Understanding Ethical Concerns in the Design, Application, and Documentation of Learning Analytics in Post-secondary Education

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ABSTRACT

The practice of predicting a student's level of success in order to provide targeted assistance, termed "learning analytics," emerged from a well-established business intelligence model popularly called "Big Data." The ethical impact of Big Data on business practices has been undeniable, from gleaning private consumer behavior unbeknownst to the consumer, to creating targeted marketing based on collected data without direct consumer input. However, the ethical concerns of Big Data methodology in academia have yet to be explored, as research in this emerging discipline is relatively new. Thus, the overarching question for this study is as follows: **How can we use rhetorical, scientific, and technical communication perspectives to understand ethical concerns in the design, application, and documentation of learning analytics in post-secondary education?**

To investigate this question, I conducted a five-stage study using a cross-disciplinary perspective based on existing frameworks in rhetoric and scientific and technical communication, united by their ethical lens, from genre, persuasion, human-computer interaction, social power, semiotics, visual design, new media literacy, and pedagogy to create a matrix for understanding ethical concerns in learning analytics in post-secondary education. In Stage 1, I performed a comparative analysis between genre theory and learning analytics to understand the nature of learning analytics tools, practices, and methodology. In Stage 2, I conducted a second comparative analysis between ethical frameworks and learning analytics in order to identify the ethical concerns of learning analytics. During Stage 2, I also assigned multiple categories to the ethical concerns using three classification systems: (1) the five stages of learning

analytics (gather, predict, act, measure, refine), (2) the overarching themes in this study (design, application, documentation), and (3) the ethical concerns of Big Data (implementation of process, interpretation of data, legality of service, statistical methods).

In Stage 3, I used framework methodology to deconstruct and survey the ethical concerns of learning analytics through tree diagrams and relational visuals, and to provide an in-depth review of the type and occurrence of ethical concerns of learning analytics. In Stage 4, I combined existing frameworks in ethical pedagogy to serve as a guide for developing responses to ethical concerns. Finally, I designed and built a matrix of strategies and choices for understanding ethical concerns in the design, application, and documentation of learning analytics in post-secondary education (Stage 5).

Based on the deconstruction of ethical concerns, the inability of students to provide input into the learning analytics process was the concern most often revealed, followed by a lack of context for interpreting the data by both institutional users and students, and the potential inaccuracies in the predictive model caused by inaccurate or incomplete data. Secondary concerns included an undefined institutional responsibility to act on data, which could put the institution at risk for legal action, as well as the possibility for discrimination to occur during the learning analytics process. Concerns identified less frequently included the potential for students to become objectified (student viewed as data), the lack of an opt-out option for students, the potential for de-anonymizing the student as at-risk, and the failure to develop and communicate college principles and policies college-wide. The final concerns identified included inadequate user training (for both students and institutional users), the potential for differential access, and a lack of a vision or mission statement, or code of ethics, created and communicated by the institution.

In general, the strategies and responses to address ethical concerns in the design and documentation of learning analytics should constitute a minimum level of ethical action. This minimal implementation would ensure that students are shown goodwill by the institution and users (design), and that institutions are properly implementing learning analytics in terms of transparency of process and equality of benefit to the student (documentation). The strategies and responses to address ethical concerns in the application of learning analytics would be more complex for each situation and type of learning analytics used, but should always consider student engagement and success as the priority.

By providing a matrix of strategies and choices for understanding ethical concerns in the design, application, and documentation of learning analytics in post-secondary education, I sought to accomplish two parallel objectives. First, developing a matrix of strategies and choices allows the learning analytics community to help educational institutions understand learning analytics research and practice through an ethical lens, and to guide educational institutions towards using new learning analytics tools with an ethical viewpoint. Second, for rhetoric and scientific and technical communication researchers and practitioners specifically, such a matrix is useful as a means to continue long-standing efforts of analyzing the ethical implications of the tools (scientific and technical communication) and the artifacts (rhetorical theory) within a genre. Both of these objectives may inform future scholarship and practice in deploying learning analytics across education.

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CHAPTER 1. INTRODUCTION

Learning analytics—the practice of predicting a student's level of success in order to provide targeted assistance—emerged from a well-established business intelligence model popularly called "Big Data." Big Data has received its fair share of negative attention, not only for its design and application methodologies, but also for its questionable ethical strategies (Anderson, 2008; boyd[1] & Crawford, 2011; Davenport & Harris, 2007; Davis, 2012; Finn, Wright, & Friedewald, 2013; Marwick, Diaz, & Palfrey, 2010; Nelson, Proctor, & Brownie, 2000; Raport, 2011; Smolan & Erwitt, 2012; Weinberger, 2012). The ethical impact of Big Data on business practices has been undeniable—from gleaning private consumer behavior unbeknownst to the consumer, to creating targeted marketing based on collected data without direct consumer input. However, the ethical concerns of Big Data methodology in academia have yet to be explored, as research in this emerging discipline is relatively new.

Faculty, students, and staff, as well as those in the learning analytics community, have all expressed concern over the use of analytics in academia (Arnold, 2010; Campbell & Oblinger, 2007; Campbell, Deblois, & Oblinger, 2007; Fournier, Kop, & Sitlia, 2011; Graf, Ives, Lockyer, Hobson, & Clow, 2012; Prinsloo & Slade, 2013; Slade & Galpin, 2012; Swenson, 2014; Willis, Campbell, & Pistilli, 2013). Several features of learning analytics can raise ethical concerns. Specifically, the visual objects created during learning analytics (design), the processes of learning analytics (application), and the evidence produced while designing and applying learning analytics (documentation) all have ethical aspects. Because these three features—design, application, and

[1] The proper format for "dana boyd" is lowercase (no capitalization).

documentation—are all encompassing, whether teaching or researching learning analytics, it is important for higher education to understand the ethical concerns of learning analytics.

In this study, I offer a cross-disciplinary perspective based on existing frameworks in rhetoric and scientific and technical communication, united by their ethical lens, from genre, persuasion, human-computer interaction, social power, semiotics, visual design, new media literacy, and pedagogy to create a matrix of strategies and choices as a means for responding to ethical concerns in learning analytics.[2] These concerns may not be ethical in the traditional sense of being guided by moral principles. Rather, the concerns are related to the fairness and consistency of learning analytics services; the sufficiency of context for data interpretation by the institution or student; the protection of students' rights to privacy, ownership of their own data, and guidance of their own education (legal issues); and the accuracy and completeness of data gathered by institutions.

Thus, in the context of this study, I provide a provisional definition of ethics that refers to the standards for learning analytics in which implementation of process, interpretation of data, legality of service, and application of statistical methods have not been compromised. This provisional definition of ethics facilitates the discussion of the ethical concerns of learning analytics in the following chapters.

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[2] This study focuses on learning analytics at the post-secondary level and, therefore, on adults who can advocate for their education and who are responsible for their own success. While learning analytics is occurring in K-12, the set of practices and concerns related to using learning analytics at this educational level are different from those discussed in this study and include, for example, attention to parental consent and advocacy and engagement with parents on intervention strategies. This K-12 application brings a complexity to ethical concerns in learning analytics that is outside the scope of this study, but ripe with potential for future research.

A matrix focused on understanding ethical concerns in the design, application, and documentation of learning analytics in post-secondary education is needed for two important reasons. First, as described above, learning analytics is based on a business model known for ethical dilemmas and, therefore, it most likely has similar inherent ethical concerns. Therefore, I turn to Big Data as a guide for discovering ethical concerns in learning analytics. Second, like many emerging disciplines, learning analytics was formed at the fringe of multiple and established disciplines (e.g., statistics, behavioral science, cognitive psychology, education, computer science), each with its own perspective on and motivation for engaging in learning analytics. Early on, emerging disciplines often focus on how to establish and define themselves, but not necessarily on what the side effects of their disciplinary activities may be, including ethical consequences.

I seek to accomplish two parallel objectives by providing a matrix of strategies and choices for responding to ethical concerns in learning analytics. First, developing a matrix of strategies and choices will allow the learning analytics community to help educational institutions understand learning analytics research and practice through an ethical lens, and to guide educational institutions towards using new learning analytics tools with an ethical viewpoint. Second, for rhetoric and scientific and technical communication researchers and practitioners specifically, such a matrix will be useful as a means to continue long-standing efforts of analyzing the ethical implications of the tools (scientific and technical communication) and the artifacts (rhetorical theory) within a genre. Both of these objectives may inform future scholarship and practice in deploying learning analytics across education.

In **Chapter 2** of this study, I review the literature on Big Data as a precursor to learning analytics in academia, critiques of Big Data methodology, and ethical concerns over the use of Big Data. The ethical concerns identified for Big Data set the stage for **Chapter 3**, a review of the rise of analytics in academia, including the refinement of the academic analytics model over time, the diversification of academic analytics into distinct types of learning analytics, the current state of learning analytics as an emerging discipline[3], and concerns expressed over learning analytics in academia. I conclude Chapter 3 by presenting the final matrix of strategies and choices for understanding ethical concerns in the design, application, and documentation of learning analytics. I provide the final matrix as a guide for the reader to follow through the rest of the study.

In **Chapter 4**, I discuss my research methods and conduct a five-stage analysis. In Stage 1, I perform a comparative analysis using genre theory and learning analytics to understand the nature of learning analytics tools, practices, and methodology. In Stage 2, I conduct a second comparative analysis between existing frameworks, united by their ethical lens, in persuasion, human-computer interaction, social power, semiotics, visual design, and new media literacy in order to identify the ethical concerns of learning analytics. During Stage 2, I also assign multiple categories to the ethical concerns using three classification systems in preparation for deconstructing ethical concerns in Stage 3.

[3] The learning analytics community is still in the process of understanding and establishing itself as a discipline, as can be gathered from Learning Analytics and Knowledge Conference themes: integrating the discipline (LAK11, 2011a), exploring the current state of learning analytics (LAK12, 2012a), consolidating the field (LAK 13, 2013a), and finding the intersection of research, theory, and practice (LAK14, 2014a). Although still emerging, I will refer to learning analytics as a discipline in this study.

During Stage 3, I use framework methodology to deconstruct and survey the ethical concerns of learning analytics through tree diagrams and relational visuals. Specifically, I organize the concerns by the classification system from Stage 2 to provide an in-depth review of the type and occurrence of ethical concerns of learning analytics. In Stage 4, I combine existing frameworks in ethical pedagogy to serve as a guide for developing responses to ethical concerns. Finally, I create a matrix of strategies and choices for understanding ethical concerns in the design, application, and documentation of learning analytics (Stage 5).

Throughout the discussion of methodology, analysis, and matrix development, I am guided by the question—**How can we use rhetorical, scientific, and technical communication perspectives to understand ethical concerns in the design, application, and documentation of learning analytics in post-secondary education?** Most importantly, the approach I use in this study—specifically, the deconstruction of ethical concerns by assigning multiple categories so as to examine relationships between and the concentration of ethical concerns—provides a rationale for the "why" of ethical concerns in the design, application, and documentation of learning analytics. Many ethical concerns raised in learning analytics are intuitive—including (broadly) privacy, labeling, and accuracy of the model—however, this study vetted ethical concerns directly through long-established ethical frameworks in rhetoric and scientific and technical communication in order to help academia understand why it should be concerned when introducing learning analytics on campus.

CHAPTER 2. REVIEW OF BIG DATA

In this chapter, I review the literature on Big Data, critiques of Big Data methodology, and ethical concerns over the use of Big Data. Because the ethical concerns of Big Data methodology in academia have yet to be explored, and research in this emerging discipline is relatively new, Big Data as a precursor to learning analytics serves as an obvious starting point for reviewing and establishing ethical concerns in the design, application, and documentation of learning analytics in post-secondary education.

What is Big Data?

Advances in computer technologies have created “Big Data,” an analytics methodology that emerged from a well-established business-intelligence model, and uses data sets that have become so large that it becomes difficult to analyze the data using traditional scientific methods. That is, Big Data uses statistical modeling to infer, predict, and locate correlations in aggregated databases, or millions of networked computers able to share petabytes (one quadrillion bytes) of data through “the cloud” (distributed computing able to share a computer program across networked computers in real-time). Thus, Big Data methodology is statistical, with a focus on inference and correlation, and supported by statistical probability. Extrapolating a general truth about a population from a sample can be problematic as similarities between variables may suggest trends, but do not necessarily imply causation. However, accuracy increases as data sets grow larger—and that is the appeal of using Big Data.

