) describe their framework as one intended to guide LA tool design and describe challenges associated with their development. They suggest that the framework is inclusive in that it can be used to transfer LA approaches between diverse applications and research contexts.

The framework consists of six critical dimensions supplemented by examples of each. The dimensions identified are stakeholders, objectives, data, instruments, external constraints, and internal limitations. Descriptions of each dimension follow.

Stakeholders. Stakeholders are categorized into data clients and data subjects. Data clients refer to the intended recipients of the results. Data subjects refer to those who create the data that is collected and analyzed by a particular LA tool. Greller and Drachsler identify learners, teachers, and educational institutions as predominant stakeholder groups in formal education settings.

Objectives. Greller and Drachsler suggest that domain specific objectives in LA relate to revealing and providing context for valuable insights derived from educational datasets. They distinguish two objectives they consider to be relevant to LA applications: reflection and prediction. These applications were addressed earlier in this chapter in the discussion on common applications of LA and will not be described again here.

Data. Educational data includes datasets from LMSs and other educational technologies that automatically collect and store data. The authors emphasize distinctions based on the accessibility of the dataset. They assert that the integrity of educational sets is the biggest technical challenge in LA. This is due to inconsistent practices in educational technology implementations and uneven technology adoption. The authors also point out that the available datasets are insufficient to inform pedagogical practices.

Instruments. Greller and Drachsler present an inclusive view of LA techniques. They consider these to include conventional data science practices as well as those associated with big data analytics. In their framework, instrument is a flexible term that can refer to a particular pedagogical practice along with other conceptual or technical tools used to implement LA.

External constraints. External constraints are distinguished as conventions or norms. Conventions include ethics, privacy issues, and other societal restrictions while norms refer to limitations imposed by laws, policies, or institutional mandates.

Internal limitations. Internal limitations refer to human factors that impact LA effectiveness. The authors highlight two main limitations: competences and acceptance. Competencies refer to the knowledge and skills required to effectively interpret LA results while acceptance refers to issues related to technology adoption.

Table 3

Greller and Draschler (2012) Design Framework for Learning Analytics

Construct	Dimension	Examples
Instruments	Technologies that support objectives including theoretical frameworks, algorithms, and 'weightings' or different ways to approach data	Can be tangible or intangible tools such as pedagogy employed, and techniques used within the instructional design
Objectives	Purpose of the application	Authors identify two kinds: reflection and prediction
Data	Data from available educational datasets and data produced from LMSs and other systems	Primarily impacted by accessibility levels
Stakeholders	data clients: beneficiaries of the LA process who are meant to act upon the outcome data subjects: suppliers of data	Learners, teachers, administrators, educational institutions
Internal limitations	human factors that enable or pose obstacles to implementation	Data competencies and technology acceptance
External constraints	Conventions and norms that impact implementation	Ethics, privacy, laws, policies, standards

Siemens (2013) learning analytics model. Siemens (2013) provides an LA model that represents a systems approach to analytics. Siemens asserts that a systemic approach allows for automating support resources that support interventions at scale by reducing the need for human action. Siemens' model is an approach to automating interventions aimed at higher education institutions based on quantitative methods. It is included here because these approaches are increasingly being developed for LA products for K12 settings. The framework is summarized in Table 3 and a brief discussion follows.

Siemens (2013) describes seven components in his LA model: collection, storage, data cleaning, integration, analysis, representation and visualization, and action. He asserts that the collective skills and knowledge required to apply a systematic analytics approach is unlikely to occur in a single individual. Consequently, Siemens emphasizes the central role of a five person data team consisting of a relevant stakeholder, data scientist, programmer, statistician, and end-user experience specialist who can design relevant visualization and reports.

Table 4

Siemens (2013) Learning Analytics Model

Stage	Dimension	Related/driving concepts
Data Loop	Collection and acquisition	Educational purpose, distributed learning environments, data quality, data completeness
	Storage	Privacy and ethics
	Cleaning	Structured and unstructured data
	Integration	Distributed datasets, varied formats
	Analysis	Applied tools and techniques
	Representation and visualization	Dashboards, reports
	Action	Intervention, optimization, alerts and warning, guiding/nudging, systemic improvements (to learning design, to teaching)
Data Team	Stakeholder (practitioner)	Provides domain and context expertise
	Data scientist	Provides analytics expertise
	Programmer	Translates analysis into code and reports
	Statistician	Provides mathematical expertise
	UX designer	Provides UX expertise to develop a visualization of results and reports
Category	Description	Examples
Levels	Contexts of LA use defined by access to different kinds of data	Macro, meso, micro levels
Techniques	Underlying algorithms and mathematical models used to conduct the analysis	Prediction, clustering, relationship mining, distillation of data for human judgment, discovery with models
Applications	How techniques are applied to the educational setting	Modeling user knowledge, behavior, and experience; user profiles; modeling knowledge domains; trend analysis; personalizing user experience
Commercial Tools	Market-driven products, startups, venture capital funding	Analytical software companies; web-based analytics tools not specific to LA, edtech with an analytical layer, LA products designed to integrate with lmss
Research Tools	Developed by the research community and open source	Created for research or by researchers primarily at higher education institutions

Knight, Shum, and Littleton (2014) epistemology, assessment, and pedagogy (EPA) triad. The perspective of the epistemology (how knowledge is defined and acquired), pedagogy (instructional methods and practices), and assessment triad as advanced by Knight, Shum, and Littleton (2014) provides the framework for mapping learning analytics applications to their corresponding pedagogical approaches and epistemological perspectives. The epistemology, assessment, and pedagogy triad refers to the relatedness of the three concepts. Knight et al. (2014) argue that conventional exams are designed to produce reliable results by severely limiting what is defined as learning and, consequently, what can be accepted as evidence that learning took place. They advance a pragmatic, socio-cultural perspective of assessment where "the content of a specific item of knowledge depends in part on how it is related to other knowledge" (Knight et al., 2014). From this perspective, evidence of learning moves beyond measuring congruence between a learner's claim and a body of given content to a focus on contextual factors to understand how learning occurs. Ultimately, the authors advance a pragmatic, socio-cultural approach to LA as a means to more accurately assess student performance and provide nuanced, meaningful insights to guide pedagogical practices. The EPA model they present is intended to identify how LA tools manifest particular assessment regimes, pedagogies, and epistemic stances. The framework is summarized in Table 5 and described in more detail below.

Table 5

Knight et al. (2013) EPA Triad

Construct	Dimension	Examples
Epistemological	The nature of knowledge	accreditation
Pedagogical	Teaching practice	pragmatist, socio-cultural, instructional
Assessment	The LA tool	based on matching student claims to given information, or process orientated

Pedagogical indicators in LA tools. Within the model, learning analytics falls under assessment within the triad. The researchers posit that learning analytics by intentional design, either explicitly or implicitly, promote a corresponding assessment regime, or, an established system of assessment. Standardized tests are one example of an assessment regime.

The resulting model describes how learning analytics, as an assessment tool, correspond to specific epistemological and pedagogical perspectives. The authors offer a brief overview of how LA tools may indicate a number of prominent pedagogical approaches. These are summarized in Table 6.

Epistemological indicators in LA tools. The authors also identify epistemological stances of LA tools by distinguishing accreditation methods employed by a particular tool. Accreditation, as it relates to particular epistemological stances, refer to when knowledge may be claimed to be mastered and when it is not. Their analysis of the relationship of certain pedagogical approaches to LA tools signals three ways that LA tools may address accreditation.

Mastering curriculum content. This approach to accreditation is currently the most frequently applied. It uses e-assessment technologies to identify particular behavioral markers which are then used to create summaries for individual learners and groups of learners. This accreditation model is related to transactional and some constructivist pedagogies.

Evidencing membership and processes. Accreditation related to this approach involves behavioral markers that demonstrate membership in a particular subgroup. Subgroups are seen to be successful or not, and positive feedback is a mechanism for encouraging students to move into successful subgroups. This accreditation model relates to affect based, apprenticeship, and sometimes connectivist approaches.

Success in use. This accreditation approach looks for evidence of learning in a student's collective representations of curriculum content and how they make sense of this material alongside their personal analytics. Social learning analytics are an example of this approach. This accreditation model relates to connectivist and pragmatic pedagogies.

Table 6

Pedagogies Defined and Linked to LA Indicators (Knight et al., 2014)

Pedagogy	Description	LA Indicators	Accreditation
Transactional or Instructionalist	Learning is viewed as the transfer of knowledge from teacher to student that is assessed by correspondence between claims made by learners and content they were given	Focus on simple metrics such as test scores without deeper analysis of more complex learning artifacts or the processes from which they were derived	Mastering curriculum content
Constructivist	Focus on learning that occurs during the learner's guided exploration of and experimentation with the world typically conducted in classrooms or online	Focus on progress through tracking and judging the modifications made to a set of materials, resources, or tools selected and arranged by the educator	Mastering curriculum content
Subjectivist	Characterized by an emphasis on personal affect over academic achievement. Relevant contexts for this approach are contexts where affect is important to the learning process. Examples include learning in complex socio-technical settings where there are too much information and no established best solution. Information seeking in this context may seek to measure a student's level of satisfaction with the information they found. Another relevant context relates to identifying learner dispositions or mindsets identified to impact the learning process.	Provides motivation assessments for understanding why a learner is or is not engaging in particular actions. May focus on self-reporting through survey tools and affect based semantic markup such as blog tagging alongside automated approaches such as textual sentiment analysis	Evidencing membership and processes

(continued)

Table 6 (continued).

Pedagogy	Description	LA Indicators	Accreditation
Apprenticeship	Sometimes used in LA with interest in whether the learner has become part of a community of practice or inquiry. Success involves the level of involvement with a given group and is based on communities of practice research where knowing a thing is indicated by how one acts towards that thing as defined by the behaviors present in that particular community.	Characterized by a focus on classifying expert and novice users and tracking how a learner moves from novice to expert. Assesses behavioral alignment with those exhibited by experts but may not address the meaning of the behaviors. Epistemic Network Analysis is an example of an LA application tied to this pedagogical approach.	Evidencing membership and processes
Connectivist	Learning is about understanding how to connect ideas appropriately and knowing where to find applicable information. Success is seen as the ability to build connections between ideas.	Uses network analysis to examine the level of connectedness of a learner's knowledge as pertains to concepts and social connections. Considers how a network's size, quality, and changes over time can serve as proxies for effective learning.	Evidencing membership and processes; success in use
Pragmatic, Socio-cultural	Learning occurs during the development and negotiation of mutually shared perspectives between learners. Conceptions of a given thing are tied to its practical application. Success is measured by how useful the information is for the purposes it is employed; it is socio-culturally embedded and mediated and may change as activities are defined and redefined.	Emphasizes process of learning over products of learning unless it relates to the products use. Tools are likely to encourage learner self-reflection to understand their own learning process. Analytics may also attend to the quality of discourse for learning, for creating a mutuality of perspectives in collaborative information seeking tasks.	Success in use

Gummer and Mandinach (2015) data literacy for teaching. Gummer and Mandinach (2015) posit that an increasing focus on education as an evidence-based practice means that educators must be able to use data to guide their practice effectively. They offer a preliminary framework meant to support research, development, and building capacities around teacher data literacy. The framework is summarized in Table 7 and described in more detail below.

Methods used to develop the framework. The authors performed a sequence of qualitative investigations focused on identifying the kinds of knowledge and skills required of teachers to effectively use data to inform their daily practice. The first of two studies examined the characteristics of data use in practical guides, books, and manuals on the same in addition to formative assessments, and related topics. The results of this initial study were integrated with definitions provided by data literacy experts. The second study centered on a review of state level licensure and certification documents to identify data and assessment related knowledge and skills required of teacher candidates. The framework presented here is the result of a synthesis of the two studies.

Table 7

Gummer and Mandinach (2015) Data Literacy for Teaching Constructs

Domains	Dimension	Examples
Content knowledge	Identify problems	knowledge from all three
	Frame questions	constructs inform the execution of
Data use for teaching	Use data	each dimension in the framework
	Transform data into information	
Pedagogical content knowledge	Transform information into decision	
	Evaluate outcomes	

Summary of the framework. The framework consists of three domains where teachers must demonstrate mastery to implement LA within their practice effectively. These required competencies are subject area content knowledge, pedagogical content knowledge, and knowledge and skills associated with data use to inform daily practices (2015). Within these competencies are six components of the inquiry cycle that, in turn, contain 59 corresponding elements of knowledge and skills.

Bakharia et al. (2016) framework linking learning (instructional) design with learning analytics. Bakharia et al. (2016) propose a conceptual framework for LA that links specific types of analytics with the corresponding elements of learning design they act upon. Teachers are centrally positioned within the framework and are the key actors in these analytical processes. They bring their knowledge of the context that is not represented in the data towards interpreting the results and making decisions that include feedback and other interventions along with responsive adaptations to the instructional design based on the results of the analysis. The framework is summarized in Table 8 and described in more detail below.

Methods used to develop the framework. The framework is an outcome of a study the authors conducted in 2014 and 2015 that sought to develop a web-based LA tool meant to support teaching and learning in blended and online courses. The authors developed the framework from three information sources: (a) a literature review of current LA tools, (b) semi-structured interviews with teaching faculty across three Australian universities, and (c) user scenarios designed for the contexts of each course in which the tool would be piloted.

First, the authors interviewed teachers to identify the kinds of LA functions they thought were useful to inform their instructional practice. Next, a literature review of LA tools was performed to determine the kinds of applications that performed the functions identified from the teacher interviews. Finally, user scenarios were applied to prioritize critical features during the development of an LA tool.

Summary of the framework. The resulting framework consists of five dimensions: temporal analytics, tool-specific analytics, cohort dynamics, comparative analytics, and contingency. A description of each of these dimensions follows.

Temporal analytics. Refers to the ability to view statistics related to the students' use patterns of single elements within a course as accessed in an LMS to provide insight into course elements were useful to students and when they were useful.

Comparative analytics. Reveals patterns and correlations between one or more elements in a course. This may include comparing levels of participation corresponding to learning activities over time. This approach is intended to enable evaluation of the structure and sequence of learning activities within a course.

Cohort dynamics. Similar to temporal analytics, however, provides individual specific use patterns for learners in a given course. The authors report that the teachers had an expectation that there would be common access patterns for student groups, i.e., those that were and were not successful in a course and that insight into these cohort dynamics would allow for informed feedback to students who were at risk of failure.

Tool specific analytics. This kind of analytics are specific to particular LMS tools that were being used for instruction. Examples of LMS tools include quiz scores and attempts and discussion forums. Teachers indicated that topical and social interaction pattern detection would provide a way to identify areas where manifest interactions diverged from expectations.

Contingency and intervention support tools. Tools that identified when a particular student was potentially at risk of failing a course based on predetermined criteria fall under this category. Examples of triggering events may be failing to access critical course content or poor performance on a particular assessment. Instructors indicated that the intervention would be emails sent to students containing suggestions for actions they could take to improve their scores.

How each tool functions within the framework. The final framework appears below. The Learning Analytics for Learning Design Conceptual Framework indicates the central role the instructor has within this system. The framework can be viewed from left to right as an analytics process whereby temporal, tool specific, and cohort analytics results are subsequently fed into the comparative analytics LA tool type for processing. This information is presented to the teacher who must then interpret the results informed by their knowledge of the learning and teaching context. The teacher interprets the results and uses the insights to identify triggering events that indicate an at risk status for students. The insights gained might also inform the feedback provided to identified students.

Table 8

Bakharia et al. (2016) A Conceptual Framework Linking Learning Design with LA

Construct	Dimension	Examples
Temporal analysis	Ability to see course statistics in an LMS	Frequency and duration of student access to course elements
Cohort dynamics/patterns	Ability to view student access to course content	Patterns that may lead to grouping students by the success of learning pathway
Contingency and decision support tools	Tools that help teachers identify and select individuals or groups of students based on determined parameters	Certain learning events trigger alert for intervention
Tools specific analysis	Analytics related to specific tools used for instruction	Discussion boards, quizzes
Comparative analysis	Allows teachers to see relationships between different aspects of the course	Patterns may reveal the value of some course elements over others

Slade and Prinsloo (2013) ethical framework for learning analytics. Slade and Prinsloo (2013) offer an ethical framework from a sociocritical perspective. A sociocritical approach considers the influences of cultural, political, social, physical, and economic contexts and power relationships on treatments of ethical issues in LA (Slade & Prinsloo, 2013). Their framework is oriented towards higher education. However, LA implementations in K12 are subject to the same kinds of privacy and ethical issues associated with data. This framework was chosen for its comprehensive presentation of privacy, and ethical concerns around data pervaded educational settings.

The authors view LA "as the collection, analysis, use, and appropriate dissemination of student-generated, actionable data with the purpose of creating appropriate cognitive, administrative, and effective support for learners" (Slade & Prinsloo, 2013, p. 1512). Slade and Prinsloo consider three general, and sometimes overlapping, categories for ethical issues in LA: (a) the location and interpretation of data; (b) informed consent, privacy, and the de-identification of data; and (c) the management, classification, and storage of data (2013, p. 1511). The authors point out that these categories are common ethical issues around data use within other domains. Their framework is summarized in Table 9 and discussed in more detail below.

Summary of the framework. The ethical framework contains six principles that: (a) views learning analytics as a moral practice; (b) considers students as agents; (c) sees student identity and performance as temporal dynamic constructs; (d) acknowledges that student success is a complex and multidimensional phenomenon; (e) requires transparency of use; and, (f) recognizes that education must use data to improve educational practices (Slade & Prinsloo, 2013).

Learning analytics as a moral practice. The first principle asserts that data analytics must not be viewed only as a means to measure what classroom practices are effective. They assert that, because education practice is, by nature, non-causal and normative, the primary role of analytics must be to identify what is appropriate and morally justified.

Students as agents. This principle asserts that LA should treat students as partners in their own learning rather than as data producers who are targets for interventions.

Student identity and performance are temporal dynamic constructs. The third principle recognizes student performance as context specific and subject to change over time. It asserts that students have the right to grow as learners unfettered by a permanent digital footprint (also referred to as the ‘right to forget’).

Student success is a complex and multidimensional phenomenon. This principle acknowledges that educational datasets are incomplete and therefore do not accurately describe the learning process. Subsequently, definitive conclusions cannot be drawn from these faulty datasets. Furthermore, it emphasizes that data use and analytics are subject to misinterpretation and inherently contain bias.

Transparency. The fourth principle indicates that educational institutions must make collection, use, and protection of student data clear. It also includes the need for underlying algorithms to be made available for public consideration.

Education cannot afford not to use data. The final principle acknowledges that educational institutions must participate in data use to achieve worthy goals.

Table 9

Slade and Prinsloo (2013) Ethical Framework for Learning Analytics

Principals	Description	Examples
LA as a moral practice	Primary purpose must be to identify what is appropriate and morally just	Personal circumstances, interventions and the obligation to act, impacts on student behavior, targeting resources appropriately
Students as agents	Students as partners in their own learning	Respecting privacy, opting out
Student identity and performance are temporal and dynamic	Performance metrics are context specific and highly variable	Stewardship, preservation, and deletion of data, anonymization, personal circumstances
Student success is complex and multidimensional	Data has shortcomings and is currently not accurately describe the learning process	Bias, misinterpretation, insufficient and inaccurate data
Transparency	Data Use (by schools and in products) should be clearly stated	Laws, institutional approaches, ownership, and control of data
Data must be used to improve education	Education must use data to achieve worthy goals	

Scheffel et al. (2014) quality indicators for learning analytics. Scheffel at al. (2014) propose the Quality Indicators for Learning Analytics framework as a means to standardize LA evaluation. The authors used Group Concept Mapping to identify twenty constructs under four main categories that serve as quality indicators for learning analytics. The five main categories and their subcategories are described below.

Objectives. Quality indicators under this category are awareness, reflection, motivation, and behavioral change.

Learning support. Quality indicators under this category are perceived usefulness, recommendation, activity classification, and detection of students at risk.

Learning measures and output. Quality indicators under this category are comparability, effectiveness, efficiency, and helpfulness.

Data aspects. Quality indicators under this category are transparency, data standards, data ownership, and privacy.

Organizational aspects. Quality indicators under this category are availability, implementation, training of educational stakeholders, and organizational change.

Summative Framework

This study seeks to measure the information quality of content found on LA product websites. It uses the findings of the literature review alongside the frameworks described in this chapter as a standard of measure. An additional objective is to develop a preliminary evaluative framework which intends to support educational data practitioners to support in identifying and implementing appropriate LA tools.

The summative framework below integrates concepts from the frameworks and shows relationships between the concepts. The model depicts ethical principles as the overarching guiding framework to reflect the emphasis on ethical considerations in the literature. Notably, the EPA triad exists outside the influence of ethics because it is determined by the relationship between the kinds of instruments and data sources that are available in a given context. For this reason, the relationship between instruments and data sources to the EPA triad is labeled as 'immutable' and, therefore, fixed.

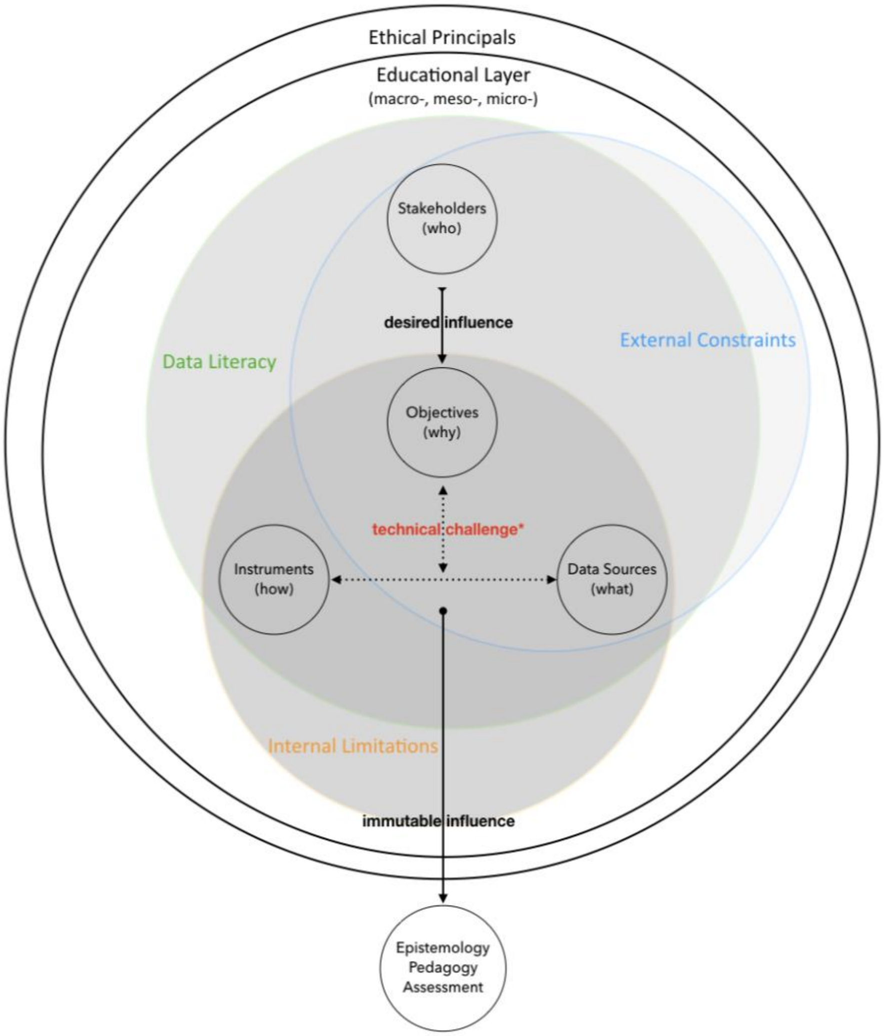

Figure 5. Integrated model of the nine LA frameworks reviewed.

Finally, the relationship between objectives to instruments and data sources is bi-directional and labeled 'technical challenge' to indicate that, while the desired relationship would be that objectives would determine the instruments and data sources, the current educational context means that objectives are limited by computational constraints and data quality. The framework implies that the extent to which we are able to solve this technical challenge will determine the level of alignment between objectives and the EPA triad. This a priori framework was applied to interpret the results of the text analyses conducted in Phase Two of this study.

Summary

This chapter began by describing how LA emerged from the big data phenomenon. Next, it addressed the distinguishing features of educational datasets that evoke big data principles. A review of current LA practices and critical concerns for the field was followed by a discussion of nine LA frameworks from the literature. Finally, this chapter concluded with a summative model of the nine papers. The next chapter describes the methods used in this study.

Chapter Three: Methods

The purpose of this study was to examine and describe the relationship between research and practice in analytics applications in K12 educational settings. It was also the purpose of this study to characterize how LA are currently implemented and understood. A secondary purpose for this research was to advance a preliminary LA implementation framework to support educational data practitioners effectively apply LA in their daily practice.

To accomplish these goals, this research applied quantitative content analysis using automated text analysis to assess the quality of information provided on analytics-based product websites as measured by LA research. This method was selected because it is one of the more practical methods for analyzing large bodies of text and because it allows for the use of both bottom-up and top-down approaches to text analysis. This study also describes the kinds of tools that were offered and how the tools were portrayed.

Restatement of the Research Questions

The central question of this study was: What is the quality of information provided on LA product websites?

Additionally, this research addressed the following related questions:

- What kinds of LA tools are being offered?
- How are the LA tools portrayed?

Overview

The remaining sections of this chapter are structured into six parts as follows. Part 1 offers a rationale for the research approach used in this study. Next, a rationale and description of the instrumentation in part 2 is followed by a rationale and description of the data sources and units of analysis in part 3. Part 4 describes the procedures used in the research and analyses.

Part 5 addresses issues of validity and reliability within this work. It also addresses human subjects and the IRB review. Finally, this chapter concludes with a summary.

Rationale for the Study Design

This study applied quantitative content analysis using automated text analysis in two research phases. It followed the process for quantitative approaches provided by Krippendorf (2004) where research occurs in two phases. Krippendorf calls the first phase a preparatory research phase where instrumentation techniques are calibrated and prepared for application in the second research phase.

Defining content analysis. Krippendorff (2004) defines content analysis as "a research technique for making replicable and valid inferences from texts (or other meaningful matter) to the contexts of their use" (p. 18). Humphreys and Wang (2017) add that automated text analysis uses computers to observe characteristics of text that would not be detectible otherwise. This research integrated these understandings and used results from automated text analysis to draw inferences from learning analytics product website content to the teaching and learning contexts of their use.

Contexts for content analysis. In education, content analysis has been described as "an intense, systematic scrutiny of a given piece of instructional material to determine its quantitative and qualitative characteristics" (Borg & Gall 1983 as cited in Stahl, Brozo, & Simpson, 1987). Stahl, Brozo, and Simpson (1987) applied content analysis to vocabulary-based instructional materials to "determine the nature of the content…and the extent to which the content is consistent with empirical evidence" (p. 204). Stahl et al. propose that content analysis can be a valuable means of improving instructional materials and for selecting and adopting classroom texts.

Content analysis of web-based text in education research is often associated with discourse analysis and social network analysis. However, there is a precedent conducting content analysis to evaluate information quality of website content in fields such as consumer research, hospitality studies, and health. Lay, Ogbogu, Taylor, Stafinski, Menon, and Caufield (2008) used content analysis to evaluate information from direct-to-consumer stem cell medicine websites. Another study by Ostry, Young, and Hughes (2008) applied content analysis to assess the information quality of popular Canadian nutritional websites. To date, education research does not appear to have any instances of the approach, suggesting an empirical novelty for this study. Because of the widespread use of educational technologies in K12 education settings, content from product websites offer insights into how teaching and learning are practiced and understood. Moreover, the widespread use of educational technologies calls for this type of research.

Quantitative approach. This study is categorized as a quantitative approach based on distinctions described by Krippendorff (2004). However, it also contains qualitative processes that will be addressed in more detail in the conclusions of this research. A brief treatment appears here to aid understanding of the methods. In regards to qualitative and quantitative approaches to content analysis, Krippendorff argues that every content analysis is qualitative because it involves text-based, or otherwise non-numeric analysis. He points out that symbolically representing text with numbers does not change the nature of the text itself. Instead, Krippendorff differentiates the two approaches by their process. He maintains that a quantitative approach to content analysis entails a systematic process while a qualitative approach relies on iterative processes to inform the research and analysis procedures. Krippendorff points out that the systematic, a priori approach used in quantitative content analysis makes it one of the more practical ways of analyzing large volumes of text. Alternatively, the ad hoc nature of qualitative approaches to content analysis is well suited for exploratory purposes because they allow for more comprehensive understandings of phenomena within specific settings. Krippendorff (2004) notes that an iterative function is also present in quantitative approaches. However, it occurs before the analysis takes place in a phase Krippendorff calls preparatory research, the sequence of activities performed before conducting the primary analysis. During the preparatory research phase in quantitative methods constructs are operationalized by developing the *data language* (Krippendorff, 2004) or *code scheme* (Neuendorf, 2002). In the automated text analysis approach applied in this research, constructs are operationalized through text analysis techniques applied to the text corpora (Humphreys and Wang, 2017).

Abductive reasoning. Quantitative approaches to content analysis use abductive reasoning to interpret the results of analysis (Krippendorff, 2004). Krippendorff (2004) explains that abductive reasoning describes a process of drawing conclusions based on two relevant but indirectly related objects by applying a third object, the analytical construct. In this study website content and information quality are the two indirectly related objects and the framework texts from the literature review serves as the analytical construct. There are different categories of analytical construct, because this study required an evaluative function, the analytical construct is described as an *application of standards* (Krippendorff, 2004).

Rationale for Computer-Aided Text Analysis (CATA). CATA, also referred to as automated text analysis in this research, is a method of quantitative analysis that uses computers, rather than humans, to implement code. Because computers are not able to detect patterns, CATA is viewed to have many limitations. However, Wiedemann (2013) argues that two developments have expanded CATA's capabilities. First, the vast amounts of digital texts that are available mean that the sample size can be large or can even consist of the entire corpus of materials. Larger sample sizes, or a sample that equals the entire corpus, equate to higher internal validity. The second development relates to context-aware algorithms along with the increasing sophistication of the lexicons available. Wiedemann (2013) describes this second phenomenon as a narrowing of "the epistemological gap between how qualitative researchers perceive their object of research compared to what computer algorithms are able to identify" (section 2, para. 6). In this study, these new developments were applied to reveal patterns which are qualitively interpreted to form the conclusions of this study. Applying computer, rather than human, coding in this study allows for more uniform application of the analytical instrumentation to a high volume of material. The CATA analyses applied in this research include word frequency measures, topic models and sentiment analysis.

Instrumentation

This study uses a bottom up approach to analysis that followed procedures for operationalizing research constructs offered by Humphreys and Wang (2017). The methods described by the authors are valuable to this study because they allow for understandings to arise from the text. This method applies text analysis techniques to the study corpus and an additional corpus (the literature corpus in this study) and then compares the results to derive insights about the study corpus. R programming language, along with the R text mining (tm) and structural topic model (stm) from the R library, will be used to determine terms prevalent in the corpus under study. These terms will be mapped to the initial framework developed from the literature and described in Chapter Two.

Developing the analytical construct as the standard of measure. As previously introduced, content analysis utilizes abductive reasoning, a form of reasoning “that moves from particular texts, through context-sensitive explanations of these texts, to particular answers to research questions” (Krippendorff, 2004, p. 344). Unlike inductive (examining a specific instance to generalize to the whole) and deductive (starting with what is generally known to identify a specific manifestation) reasoning, abductive reasoning is an inferential technique without a direct path from the object of study to the conclusions that are drawn. It requires making inferences about the content under study towards what the content suggests about the target phenomena. Ensuring validity necessitates a justification for how the selected content indicates the target phenomena. To maintain internal validity, Krippendorff advises requiring a justification for how the selected content indicates the phenomenon. This justification occurs in the development of an analytical construct.

Krippendorff defines analytical constructs as an operationalization of what a content analyst understands about the context of a text, which is then used to draw inferences from a text systematically (2004). Krippendorff proposes that analytical constructs are akin to the best possible hypothesis an analyst can offer to explain “how a body of text is read, what it does, or to what use it may be put in a context of the analyst’s choice” (Krippendorff, 2004, p. 171).

Krippendorff offers the application of standards as an analytical construct appropriate for identifying, evaluating, or auditing content. Applications of standards involve comparing a variable with a standard and, subsequently, deriving meaning from the comparison. This study will involve the application of standards, where standards are derived from the LA literature, to evaluate information quality and identify the kinds of LA tools represented in the corpus under study.

To maintain internal validity, analytical constructs must be founded on one or more sources of certainty (Krippendorff, 2004). Krippendorff lists four sources of certainty that can be used to develop analytical constructs: previous successes and failures of the construct in content analysis, expert knowledge, and experience related to the context, established theories about a context, and embodied practices. This study draws from two of the four sources of certainty listed, established theories and embodied practices:

- Using established theories to develop the analytical construct. Established theories "argue for structural correspondences between the construct and that context" (Krippendorff, 2004, p. 173).
- Using embodied practices to develop the analytical construct. Embodied practices are "sampled from a context, to argue for the representative nature of the inferences obtained from these practices" (Krippendorff, 2004, p. 173).

The analytical construct applied in this study consisted of text extracted from nine papers reviewed under the frameworks section of the literature review of this study. The analysis approach used is described by Humphreys and Wang (2017) as appropriate for making a posteriori discoveries or when "the operationalization of the construct in words is not yet clear" (p. 29). In this study, both contexts posed by Humphreys and Wang apply. This study applies a classification approach recommended by Humphreys and Wang that analyzes patterns that occur within the two groups. The kinds of patterns that were analyzed and how the analytical construct was applied in this study are depicted below in Figure 6.