Critiques of Big Data Methodology

In *The Human Face of Big Data*, Rick Smolan and Jennifer Erwitt (2012) describe the prevalence and use of Big Data as follows: "Each of us now leaves a trail of digital exhaust, an infinite stream of phone records, texts, browser histories, GPS data, and other information, that will live on forever" (p. 9). They believe that "no event in human history has ever generated as much wealth and changed as many lives as this transition into a digital world" (p. 19). Big Data can detect personal behavior patterns, of which even we are unaware, and use them for targeted marketing, which Smolan and Erwitt highlight as a problem with Big Data business practices. That is, humans become products—a species-level commodity—and are no longer treated as individuals (p. 202).

Popular media have proclaimed Big Data to be "the end of theory," ushering in an era in which the scientific method is obsolete because the sheer amount of available information allows us to "analyze data without hypothesis about what it might show" (Anderson, 2008). David Weinberger (2012), Senior Researcher at Harvard's Berkman Center, has stated that the amount of shared data in knowledge networks allows us to make predictions without understanding the model. In fact, he writes, "It's a bit as if Einstein dreamed $e=mc^2$, and we confirmed that it worked, but no one could figure out what the c stands for" (p. 8). What separates Big Data methodology from scientific methodology is that Big Data are clearly about the volume and variety of data used in predictive modeling and "fishing" for random correlations rather than about the discovery of finite causation through meticulous testing and retesting.

In their paper "Six Provocations for Big Data," dana boyd and Kate Crawford (2011) cast doubt on the use of Big Data as an alternative to proper scientific analysis.

They warn that the former approach is rife with assumptions and underlying biases, and outline specific areas in which Big Data are problematic. For example, boyd and Crawford believe that automating the research process gives us a scan of "right now," a scan that does not include important historical context (p. 4). They assert that this lack of context changes the definition of knowledge itself: Big Data represents a sliver of knowledge, but does not include the crucial overview of the process in its entirety. Therefore, they are concerned that Big Data points to trends that must be interpreted subjectively to derive meaning and, furthermore, that accuracy is called into question as data are often "cleaned" during Big Data's predictive modeling stage, potentially "erasing" important variables and key attributes (p. 5).

For boyd and Crawford, Big Data research implies that historical research methods in social science are no longer valid. However, large data sets do not necessarily lead to better results and Big Data, as aggregate information, may consist of "multiple error prone data sets" (boyd & Crawford, 2011, p. 8). In addition, they warn that the availability of data does not ratify its use and that aggregating inaccurate data sets and de-anonymizing individuals carries ethical implications. In de-anonymization, for example, individuals are re-identified by cross-referencing anonymous, personally identifiable information. Finally, boyd and Crawford caution that questions related to human subject research, consent, and responsibilities have yet to be defined for Big Data research.

Ethical Concerns over the Use of Big Data

In descriptions of the ethics of Big Data, privacy is an emotional topic (Davis, 2012; Marwick, Diaz, & Palfrey, 2010; Raport, 2011). As early as 2007, concerns over the ethics of Big Data methodologies were being published in the popular literature. In "The Dark Side of Customer Analytics," Thomas Davenport and Jeanne Harris (2007) brought to light some of these concerns. Specifically, what if, while performing analytics on consumer purchasing data, a company uncovered correlations between certain foods and a specific disease. What would their responsibility be in reporting this critical piece of information, especially if disclosing their methods revealed private customer data through de-anonymization or caused a loss in sales? Davenport and Harris claim that "all analytics is a form of discrimination" and that the only way to protect customers is to allow them to opt out of personal data gathering (p. 7). Furthermore, they believe that companies should only use data for relationship building and would do well to tie the use of data to the "principles of the organization" (pp. 8-9).

Larry Nelson, Charles Proctor, and Cavell Brownie (2000) discuss the ethics of Big Data's statistical methods and provide insight into the inappropriate use of statistical methods as well as solutions specific to Big Data. First, all instances of statistical data trimming, which occurs when all data points are not reported, specifically outliers, should include information about this practice in a footnote. Second, any instances of imputation—where data points are estimated to round out a set of numbers—need to be disclosed.

Using the lens of Big Data, Rachel Finn, David Wright, and Michael Friedewald (2013) redefine privacy to include the right to have control over one's own data and images (such as those collected by Big Data analytics). More specifically, they define seven types of privacy, which include the right to

- keep body functions and body characteristics private,
- behave and act in both private and public as long as there is no harm to others (e.g., preferences, habits, practices, and activities),
- not have communication intercepted,
- have control over personal data including images,
- not share thoughts and feelings,
- not be surveilled in location or space, and
- associate with others as wished without being monitored (pp. 11-13).

Thus, they find the most dangerous loss of privacy to be that of second generation biometrics (i.e., recognition scanning of personal identity traits such as face, eye, voice, or fingerprints), because it is a "systematic collection of information that could be used for classification purposes" and violates all seven types of privacy (p. 16).

What does Big Data mean for academia? Initial work with analytics in academia, referred to as "academic analytics," focused on developing predictive models through statistical analysis to find at-risk students and then providing intervention(s) to increase both the retention and success of those students (e.g., data triggering an action). What drove this early work in analytics? John Campbell and Diana Oblinger (2007) attributed the change in institutional focus to the mediocre retention and graduation rates at U.S. academic institutions as well as the institutional costs associated with those rates. John Campbell, Peter Deblois, and Diana Oblinger (2007) describe an ominous situation in the United States, in which a less than competitive educational system is coupled with a growing need for college graduates, and the resulting negative consequences these two factors will have on U.S. economic security.

As a precursor to learning analytics in academia, the ethical concerns of Big Data practices and methodology are broadly summarized as concerns over:

- implementation of process,
- interpretation of data,
- legality of service, and
- application of statistical methods.

As they provide a glimpse into the ethical concerns that may arise as analytics crosses over to academia, I use these four categories of concerns as one classification system during the comparative analyses in Stage 2. Having reviewed Big Data as a precursor to learning analytics, the critiques of Big Data methodology, and the ethical concerns over the use of Big Data, I turn to the rise of academic analytics in academia.

CHAPTER 3. ANALYTICS IN ACADEMIA

In this chapter, I review the rise of analytics in academia, including the refinement of the academic analytics model over time, the diversification of academic analytics into distinct types of learning analytics, the current state of learning analytics as a discipline, and the ethical concerns raised over learning analytics in academia. I end Chapter 3 with the culmination of my study—the final matrix of strategies and choices for understanding ethical concerns—to serve as a guide for the reader through the five stages.

It should be noted that the learning analytics community is still in the process of understanding and establishing itself as a discipline, as can be gathered from the annual Learning Analytics and Knowledge Conference themes: integrating the discipline (LAK11, 2011a), exploring the current state of learning analytics (LAK12, 2012a), consolidating the field (LAK 13, 2013a), and finding the intersection of research, theory, and practice (LAK14, 2014a). Although still emerging, I will refer to learning analytics as a discipline for the remainder of my study.

The Initiation of Analytics in Academia

In early 2005, Phillip J. Goldstein and Richard Katz published "Academic Analytics: The Uses of Management Information and Technology in Higher Education." This seminal work examined whether U.S. educational institutions were capable of producing, analyzing, and using information to create a predictive model for student success, persistence, and retention. To describe this model, Goldstein and Katz borrowed the term "academic analytics"—a combination of academic data and educational goals—from Karen Gage of WebCT (p. 21). Goldstein and Katz's initial report provided an in-depth analysis of the then current state of analytics in education, and they used two survey frameworks to explore reporting, modeling, analysis, and decision support: (1) technology infrastructures and (2) deployment of analytic applications.

Predictably, Goldstein and Katz found that those institutions using higher-level technology infrastructures such as data warehouses/data marts, extract/transform/load (ETL) tools, reporting tools, dashboards, and alerts were most satisfied with their technological abilities, in spite of the higher costs, as compared to non-users. Exploring the breadth and depth of analytics-application deployment and adoption was more complicated, in that they found that relatively few institutions had achieved both frameworks (technology infrastructures and deployment of analytic applications). Furthermore, while the functional areas deploying applications varied widely, they most commonly emanated from institutional research, centralized finance and admissions, human resources, and, more rarely, from department chairs or deans and their staff.

By exploring the types of applications available for deployment more in depth, Goldstein and Katz were able to describe five stages of the analytics process: (1) extracting and reporting data, (2) performance monitoring and analysis, (3) creating what-if decision trees, (4) using a predictive model (based on parameters 1-3 above), and (5) automatically triggering processes (p. 60). Goldstein and Katz noted that a number of institutions in their study remained at Stage 1 (70%) and that only 8% had advanced to Stage 3 or beyond.

At the time of their study, Goldstein and Katz found that commonly reported uses of academic analytics occurred in student services, mainly to identify prospects for admission and to identify students who were at high risk for academic success. The researchers also found that training effectiveness and leadership commitment to "evidence-based decision making" were the main attributes of success, with failure most likely occurring if the institution lacked skilled staff who could understand and perform the data analysis (p. 93).

Building on Goldstein and Katz' work, Campbell and Oblinger's (2007) "Academic Analytics" called for analyses of the wealth of information in institutional databases and then, using predictive modeling, the creation of appropriate interventions for use by college faculty and staff. They believed that institutions had an opportunity to address increasing demands for accountability, while increasing student success, by using new techniques such as data mining—a process that "use[s] a discovery-based approach in which algorithms find patterns in data, identifying trends that might not have surfaced" with traditional decision-making strategies (pp. 2-3). For academic institutions that aspire to raise retention and graduation rates and increase student success by integrating analytics, Campbell and Oblinger presented a five-step process of academic analytics: (1) capturing student data, (2) reporting student data, (3) predicting at-risk students, (4) acting on that prediction by offering intervention strategies to students with the goal of increasing success, and (5) refining the prediction model based on measurements of intervention success. This five-stage process has served as the guide for academic analytics ever since.

A second paper by Campbell, Deblois, and Oblinger (2007), "Academic Analytics: A Tool for a New Era," suggested marrying "large data sets, statistical techniques, and predictive modeling" in an effort to produce "actionable intelligence" (p. 42). Campbell et al. established guidelines for success by insisting that projects have leaders with a commitment to evidence-based decision-making, administrative staff with skills in data analysis, and a flexible technology platform that facilitates collecting, mining, and analyzing data. With the model of academic analytics defined, others turned to refining the model and exploring applications.

Refining the Academic Analytics Model

Expanding on earlier work in academic analytics, Donald Norris, Linda Baer, Joan Leonard, Louis Pugliese, and Paul Lefrere moved beyond "tools, solutions, and services" to focus on measuring the effectiveness of action following data analysis in their article "Measuring and Improving Performance That Matters in Higher Education" (2008a, p. 44). In their companion paper, "Framing Action Analytics and Putting Them to Work" (2008b), they suggested a working model, "Action Analytics" (registered trademark of Strategic Initiatives, www.strategicinitiatives.com), that described both academic performance analytics and operational performance analytics. Performance analytics include intrusive interventions based on student engagement and accomplishments or individualized articulations and degree programs (often based on employment requirements) in order to give credit for prior learning and reduce student costs (p. 46). Operational performance analytics include student success dashboards, early alert systems and, in some instances, outsourced predictive modeling services (pp. 46-47). Action Analytics was defined by four elements of academic analytics: strategic planning, administration, academic assessment, and learning/career, and Norris et al.

encouraged leaders to achieve “performance on as many measures as possible” (p. 13). Finally, they warned that the largest hurdle to implementing academic analytics would be the culture shift needed in terms of institutional commitment to “action-oriented performance” (p. 48, p. 52).

Purdue University’s Signals project was an early success story for academic analytics (Kim Arnold, 2010). Using a student-success algorithm, the Signals project was able to identify at-risk students as early as the second week of the semester, provide targeted instructional services to those students, and, to complete the continuum of quality improvement, change student-orientation practices to better address student needs. Under this model, student grades improved as did student self-advocacy in that, once made aware of their at-risk status, students sought help.

With the firm establishment of academic analytics methodology, researchers and practitioners from many disciplines, such as statistics, behavioral science, cognitive psychology, education, and computer science, continued to define and refine academic analytics. Correspondingly, the emerging discipline of academic analytics began to diversify, as described in the next section.

Diversification of Academic Analytics: Learning Analytics

In 2011, the first International Conference on Learning Analytics and Knowledge (LAK) was launched with the mission of establishing learning analytics as a discipline. It was sponsored by Athabasca University, Desire2Learn, Bill and Melinda Gates Foundation, Kaplan Ventures, and EDUCAUSE (LAK, 2011a). Conference chairs included George Siemens from Athabasca University, Canada, and Phillip Long from University of Queensland, Australia.

In their LAK12 conference paper, "Social Learning Analytics: Five Approaches," Rebecca Ferguson and Simon Buckingham Shum (2012) identified differences between academic analytics, using general static data records such as first generation status, ethnicity, PELL eligibility, suspensions, and loan defaults, and learning analytics, using dynamic and behavioral data in the classroom such as attendance, test grades, and quantified participation. Shum and Ferguson viewed learning analytics as a social process that builds on knowledge created through cultural settings, and examined five categories of learning analytics: social network, discourse, content, disposition, and context.

Social Network analytics uses data harvested from social platforms such as Facebook, Twitter, and Flickr to investigate the relationships of the networked individuals and the strength of those relationships. Social network analytics identifies students who are disconnected from other students or who are at the center of receiving and delivering information. Social network analytics can also be used to measure the growth of a learning community. NodeXL (a free open-source add-in for Microsoft Excel available from nodexl.codeplex.com) is an example of software used to explore a social network using visualizations.[4] See Figure 1.

[4] NodeXL hosts a user gallery at with the intent of sharing visualizations among social media researchers (see: http://nodexlgraphgallery.org).

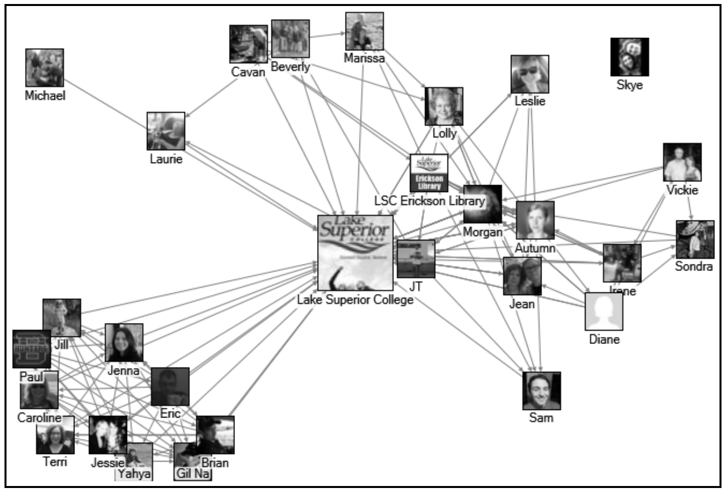

Figure 1. Facebook Visualization using NodeXL

In generating Figure 1 above using NodeXL and Lake Superior College's Facebook Fan Page (www.facebook.com/LakeSuperiorCollege), NodeXL harvested the Facebook user data shown in Table 1, if made available by an individual in his or her user settings:

Table 1. Personal Data Harvested from Facebook during NodeXL Query

About Me	Email	Languages	Quotes
Age Range	Favorite Athletes	Locale	Relationship
Bio	Favorite Teams	Religion	Significant Other
Birthday	Gender	Location	Time Zone
Books	Hometown	Middle Name	Website
Devices	Profile Picture	Picture	Work
Education	Inspirational People	Political Views	

Additional information that is publicly available regardless of user privacy settings is also harvested, including cover photo, a list of networks, user name, and account number.

Discourse analytics gathers data from student discussion boards to view the quality of students' dialogue as well as to map their construction of knowledge through language and interactions. Social Networks Adapting Pedagogical Practice (SNAPP, http://www.snappvis.org/) is a discussion board-based visualization tool embedded in course management systems such as Bright Space (www.brightspace.com) or Moodle (moodle.org). See Figure 2.

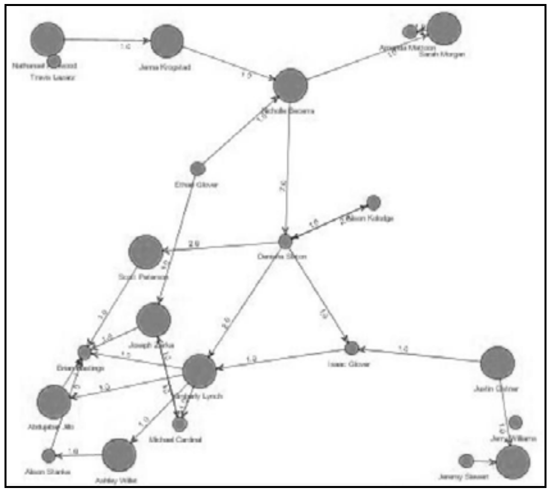

Figure 2. Discussion Board Visualization using SNAPP[5]

Discourse analytics follows the same model as social network analytics, but differs in that analysis occurs within the course management system and within each course discussion board rather than from external social networked data.

Content analytics uses data harvested from social networks through student-generated hashtags (e.g., #anyword), and uses the hashtags to catalogue resources as identified by each student. Content analytics tracks students' progress by documenting if (and how) they construct knowledge. See Figure 3.

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[5] K. Lynch, personal communication, March 15, 2015

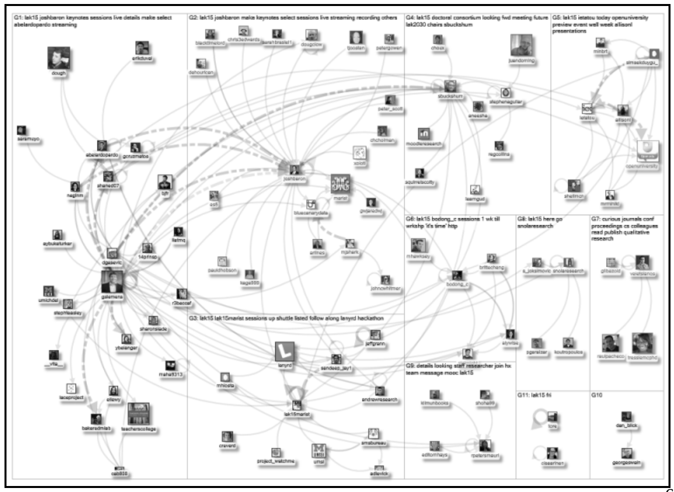


Figure 3. Twitter Visualization (#LAK15) using NodeXL[6]

As with Facebook, NodeXL downloads personal user data connected to a Twitter hashtag tweet, but focuses more on the number of individuals an account holder is following or is followed by, as well as on the number of tweets, shares, replies, and favorites of the account holder using the specific hashtag. NodeXL also gathers domain names and other hashtags connected to the hashtag query results.

Disposition analytics uses a self-reporting tool, such as the College Student Inventory™ offered by Noel Levitz, Higher Ed Consultants, to gather behavioral information including

- Proneness to dropping out
- Receptivity to institutional help (tutoring, counseling, extra-curricular)
- Educational stress
- Motivation (study habits, intellectual interests, confidence in math and writing, desire to finish, attitude towards instructors)

[6] From the NodeXL Graph Gallery at http://www.nodexlgraphgallery.org/Pages/Default.aspx (marc_smith, 2015)

- Coping skills (social, family, opinion, financial) (Noel Levitz, 2015, p. 8)

The results of these inventories are used to suggest intervention strategies that better fit a specific student's personality or behaviors.

Context analytics is an emerging form of learning analytics that measures and reports information relative to where the student is and what the student is doing while constructing knowledge. Context analytics uses sophisticated models of learning analytics and gathers data such as biological feedback, daily activities (both type and location), and environmental data through mobile computing apps. For example, such computer apps might include Google Now (tracks weather, calendar appointments, and location, see: https://www.google.com/landing/now/), MotionX 24/7 (monitors sleep and snoring, see: http://24-7.motionx.com/), SpeedSpot (indicates location and strength of WiFi access, see: http://speedspot.org/), and MapMyFitness (records type and location of exercise, see: http://www.mapmyfitness.com/).

With Ferguson and Shum's definition of the five categories of learning analytics, the LAK discipline moved from the more static and less accurate academic analytics to the more personalized and more accurate learning analytics. To date, little attention has been paid to the implications of learning analytics and, specifically, to the ethics of the design, application, and documentation of learning analytics in post-secondary education. However, given its youth, the LAK community has made considerable progress towards defining its diverse research and practice and has embraced and settled on these expanded categories and definitions of learning analytics.

The State of Learning Analytics and Knowledge

What, then, has been the focus of the Learning Analytics and Knowledge community to date? Growth or change in the LAK discipline is difficult to track, but can be assessed through content analysis. One method of content analysis is the use of "word clouds"—a grouping of words used in a source document or documents displayed visually and indicating the weight (frequency or importance) of a word by size. For example, using Wordle word cloud generator (www.wordle.net), I created word clouds from the LAK 2011-2014 conference abstracts to help determine the focus of LAK from year to year as well as to help understand where LAK attendees situate their knowledge in the emerging discipline of learning analytics. Figures 4-7 indicate word strength (the frequency of mentions) of the top 15 words used in each year of the LAK proceedings. Figure 8 combines word strength from all four conferences, and Figure 9 shows the top 10 common words prevalent at every conference.

Figure 4. Word Cloud: LAK 2011

Figure 5. Word Cloud: LAK 2012

Figure 6. Word Cloud: LAK 2013

Figure 7. Word Cloud: LAK 2014

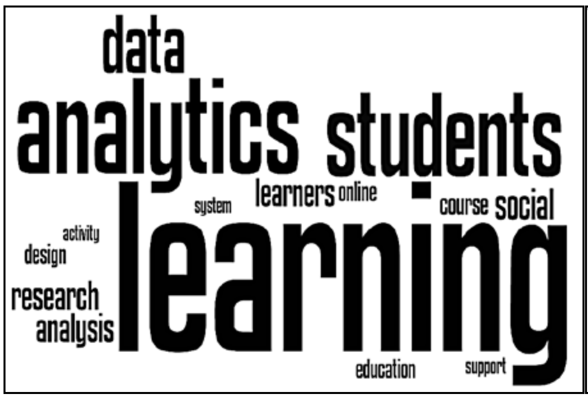


Figure 8. Word Cloud: Combined LAK 2011-2014

Figure 9. Word Cloud: Ten Most- Mentioned Words LAK 2011-2014

Table 2 summarizes the above word clouds in relation to conference year using the following key:

- Arrow (→): Topic moved forward to a subsequent conference
- **Bold font/highlight**: Topic mentioned all four years
- *Italicized*: Topic mentioned in three years and global LAK
- ~~Struck through~~: Topic had variable frequency across years
- Double dash (—): Topic unmentioned during a specific year

Table 2. Dominant Topics LAK 2011-2014

LAK 2011	LAK 2012	LAK 2013	LAK 2014	LAK 2011-2014
—	—	—	~~Academic~~	
~~Activity~~	—	—	—	Activity
Analysis →	Analysis →	Analysis →	Analysis →	Analysis
Analytics →	Analytics →	Analytics →	Analytics →	Analytics
—	—	~~Assessment~~	—	
—	~~Community~~	—	—	
—	Course →	→	Course	Course
Data →	Data →	Data →	Data →	Data
—	Design →	→	Design	Design
Education →	*Education* →	→	*Education*	*Education*
—	—	~~Environments~~	—	
~~Interaction~~	—	—	—	
Learners →	Learners →	Learners →	Learners →	Learners
Learning →	Learning →	Learning →	Learning →	Learning
—	Model →	Models	—	
~~Network~~	—	—	—	
Online →	→	*Online* →	*Online*	*Online*
—	—	—	~~Performance~~	
—	—	~~Process~~		
Research →	Research →	Research →	Research →	Research
Social →	Social →	Social →	Social →	Social
Students →	Students →	Students →	Students →	Students
—	~~Success~~	—	—	
—	—	Support	—	Support
System →	*System* →	→	*System*	*System*
~~Teach~~	—	—	—	
—	—	~~Tools~~	—	

Based on this content analysis, I can assume that the focus of the LAK community clearly has been on **Learning Analytics, Student Learners**, and **Data Research and Analysis**. The word **Social** stands out as an indicator of the type of data being collected, typically through social networks (e.g., Facebook, Twitter, Flickr) and social mobile applications (e.g., Google Now, MotionX 24/7, WiFi).