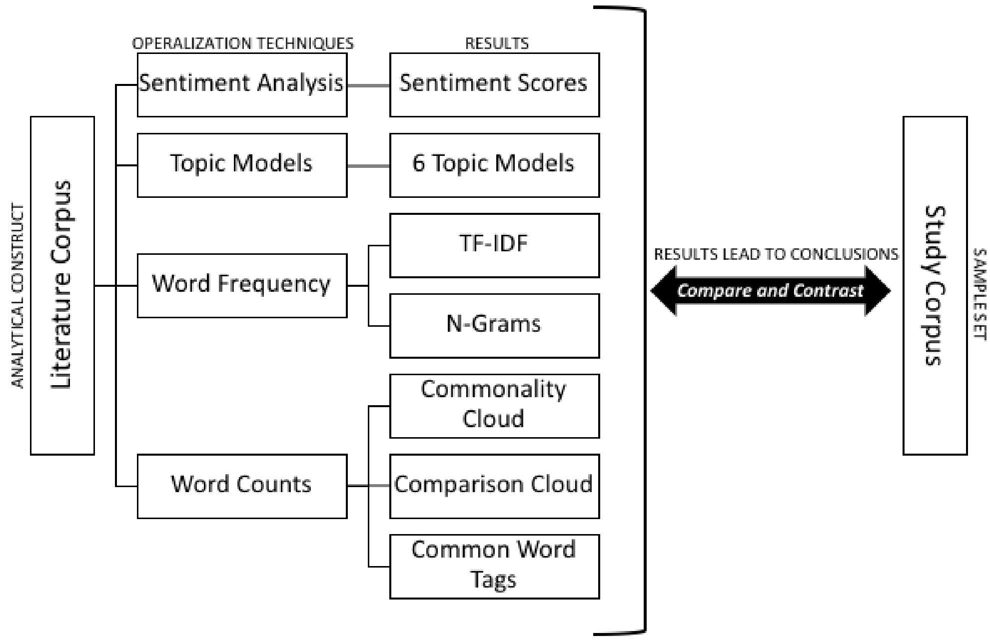

Figure 6. Instrumentation and operationalization of the construct.

This study compared and contrasted the results of four operationalization techniques described by Humphreys and Wang (2017). Three are bottom-up approaches (topic models, word frequency, and word counts) and one is a top-down approach (sentiment analysis). The results of the operationalization techniques within each group were compared and contrasted in order to derive the conclusions described in chapter five. Word frequency and word count measures are addressed in detail in chapter four. Here a discussion of two lesser known text analysis procedures are described to facilitate validity and reliability explanations that occur later in this chapter.

Sentiment scores. The sentiment analysis applied in this study is a dictionary-based approaches features of interest are first defined and then occurrences of those features are measured in the text and summarized (Humphreys & Wang, 2017). It is considered a top-down approach because the constructs of interest are predefined. Sentiment scores in this study were used as a basis for comparison between the two text corpora. The resulting scores were not analyzed with respect to the sentiment scores themselves.

Topic models. All topic models are generative models of word counts in a document group (Roberts, Stewart, & Tingley, in press). Generative models produce all potential outcomes for a given dataset (Goodman, Tenenbaum, & The ProbMods Contributors, 2016). Many methods exist for calculating topic models, this study used the structural topic model (stm) R package (Roberts et al., in press) to model topics using *correlated topic models* (CTM) developed by Blei and Lafferty (2005). Topics are defined as a possible combination of words where the probability of belonging to a topic has been calculated for each word as shown in Figure 7. A document can contain multiple topic models and belong to different topic groups within a corpus.

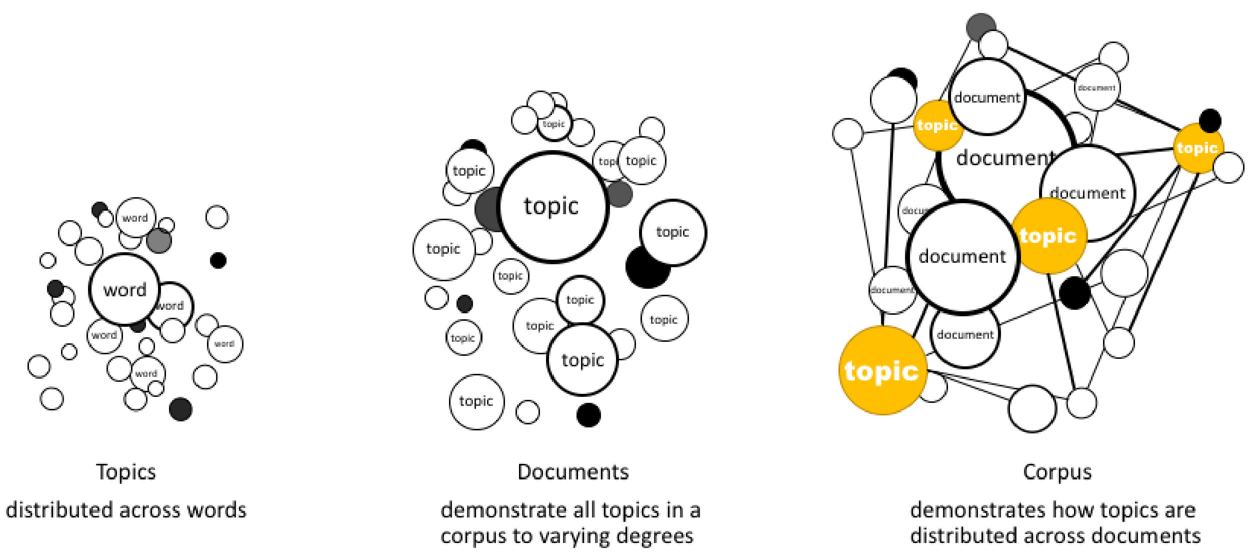

Figure 7. Topic model representations of text at the word, document, and corpus levels.

Data sources. The study corpus for this research consisted of text content from 148 individual webpages from 54 product website domains. Purposive sample was used to identify relevant products from the EdSurge (ES) product index which was the sampling frame used to during the selection process based on the following criteria:

- Products developed for typical K-12 education settings.

- Products that collected, stored, or analyzed student created data.
- Products that did not refer to data, analytics, personalized learning, dashboards, or adaptive learning in a context outside of market places or curriculum galleries.

The rationale for selecting the first criteria involves two parts. First, the focus of this study was K-12 education and second, a focus on typical settings was chosen to align with the context addressed in the frameworks. Special education, for example, has implemented individualized instruction and behavior tracking long before learning analytics began to popularize these terms in mainstream school settings. Therefore, the use of the terms would not necessarily indicate the influence of LA practices. The second criteria was selected to maintain focus on teaching and learning and align with the focus of the frameworks in the literature corpus. Finally, the third criteria was applied to filter out products that did not use educational data or analytics as a main feature of their product offering. This was important because many marketplace based services and curated collections used the terms to refer to the opportunity that a broad selection of materials offered. They used filter-based search engines but did not implement any analytics or collect data and consequently were not relevant to this study.

The sampling frame applied to select the Weare and Lin (2000) A number of sampling frames have been established for collecting relevant materials from the web for research purposes (Weare & Lin, 2000). A popular method, not employed by this study relies on search engines to develop a sampling frame. Researchers who use this method exhaustively enter relevant terms, variations of those terms, and various combinations along with qualifiers into search engines to identify sites suitable for the study. A description of collector sites, the sampling frame used in this study, follows.

Collector sites are individual or organizational websites that collect and post links related to a central topic. The use of collector sites are most appropriately applied to examining sites from particular sources, or that relate to a specific topic (Weare & Lin, 2000). Some limitations associated with this application include a lack of standards applied to the selection process on the hosting site. This has the potential to result in a biased sample set.

EdSurge product index. The First, the focus of the EPI is better aligned with the purposes of this study. ALD indexes startup companies across sectors, while EPI focuses solely on educational technology products. Additionally, products listed on ALD are in various stages of development. Many of these companies are either in the pre-seed or seed stage of funding and have yet to bring their product to market. Secondly, and perhaps most importantly, the audience for the EPI is better aligned with the research questions. AngelList aims to connect startups with angel investors and other resources they may require. Thus, the ADL is oriented towards the needs of the startup and venture capitalist communities.

In contrast, EdSurge describes itself as "the best resource on how and when to use technology in K-12 and Higher Ed" (www.edsurge.com). The orientation of the site is towards assisting educational practitioners in making the right choices in educational technologies and connecting them to resources that will assist them in doing so. An additional benefit is that EdSurge invites teachers to review the educational technology products listed in their index. To date, there are over 14,276 reviews from practitioners at all levels of education. This content provides an opportunity for greater understandings around what practitioners know and understand about data, analytics, and their uses in educational settings.

Data Sources and Units of Analysis

Quantitative content analysis is a reductionist approach (Riff, Lacy, & Fico, 2005) that requires reducing the corpus under study into smaller segments that lend themselves to manipulation and analysis. These units are meant to represent the entire corpus at varying levels so that conclusions drawn from the study of the units can be generalized to the entirety. The three units relevant to this study are the sampling unit (a single instance within the corpus under study), the recording unit (the variables that will be measured and accounted for), and the context unit (the level at which the recording units will be searched for). The following sections describe the methods used to define the three units of analysis.

Sampling units. The sampling unit for this study was a single product website. Syntactical distinction is among the accepted methods for determining sampling units and was the method used in this study. Krippendorff defines syntactical distinctions as natural distinctions which are evident in the culture and do not require judgment to distinguish. Examples would include a TV show, newspaper article, or, in this study, a webpage.

Recording units. Recording units are the level of information that will be selected from the content for study. These may be the categories identified in the data language or coding scheme. Information about a recording unit may occur in different places within a sampling unit, such as on various pages of a website (Krippendorff, 2004). This study uses categorical distinctions to define recording units. According to Krippendorff, categorical distinctions can be based on the theoretical framework of a study, which is the method followed in this research (2004).

Context units. Krippendorff (2004) defines context units as the “units of textual matter that set limits on the information to be considered in the description of the recording units” (p.

116). Context units represent the parameters that distinguish the block of content to be considered concurrently during the analysis process. For example, a single article is often used as a context unit in content analysis of newspapers where a single issue serves as the sampling unit. In such a case, the content of a single article is considered during one coding instantiation. Context units can be identified using natural boundaries that were created by the authors of the text. In this proposed study, web page blocks, which are the design components of websites, will serve as the context unit for analysis (Song, Liu, Wen, & Ma, 2004).

Procedures

This study design is adapted from Krippendorff's (2004) steps for conducting content analysis research. Additionally, automated text analysis (ATA) methods followed procedures described by Humphreys and Wang (2017). This research was conducted in two phases. The first corresponds with what Krippendorff refers to as *preparatory research*. Three objectives were identified for the first research phase, these were to

- select the study corpus,
- extract and prepare data for analysis, and
- conduct a pilot study to calibrate the analytical instruments applied in this research.

R programming was used along with R packages required for each analysis applied in this study. Topic modeling is an analytic technique resulting in probabilistic modeling of term frequencies in documents belonging to a particular corpus (Grün & Hornik, 2011). The resulting model is called a fitted model and can be used to infer similarities between documents as well as between a set of keywords (Grün & Hornik, 2011).

Sampling procedure. To start, a web scraper extension will be used to extract information about the products from the index using the Google Chrome browser. This initial extraction will rely on the sampling model developed in phase one of this research. Once the initial scraping is completed, the resulting data will be exported to an excel spreadsheet, and then subsequently filtered to remove duplicates and products with incomplete information on their web pages. When this initial cleanup is completed, the list of product links will be parsed to identify outdated and broken web addresses.

The remaining products will be manually sorted and filtered to identify those products that fit the sampling criteria identified in this study.

Criteria for selecting websites. Product websites that will be selected for this study must meet the following criteria:

- Interact with data at any stage of the collection, analysis, or reporting phases
- Designed for implementation in K12 educational settings
- Designed for use by educational data practitioners, such as students, teachers, administrators, and instructional designers

Visual Web Spider (http://www.newprosoft.com) is a web crawler that will be used to extract content from the remaining websites. The software allows for extracting text from between selected HTML tags. In this study, only text identified by the HTML "body text" tag will be extracted from the home, about, and product pages of each website in the corpus. The content corpus will be loaded into Sketch Engine where they will be cleaned and normalized using, but not limited to, the following common techniques: removing boilerplate and other irrelevant content, normalizing the data, removing stop words, and removing stemming (Günther & Quandt, 2015).

Data analysis. Data management and analysis will be performed using R and the following R packages: tm, topicmodels. Ostry et al. (2008) used topic models to code for conflicting claims. Computer coding will be used in two ways: first, to create the corresponding terms for the literature framework-based recording units; and second, to code the websites with the resulting framework. The R programming language will be used, along with the WordNet dictionary and the R text mining (tm) package and the R structural topic modeling (stm) package, to analyze website content according to prevalent topics and the structure of information contained on the websites. A number of analyses will be performed using the following approaches: descriptive statistics, visualizations, and corpus comparison. These results will inform the conclusions drawn from this research.

Corpus comparison. Corpus comparison between the website content and LA research papers used in the study will contribute to the primary research question: What is the quality of information provided on LA product websites? A corpus comparison will also reveal distinct features of the study corpus (Günther & Quandt, 2015) as compared to the research base.

Automated analysis procedures. Sentiment analysis will be performed to answer the secondary research question: How are these tools portrayed? Sentiment analysis will be performed using a dictionary-based approach using R programming language and Bing Liu's sentiment lexicon, a widely applied sentiments dictionary.

Reliability, Validity, and Human Subjects

Computer Aided Text Analysis (CATA) is one of the more practical ways of processing a large amount of textual data reliably (Krippendorff, 2004). Krippendorff indicates that transferring the analysis task to computing devices eliminates errors because computers are deterministic, meaning that only text can be processed in a reliable manner. The purpose of establishing reliability is to account for discrepancies among multiple coders as well as inconsistencies in the performance of individual coders. Computers are not, for example, capable of being affected by context, i.e., differences in understandings or perspectives. As 'readers,' computers do not read meaning, they recognize strings. Thus, in CATA, the methodological concern is not generating reliable coding.

Study validity. Validation of research methods "reduces the risk of making decisions based on misleading research findings" (Krippendorff, 2004, p. 316). Krippendorff (2004) defines validity as the "quality of research results that leads us to accept them as true" (p. 313). Measurement instruments are valid if they measure what is intended. Neuendorf and Kumar (2015) refer to validity in content analysis as the degree to which a study measures the desired construct. This section explains how both internal and external validity will be achieved in this study.

Krippendorff (2004) identifies three kinds of evidence associated with validating quantitative content analysis research:

- Evidence that justifies the treatment of text, what it is, what it means, and how it represents what (external validity by sampling validity, semantic validity)
- Evidence that justifies the abductive inferences that a content analysis is making (internal validity by structural validity, functional validity)
- Evidence that justifies the results, whether a content analysis contributes answers to the research questions of other researchers or is borne out in fact (p. 318)

Internal validity. Internal validity refers to the extent to which a conceptual definition and an operational definition align (Neuendorf, 2002). In essence, it relates to the validity of the methods taken to operationalize the phenomena under study. This definition aligns with Krippendorff's (2004) second criteria, which requires evidence to support the abductive inferences in a content analysis. This can be achieved through evidence supporting structural validity. The evidence Krippendorff suggests is tied to the development of the analytical construct used in the study.

In this study, the method used to validate the analytical construct is the application of standards. Krippendorff notes that the standards applied may be derived from established knowledge in a field, or knowledge contained in the research base. As this study aims to measure the information quality contained on LA product websites, the applied standard is as derived from the literature. The literature is seen as an expert perspective in the field, and therefore serves to validate the abductive analysis applied in this study.

Procedures to enhance construct validity when using CATA. Short et al. (Short, Broberg, Cogliser, & Brigham, 2010) suggest a series of procedures that increase construct validity when using CATA. Two of these procedures, deductive content validity and inductive content analysis, are applied in this study.

- Deductive content validity. Deductive content validity relies on developing "a working definition of the construct, preferably derived from existing literature" (Short et al., 2010, p. 327). This will be performed using the a priori method previously mentioned during the preparatory research phase.
- Inductive content analysis. Unsupervised machine learning will be applied using the topic modeling procedure previously mentioned in this chapter. The topic models will be generated using R programming language along with the topicmodels package.

External validity. Also referred to as generalizability, external validity is concerned with how the study applies to other contexts (Neuendorf, 2002). External validity may be established through the sampling process in a study (Neuendorf, 2002). This study relies on the precedence of sampling frames used for web research purposes offered by Weare and Lin (2000). Weare and Lin list a number of sampling frames that have been used in web research, including the use of collector sites, which, as previously mentioned in this chapter, will be applied in this study. The authors suggest that collector sites are well suited to studies that examine sites from particular sources or that relate to a particular topic, as this study intends to do.

Human subject considerations. A non-human subjects IRB application was submitted before conducting this study and the approval letter can be viewed in the appendixes of this study.

Chapter Summary

This chapter described the methods and procedures applied in this study. It provided an explanation of the kinds of analyses that were applied and the types of outcomes that resulted from their application. It also described how the analyses conducted lead to the conclusions presented in chapter five. The next chapter presents the process followed for phase one of this research and the results of both research phases.

Chapter Four: Results

This chapter describes the results of the quantitative content analysis. The research examined, compared, and contrasted content collected from LA product websites with content extracted from nine framework papers reviewed in chapter two of this study. The remainder of this chapter describes procedures followed in the first research phase and the results of the analyses applied in the second research phase. It is structured in five sections. The first restates the research questions addressed in this study. The second provides a brief description of the EdSurge (ES) product index, the sampling frame used in the study. A description of the procedures and results from phase one of this study follows. The next section presents procedures and results of analyses conducted in the second research phase. A summary of the results concludes this chapter.

Restatement of the Study Purpose Research Questions

The purpose of this study was to examine and describe the relationship between research and practice in analytics applications in K12 educational settings. It was also the purpose of this study to characterize how LA are currently implemented and understood. A secondary purpose for this research was to advance a preliminary LA implementation framework to support educational data practitioners effectively apply LA in their daily practice.

The central research question was: What is the quality of information provided on LA product websites?

Additionally, this research addressed the following related questions:

- What kinds of LA tools are being offered?
- How are the LA tools portrayed?

The Sampling Frame

The EdSurge (ES) product index was used as the sampling frame for this research. A brief description of the index follows. The ES Index homepage points to a database of EdTech products and services. EdTech companies listed on the site develop and maintain a company profile page where educational practitioners can leave reviews of their products. Table 10 contains a list of five top level categories and the number of products listed under each as listed on the index's homepage.

Table 10

ES Index List of Products by Category

Categories	Products
Curriculum Products	618
Teacher Needs	486
Educational Operations	437
Post-Secondary	321
Everything Else	560

Phase One Analysis

Phase one analysis had three objectives. These were to

1. select the study corpus,
2. extract and prepare data for analysis, and
3. calibrate the analytical instruments.

Selecting the study corpus. This section describes the process followed to identify the 54 product websites that were included in the study corpus. A variable-based sampling approach was applied to select the study corpus using the ES index as the sampling frame. The selection process occurred in the four steps depicted in Figure 8. Step one applied filters to content scraped from the ES Product Index search page. The second step applied filters to each products corresponding ES profile page. The third step applied filters to each product's home page contents. Finally, the fourth step applied filtering criteria to contents extracted from pages describing the product and its use. The 54 remaining products comprised the study corpus in the study.

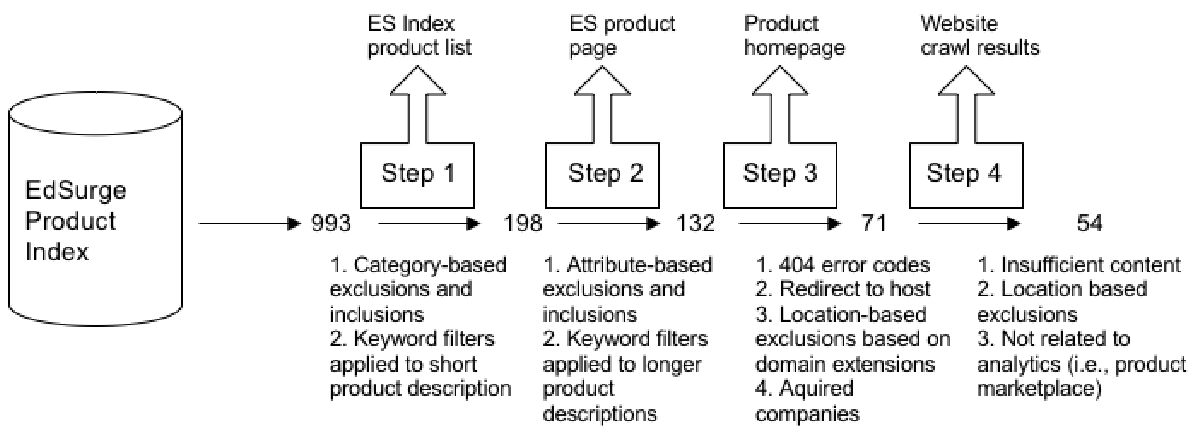

Figure 8. Product selection process overview.

Step one. Data from the ES index search pages were extracted using Web Content Extractor (WCE) developed by Newprosoft. WCE extracted 993 product listings, and these were stored in a spreadsheet for further processing. Figure 9 indicates the selection elements and the contents that were extracted from each and Figure 10 depicts the click through path used in the index crawl.

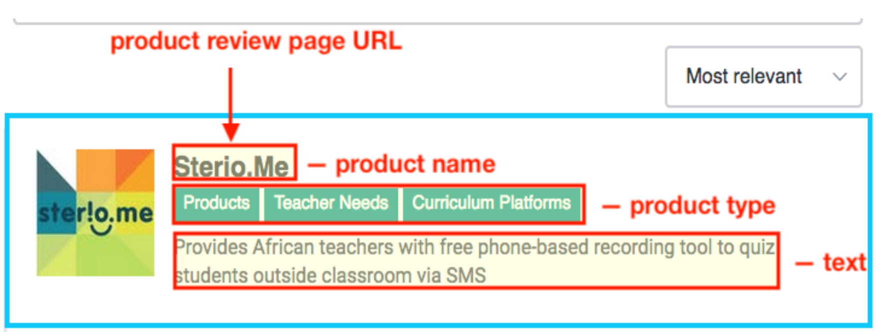

Figure 9. Extraction path in step 1.

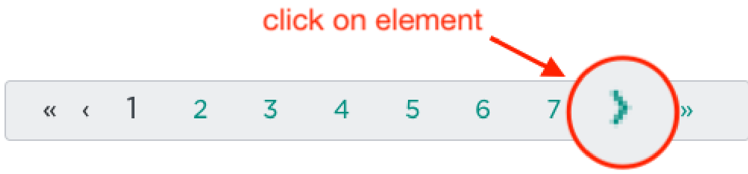

Figure 10. Extraction click through path in step 1.

Filters were applied in the following order:

1. Exclusions by category
2. Inclusions by category
3. Exclusions using keyword filters by the product description
4. Inclusions using keyword filters by the product description

At the end of step one, 198 products remained for stage two processing. Table 11 lists the number of products remaining in by main level category.

Table 11

Products Remaining After Step One by Category

Category	Products
Curriculum Products	49
Educational Operations	86
Everything Else	4
Teacher Needs	55
Uncategorized	4
Total	198

Step two. Product descriptors were extracted from each product's ES profile page as indicated in Figure 11.

After cleaning and sorting the extracted dataset, it was filtered as follows:

1. Exclusions by attribute
2. Inclusions by attribute

3. Exclusions using keyword filters by the product description

4. Inclusions using keyword filters by the product description

5. Stage two resulted in 132 products marked for final filtering in stage three.

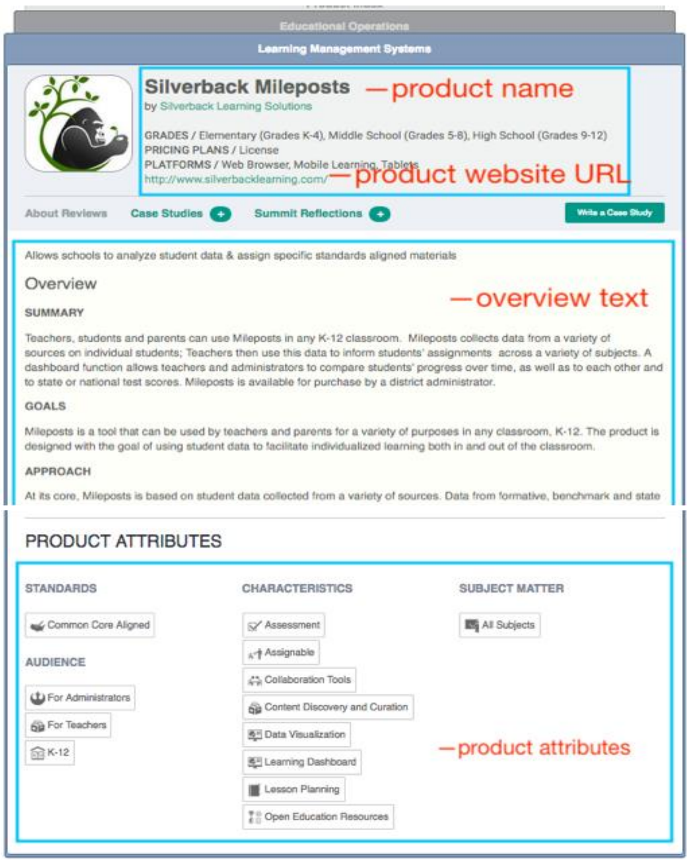

Figure 11. Content extraction path.

Step three. Content from each of the remaining product home pages was scraped using Visual Content Spider (VCS) software, also developed by Newprosoft. VCS collected the http status code and body level text content from each URL address and stored it in a spreadsheet. After cleaning the dataset, step three filters excluded the following product listings:

1. Pages that returned 404 http status codes

2. Pages that redirected to a hosting provider website

3. Products with domain extensions for countries outside of the US

4. Finally, products that returned URL's different from the one originally entered were marked and excluded if the redirect page indicated it had been acquired.

After the third filtering step, 71 products remained for additional filtering in step four.

Step four. The 71 product websites were loaded into VCS and, after a number of webpages from each site were collected. Products were excluded that:

1. Did not contain enough content
2. Were not located in the US
3. Had been missed by previous filtering

At the end of step four, 54 products belonging in seven categories were left and included in the study corpus.

Objective two: Prepare data for analysis. This section describes the procedures followed to extract and process data for each corpus.

Study corpus data extraction. Abblebits for Excel was used to randomly generate ten numbers in the range of the product row numbers. The products that corresponded with the row numbers in the spreadsheet were used to calibrate parameters for study corpus data extraction and processing. The procedure followed is outlined below.

1. Determined website crawling path based on pilot corpus to a depth of two levels
2. Determined CSS selectors for relevant website content based on the pilot corpus
3. Applied parameters identified in steps one and two to extract web content from all product websites in the study corpus and stored content in a spreadsheet
4. Sorted and filtered webpages using the URL path and webpage content variables
5. Adjusted parameters based on results of step four

6. Conducted final web crawl using adjusted parameters and stored collected data in a spreadsheet

The resulting dataset was segmented by URL address with the product name, and webpage text making up the other two variables contained in the dataset. The final step was to merge the three variables in the study corpus dataset with their corresponding categories extracted from EdSurge. The category attributes were labeled as 'product type'. The resulting study corpus dataset contained four variables, name, type, URL, and text and was segmented by URL address in rows.

Processing data. The study corpus dataset was cleaned using widely accepted data cleaning protocols listed below:

1. Converted line breaks into spaces
2. Changed all text to lower case
3. Removed symbols and punctuation
4. Removed numbers
5. Removed data enclosed in parenthesis
6. Ran spell check and correct spelling errors
7. Structured the data with variables in columns and observations of those variables contained in rows.

Literature corpus data extraction. Text content from the nine papers listed in Table 12 was extracted to form the literature corpus. The papers were reviewed in chapter two and were the source of the summative framework presented at the end of the chapter. The combined texts were the analytical construct applied in the analyses. UI Path was used to extract text content from pdfs of the nine journal papers using Microsoft OCR and the contents were exported as tab delimited text files segmented by line.

Table 12

Journal Papers Included in the Literature Corpus

Author	Year	Title
Bakharia et al.	2016	A conceptual framework linking learning design with learning analytics
Chatti et al.	2015	A reference model for learning analytics
Greller & Drachsler	2014	Translating learning into numbers: A generic framework for learning analytics
Gummer & Mandinach	2014	Building a conceptual framework for data literacy
Knight et al.	2013	Epistemology, Assessment, Pedagogy: Where Learning Meets Analytics in the Middle Space
Prinsloo & Slade	2013	An evaluation of policy frameworks for addressing ethical considerations in learning analytics
Scheffel	2012	Quality Indicators for Learning Analytics
Shum	2012	UNESCO Policy Brief: Learning Analytics
Siemens	2012	Learning analytics: The emergence of a discipline

Processing data. The Text Wrangler application developed by Bare Bones Software was used to remove the following sections: title and front matter, abstract, acknowledgements, and references. The literature data files were formatted as tab delineated based on line number during the extraction process, however, there were errors in some of the files such as line breaks splitting words, the appearance of 'gremlins' (atypical characters that often appear when text from one format is copied to another), and extraneous header and footer content. These formatting issues were corrected in Text Wrangler. Then the files were converted to spreadsheets using Abblebits add-on for Excel. The text was further processed in a similar manner to the study corpus dataset and according to established data processing procedures as follow:

1. Convert line breaks into spaces
2. Change all text to lower case

3. Remove symbols and punctuation
4. Remove numbers
5. Remove data enclosed in parenthesis
6. Run spell check and correct spelling errors
7. Structure table in two columns by variable

Calibrating analytical instruments. A pilot study was conducted to calibrate the analytical instruments and procedures for phase two analysis. Word counts, word frequencies, and topic modeling analyses were conducted on both corpora in an iterative process. The analyses were repeated until errors were no longer observed in the results. Results from each analysis informed tuning the analytical instruments and tools in the following ways:

- Results of word counts, and frequency measurements were used to identify corpus specific stop words.
- Results from all three analyses revealed inconsistencies and errors in the text corpora that required additional data processing.
- Results from topic modeling were used to determine the appropriate number of topics that best fit the corpora.

Phase Two Analysis Results

The following text analysis techniques were applied during the second analysis phase: word counts, word frequencies, term frequency-inverse document frequency (tf-idf), sentiment analysis, topic modeling, and Ngram analysis. Word cloud visualizations were also processed for each corpus. Results from the analyses were used to compare and contrast the two corpora and to theorize about the relationship between them.

Word counts. Word counts were used as a baseline for comparing the results of other text analysis techniques. The datasets were imported into R and organized in a document matrix with each word in a row. Stop words identified in phase one were filtered. Table 13 contains the top ten words from each corpus and the number of times the word appears in each corpus.

Table 13

Top Ten Words Lists by Count in Each Corpus

Literature Corpus		Study Corpus	
Word	*N*	*Word*	*N*
knowledge	251	instruction	222
information	208	report	220
process	169	support	158
system	168	level	156
assessment	156	provide	155
approach	146	skill	152
epistemology	127	time	139
teach	126	perform	125
support	118	progress	117
domain	116	district	116

Word frequency. Term frequency-inverse document frequency (tf-idf) is a weighted frequency measure. It is applied in text analysis to offset common high frequency words that occur in documents without using stop words. It balances the term frequency, the number of times a term appears in a document divided by the total number of terms in the document, with the term's inverse document frequency measurement. Inverse document frequency is a calculation of the number of documents within a corpus that contain the term divided by the number of documents in the corpus. When tf-idf is measure, term frequency will:

- be highest when the term appears many times in a small number of documents,
- lower when the term appears less often in a document or appears in many documents,

- be lowest if the term appears in all documents in a corpus.

There is more than one way to measure tf-idf, the analysis applied in this study used an approach that defines inverse document frequency as appears in Figure 12 below.

$$idf(\text{term}) = \ln\left(\frac{n_{\text{documents}}}{n_{\text{documents containing term}}}\right)$$

Figure 12. Tf-idf measurement.

Tf-idf was used to rank terms in each corpus and also to rank terms by product type (study corpus) and author (literature corpus). These word frequency rankings appear below in Figure 13 and 14.

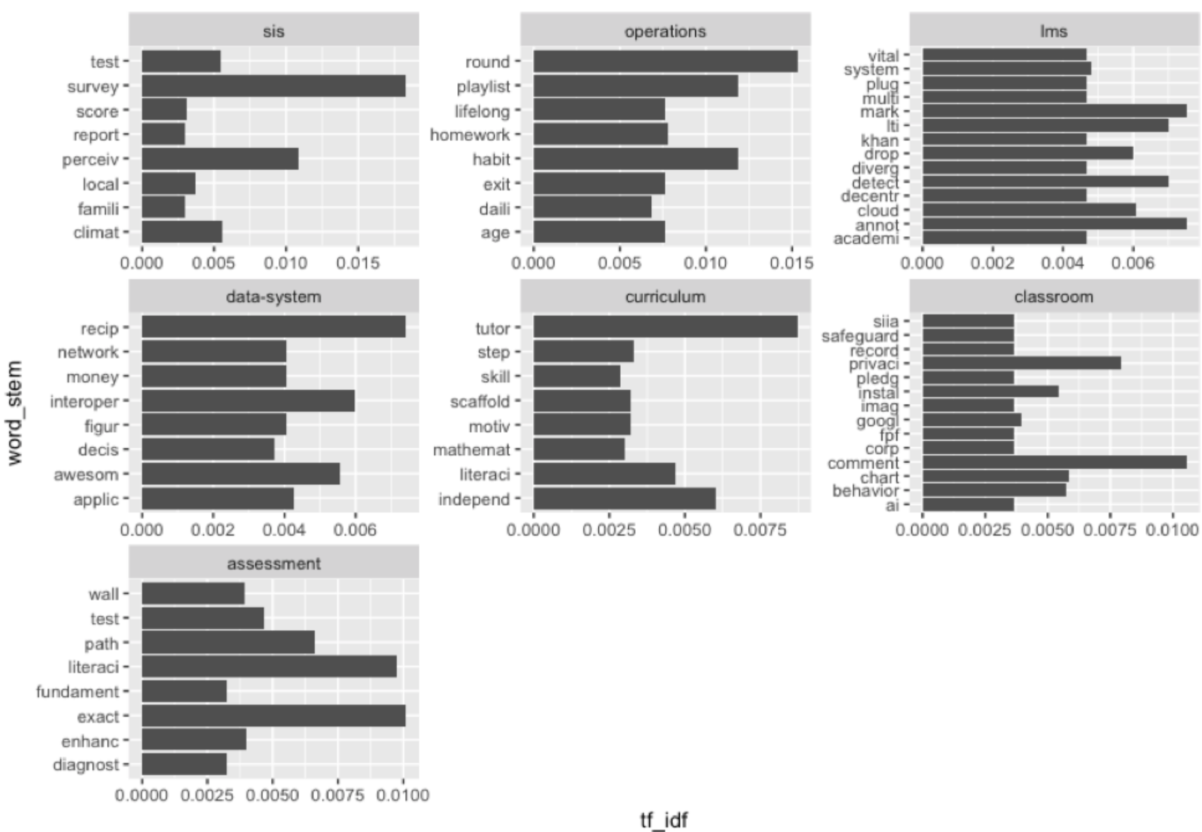

Figure 13. Tf-idf by product type.