However, what have been the efforts of the LAK community regarding ethics? In a search of the 2011-2014 LAK conference abstracts for the term “ethic” (including “ethics” and “ethical”), I uncovered very few occurrences. Table 3 shows those few occurrences (five total). I also performed a search on common synonyms of ethics, including “moral,” “integrity,” “code,” and “value,” but these searches returned zero results.

Table 3. Search for “Ethic(s)(ical)” in LAK Conference Proceedings 2011-14

Year	Title	Authors	Mention
2011 (total of 26 abstracts in proceedings)	The value of learning analytics to network learning on a personal learning environment	Fournier, Kop, & Sitlia	“Methodological concerns related to the analysis of Big Data collected on online network as well as ethical and privacy concerns will also be highlighted…” (p. 4)
2012 (total of 52 abstracts in proceedings)	Learning analytics and higher education ethical perspectives	Slade & Galpin	Mentioned in title only (pp. 16-17)
	Building a data governance model for learning analytics	Graf, Ives, Lockyer, Hobson, & Clow	“In this panel, data governance considerations will be discussed from organizational, ethical, learning design, and technical points of view.” (p. 21)
2013 (total of 47 abstracts in proceedings)	An evaluation of policy frameworks for addressing ethical considerations in learning analytics	Prinsloo & Slade	“Institutional policy frameworks should provide not only an enabling environment for the optimal and ethical harvesting and use of data, but also clarify who benefits and under what conditions, establish conditions for consent and the de-identification of data, and address issues of vulnerability…“ (p. 240)
2014 (total of 54 abstracts in proceedings)	Establishing an ethical literacy for learning analytics	Swenson	“This paper borrows multiple frameworks from the field of technical communication in order to review theory, research, practice, and ethics of the Learning Analytics and Knowledge discipline. These frameworks also guide discussion on the ethics of learning analytics “artifacts” (data visualizations, dashboards, and methodology), and the ethical consequences of using learning analytics (classification, social power moves, and absence of voice). Finally, the author suggests a literacy for learning analytics that includes an ethical viewpoint.” (p. 246)

Certainly, the topic of ethics has been raised within the learning analytics community (Slade & Galpin, 2012; Swenson, 2014), but often from an institutional perspective (Fournier et al., 2011; Graf, et al., 2012; Prinsloo & Slade, 2013). These five abstracts indicate the beginning of a discussion of ethics in learner analytics. However, given that ethics touches on every aspect of the LAK discipline (design, application, and documentation), five abstracts out of 179 total from 2011-2014 (2.8%) indicates that more work is needed.

Ethical Concerns over Learning Analytics in Academia

Early on, ethical issues regarding the academic analytics (not yet learning analytics) process began to surface, including concerns from students, faculty, and administration. Kim Arnold (2010) reported that students found the Purdue Signals' student dashboard (the interface for the predictive model) to be informative and motivating; however, they were concerned that the tool was being used to over-message (too many emails), that the information was out-of-date, or that the intervention strategies were too general to be helpful. Arnold also found faculty concerns with a “lack of best practices for using Signals” (p. 6). Arnold, Campbell, and Oblinger (2007) identified concerns from faculty stakeholders including the potential for additional demands on time, a lack of clarity regarding where their role in student success ended, and fears that the student success data could be used to evaluate teaching effectiveness.

By far, the largest number of concerns surfaced at an organizational level and included data privacy, data storage and sharing, students being “reduced to a number” or being tracked akin to “big brother,” and the potential for profiling and bias (Campbell et al., 2007, pp. 52-54). Campbell and Oblinger (2007) expanded the list of administrative concerns to include data accuracy and ownership. Arnold (2010) gathered extensive stakeholder feedback from Purdue's Signals project, including concerns from the administration about the "consistency of use across courses" (p. 6). She found that the largest obstacles for implementing academic analytics included the difficulty of procuring and managing dynamic data, ensuring consistent intervention practices between faculty members, and maintaining data privacy (p. 8).

Arnold (2010) cited both legal and ethical concerns for institutions that do not take action after the data indicates that a student is experiencing difficulty. This concern was echoed by James Willis, John Campbell, and Matt Pistilli (2013) when they connected ethics directly to academic analytics and maintained that the institution is responsible for analyzing the data as well as fulfilling an "obligation of knowing" by providing students with tools for success, faculty with training to use the prediction models, and a campus climate that enhances student success (p. 6).

During a 2012 Learning Analytics and Knowledge conference workshop titled "Learning analytics and higher education: Ethical perspectives," Sharon Slade and Fenella Galpin (2012) discussed specific ethical concerns related to academic analytics from the broader perspective of the responsibility of the institution for student success to the rights of students to remain individuals. Slade and Galpin questioned the process of making ethical decisions, the effects on students of labeling, and the beneficiaries of the analytics (students or the institution).

Acknowledging that privacy and transparency must be addressed at a minimum, Slade and Galpin focused on power (who decides which students get support), ownership (how data are shared and with whom, what the consequences are of opting out, and how long are data kept), and responsibility (who is responsible for data accuracy and the equitable treatment of students).[7] More recently, concerns over the use of Big Data in academic analytics have focused on student rights and the questionable motivation of institutions in helping students versus increasing profits by increasing retention and thus tuition (Slade & Galpin, 2012). For Slade and Galpin, the global questions become (1) are we manipulating student behavior and (2) will academic analytics change recruitment efforts?

What may be the most informative criticism of learning analytics' search for at-risk students comes from outside the discipline. In *Sorting Things Out: Classification and Its Consequences*, Geoffrey Bowker and Susan Leigh Star (2000) focused on the ambiguous process of classification and the "invisible forces of categories and standards" (p. 5). Bowker and Star explain that, for the most part, we are trained to accept classification systems as fact even though the process of classification is subject to data entry errors, data storage limitations, data "cleaning," and data revision (through economic, social, and political pressures) (pp. 108-109). For Bowker and Star, classifying people involves generalizing and/or stereotyping in order to create a data profile that "fits" into categories and, in doing so, "existing differences are covered up, merged, or removed" (p. 230). As classifying is exactly the work of learning analytics, the biggest

[7] These insights are drawn from collaborative participant notes taken while attending the LAK12 workshop discussion on "Learning Analytics and Higher Education: Ethical Perspectives," as guided by Slade and Galpin, 2012.

setback to the process may be, as Bowker and Star explain, that once categorized, people will "bend and twist their reality to fit into a more 'desirable' category" (p. 190). Or, even more problematic for learning analytics as it classifies students as at-risk, people will "socialize to their category" (p. 230).[8]

The above concerns point toward a need for guidance in the ethical design, application, and documentation of learning analytics in post-secondary education. Not only is learning analytics subject to the same critiques as Big Data, it also has its own set of ethical concerns. For example, anyone with access to the Internet and open source software can create and publicly post learning analytics visualizations, without participant consent, when using social network (if not protected within a course management system), content, and discourse analytics. The data behind the visualizations can reveal personal details such as connections outside of the classroom; a participant's "likes," interests, and followed groups; location and whether a participant is currently online; relationship status; and date and place of birth. Furthermore, disposition analytics can be conducted via self-reporting or a more formal survey and, in each case, faculty and/or administration could have access to protected behavioral data such as motivation, anxiety, or willingness to seek help.

Finally, context analytics, which is currently less common but gaining in popularity, gathers highly personal data that is shared through mobile technology applications. While data derived from context analytics may require a student to opt-in, the risk of gathering contextual data that is subsequently stripped of context for predictive

[8] "As will those [educational institutions] who have vested interest in how many are in particular categories," as noted by Dr. Darwin Hendel (personal communication, June 18,2015), Associate Professor in Organizational Leadership, Policy, and Development, University of Minnesota.

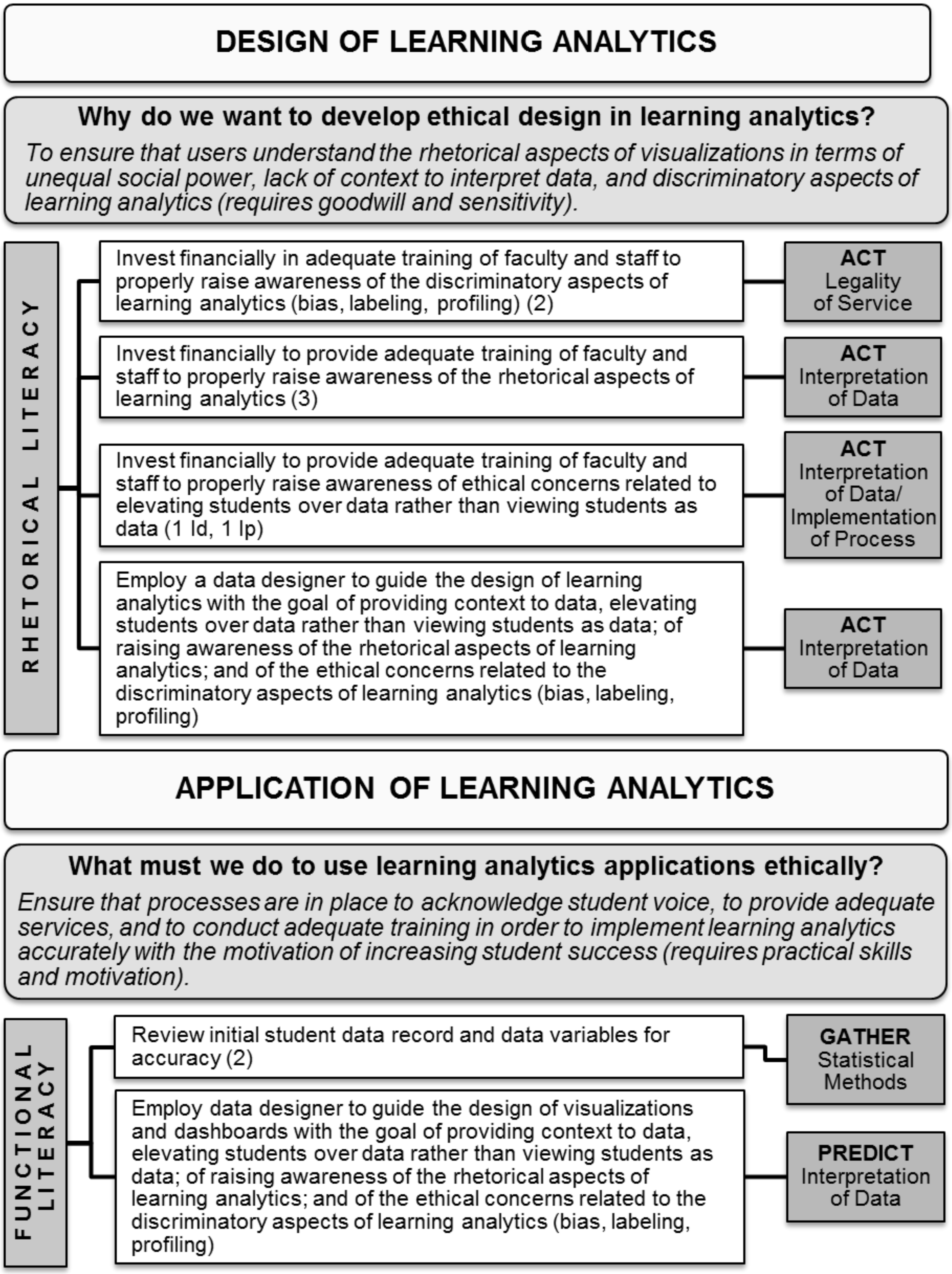
models may be subject to conjecture when or if the non-contextualized data are revealed to intended or unintended audiences.