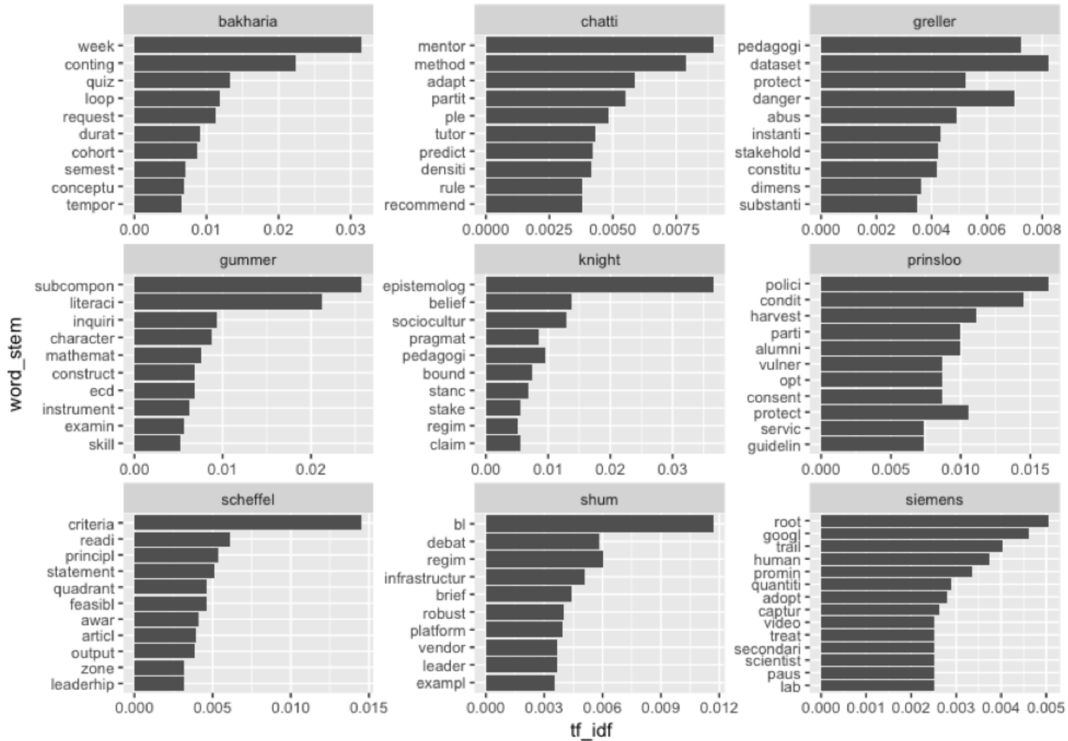

Figure 14. Tf-idf by author.

N-grams. Bi-grams and tri-grams were generated to answer the primary research question: What is the quality of information provided on LA product websites? N-grams are helpful to provide context for measurements performed on tokenized (single word) text units. Tables 14 and 15 show tf-idf rankings for the study corpus and literature corpus respectively.

Table 14

Study Corpus Bigrams Ranked by TF-IDF

Bigram	*N*	*TF*	*IDF*	*TF-IDF*
Learning Session	3	0.017647059	1.9459101	0.034339591
Academic Design	2	0.011764706	1.9459101	0.022893061
Daily Schedule	2	0.011764706	1.9459101	0.022893061
Design Include	2	0.011764706	1.9459101	0.022893061
Develop Habit	2	0.011764706	1.9459101	0.022893061
Exit Slip	2	0.011764706	1.9459101	0.022893061
Learn World	2	0.011764706	1.9459101	0.022893061
Lifelong Success	2	0.011764706	1.9459101	0.022893061
Page Provide	2	0.011764706	1.9459101	0.022893061
school based	2	0.011764706	1.9459101	0.022893061

Table 15

Literature Corpus Bigrams Ranked by TF-IDF

Bigram	*N*	*TF*	*IDF*	*TF-IDF*
Data Literacy	70	0.063810392	2.1972246	0.140205762
Epistemology Belief	36	0.025604552	2.1972246	0.056258951
Domain Analysis	21	0.019143118	2.1972246	0.042061728
Cohort Dynamic	18	0.017769003	2.1972246	0.03904249
Learning Design	35	0.034550839	1.0986123	0.037957976
Policy Framework	13	0.017195767	2.1972246	0.037782962
Loop Tool	16	0.015794669	2.1972246	0.034704436
Content Knowledge	17	0.015496809	2.1972246	0.034049971
Inquiry Process	13	0.011850501	2.1972246	0.026038213
Pedagogical Content	13	0.011850501	2.1972246	0.026038213

Sentiment analysis. Sentiment analysis was conducted to answer the secondary research question: How are the LA tools portrayed?

Overall sentiment scoring. The results of three standard sentiment lexicons are visualized in Figure 15 and 16. The results show a general pattern similarity in sentiment scores with variations between rows. The y axis represents sentiment scores (positive score – negative score), and the x axis represents the combined lines of text in each corpus.

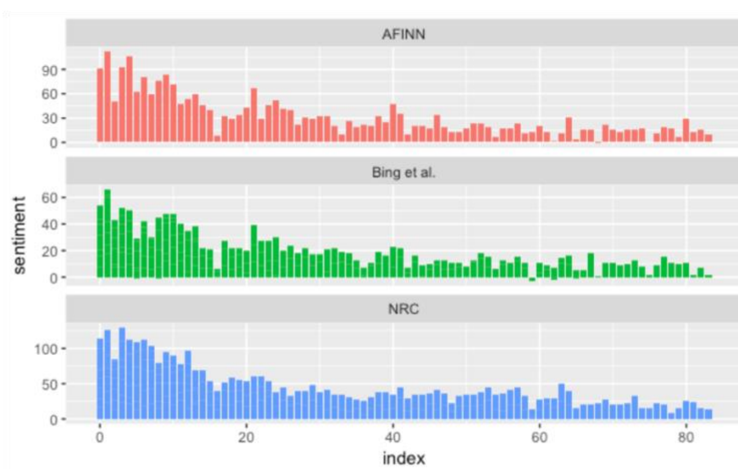

Figure 15. Study corpus sentiments scores.

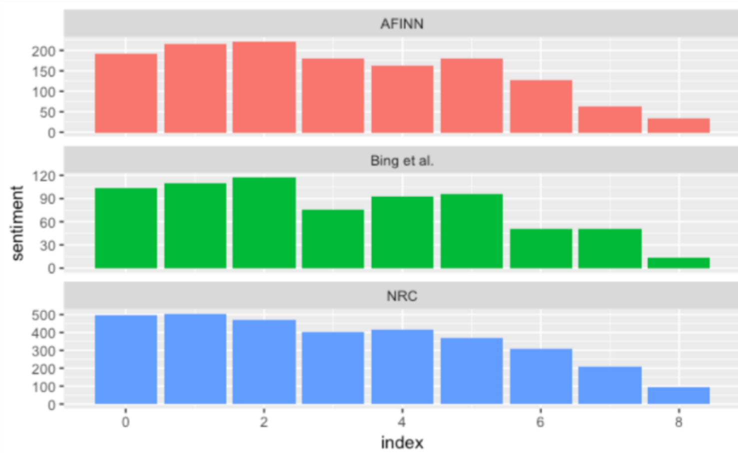

Figure 16. Literature corpus sentiments scores.

These scores indicate that both corpora express more positive than negative sentiments overall. Comparing the results of the two corpora shows that the literature corpus scores are more than double those of the study corpus.

Comparing contributing words to sentiment. Sentiments were examined further using Bing Liu's Opinion Lexicon (bing). Bing's lexicon consists of 2006 positive words and 4783 negative words and includes mis-spellings and morphological variants. The lexicon measures individual words in negative and positive gradients, then allows for the highest contributing positive and negative words to be examined. The bar charts in Figures 17 and 18 present the top ten contributions to sentiment for each corpus.

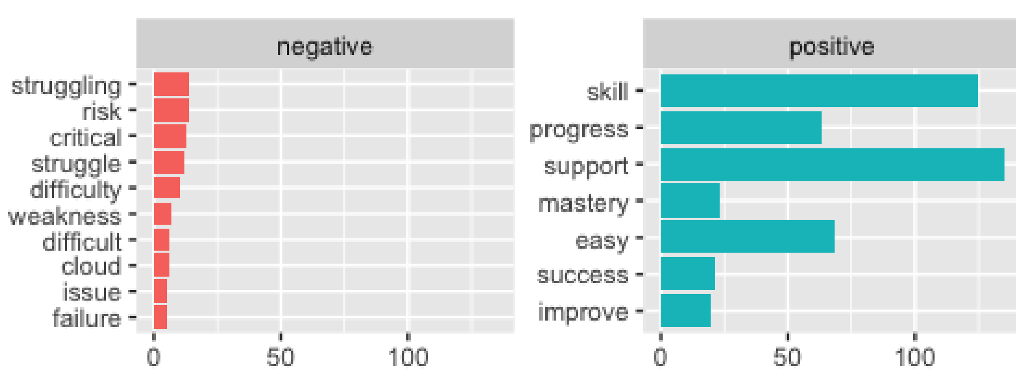

Figure 17. Study corpus contributions to sentiment.

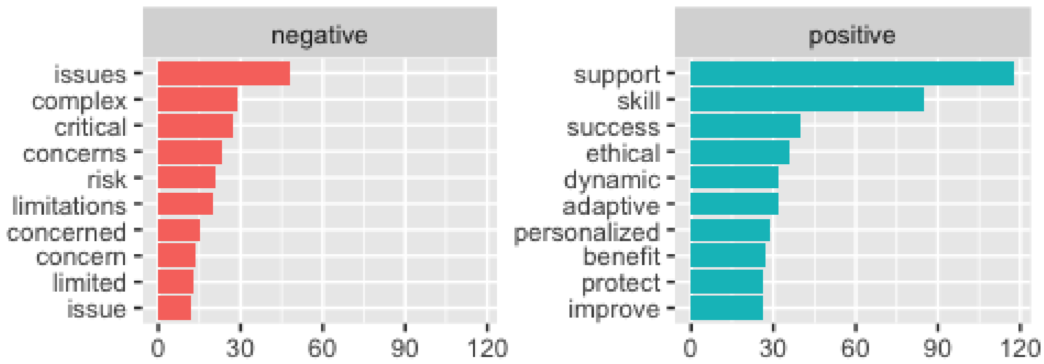

Figure 18. Literature corpus contributions to sentiments.

The study corpus scores show wide variation between negative and positive contributions to sentiment for the individual words with less variety in the top contributing positive words. Table 16 below contains the highest contribution negative and positive scores from each corpus side by side. The two columns on the left are negative word contributions and the ones on the right show the positive word contributions side by side.

Table 16

Contributing Words to Sentiment Side-by-Side Listing

StudyCorp	*LitData*	*StudyCorp*	*LitData*
Negative	Negative	Positive	Positive
struggling	issues	support	support
risk	complex	skill	skill
critical	critical	easy	success
struggle	concerns	progress	ethical
difficulty	risk	mastery	dynamic
weakness	limitations	success	adaptive
difficult	concerned	improve	personalized
cloud	concern		benefit
issue	limited		protect
failure	issue		improve

A comparison of the corpora show three common negative words and three common positive words. These have been highlighted in Table 15. The context in which the shared words appear suggest that different reference points for the shared words within the table.

Topic models. Topic models were generated for each corpus and compared to address the primary research question: What is the quality of information provided on LA product websites? Topic modeling is an automated bottom-up approach to data processing that applies machine learning algorithms to process word frequency measures. It is designed to reveal latent characteristics in text content. Topic modeling is well suited to summarize, visualize, explore, and theorize about a corpus (Blei, 2012). Topic modeling is also a good method for comparing and contrasting text content. Latent Dirichlet Allocation (LDA) is described by Blei (2012) as the simplest way to model latent topics in a text corpus. LDA approach to topic modeling is based on two assumptions: (a) that there are a fixed number of word patterns that co-occur in any given text corpus, and (b) that every document in the given corpus will contain these topics to varying degrees. Although varied approaches to topic models exist, all topic models measure word frequency in some way. The Structural Topic Model (STM) package in R was selected to implement topic modeling after reducing each word to its word-stem. STM applies correlated topic models (Blei & Lafferty, 2005) which is an approach developed to allow for uncovering topic correlations between documents in a corpus. Figure 19 and 20 depict the topic model results for the study corpus and literature corpus respectively.

1 person learn include session classroom	2 system assign manag integr parent	3 easi feedback portfolio track provid
4 instruct skill level report provid	5 time district inform creat technology	6 district report support perform test

Figure 19. Topic models from the study corpus.

1 knowledge literaci domain teach skill	2 polici inform univers person privaci	3 design access activ week compare
4 epistemolog knowledg assess approach belief	5 system process method adapt technique	6 inform process dataset support technolog

Figure 20. Topic models from the literature corpus.

The six topic models generated from each corpus demonstrate distinct differences. There were four cross corpora topic model pairs. One of the four shared two words (pair 3) and the remaining three shared one. Figure 21 presents these pairs side by side for comparison. Topics from the literature corpus appear on the left and topics from the study corpus appear on the right. The remaining topic models are presented in Figure 21. The 4-6 pair that appear in Figure 22 shares a 'fuzzy' common term, test and assess. Figure 22 also presents the 3-3 topics that did not have any common pairs in the other corpus.

2 polici inform univers **person** privaci	pair 1	1 **person** learn include session classroom	5 **system** process method adapt technique	pair 2	2 **system** assign manag integr parent
6 **inform** process dataset support **technolog**	pair 3	5 time district **inform** creat **technology**	1 knowledge literaci domain teach **skill**	pair 4	4 instruct **skill** level report provid

Figure 21. Topic models by common words.

4	6	3	3
epistemolog	district	design	easi
knowledg	report	access	feedback
assess	support	activ	portfolio
approach	perform	week	track
belief	test	compare	provid

Figure 22. Unmatched topic models.

These results resemble the variation observed in the contributing sentiments words list from the previous section. Pair two demonstrates the difference more intensely than the other pairs. The context in which 'system' appears strongly suggests contrasting understandings of the word.

Word cloud visualizations. Word cloud visualizations were generated to answer the secondary research question: How are LA tools portrayed? Figure 23 depicts the results of commonality (visualizes most common terms between corpora) and comparison (visualizes terms most unique to each corpus) clouds. The results of a word count visualization called words in common tags appear in Figure 24. The words in common tag results show a ranked list of the top common words between each corpus that demonstrate the largest difference in use.

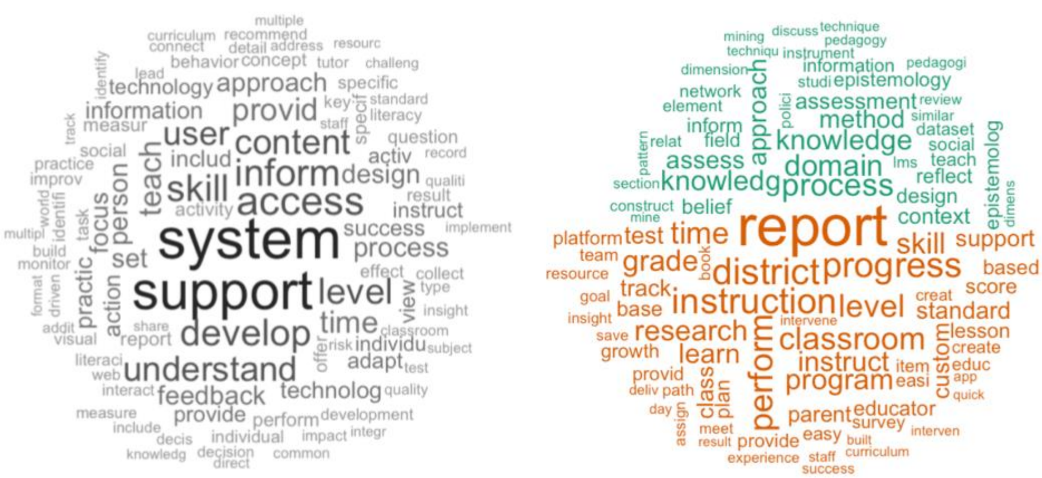

Figure 23. Commonality cloud and comparison cloud.

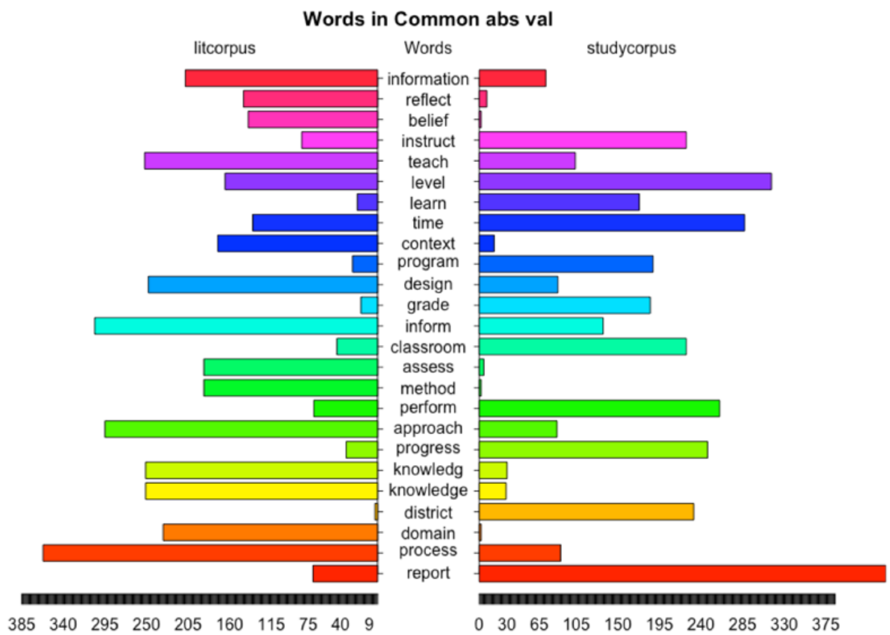

Figure 24. Words in common tags.

Summary

This chapter described the procedures and results of the research and analyses conducted in this study. The results from these analyses were used to measure content extracted from 54 analytics-based product websites against content found in LA research literature to answer the research questions. The following chapter describes the results in the context of the research questions and offers a discussion of their significance.

Chapter Five: Conclusions

This chapter presents a summary of this study and important conclusions drawn from the results presented in Chapter Four. It also provides a discussion of implications for action and recommendations for further research.

Summary of the Study

Restatement of the problem addressed by this study. Equitable access to education for all students continues to be a national priority. Policy document point to LA as a potential solution through applications such as personalized learning. Heightened policy support for LA implementations has resulted in a high number of analytics products entering the educational technology marketplace. The rapid implementation of LA rhas raised concerns from the LA research community around

- the lack of data competency among end-users,
- the implications of a widening research to practice gap, and
- market interests that conflict with the daily practices that occur around teaching and learning in schools.

This context requires additional support for educational data practitioners who are tasked with applying educational data in their daily practice. However, studies mainly focus on building knowledge for product developers and researchers and too few studies focus on knowledge building for practitioners (Wise, Vytasek, Hausknecht, & Zhao, 2016).

Restatement of the purpose and research questions. The purpose of this study was to examine and describe the relationship between research and practice in analytics applications in K12 educational settings. It was also the purpose of this study to characterize how LA are currently implemented and understood. A secondary purpose for this research was to advance a preliminary LA implementation framework to support educational data practitioners effectively apply LA in their daily practice.

The central question of this study was: What is the quality of information provided on LA product websites?

Additionally, this research addressed the following related questions:

- What kinds of LA tools are offered?
- How are the LA tools portrayed?

Discussion of the Methods

This research was conducted in two phases. Phase one of this research had three objectives, to select the study corpus, to extract and prepare data for phase two analysis, and to calibrate the analytical instruments in a pilot study. The pilot study used an iterative process to fit the topic models and identify corpus specific stop words. Phase two of this research applied the analyses in a linear process. Although this content analysis is characterized as a quantitative approach, it is important to note that qualitative methods were also applied in the both phases of this research. In chapter three, Krippendorff's (2004) distinctions between qualitative and quantitative approaches to content analysis were presented.   In brief, Krippendorff, identifies the key difference between the two approaches in their process were quantitative approaches are systematic and qualitative approaches are iterative.

Similarly, Bernard (1996) also discusses how the terms are applied in research literature and offers distinctions in two areas. The first is based on the type of data analyzed in a study and the second concerns the processes applied to analyze the data of interest. Bernard views quantitative data types as numerical data and qualitative data types as text-based and includes text translated to numbers for analysis. Bernard identifies four types of research based on these distinctions that he calls QDA phrases where the ‘Q’ represents the term quantitative or the term qualitative and ‘DA’ stands for data analysis. Table 17 presents and adapted version of Bernard’s QDA phrase quadrants.

Table 17

Adapted from Bernard (1996)

		Data (type)	
		Qualitative	***Quantitative***
Analysis (type)	Qualitative	A Qualitative analysis of Qualitative data	B Qualitative analysis of ***Quantitative*** data
	Quantitative	C ***Quantitative*** analysis of Qualitative data	D ***Quantitative*** analysis of ***Quantitative*** data
	Examples mirror quadrants above	A Interpretive studies of text	B Deriving meaning from quantitative data processing
		C Coding text to look for patterns and predictors	D Statistical analysis of questionnaire data

The research conducted in this study aligns with Bernard’s C quadrant, the quantitative analysis of qualitative data. Figures 25 and 26 map each step of research in both research phases to their corresponding qualitative or quantitative approach. Krippendorff (2004) notes that a quantitative approach also includes an iterative process that occurs during preparatory research. Figure 31 depicts the iterative process followed during the pilot study conducted during phase one of this study. The pilot study first conducted analyses to identify stop words in each corpus, then applied those words to each corpus to determine the best fitting number of topics and number of words per topic that were generated in phase two. The results were used to adjust the parameters for the two desired outcomes which appear at the top of the figure. This process was repeated until the instruments were determined to fit the characteristics of each corpus. These results were then applied in phase two with no further alterations to the instruments. As depicted in the figure, the results of the analyses were used to make adjustments to the corpora.

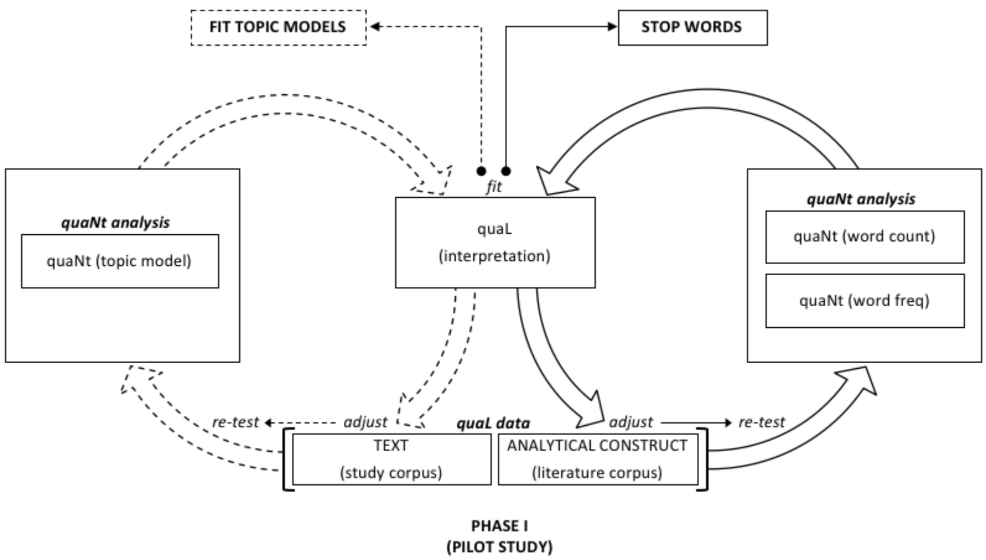

Figure 25. Phase one procedure mappings.

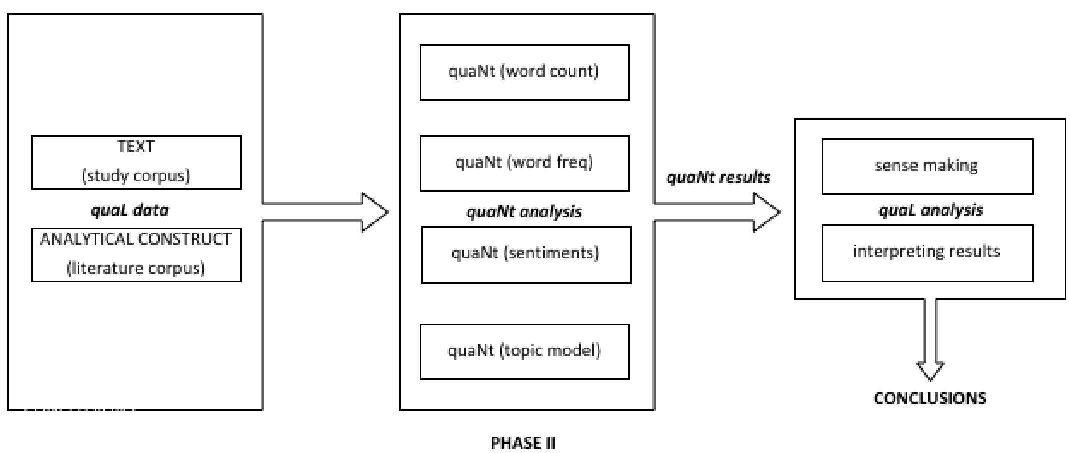

Figure 26. Quantitative analysis of qualitative data applied in current study.

Figure 26 depicts the procedures followed during Phase two of this study. Phase two procedures were conducted in a linear fashion and aligns with the systematic process that characterizes quantitative methods (Krippendorff, 2004). Within this quantitative process is where we can apply Berman's QDA phrases, with the current research falling under the quantitative analysis of qualitative data. The process as pictured began with qualitive data, moves through the quantitative analyses, and ended with a qualitative interpretation of quantitative computer analysis. Although Bernard does not include the third layer in his QDA phrase structure, he argues that all research ends in qualitive interpretation to reach the conclusions. This figure is presented here to emphasize that this research relied heavily on qualitive interpretation of results from quantitative analysis.

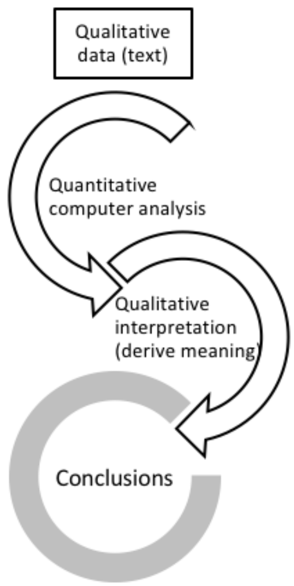

Figure 27. Relationship between qualitative and quantitative processes.

Distinguishing quantitive and qualitative aspects of this research was critical to conducting the analysis and interpreting the results. Figure 27 depicts how the two approaches were applied in the research and analysis conducted in this study. The process begins with qualitative text data that were analyzed using quantitative procedures. A final qualitative layer applied leads to the conclusions of the study. While it doesn't appear in Bernard's (1996) QDA quadrant, Bernard discusses qualitative analysis as the final stage of all research. Quantitative approaches, for example, still require a final interpretation of the results of mathematical models and statistical analysis. This interpretation may have been applied by others such as how significance is assigned to the results of statistical analysis.

In the context of this study, clarity between the two approaches is emblematic of a similar need to better understand the correct and effective uses of different data types and how they can be analyzed. Moreover, is the analytical approach appropriate for deriving conclusions in a given context? And what other analysis can be applied to verify the results? With respect to the learning process, what do we know about how learning occurs attributes of data that make less reliable in particular contexts?

Discussion of the Results with Respect to the Research Questions

This section discusses the results with respect to the research questions. To aid discussion, Table 18 presents a summary of the analyses applied in this study. The table lists the technique applied, it's associated approach, and a list of the results. A discussion of the findings related to each research question based on these results follows.

Table 18

Overview of Analytical Techniques Mapped to Results

Technique	Approach	Results generated
Word clouds	Visualization; bottom up	Commonality cloud Comparison cloud Common words tags
Tf-idf	Word frequency; bottom up	Word rankings Bigram rankings Trigram rankings
Sentiment analysis	Dictionary-based; top down	Sentiment scores Contributing words list
Topic models	Unsupervised; bottom up	Six models from study corpus Six models from literature corpus

Central research question: **What is the quality of information provided on LA product websites?** The literature corpus was used as the measurement standard to assess content quality in the study corpus. The results of this study indicate significant misalignment between the study corpus and the literature corpus around fundamental understandings around educational data and its use. Figure 28 presents results of three analysis techniques that support this conclusion.

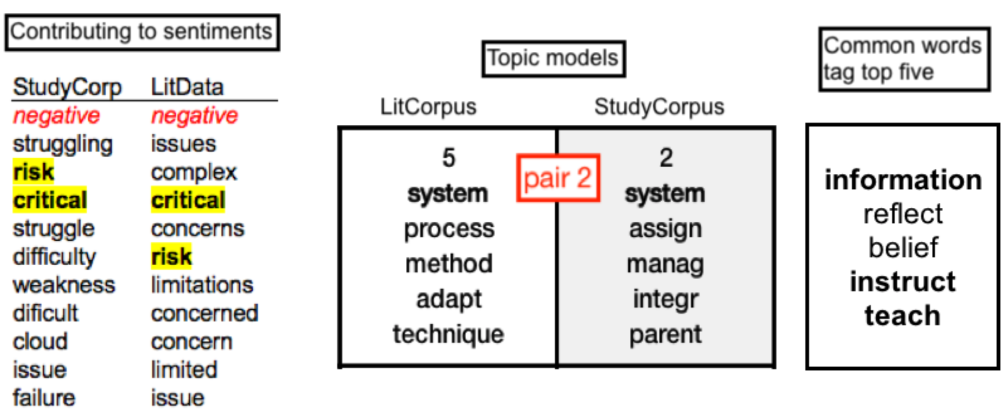

Figure 28. Examples of common word comparisons.

Evidence of philosophically opposed perspectives. The first column in Figure 28 contains a ranked list of the top negative words contributing to sentiments from each corpus. Negative words indicate problem areas and also point to the perceived source. The top contributing words to negative sentiment for each corpus include the terms *risk* and *critical.* The study corpus lists words that characterize student performance while the literature corpus lists terms associated with educational structures.

The topic models in Figure 28 present the common word, *system*, also used in philosophically opposed ways. In the literature, the term appears in the context of terms that suggest flexibility (adapt) and 'ways of doing' (process, method, technique). In the study corpus, the context suggests that systems are seen as a management tool (assign, manage).

Finally, the last column lists the top five ranked common terms between the two corpora that demonstrate the highest difference in use. Three terms appear on this list that are significant to learning analytics: “information,” “instruct,” and “teach.”

Conclusions based on the evidence. The results from the first two columns resulted from two different analytical techniques. When the results are considered together, they show misalignment between the two corpora while maintaining alignment within each corpus. For example, sentiments results indicate a paradigm where student performance is perceived to be the source of problems. This paradigm aligns with a perspective that views systems as a management tool. The sentiments results from the literature corpus frames problems around the limitations of educational structures. This perspective aligns with the results of the topic model in the second column where systems seem to be expected to adapt to the context in which it exists. The results from these analysis demonstrate a philosophical alignment. Both results indicate a systems perspective. Between the corpora, however, the outcomes are incompatible.

Secondary research question: What kinds of LA tools are available? In this study, the results indicate an emphasis on tools that enable reporting, facilitate communication, and allow for interoperability. Figure 29 shows the top five tf-idf rankings for each product type. The terms highlighted in green both point to a focus on the interoperability of data systems. Under LMS (learning management systems) the term LTI (learning tools interoperability) and under data-systems the word stem *interoper* indicate a focus on decentralized data systems. This focus aligns strongly with research. Also, of note is the high frequency terms listed in the first entry under SIS (student information systems). Under this category, the term *survey* in the context of the term stems *local* and *perceive* suggests the intent to gather data that are not typically collected in schools.

Evidence of alignments. In combination, these results suggest that school-wide systems are extending the types of data that are available and enabling data exchange between different platforms. Both of these themes enhance data quality within schools and are aligned with the literature.

sis	operations	lms	data-systems	curriculum	classroom	assessment
test	round	mark	recip	tutor	privaci	wall
survey	playlist	lti	network	step	instal	test
perceiv	lifelong	detect	money	scaffold	comment	literaci
local	homework	cloud	interoper	literaci	chart	fundament
climat	habit	annot	figur	independ	behavior	enhance

Figure 29. Tf-idf by product type.