In this chapter, I reviewed the rise of analytics in academia, including the refinement of the academic analytics model over time, the diversification of academic analytics into distinct types of learning analytics, the current state of learning analytics as an emerging discipline, and the ethical concerns raised over learning analytics in academia. In this review, I provided insight as to the lack of conversation surrounding ethics in learning analytics as well as helped to identify initial definitions and to recognize four broad categories of ethical concerns for this study:

- Implementation of process: How learning analytics is implemented,
- Interpretation of data: How data are interpreted within the context of learning analytics,
- Legality of service: Whether action or inaction based on the predictive category may bring harm to the institution or student, and
- Statistical methods: How accuracy and completeness of the data gathered and the prediction model are maintained.

Ultimately, I use these four categories to classify ethical concerns during the comparative analyses in Stage 2 of this study.

In Figure 10 below, I provide the final matrix developed during this study before the research so as to guide the reader through the five stages. In the next chapter, I discuss methodology and conduct the research for creating the final matrix of strategies and choices for understanding ethical concerns in the design, application, and documentation of learning analytics in post-secondary education.



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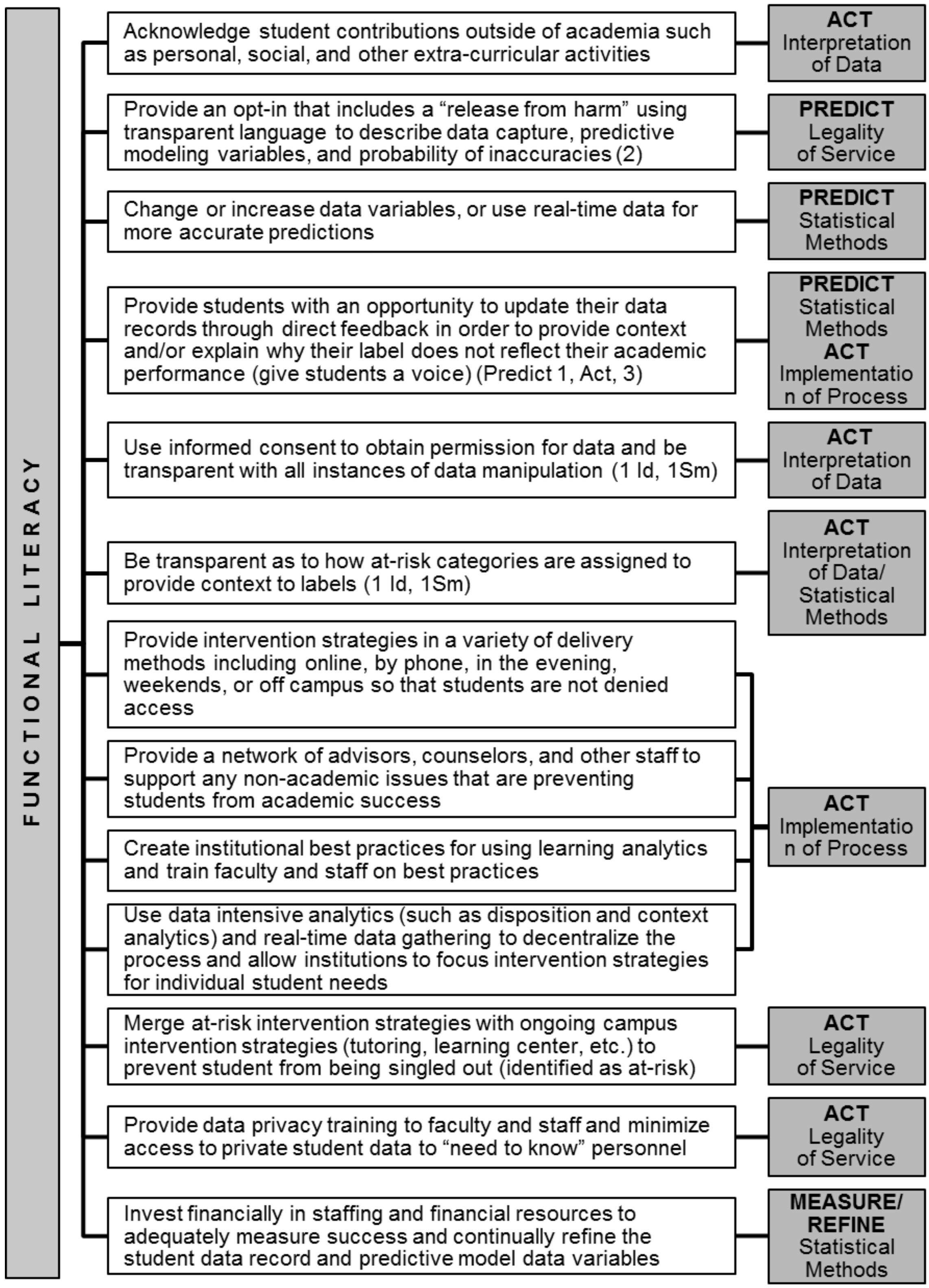

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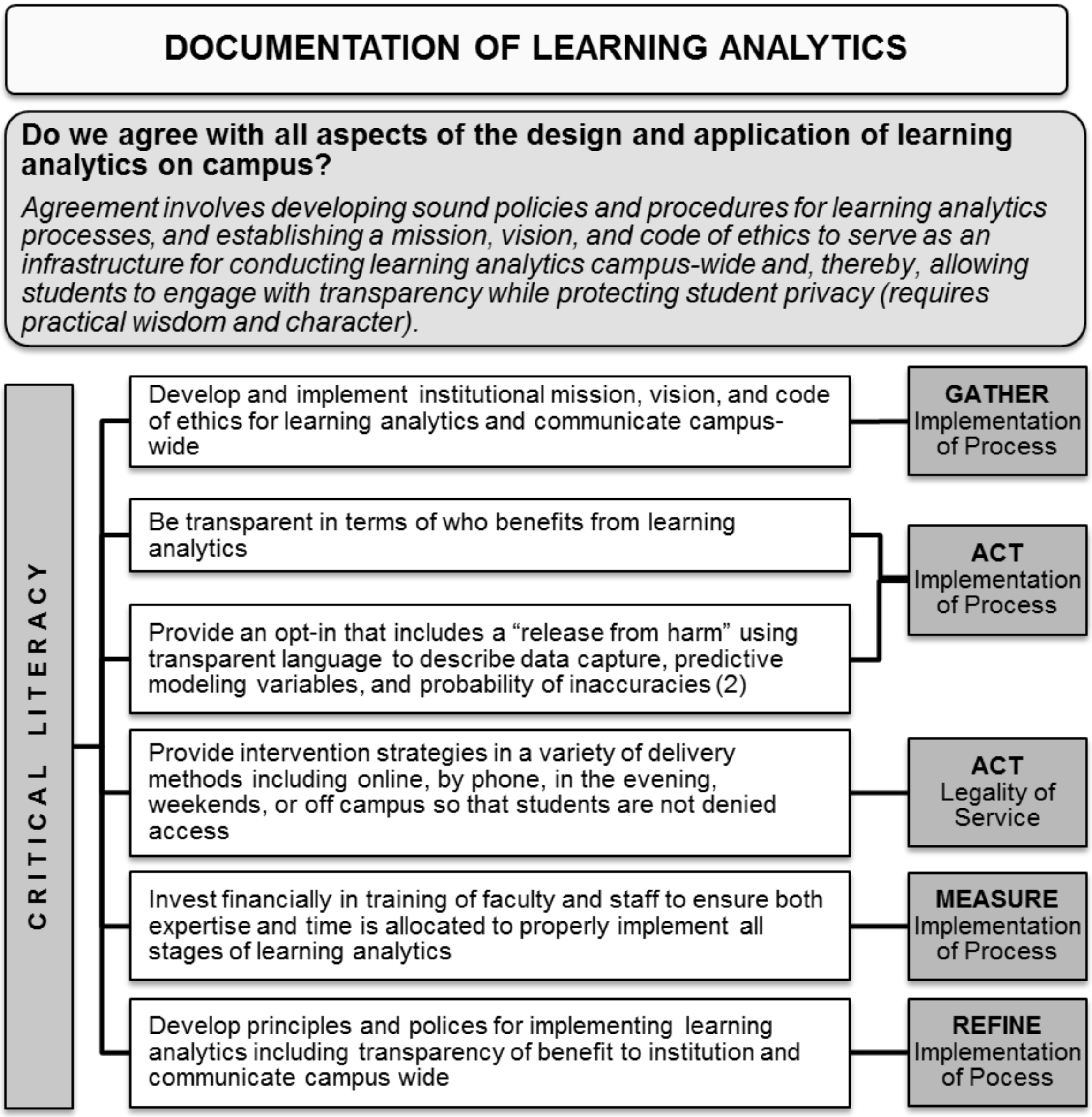

Figure 10. Matrix for Understanding Ethical Concerns in the Design, Application, and Documentation of Learning Analytics in Post-Secondary Education

CHAPTER 4. METHODOLOGY AND RESEARCH

In this chapter, I discuss the methodologies used in this study—comparative analysis, framework methodology, matrix development—and conduct the research. The choice of methodologies and research was guided by the research question: **How can we use rhetorical, scientific, and technical communication perspectives to understand ethical concerns in the design, application, and documentation of learning analytics in post-secondary education?** With this question in mind, I developed a study consisting of five stages (see Figure 11). Each stage is described in detail following Figure 11 below.

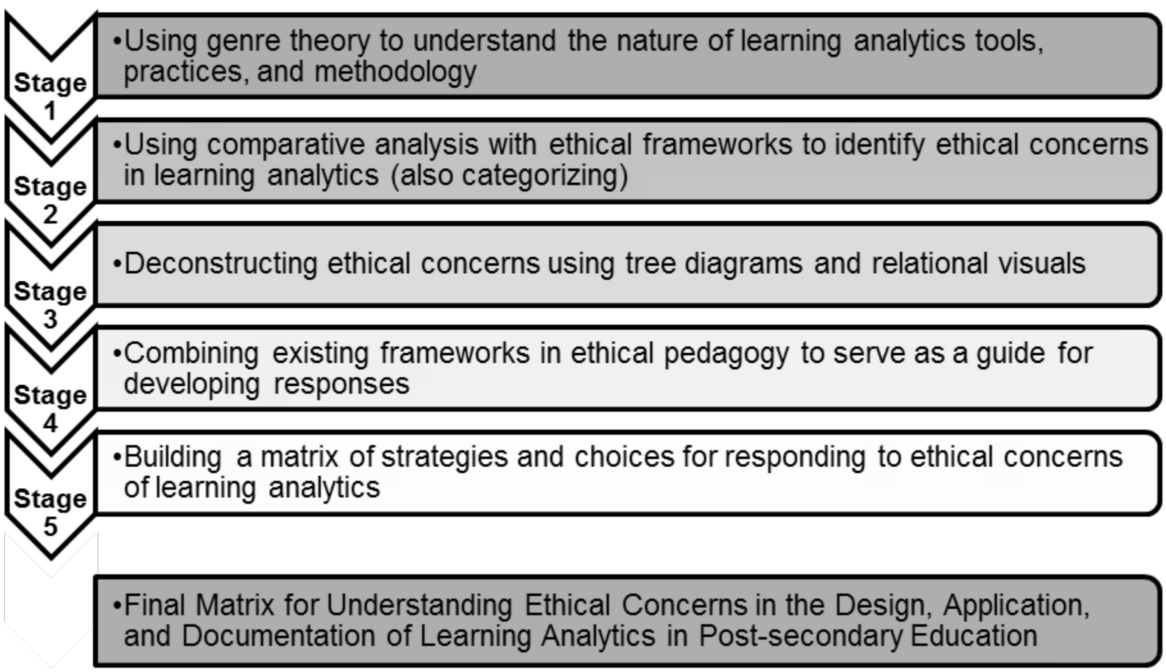

Figure 11. Five-Stage Research Process

I begin by conducting two comparative analyses. The first analysis establishes learning analytics as a genre, which allows me to use genre theory as an overarching framework for understanding the nature of learning analytics' tools, practices, and, methodology (Stage 1). The second comparative analysis serves to identify the ethical concerns of learning analytics (Stage 2). As part of this second analysis, I select frameworks from persuasion, human-computer interaction, social power, semiotics, visual design, and new media literacy, because these disciplines provide a strong basis for identifying ethical concerns in the design, application, and documentation of learning analytics. During this analysis, I also assign multiple classification categories to ethical concerns in preparation for deconstructing the concerns (Stage 3).

To deconstruct the ethical concerns of learning analytics (Stage 3), I apply a framework methodology using tree diagrams and relational visuals. Specifically, I organize the concerns using the classification system from Stage 2 and provide an in-depth review of type and occurrence. Finally, I combine existing frameworks in ethical pedagogy to serve as a guide for developing responses to the ethical concerns of learning analytics (Stage 4). The study culminates with the development of a matrix of strategies and choices for understanding ethical concerns in the design, application, and documentation of learning analytics (Stage 5).

Stage 1. Genre Theory and Learning Analytics

In Stage 1, I lay the foundation for this study by using genre theory to understand the nature of learning analytics' tools, practices, and methodologies. Using definitions of genre and genre frameworks by Carolyn Miller and Dawn Shepherd (2004), Carol Berkenkotter and Thomas Huckin (1995), and Carolyn Miller (2004a), I compare genre theory to learning analytics tools, practices, and methodology. I conduct this initial review to help those in the learning analytics community as well as practitioners and researchers in rhetoric and scientific and technical communication to understand how learning analytics behaves as a genre. As mentioned previously, the learning analytics community is still emerging as a discipline. I hope to further that emergence by viewing learning analytics through the lens of genre theory.

Understanding Learning Analytics as a Genre

Genre theory can be used to reveal the traits of a discipline (in this case, the emerging discipline of learning analytics) as well as to identify the artifacts of the discipline's body of work. Berkenkotter and Huckin (1995) defined a genre as a "repertoire of situationally appropriate responses to recurrent situations" (p. ix), describing it as inseparable from a discipline's methodology and a reflection of the discipline's "norms, values, and ideology" (p. 1). Berkenkotter and Huckin noted that "genre users manipulate genres for particular rhetorical purposes" and, as a result, genres can only be fully understood by observing insiders, within the context of use, in order to understand how that manipulation occurs (p. 2). For learning analytics, the context of use could occur in the classroom, on a larger institutional level, or as documented within scientific and scholarly work such as that published in the LAK conference proceedings.

Berkenkotter and Huckin's (1995) definition of genre provides support for defining the methodology of learning analytics (gather, predict, act, measure, refine) as genre. Specifically, institutions **gather** data and use a **predictive** model to generate levels of student success and specifically look for at-risk students (expressed in visual artifacts). The stages of gather and predict create *recurring situations* of identifying students as at-risk. Subsequently, the institution **acts** upon the at-risk status by suggesting intervention strategies to students. Those intervention strategies are considered a *collection of appropriate responses* by the institution. Finally, learning analytics methodology is *embedded* in the discipline. A student responds to the at-risk label, the at-risk situation is intended to produce a certain behavior, the effectiveness of that behavior is **measured,** and the process is **refined** (thereby updating the predictive model in a recurring cycle).

Berkenkotter and Huckin (1995) proposed that, in any given situation, manipulation of a genre gives that genre a dynamic nature and, with this characteristic in mind, they proposed a theoretical framework for classifying genre based on principles of:

- dynamism, how genres change over time based on user need and how these changes are reinforced over time by recurring social situations (p .6);
- situatedness, how a community participates in activities that encourage and support its genre knowledge (p. 7);
- form and content, the appropriateness, relevance, and timeliness of content for a given audience, assuming background knowledge of the genre while allowing for novelty (p. 17);
- duality of structure, the balance between genres as providing guidelines to the community, and genres also being produced by guidelines of the community (p. 25); and
- community ownership, how genres reveal and protect standards, beliefs, and values of the specific community in which they are used (p. 25).

The overall purpose of Berkenkotter and Huckin's framework was to reveal the "unspoken" knowledge of genre users (p. 117). Thus, Berkenkotter and Huckin's framework can be used to explore further the nature of learning analytics.

To describe **dynamism**, Berkenkotter and Huckin studied changes in scientific journals over time. For example, unable to stay abreast of literature important to the scientific community, scientists began "skimming" articles and, as a result, a hint of the experimental results became more prominent in "titles, abstracts, introductions, and section headings" (p. 7). The scientific article (as genre) changed over time based on user needs (scientists) and recurring social situations (participation in scientific community). Learning analytics is a **dynamic** process. Institutions and students (acting as a social community) effect change in learning analytics artifacts over time (dashboards and visualizations) based on the social community's needs. The changes are embedded in two stages of learning analytics methodology: measure and refine. Institutions refine methodology by adding data that better predicts student success, or disregarding data that does not, and updating visualizations and dashboards (artifacts) to achieve higher levels of student engagement and retention. Students engage in intervention strategies that best suit their needs, and this participation affects the feedback loop and subsequently changes the artifact.

According to Berkenkotter and Huckin, **situatedness** occurs, for example, when students participate in lab experiments and reinforce the genre of scientific writing while learning the scientific method. The learning analytics community has **situated** activities in the form of intervention strategies. Institutional recommendations for, and student engagement in, intervention strategies are intended to increase student success. Participation gives students the opportunity to change their success status as presented on learning analytics artifacts (dashboards or visualizations).

Berkenkotter and Huckin's principles of **form** and **content** are self-explanatory. Visualizations, dashboards, and the learning analytics methodology all have **form** (predictive model) and **content** (student data). Learning analytics is timely in that much of the data are collected in real-time. However, these artifacts are only as appropriate and relevant as the data are accurate and complete, and this may be the motivation behind the pursuit of more-intrusive data collection by the learning analytics community.

Berkenkotter and Huckin described **duality** using the change in formality of business writing that occurred with the advent of the typewriter (that is, the introduction of the less formal office memo) as an example. Learning analytics has a **duality of structure** inherent in its methodology through a continual feedback loop (refine stage). The predictive model provides guidelines to the institution (predicting at-risk and suggesting intervention strategies), while student engagement and assessment of success refines guidelines for the institution’s modeling activity (both in data gathered and an improved predictive model).

Finally, Berkenkotter and Huckin provided an example of **community ownership** when, after an article was submitted for review and rejected due to an “underdeveloped” introduction, subsequent exchanges between reviewers and the author of the abstract restructured the introduction to “reinforce a view of scientific activity as collective, inductive, and cumulative” (p. 23). **Community ownership** of learning analytics is embedded in an institution's core values and mission. This ownership is reflected in such things as institutional policies, procedures, codes of ethics, data privacy, and provisions for student opt-out. Unfortunately, while there is potential for social exchange between the community members of learning analytics, to date, the conversation has been one-sided in favor of the institutional voice. Data gathering and the predictive process have largely been invisible to students and less open to student input, or the student voice. As well, student dashboards, such as Purdue's Signals, often "push" information to the student rather than provide a platform for two-way conversation.

Mapping Berkenkotter and Huckin's (1995) genre framework to learning analytics reveals how the emerging discipline of learning analytics is defining and presenting itself through tools, practices, and methodology. That said, learning analytics is a rapidly evolving field of study, as can be seen in the evolution of learning analytics from social network analytics, which harvests networked data without student (and sometimes without institutional) consent, to context analytics, which mandates student participation, self-quantification, and advocacy. This evolution happened within the span of a few years, mainly due to the rapid change of, and increased access to, new technologies. As such, learning analytics is in a dynamic state with players challenging each other and constantly disrupting the genre. In this sense, learning analytics has an inherent potential to be studied as an emerging genre.

Learning Analytics as Social Action

Learning analytics as a genre includes both methodology and artifact production and, therefore, can be studied for rhetorical and social action. In her article, "A

Humanistic Rationale for Technical Writing," Miller (2004a) furthered genre work by requiring discourse to be classified not only by similarities within the genre and its contributions to "an understanding of how discourses work," but also by the "action it is used to accomplish" (p. 152). According to Miller, artifacts can have ethical action, but the purpose behind the design and application of artifacts is also of importance and can have ethical implications. For Miller, discourse is given meaning through semantics (rhetorical **substance**), provided rules through syntax (rhetorical **form**), and has an effect through pragmatics (rhetorical **action**) (p. 152). It is the pragmatic aspect of discourse—or a rhetorical action—which mandates that any review of genre must include the context of the situation in order to understand the motive for its occurrence. Genre, then, can be recognized as connecting intention with effect and thus becomes a social action creating social meaning.

Miller's work on using genre theory to classify the traits of a discipline and to identify discipline artifacts (relying on situational context and motive) can be used to assess social action and the intentional effect of learning analytics. For example, learning analytics has rhetorical **substance** (semantics or language meaning) when viewing data as informing the predictive model. Viewing the predictive model as a set of rules for analyzing data and identifying at-risk students gives learning analytics **form** (syntax, language rules). Finally, learning analytics has rhetorical **action** (pragmatics, language effects) when viewing the suggested intervention strategies as potentially increasing student success. The learning analytics process is conducted within the context of education, as delivered by the academic institution, with the motive of creating successful students. Viewed as such, learning analytics becomes genre as social action.

Miller and Shepherd (2004) compared genre to Darwinism, describing genre as evolving and having socially perceived space-time, or *kairos*, and as taking advantage of an opportunity, both appropriate and timely. The cultural moment at which analytics appeared in academia was tightly bound to the work done by Campbell and Oblinger (2007) and by Campbell et al. (2007). They described an urgency to act based on poor academic performance and the need for an institutional response to low student retention rates, resulting in the creation of learning analytics.

Following Miller and Shepherd's definition of genre (connecting intention with effect and thereby creating social action and social meaning), learning analytics is a way for educational institutions to find more and better ways (evolving) to provide personalized intervention strategies (intent) in a timely and appropriate way (*kairos*) in order to increase student success (effect). As such, learning analytics can be considered a social action that creates social meaning. Having reviewed learning analytics tools, practices, and methodology as a genre that creates social meaning (in its present state), I next turn to what "artifacts" learning analytics creates.

Learning Analytics Artifacts

For those in technical communication, the process of understanding a discipline often begins by defining its artifacts. Grouped by content similarities of design (such as illustrations or discourse patterns) or context relatedness of application (for learning analytics this could include classroom or institutional applications), artifacts are the products of a genre frequently studied for rhetorical action. The most obvious and general categories of learning analytics artifacts are the visualizations, created using software packages, such as NodeXL or SNAPP (see Figures 1-3), and the interactive dashboards, such as Purdue's Signals (see http://www.itap.purdue.edu/studio/signals/).

Dashboards are visuals that may include graphs or color-coding to show student progress in a course as well as more detailed information on assessment and engagement. Visualizations and dashboards share both content similarities in design and context relatedness in application. The methodology of learning analytics (as content) is exact in design through its five distinct stages, and the application of learning analytics (in context) is related to student success through intervention strategies. Therefore, the artifacts of learning analytics—both methodology (process) and visualizations (product)—can be grouped as a genre and studied for rhetorical action.

Learning analytics responds appropriately to a recurring situation, producing identifiable artifacts (broadly defined as visualizations, dashboards, and methodology) in the context of education delivered. Learning analytics is motivated by the institutional need for increasing student success, creating meaning through the social semiotics of data, predictive category, visualizations, and intervention strategy. Learning analytics can be viewed as generating a social action, within the situational context of education, delivered by the institution, with the motive of creating more students that are successful and, therefore, can be used to assess the social action of a discipline's intentional and rhetorical effects.

Having explored the tools, practices, and methodologies of learning analytics in Stage 1 of this research, in the next section I conduct a comparative analysis intended to identify ethical concerns of learning analytics using ethical frameworks in persuasion, human-computer interaction, social power, semiotics, visual design, and new media literacy (Stage 2).