The topic models generated from the study corpus in Figure 30 also provide insight into the kinds of tools that are available. Using results from bigram and trigram analyses for contextual reference, these models can be interpreted to indicate a focus on tools that personalize learning (topic 1), functions that enable reporting at the classroom (topic 3 and (d) and district (topic 5 and 6) levels, and systems that support communication between home and school regarding student progress (topic 2).

1	2	3
person	system	easi
learn	assign	feedback
include	manag	portfolio
session	integr	track
classroom	parent	provid
4	**5**	**6**
instruct	time	district
skill	district	report
level	inform	support
report	creat	perform
provid	technology	test

Figure 30. Topic models generated from study corpus.

Conclusions based on the evidence. Examining the results of analysis from the study corpus show alignments in the treatment of data infrastructures between the two corpora. The first topic model indicates a topic addressing personalized learning which also aligns with the literature.

How are LA tools portrayed? The final research question addressed in this study was: How are LA tools portrayed? The results of sentiments scoring indicated that both corpora demonstrate more positive than negative sentiments. The general sentiment scores were less interesting than the results of the contributions to sentiment words lists. They appear again in Table 19 below to aid the discussion.

Table 19

Contribution to Sentiment Scores Side-by-Side Comparison

StudyCorp	LitData	StudyCorp	LitData
Negative	*Negative*	*Positive*	*Positive*
struggling	issues	support	support
risk	complex	skill	skill
critical	critical	easy	success
struggle	concerns	progress	ethical
difficulty	risk	mastery	dynamic
weakness	limitations	success	adaptive
difficult	concerned	improve	personalized
cloud	concern		benefit
issue	limited		protect
failure	issue		improve

The results of contributing words to sentiment provide interesting comparison of how positive vs. negative words are used in the study corpus. A comparison of common words used in both corpora indicate distinctly different perspectives on the kinds of problems that can be solved, and the outcomes expected.

Finally, the comparative cloud that appears in Figure 31 depicts patterns of word use that are unique to each corpus. The visualization echoes results from the topic model analysis which emphasize reporting.

Figure 31. Comparison cloud visualization

Conclusions based on the evidence. As mentioned in the earlier in this discussion, the negative terms in the study corpus appear to emphasize improving student performance in contrast to the literature corpus results that suggest a focus on improving the systems that support learning. The difference between these perspectives are not insignificant and require further investigation. The results taken together indicate that learning analytics are portrayed in fundamentally different ways.

Implications for Action

Data does not appear to be applied in ways that will improve instructional practices. Study corpus results across the analysis techniques show little evidence that the tools are prompting the changes to pedagogical practices that research shows are required to improve learning outcomes. Analytics practices currently appear to be leveraged in support of existing practices. When analytics tools appear in instructional contexts, they are enacted through algorithms that bypass the teacher's role in classrooms. This is not a practice recommended in the literature. Rather, studies support the opposite. Monroy and Rangel (2014) found that increasing teacher involvement by enabling qualitative data collection alongside quantitative analysis allowed for more accurate results.

Conflicts within the policy structure in K12 educational settings can be observed in the results. The emphasis on reporting is demonstrated consistently in the results of analysis for the Study Corpus. The attention paid to reporting and demonstrating progress overshadow the attention paid to improving learning which policy documents emphasize as the main purpose for measuring learning. Information does not appear to be used to improve instructional practices, rather, information is used to report progress. This indicates that changes are required at the policy level to resolve these competing interests.

Conclusions

Overall, these results indicate fundamental distinctions between content found on LA product websites and the LA research literature. These preliminary findings reveal contrasting perceptions of the impact of analytics on educational environments. This perspective is supported by the literature reviewed in Chapter Two of this study. More compelling support for the validity of these results is that results show misalignment between the two corpora but demonstrate alignment between the results of difference analysis techniques within each corpus.

The Significance of the Findings

The objective of this research was to assess the quality of information provided on LA product websites against the research base. The current findings enhance our understanding of the nature of the research to practice gap. In particular, it provides insight into how specific constructs are interpreted differently between corpora. This kind of information is useful in the following ways:

- Research can be used to guide professional development
- Results of this study and similar research can be used to understand alignment between educational policy priorities and practice
- Results of this study and similar research can be used to make adjustments to current educational policy to achieve better alignment between policy goals and their impact on practice
- Similar research can be used to better understand classroom practices in light of prevalent use of educational technologies

Limitations of the Current Work

Finally, important limitations need to be considered regarding the results of this study.

- This study only examined a limited number of webpages for each product. Therefore the results only reflect the information shared on those pages.
- This study did not examine any multimedia elements, and solely focused on text content. This is important to note because the websites contain many multimedia elements.
- The sampling approach was intentionally conservative to favor relevancy over scope. Different sampling frames may expand understandings that can be derived from the results.

Concluding Thoughts

The text analysis techniques applied in this research make it easy to evaluate a large amount of information quickly. This is useful for evaluating and identifying which educational technologies that add value to a given learning environment.

Supporting teachers, administrators, and technology staff to evaluate and implement analytics based educational technologies relates to a secondary objective of this research. As mentioned in Chapter One, this study also intended to present a preliminary framework for learning analytics oriented towards educational data practitioners (i.e., teachers, administrators, and technology staff) to support evaluation and selection of data related applications.

Ethics research makes a compelling case for a student's right to forget their academic data trail. Collecting, tracking, and referencing [poor] academic performance impacts how students see themselves and what they believe that can achieve. Struggling students and students perceived as 'at-risk' are especially vulnerable when data are applied inaccurately.

Figure 32 contains an early model of the preliminary framework of constructs that are critical to practitioners. In the preliminary framework, *data attributes* describes characteristics of data that are unchanging. Data attributes must be considered in every LA implementation and align with ethics issues described in the literature. Below data attributes are the three components of *learning analytics implementations*, a phrase used to describe adopting and applying analytics to a given educational setting. The three key components of a learning analytics implementation are *dataset quality*, *data competency*, and *LA tool. Dataset quality* describes the robustness of the data environment including, but not limited to, types of data available, the interoperability of the platforms used to store data (i.e., are data accessible across platforms), and the completeness of the dataset (i.e., are there enough data to enable accurate results). *Data competency* refers to the skills required of end-users or the educational data practitioners who are being informed by the analysis. Finally, *LA tool* refers to the software, application or platform intended for adoption.

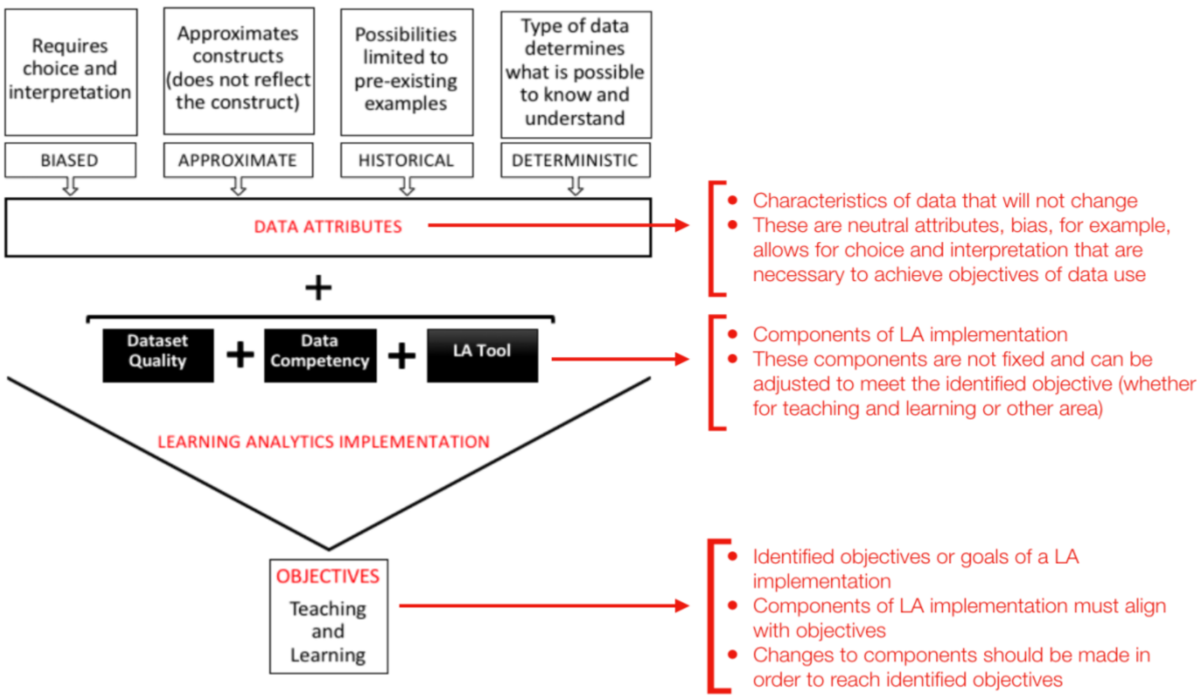

Figure 32. Preliminary framework for educational data practitioners

The combination of these components define the learning analytics implementation. The final tier labeled *objectives* refers to the identified goal for the learning analytics implementation. Objectives relate to the aspects of an educational setting that stakeholders desire to better understand. Although the preliminary framework indicates teaching and learning as the impact area, objectives can refer to any aspect of an educational setting where stakeholders seek insight. A final and critical point about the preliminary framework is that alignment between the learning analytics implementation and the objective must be aligned. When objectives are new ones within an educational setting, it is unlikely that there will be full alignment between them. However, the components of a learning analytics implementation are not fixed. So, the task for educational data practitioners is to identify what aspects of the components to adjust and how to adjust those aspects in order to achieve alignment with the identified objective. Figure 33 presents the second iteration of the model and identifies how practitioners engage with the preliminary model to guide implementation.

The framework depicts the critical components of any LA implementation in K12 educational settings. This preliminary model requires additional development. In particular, mapping components of data quality, data competency, and LA tools to their corresponding teaching and learning objectives is required. This can be done by integrating the frameworks from the LA literature base with the components of this preliminary framework.

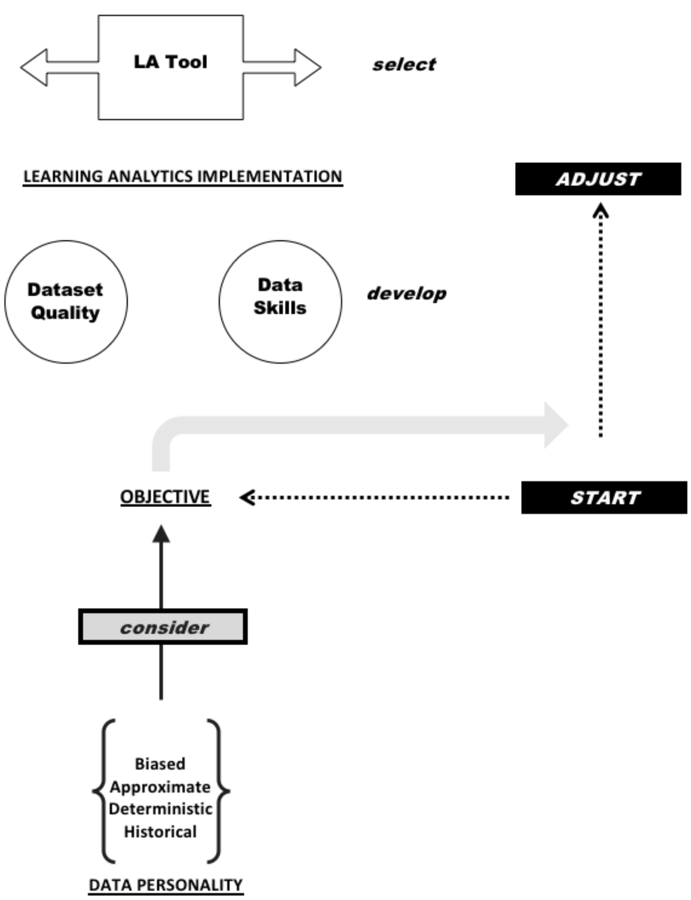

Figure 33. Preliminary learning analytics implementation framework for practitioners

Future Directions

More research is required in developing an approach to enable accurate automated multi-domain web content extraction is required to scale this approach to content analysis in the education domain. Additional research areas are:

- Examine individual categories with more depth
- Analyze contents of practitioner reviews on EdSurge Index
- Compare the products available on other educational technology product indexes
- Research using other types of educational technologies to better understand the research to practice gap in other areas of educational research

REFERENCES

Baker, R., & Siemens, G. (2014). Educational data mining and learning analytics. In R. K. Sawyer (Ed.), *The Cambridge handbook of the learning sciences* (pp. 253–272). http://doi.org/10.1017/cbo9781139519526.016

Bakharia, A., Corrin, L., de Barba, P., Kennedy, G., Gasevic, D., Mulder, R., … Lockyer, L. (2016). A conceptual framework linking learning design with learning analytics. *Proceedings of the Sixth International Conference on Learning Analytics & Knowledge,* 329-338. http://doi.org/10.1145/2883851.2883944

Bienkowski, M., Feng, M., & Means, B. (2012). Enhancing teaching and learning through educational data mining and learning analytics: An issue brief. *US Department of Education, Office of Educational Technology*, *1*, 1-57.

Berman, J. J. (2013). *Principles of big data: Preparing, sharing, and analyzing complex information.* Waltham, MA: Elsevier.

Bernard, H. R. (1996). Qualitative data, quantitative analysis. *CAM Journal, 8*, 9–11. http://doi.org/10.1177/1525822X960080010401

Blei, D. M. (2012). Probabilistic topic models. *Communications of the ACM, 55*, 77–9. http://doi.org/10.1145/2133806.2133826

Blei, D. M., & Lafferty, J. D. (2005). Correlated topic models. *Proceedings of the Advances in Neural Information Processing Systems, Canada, 18,* 147-154.

Boyd, D., & Crawford, K. (2012). Critical questions for big data: Provocations for a cultural, technological, and scholarly phenomenon. *Information, Communication & Society, 15*, 662-679. http://doi.org/10.1080/1369118X.2012.678878

Chatti, M. A., Dyckhoff, A. L., Schroeder, U., & Thüs, H. (2012). A reference model for learning analytics. *International Journal of Technology Enhanced Learning, 4*, 318. http://doi.org/10.1504/ijtel.2012.051815

Dawson, S., Gasevic, D., & Joksimović, S. (2014). Current state and future trends: A citation network analysis of the learning analytics field (pp. 231–240). *Proceedings of the Fourth International Conference on Learning Analytics and Knowledge, USA*, 231-240. http://doi.org/10.1145/2567574.2567585

Edwards, R., & Fenwick, T. (2016). Digital analytics in professional work and learning. *Studies in Continuing Education, 38*, 213–227. http://doi.org/10.1080/0158037X.2015.1074894

European Union Joint Reserch Centre. (2016). *Research evidence on the use of learning analytics: Implications for education policy*. http://doi.org/10.2791/955210

Freeman, A., Becker, S. A., Cummins, M., Davis, A., & Hall Giesinger, C. (2017). *NMC/CoSN horizon report: 2017 K*. Retrieved from https://www.nmc.org/publication/nmccosn-horizon-report-2017-k-12-edition

Gasevic, D., & Dawson, S. (2014). Let's not forget: Learning analytics are about learning. *TechTrends, 59*, 64–71. http://doi.org/10.1007/s11528-014-0822-x

Goodman N. D., Tenenbaum J. B., & The ProbMods Contributors. (2016). *Probabilistic models of cognition*. Retrieved from http://probmods.org

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

Grün, B., & Hornik, K. (2011). Topicmodels: An R package for fitting topic models. *Journal of Statistical Software, 40*, 1–30. https://doi.org/10.18637%2Fjss.v040.i13

Gummer, E. S., & Mandinach, E. B. (2015). Building a conceptual framework for data literacy. *Teachers College Record, 117*(4). Retrieved from http://www.tcrecord.org

Günther, E., & Quandt, T. (2015). Word counts and topic models. *Digital Journalism, 4,* 75–88. http://doi.org/10.1080/21670811.2015.1093270

Humphreys, A., & Wang, R. J.H. (2017). Automated text analysis for consumer research. *Journal of Consumer Research, 30*, 212–33. http://doi.org/10.1093/jcr/ucx104

Knight, S., & Buckingham Shum, S. (2017). Theory and learning analytics. In C. Lang, G. Siemens, A. Wise, & D. Gasevic (Eds.), *Handbook of learning analytics – first edition* (pp. 17–22). http://doi.org/10.18608/hla17.001

Knight, S., Shum, S. B., & Littleton, K. (2014). Epistemology, assessment, pedagogy: Where learning meets analytics in the middle space. *Journal of Learning Analytics, 1*, 23–47. http://doi.org/10.18608/jla.2014.12.3

Krippendorff, K. (2004). *Content analysis*. Thousand Oaks, CA: SAGE Publications.

Lau, D., Ogbogu, U., Taylor, B., Stafinski, T., Menon, D., & Caulfield, T. (2008). Stem cell clinics online: The direct-to-consumer portrayal of stem cell medicine. *Cell Stem Cell, 3,* 591–594. https://doi.org/10.1016/j.stem.2008.11.001

Lazer, D., Kennedy, R., King, G., & Vespignani, A. (2014). The parable of Google flu: Traps in big data analysis. *Science, 343,* 1203-1205. http://doi.org/10.1126/science.1248506

Lonn, S., Aguilar, S. J., & Teasley, S. D. (2015). Investigating student motivation in the context of a learning analytics intervention during a summer bridge program. *Computers in Human Behavior, 47*, 90–97. http://doi.org/10.1016/j.chb.2014.07.013

Roberts, M., Stewart, B. M., & Tingley D. (2018). *stm: R Package for Structural Topic Models*. Retrieved from: https://cran.r-project.org/web/packages/stm/vignettes/stmVignette.pdf

Mayer-Schonberger, V., & Cukier, K. (2013). *Big data: A revolution that will transform how we live, work and think*. New York, NY: Houghton Mifflin Harcourt.

Mcafee, A., & Brynjolfsson, E. (2012). Big data: The management revolution. *Harvard Business Review, 90*(10), 60–6.

Monroy, C., & Rangel, V. S. (2014). A strategy for incorporating learning analytics into the design and evaluation of a K–12 science curriculum. *Journal of Learning Analytics, 1*, 94–125. http://doi.org/doi:10.18608/jla.2014.12.6

Neuendorf, K. A. (2002). *The content analysis guidebook*. Thousand Oaks, CA: Sage Publications.

Neuendorf, K. A., & Kumar, A. (2015). Content analysis. In G. Mazzoleni (Ed.), *The international encyclopedia of political communication.* http://doi.org/10.1002/9781118541555.wbiepc065

Neuman, S. B. (2016). Code red: The danger of data-driven instruction. *Educational Leadership, 74*(3), 24–29.

Ostry, A., Young, M. L., & Hughes, M. (2008). The quality of nutritional information available on popular websites: A content analysis. *Health Education Research, 23*, 648–655. http://doi.org/10.1093/her/cym050

Papamitsiou, Z. K., & Economides, A. A. (2014). Learning analytics and educational data mining in practice: A systematic literature review of empirical evidence. *Educational Technology & Society*, *17*(4), 49–64.

Pea, R. (2014). *The learning analytics workgroup: A report on building the field of learning analytics for personalized learning at scale.* Retrieved from: https://ed.stanford.edu/sites/default/files/law_report_complete_09-02-2014.pdf

Pigliucci, M. (2009). The end of theory in science? *EMBO Reports, 10*, 534–534. http://doi.org/10.1038/embor.2009.111

Riff, D., Lacy, S., & Fico, F. (2005). *Analyzing media messages: Using quantitative content analysis in research 2nd Edition.* Mahwah, NJ: Lawrence Erlbaum Associates Publishers.

Scheffel, M., Drachsler, H., & Stoyanov, S. (2014). Quality indicators for learning analytics. *Journal of Educational Technology & Society, 17*(4), 117.

Short, J. C., Broberg, J. C., Cogliser, C. C., & Brigham, K. H. (2010). Construct validation using computer-aided text analysis. *Organizational Research Methods, 13*, 320–347. http://doi.org/10.1177/1094428109335949

Shum, S. B. (2012). *Learning analytics.* Retrieved from: https://iite.unesco.org/publications/3214711/

Shum, S. B., & Crick, R. D. (2012). Learning dispositions and transferable competencies: Pedagogy, modelling and learning analytics. *Proceedings of the 2nd International Conference on Learning Analytics and Knowledge, Canada*, 92-101. https://doi.org/10.1145/2330601.2330629

Siemens, G. (2012). Learning analytics: Envisioning a research discipline and a domain of practice. *Proceedings of the 2nd International Conference on Learning analytics and Knowledge, Canada*, 4-8. http://doi.org/10.1145/2330601.2330605

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

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

Slade, S., & Prinsloo, P. (2013). Learning analytics: Ethical issues and dilemmas. *American Behavioral Scientist, 57*, 1510–1529. http://doi.org/10.1177/0002764213479366

Smith, R. (2016). The emergence of the quantified child. *Discourse: Studies in the Cultural Politics of Education, 38,* 701–712. http://doi.org/10.1080/01596306.2015.1136269

Song, R., Liu, H., Wen, J. R., & Ma, W. Y. (2004). Learning important models for web page blocks based on layout and content analysis. *ACM SIGKDD Explorations Newsletter, 6*(2), 14-23.

Stahl, N. A., Brozo, W. G., & Simpson, M. L. (1987). Developing college vocabulary: A content analysis of instructional materials. *Literacy Research and Instruction, 26*, 203–221. http://doi.org/10.1080/19388078709557910

Suthers, D., & Verbert, K. (2013). Learning analytics as a middle space. *Proceedings of the Third International Conference on Learning Analytics and Knowledge, Belgium,* 1-4. http://doi.org/10.1145/2460296.2460298

US Department of Education, Office of Educational Technology. (2014). *The future ready district: Professional learning through online communities*. Retrieved from: https://tech.ed.gov/futureready/professional-learning/future-ready-district

US Department of Education, Office of Educational Technology. (2017). *Reimagining the role of technology in education: 2017 national education technology plan update*. Retrieved from: https://tech.ed.gov/files/2017/01/NETP17.pdf

Weare, C., & Lin, W. Y. (2000). Content analysis of the World Wide Web: Opportunities and challenges. *Social Science Computer Review, 18,* 272-292. http://doi.org/10.1177/089443930001800304

Wiedemann, G. (2013). Opening up to big data: Computer-assisted analysis of textual data in social sciences. *Historical Social Research*, *38*, 332-357. http://dx.doi.org/10.17169/fqs-14.2.1949

Williamson, B. (2015). *Smarter learning software: Education and the big data imaginary*. Paper presented at Big Data—Social Data, Warwick, UK.

Wise, A., & Schaffer, D. (2015). Why theory matters more than ever in the age of big data. *Journal of Learning Analytics, 2,* 5–13. http://doi.org/10.18608/jla.2015.22.2

Wise, A. F., Vytasek, J. M., Hausknecht, S., & Zhao, Y. (2016). Developing learning analytics design knowledge in the "middle space": The student tuning model and align design framework for learning analytics use. *Online Learning, 20*. http://doi.org/10.24059/olj.v20i2.783

APPENDIX A

IRB Approval Letter

PEPPERDINE

Pepperdine University
24255 Pacific Coast Highway
Malibu, CA 90263
TEL: 310-506-4000

NOTICE OF APPROVAL FOR HUMAN RESEARCH

Date: February 09, 2018

Protocol Investigator Name: Sandra Sarmonpal

Protocol #: 17-10-629

Project Title: Learning Analytics from Research to Practice: A Content Analysis to Assess Information Quality on Learning Analytics Product Websites

School: Graduate School of Education and Psychology

Dear Sandra Sarmonpal:

Thank you for submitting your application for exempt review to Pepperdine University's Institutional Review Board (IRB). We appreciate the work you have done on your proposal. The IRB has reviewed your submitted IRB application and all ancillary materials. Upon review, the IRB has determined that the above entitled project meets the requirements for exemption under the federal regulations 45 CFR 46.101 that govern the protections of human subjects.

Your research must be conducted according to the proposal that was submitted to the IRB. If changes to the approved protocol occur, a revised protocol must be reviewed and approved by the IRB before implementation. For any proposed changes in your research protocol, please submit an amendment to the IRB. Since your study falls under exemption, there is no requirement for continuing IRB review of your project. Please be aware that changes to your protocol may prevent the research from qualifying for exemption from 45 CFR 46.101 and require submission of a new IRB application or other materials to the IRB.

A goal of the IRB is to prevent negative occurrences during any research study. However, despite the best intent, unforeseen circumstances or events may arise during the research. If an unexpected situation or adverse event happens during your investigation, please notify the IRB as soon as possible. We will ask for a complete written explanation of the event and your written response. Other actions also may be required depending on the nature of the event. Details regarding the timeframe in which adverse events must be reported to the IRB and documenting the adverse event can be found in the *Pepperdine University Protection of Human Participants in Research: Policies and Procedures Manual* at community.pepperdine.edu/irb.

Please refer to the protocol number denoted above in all communication or correspondence related to your application and this approval. Should you have additional questions or require clarification of the contents of this letter, please contact the IRB Office. On behalf of the IRB, I wish you success in this scholarly pursuit.

Sincerely,

Judy Ho, Ph.D., IRB Chair

PEPPERDINE

Pepperdine University
24255 Pacific Coast Highway
Malibu, CA 90263
TEL: 310-506-4000

cc: Dr. Lee Kats, Vice Provost for Research and Strategic Initiatives

Mr. Brett Leach, Regulatory Affairs Specialist

APPENDIX B

Study Corpus by Category

Table B1

Study Corpus by Category

Category	Name
assessment	blueribbontesting edmentum ioeducation learnerpal
classroom	branchingminds catalystk12 classcharts classkick freshgrade kaizena learnboost playposit
curriculum	adaptedmind ascendmath booksthatgrow carnegielearning educationcity frontrowed imaginelearning istation knowre learnbop lexialearning myclasstracks pearsonschool practutor renaissance squigglepark whizz
data-system	brightbytes chalkschool clever ed-fi five-startech forefrontmath learnmetrics projectell schoolrunner eduvant

(continued)

Table B1 (continued).

lms	ebackpack edvance360 revolutionnext silverbacklearning
operations	newclassrooms
sis	Alpineachievement bocavox-maestro edupoint illuminateed infinitecampus mzdevinc pacificmetrics panoramaed temboinc

APPENDIX C

Study Corpus Content URLs

Table C1

Study Corpus Content Extraction URL Pages

Category	URL Page Path
assessment	blueribbontesting
assessment	edmentum
assessment	edmentum_about_commitment
assessment	edmentum_products_assessments
assessment	edmentum_products_exact-path
assessment	edmentum_products_study-island
assessment	edmentum_programs
assessment	edmentum_programs_k-8_classroom-assessment
assessment	edmentum_programs_k-8_individual-learning
assessment	ioeducation
assessment	ioeducation_our-commitment_data-integration
assessment	ioeducation_what-you-need_student-assessment-data-analytics
assessment	ioeducation_what-you-need_student-assessment-data-analytics_data-analytics-reporting
assessment	ioeducation_what-you-need_student-assessment-data-analytics_literacy-screening-diagnostics
assessment	ioeducation_what-you-need_student-assessment-data-analytics_literacy-screening-diagnostics
assessment	ioeducation_what-you-need_student-assessment-data-analytics_student-assessment
assessment	learnerpal
assessment	learnerpal_learnerpal-rp
classroom	branchingminds
classroom	branchingminds_solution
classroom	catalystk12
classroom	classcharts
classroom	classkick
classroom	freshgrade
classroom	freshgrade_school-and-district
classroom	freshgrade_teachers
classroom	kaizena
classroom	learnboost_en_US_home
classroom	playposit
classroom	playposit_learn_k12
curriculum	adaptedmind
curriculum	adaptedmind_about.php
curriculum	ascendmath
curriculum	booksthatgrow
curriculum	booksthatgrow_our-story
curriculum	carnegielearning
curriculum	carnegielearning_products_our-products_overview
curriculum	carnegielearning_products_software-platform_mathia-learning-software
curriculum	carnegielearning_products_software-platform_mika-learning-software
curriculum	carnegielearning_why_edreports
curriculum	carnegielearning_why_our-approach

(continued)

Table C1 (continued).

Category	URL Page Path
curriculum	educationcity_us
curriculum	educationcity_us_explore
curriculum	educationcity_us_features
curriculum	frontrowed
curriculum	imaginelearning_curriculum
curriculum	imaginelearning_programs_math
curriculum	istation
curriculum	istation_About
curriculum	istation_SuperSeven
curriculum	istation_SuperSeven_adaptCurriculum
curriculum	istation_SuperSeven_adaptCurriculum
curriculum	istation_SuperSeven_adaptCurriculum
curriculum	istation_SuperSeven_adaptCurriculum
curriculum	istation_SuperSeven_adaptCurriculum
curriculum	istation_SuperSeven_FormativeAssessments
curriculum	istation_SuperSeven_FormativeAssessments
curriculum	istation_SuperSeven_personalizeDataprofile
curriculum	knowre
curriculum	learnbop
curriculum	learnbop_about
curriculum	learnbop_features_assessments
curriculum	learnbop_features_assessments
curriculum	learnbop_features_math-intervenes
curriculum	learnbop_features_math-intervenes
curriculum	learnbop_features_reporting
curriculum	learnbop_features_step-by-step-tutor
curriculum	learnbop_in-the-classroom
curriculum	learnbop_learnbop-for-school
curriculum	lexialearning
curriculum	lexialearning_about
curriculum	lexialearning_products
curriculum	lexialearning_products_core5_assessment-without-testing
curriculum	lexialearning_products_core5_student-driven-learning
curriculum	lexialearning_products_powerup_embedded-progress-monitoring
curriculum	lexialearning_products_powerup_independent-student-driven-learning
curriculum	lexialearning_products_rapid_computer-adapt-testing
curriculum	lexialearning_products_rapid_predicts-read-success
curriculum	lexialearning_solutions_personalize-learning
curriculum	lexialearning_why-lexia
curriculum	lexialearning_why-lexia_assessment-without-testing
curriculum	lexialearning_why-lexia_personalize-learning-model
curriculum	myclasstracks
curriculum	pearsonschool_index.cfm?locator= [cont…]
curriculum	pearsonschool_index.cfm?locator=PS2qK8
curriculum	pearsonschool_index.cfm?locator=PS2qKb
curriculum	practutor
curriculum	practutor_PractutorQuality

(continued)

Table C1 (continued).

Category	URL Page Path
curriculum	renaissance
curriculum	renaissance_about-us
curriculum	renaissance_learning-analytics
curriculum	renaissance_Products_Accelerated-Reader_ATOS_ATOS-Analyzer-for-Books
curriculum	renaissance_products_practice_accelerated-reader-360_atos-and-text-complexity
curriculum	renaissance_solutions
curriculum	renaissance_wkar-report
curriculum	squigglepark
curriculum	squigglepark_about-squiggle-park
curriculum	whizz_?force
curriculum	whizz_about_?force
curriculum	whizz_school_assessment-and-reporting
data-system	brightbytes
data-system	chalkschool
data-system	clever
data-system	ed-fi
data-system	eduvant_solutions
data-system	five-startech
data-system	forefrontmath
data-system	forefrontmath_about-us
data-system	learnmetrics
data-system	learnmetrics_7-ideas-figuring-data
data-system	learnmetrics_interoperability-education-datas-biggest-problem
data-system	projectell
data-system	projectell_our-product
data-system	schoolrunner
data-system	schoolrunner_administrators
data-system	schoolrunner_how-it-works
lms	ebackpack
lms	ebackpack_features
lms	edvance360_k12
lms	revolutionnext
lms	revolutionnext_iems.do
lms	silverbacklearning
operations	newclassrooms_a-new-approach
operations	newclassrooms_a-new-approach_personalize-learning-101
operations	newclassrooms_about
operations	newclassrooms_how-it-works
operations	newclassrooms_how-it-works_daily-individual-schedule
operations	newclassrooms_how-it-works_measuring-student-progress
sis	aeries_products_aeriessis
sis	alpineachievement_services.php
sis	bocavox
sis	bocavox_features-2
sis	bocavox_key-differentiators
sis	edupoint_About
sis	edupoint_Products_Synergy-Analytics

(continued)

Table C1 (continued).

Category	URL
sis	edupoint_Products_Synergy-Education-Platform
sis	edupoint_Products_Synergy-Education-Platform_Synergy-RTI-MTSS
sis	edupoint_Services
sis	Illuminateed
sis	illuminateed_about
sis	illuminateed_products_educlimber
sis	illuminateed_products_illuminate-data-assessment
sis	infinitecampus_services
sis	mzdevinc
sis	pacificmetrics
sis	pacificmetrics_about-us
sis	pacificmetrics_products-and-solutions
sis	pacificmetrics_products-and-solutions_cde
sis	pacificmetrics_products-and-solutions_crase
sis	pacificmetrics_products-and-solutions_custom-solutions
sis	pacificmetrics_products-and-solutions_echo-adapt
sis	pacificmetrics_products-and-solutions_unity
sis	panoramaed
sis	panoramaed_about
sis	panoramaed_early-warning-system
sis	panoramaed_panorama-student-survey
sis	panoramaed_panorama-teacher-survey
sis	panoramaed_products_platform
sis	panoramaed_school-climate-survey
sis	panoramaed_survey
sis	temboinc_about
sis	temboinc_project_bringing-your-data-to-life
sis	temboinc_project_designing-an-accountability-framework
sis	temboinc_project_educator-prep-program-evaluation-reporting
sis	temboinc_project_public-assessment-reporting
sis	temboinc_project_public-essa-reporting
sis	temboinc_project_student-score-reports