Stage 2. Comparative Analysis using Ethical Frameworks

In this stage, I conduct a comparative analysis between learning analytics and existing ethical frameworks in rhetoric and scientific and technical communication in order to identify ethical concerns in the design, application, and documentation of learning analytics. For this comparative analysis, I select ethical frameworks from a variety of disciplines. The frameworks are drawn from the literature specifically for their potential usefulness as guides in the development of a matrix for understanding ethical concerns associated with the design, application, and documentation of learning analytics. Many of the selected frameworks, which are well established in the literature, are also seminal works by well-known researchers and practitioners within the disciplines of rhetoric and scientific and technical communication. The selected authors and frameworks are listed in Table 4. Additional authors are cited during the comparative analysis in support of and to validate the choice of frameworks.

Table 4. Frameworks Selected for the Comparative Analysis

Area	Author	Framework Summary
Persuasion	Aristotle	Elements of Persuasion
Human-computer Interaction	Katz & Rhodes (2009)	Ethical Frames
Social Power	Selber (2004)	Power Moves
Semiotics	Kress (2010)	Three Types of Social Signs
Visual Design	Allen (1996)	Persuasive Elements of Visual Design
New Media Literacy	Gurak (2002)	Four New Features of the Internet

In Stage 2, I also categorize ethical concerns using three types of categories: meta-categories, process categories, and ethical categories. The categories by no means encompass all of the potential ways in which ethical concerns can be classified—and, indeed, the ethical categories are highly generalized—but were chosen to serve as a baseline of classification for the scope of this study. Future research could refine these categories or propose new classification systems. **Meta-categories** refer to the three overarching themes of this study: design, application, and documentation. **Process categories** refer to the five stages of learning analytics: gather, predict, act, measure, and refine. Finally, **ethical categories** refer to the broad ethical concerns of Big Data identified in Chapter 2 (Anderson, 2008; boyd & Crawford, 2011; Davenport & Harris, 2007; Davis, 2012; Finn et al., 2013; Marwick et al., 2010; Nelson et al., 2000; Raport, 2011; Smolan & Erwitt, 2012; Weinberger, 2012). These concerns include interpretation of data, implementation of process, legality of service, and application of statistical methods. Categorizing ethical concerns facilitates the development of tree diagrams and relational visuals in Stage 3 for an in-depth review of the type and occurrence of concerns in each of the categories.

With the chosen frameworks and classification in place, I now turn to conducting the comparative analysis using ethical frameworks, united by their ethical lens, in persuasion, human-computer interaction, social power, semiotics, visual design, and new media literacy to identify ethical concerns of learning analytics and assign categories to each concern.

Elements of Persuasion

To understand the rhetorical effects of each stage in learning analytics, we can view its process as using data as information, using the predictive model to make meaning or create knowledge, and using the predictive category as speech requiring action. Furthermore, Aristotle's basic elements of persuasion provide insight into the reception of learning analytics by students, the credibility of the institution, and the importance of a sound predictive model. Aristotle defined rhetoric as "an ability, in each case, to see the available means of persuasion" (1991, 1354a) and rhetorical persuasion (*pisteis*) as having three species, stating, "The first kind depends on the personal character of the speaker [*ethos*]; the second on putting the audience into a certain frame of mind [*pathos*]; and the third on the proof, or apparent proof, provided by the words of the speech itself [*logos*]" (1991, 1356a1-3). Pathos is tied to the emotional condition of the hearer (either current condition or condition as imparted by the speaker), and its effectiveness relies on the temperament of the speaker or on the emotional situation. Logos is the use of convincing arguments. Finally, referring to the character of the speaker, ethos represents how much the audience respects and trusts the speaker. Applying Aristotle's framework of persuasive species to the learning analytics methodology reveals where ethos, pathos, and logos might have the strongest influence during each stage of the process. See Table 5.

Table 5. Learning Analytics and Persuasive Species

Species	Traits	Example	Stage in Learning Analytics
Ethos	Institution as character of speaker	Respect and trust	The educational institution **Gathers**, **Measures**, **Refines** data from or to student record.
Pathos	Emotional condition of student and faculty or staff as audience	Temperament or situation	The faculty as audience **Act** on the predictive category of at-risk to suggest an intervention strategy.
			The student as audience (re)**Acts** to the predictive category of at-risk and engages in an intervention strategy.
Logos	Arguments	Proof	Enthymemes replaced by inferential statistics to make a **Prediction** using student data.

When viewed with respect to the learning analytics process, each persuasive species links to the entity(ies) and stage(s) of learning analytics: ethos to the educational institution (gather, measure, and refine), pathos to the student and faculty (act), and logos to the statistical model (predict). In order to more thoroughly analyze the ethics of learning analytics, a complete explanation of how each persuasive element (*ethos, pathos, logos*) can be successfully persuasive, or unpersuasive, within the learning analytics process follows.

Ethos

As a form of persuasion, ethos refers to how much influence a speaker may wield through his or her reputation, or in terms of respect and trustworthiness. Aristotle outlined three explanations as to why speakers are persuasive through ethos and three corresponding explanations as to why they may fail to persuade. First, a speaker can be persuasive when he or she shows **goodwill** towards an audience (*eunoia*), but will fail to persuade if perceived to have an ulterior motive. Second, a speaker can be persuasive through his or her actual or perceived practical **wisdom and skills** (*phronesis*), but will fail to persuade if he or she does not have adequate expertise in the subject. Finally, a speaker can persuade through his or her **virtue or goodness** (*arête*), but will fail to persuade if it is clear that he or she will benefit from the outcome of the argument. Aristotle considered the attributes of ethos (good character) to be the "most effective means of persuasion" (1991, 1356a9-10).

Returning to Table 5, the stages of **gather**, **measure**, and **refine** are most affected by the ethos of the educational institution. Therefore, the institution can successfully "persuade" during learning analytics if it gathers accurate and complete student data (goodwill), maps and measures intervention strategies for student success (practical wisdom), and refines student records accurately and completely (virtue). In Table 6, I provide examples of how ethos can fail in each stage of learning analytics—if the institution has an ulterior motive, has no expertise, or is receiving benefits from its actions. For each of these three failures, I identify an ethical concern and classify each concern within a process, meta-, and ethical category.

Table 6 is the first table in this study to identify ethical concerns and to align those concerns to meta-, process, and ethical categories. While repetitive, I believe thorough labeling is imperative for developing the tree diagrams and relational visuals in Stage 3 and for creating the context-specific responses in Stage 4.

Table 6. Learning Analytics and Ethos (Institution)

Failure	Ethical Concerns	Meta-category	Process Category	Ethical Category
Ulterior motive **Fewer at-risk students reduces the need for funding intervention strategies**	What is the institutional vision, mission, or code of ethics for adopting or implementing learning analytics	Documentation	Gather	Implementation of Process
No expertise **Inability to track intervention success based on complexity of tracking, or added expertise increases costs (added staff or professional development)**	Inadequate user training for staff or faculty to properly conduct learning analytics	Documentation	Measure	Implementation of Process
Receiving benefit **Refining student data record increases chance for success—institutions benefit from retention and increased tuition**	Institutional principles or policies for using learning analytics not communicated college-wide (including transparency of benefit)	Documentation	Refine	Implementation of Process

When viewing the **gather**, **measure**, and **refine** stages of learning analytics through the rhetorical persuasive species of ethos, ethical concerns over methodological practices are strongly connected to the implementation of process (ethical category) and during the documentation (meta-category) of learning analytics. Concerns include an institution's failure to adopt a clear vision, mission, or code of ethics; failure to train users adequately; or failure to communicate policies and procedures for using learning analytics transparently.

Pathos

Regarding pathos, Aristotle wrote, "persuasion may come through the hearers, when the speech stirs their emotions" [pathos], for "our judgments when we are pleased and friendly are not the same as when we are pained and hostile" (1991, 1356a10-12). Aristotle outlined three features of pathos that address audience condition (what they are feeling), object (the target of those feelings), and groundedness (the reasons behind the emotions).

According to Table 5 above, the **act** stage of the learning analytics process is most affected by pathos. The student's emotion is **grounded** in being labeled at-risk and asked to engage in an intervention strategy by the institution (as speaker), with the **object** of the student's feeling being either the institution or the student's attitude regarding his or her own level of success when made aware of the at-risk label. Based on this analysis, in Table 7, I provide four possible **conditions** that the student may feel during the act stage of learning analytics, as well as the meta-category, ethical category, and ethical concerns related to those conditions. The concerns focus on the potentially negative reaction of the student (as audience) to the at-risk label. The emotional condition of the student (as created by the institution) should elicit an institutional response (as speaker). This focus is intentional, as I was looking for failures of pathos as possible ethical concerns.

Table 7. Learning Analytics and Pathos (Student)

Student Condition	Ethical Concerns	Meta-Category	Process Category	Ethical Category
Frustration or Resentment **Student does not believe the at-risk label is correct**	*If label is incorrect:* Inaccurate or incomplete data used in predictive model	Application	Act	Statistical Methods
	If label is correct: Student is unaware of data used in predictive model and therefore does not have context to interpret data	Application	Act	Interpretation of Data
Helplessness **Student knows why the at-risk label is incorrect (for academic or non-academic reasons) but there is no process in place to question the label**	Student is not given an opportunity to question or correct data used in predictive model	Application	Act	Implementation of Process
Embarrassed/ Concerned **Student is uncomfortable with being labeled at-risk by the institution and wonders who has access to the information**	Potential for revealing student status beyond "need to know" personnel (by student or institution)	Application	Act	Legality of Service
	Student not given an opportunity to opt-out	Documentation	Act	Implementation of Process
Resignation **Student is unable to engage in intervention strategies needed for success (or to change at-risk label)**	Lack of institutional best practices for using learning analytics	Application	Act	Implementation of Process
	Undefined responsibility to act on data makes institution vulnerable to legal action	Documentation	Act	Legality of Service

When viewing the **act** stage of learning analytics through the rhetorical persuasive species of pathos, numerous ethical concerns can be raised over the methodological practices connected to both the documentation and application of learning analytics. During the application of learning analytics, concerns involve inaccurate or incomplete data, a lack of context for the student, an absence of the student voice, the potential for de-anonymization, no opportunity for opting-out, and a lack of best practices for using learning analytics. Ethical concerns with respect to documentation include a lack of institutional principles or policies for using analytics and an undefined responsibility to act on the data that could make the institution vulnerable to legal action.

Logos

Moving on to the persuasive element of logos, Aristotle stated that "persuasion is effected through the speech itself when we have proved a truth or an apparent truth by means of the persuasive arguments suitable to the case in question" (1991, 1356a14-15). Aristotle believed that logos is an appeal to reason through proof (by example or through deductive reasoning). When implementing learning analytics, institutions use two forms of proof to guide the predictive model. The first form is used to determine which variables are needed to accurately identify at-risk students (gather, predict stages). The second form is used to verify whether the predictive model was successful (measure and refine stages). If the model fails for either of these two forms of proof, the institution loses credibility in its use of learning analytics.

During learning analytics, the predictive process begins by defining academic achievement—defined by most academic institutions as grades (i.e., C or better)—as well as retention, completion, transfer, or graduation. Then, the institution gathers student data records related to factors believed to have historically put students at-risk (e.g., GPA, first-generation student, ethnicity, PELL eligibility, suspensions, or loan defaults).

Based on Table 5 above, logos is primarily controlled by the **predictive model** (in fact, logos is the predictive model). The predictive model fails to persuade when a student's data record does not accurately predict the student to be at-risk for academic failure. Further, failure may take place when the predictive model is neither timely nor accurate in terms of why the student may be at-risk for academic or nonacademic reasons. In Table 8, I provide examples of failure and ethical concerns.

Table 8. Learning Analytics and Logos (Predictive Model)

Failure	Ethical Concern	Meta-Category	Process Category	Ethical Category
Inaccurate/Incomplete Predictive model labels student at-risk when he/she are not at-risk	Inaccurate or incomplete data used in predictive model	Application	Predict	Statistical Methods
Vulnerability Predictive model does not labels student at-risk when he/she is; student in need of intervention strategy does not receive assistance	Undefined responsibility to act on data makes institution vulnerable to legal action	Application	Predict	Legality of Service
Absence of Student Voice Predictive model does not provide an opportunity for student input	Institution does not give student an opportunity to question or correct data used in predictive model	Application	Predict	Implementation of Process

When viewing the **prediction** stage of learning analytics through the rhetorical persuasive species of logos, ethical concerns over methodological practices are connected to the application phase of learning analytics. Ethical concerns include the use of inaccurate or incomplete data, a vulnerability to legal action if the predictive model is flawed, and the absence of the student voice.

As shown, Aristotle's persuasive species can help identify the persuasive elements of learning analytics methodology. Based on the above dissection, and embracing learning analytics methodology as a communicative process in which data are information, the predictive model makes meaning or creates knowledge, and the predictive category is speech requiring action, traditional rhetorical frameworks of persuasion (ethos, pathos, logos) reveal that each element of the learning analytics process is persuasive. That is, institutions persuade through goodwill, practical wisdom, and virtue (ethos); students, through invoking a condition that requires an institutional response (pathos) and thereby increases institutional ethos; and predictive model, through logos (proof), regardless of whether it is correct or fails. In the case of failure, an institutional response is also required, providing another opportunity for the institution to increase ethos.

The institution has the most opportunities to persuade via ethos, not only by showing good will, practical wisdom, and virtue, but also by responding to failures of pathos (with student as audience) and failures of logos (as predictive model). The learning analytics process relies as much on the institution's reputation as it does on a student's willingness to engage in intervention strategies. Thus, it may be easiest to guide ethical decision-making processes by monitoring where persuasive species fail: where ethos can be questioned, pathos can incur harm, and logos is unsound.

In conclusion, researchers and practitioners in rhetoric and scientific and technical communication have a chance to embrace new genres by examining whether frameworks of persuasion (ethos, pathos, and logos) are useful for finding sites of persuasion or for guiding ethical decisions. Having reviewed the persuasive aspects of learning analytics through a comparative analysis of persuasive elements, I now turn to frameworks in human-computer interaction to identify and classify ethical concerns.

Human-Computer Interaction

In this section, I assess the learning analytics dashboard as a user interface, exploring how people relate to it. Miller (2004b) examined the concept of ethos in human-computer interaction by defining ethos as "personal or moral character" (p. 198). For Miller, there are two modes of human-computer interaction that influence ethos.

In the first mode, expert systems, humans have delegated expertise to a machine and have given that machine a level of credibility. Expert systems are computer programs dependent on a "database of knowledge" and expected to provide reasonable responses where knowledge is incomplete (pp. 199-200). The machine operates under certain virtues such as "speed, consistency, precision, tirelessness," and these virtues, along with the machine's credibility of achieving those virtues, endow the machine with a type of ethos (p. 200). However, Miller believed that expert systems fail to persuade through ethos because they are impersonal and detached from a user. That is, the expert system is judged on its trustworthiness to deliver a "correct" product, but the product is delivered based on rules (logos) and independent of the ethos of the expert system (p. 207). For Miller, any inherently ethos-based characteristic of the expert system is therefore repurposed as logos.

Miller described the second mode of human-computer interaction, intelligent agents, as the interaction between human and computer. Intelligent agents "make choices among conflicting goals" and rely on an interface and interaction with humans (p. 208). The interaction makes intelligent agents social as well as gives them an opportunity to offer ethos through trust. Here Miller uses the Ciceronian concept of ethos as feeling sympathy towards the speaker, and aligns the ethos of the intelligent agent with pathos because of its focus on sympathy over rationality.

Following Miller's concept of ethos as aligned with pathos, the learning analytics dashboard would be considered an intelligent agent rather than an expert system. The learning analytics process does contain ethos-controlled components (i.e., the institution as trusted and respected based on exhibiting good will, practical wisdom, and virtue). However, both systems, according to Miller, are void of moral virtue, the ethical component of ethos.

Steve Katz and Vicki Rhodes (2009) also examined ethical concerns in relation to human-computer interaction and proposed that technical communicators identify "ethical frames" as a "set of philosophical assumptions, ideological perceptions, and normative values underlying and/or guiding how people relate to and exist with technology" (p. 231). The frames define human-machine interaction by looking at the relationship between humans and machines, the changes in this relationship due to digital communication, and the side effects of depending on technology. The frames reveal both social and moral values attributed to technology as constructed by human relations with that technology. See Table 9 (summary of Katz and Rhodes, Table 9.1, p. 239).

Table 9. Katz and Rhodes' Ethical Frames

Frame	Definition	Example	Ethical and Social Implications	Citation
0 False	Nothing of value	Entertainment, indulgence	Is there any redeeming value or is it harmful	(p. 232)
1 Tool	A means	Calculator, hammer	How well the producer uses the tool	(p.232)
2 Means-end	A means and an end	Web site for Internet sales	Does the technical end justify the technical means	(p. 234)
3 Autonomous	Value system	Content Management Systems	Is technology a self-contained ethical entity with moral code	(p. 235)
4 Thought	Rational calculation	Common technical language	Does technology become a thinking machine	(p. 236)
5 Being	Consciousness	Electronic devices, virtual networks	Is technology incorporated as daily routine	(p. 237)
6 Sanctity	Undefined, non-technical	Mutual respect	Does the human-machine interaction show reverence and caring for their unity	(p. 250)

Describing ethics as being "socially dynamic and [socially] constructed," Katz and Rhodes revealed that, when viewed through ethical frames, technology also constructs social values and creates differentials in social power (p. 231).

Katz and Rhodes furthered ethics research in human-computer interaction with the use of ethical frames to view technology as both "being" and "constructing" social values (p. 231). Their ethical frames can be used to identify where technology failures can create ethical concerns during learning analytics. The stages of learning analytics, when viewed as a methodology capable of generating a social value, connect to Katz and Rhodes' False Frame (0), Tool Frame (1), and Means-end Frame (2), as shown in Table 10.

Table 10. Learning Analytics and Ethical Frames

Frame	Ethical Concerns	Meta-category	Process Category	Ethical Category
False Frame Learning analytics may be harmful if predictive category is wrong	Undefined responsibility to act on data makes institution vulnerable to legal action	Application	Predict	Legality of Service
Tool Frame Prediction is only as good as the data are accurate and complete	Inaccurate or incomplete data used in predictive model	Application	Gather Measure Refine	Statistical Methods
Means-end Frame Suggested intervention strategy decreases student success	Lack of institutional best practices for using learning analytics	Application	Act	Implementation of Process

Viewing methodology as artifact, as being, and as creating social values shows that learning analytics can fail in all three ethical frames and during all five stages of the learning analytics process. Specifically, learning analytics may be harmful if (1) the predictive category is wrong (predict), (2) the predictive model is inaccurate or incomplete (gather, measure, and refine), or (3) the student becomes less successful after completing the intervention strategy (act). The ethical concerns are application-focused and include the potential for legal action if the learning analytics process causes harm, the use of inaccurate or incomplete data, and a lack of institutional best practices for using learning analytics.

Having determined using Katz and Rhode's social frames that learning analytics can be viewed as constructing social value, and having identified and classified the ethical concerns through ethical frames, I now turn to the power differentials created in response to the social situation of learning analytics.

Social Power

Implementing learning analytics in the classroom or campus-wide can create power differentials between students and faculty or staff, and between students and the institution. In his 1996 article "Is This Ethical?," Sam Dragga confirmed the changing role of technical writers to technical communicators engaged in information design. Dragga identified the change in technical communication as one that came with "new rhetorical power" and that imposed "new ethical obligations on using that power" (p. 256). In *Spurious Coin*, Bernadette Longo (2000) proposed that a humanistic approach to technical writing provided "an invisible conduit transmitting reality through clear language," the result of which is to reveal the "social implications of technical writing practice" (p. 610). Longo maintained that technical writers marginalize, either intentionally or unintentionally, some knowledge in their efforts to legitimize certain knowledge and that the only way to change this practice is to fully explore how and why this marginalization and associated legitimization occurs within a social system. Similarly, John Monberg (2002) highlighted the concern regarding power in technical communication as one in which technical writers give precedence to groups that are more powerful and downplay (or make invisible) the less powerful. He argued that "because technical writing mediates relationships at the heart of the complex, global social order," the discipline of technical communication has an opportunity to "make significant social and intellectual contributions" by bringing questions of power differentials to light (p. 226).

In another work by Longo (2009), "Human+Machine Culture: Where We Work," she described technical communicators as being at the forefront of developing social reality through their choice of inclusion or exclusion of information. Through these choices, technical communicators create both culture and community. Because of the potential implications, technical communicators should be aware of the consequences of any choice that can affect social relations. This process of awareness starts by considering who has the power to make decisions, to legitimate some kinds of knowledge and repress others, to realize some possibilities and not others, and to give voice to some ideas and silence others by recording some stories while leaving others to be forgotten. In their position of power, Longo maintained that technical communicators can use language and metaphor to help users move from the known to the unknown and to move people from basic knowledge to useful knowledge. For Longo, invoking nostalgic metaphorical references can help users by providing familiar concepts (metaphor) that allows them to move beyond inequality and injustice (both social and power) into the future.

The arguments provided by Dragga (1996), Monberg (2002), and Longo (2000; 2009) can contribute to understanding learning analytics in terms of unequal social power. Dragga argued that new rhetorical power, such as that that would occur with implementing learning analytics, comes with new ethical obligations. In the case of learning analytics, institutions have rhetorical power over students as to whether they have a voice in the process and whether they own their personal data. The institution as gatherer of data and developer of the predictive model also would hold social power, according to Monberg's work. Finally, from the viewpoint of Longo's work, students would become less powerful (invisible) during the institutional implementation of learning analytics because there currently is very little opportunity for them to provide input or feedback. Allowing students to give feedback, including that related to non-academic concerns, would mitigate power differentials between institution and student.

In *Multiliteracies for a Digital Age*, Stuart Selber (2004) expressed concern over a lack of involvement of educators in the design of technology. If left "to those outside of the field," Selber had concerns that students would struggle to understand technology ("in critical, contextual, and historical ways"), that technology could "redefine literacy practices," and that eventually these concerns would preserve social inequities (p. 13). Selber carefully dissected where institutional technology regularization (required use of hardware or software) imposed a social power differential on individuals, terming these "power moves." Selber describes power moves and their consequences as follows:

- **Exclusion**. Access to technology and its social context is denied to persons who fit into certain race, class, gender, or achievement categories
- **Deflection**. Technology provides compensatory goods or services to people in an attempt to deflect attention from what is really going on.
- **Differential Incorporation**. Technology is structural so people of different social categories are incorporated in ways that reflect and attempt to reinforce their status.
- **Compartmentalization**. Access to technology and its benefits is in principle open to all, but access is rigidly structured to keep some persons at arms-length.
- **Segregation**. Access to technology and its benefits is in principle open to all, but is so expensive or difficult to obtain that few can enjoy it.

- **Centralization**. Access to technology and its benefits is in principle open to all, but the system is constructed so that users have little autonomy and so that significant decisions are reserved for central management.
- **Standardization**. Access to technology and its benefits is in principle open to all, but at the price of conformity to zealously maintained system standards and rules of procedure, which diminish local autonomy and marginalize local culture.
- **Polarization**. Different versions of the same artifact are created for no reason other than to reflect and reinforce race, class, gender, or achievement categories.
- **Marginalization**. Inferior versions of artifacts are expressly created for or distributed to persons within subordinate race, class, gender, or achievement categories.
- **Delegations**. An artifact feature is deliberately designed to make up for presumed moral deficiencies in users and is actively projected into social contexts of use.
- **Disavowal**. Artifact developed for menial/poorly compensated occupations is actively avoided/rejected by those of higher status, thus reinforcing status distinctions. (summary of Selber, 2004, Table 3.2, p. 102)

Selber's (2004) power moves specifically describe how the required use of technology imposes unequal social power and causes social inequity within institutions. Reviewing Selber's power moves through the lens of learning analytics, power moves could surface at any of the five stages of the learning analytics methodology, when viewed as technology. See Table 11.

Table 11. Learning Analytics and Power Moves

Power Move	Ethical Concerns	Meta-category	Process Category	Ethical Category
Exclusion, Compartmentalization, Segregation Intervention strategies are campus-based, face-to-face activities making it difficult for online students, those without transportation (or affordable transportation), or those with day jobs	Differential access	Application	Act	Implementation of Process
Deflection Deflection occurs because, while students can benefit from intervention strategies, the college benefits from increased tuition as a result of increased retention	Institutional principles or policies for using learning analytics not communicated college-wide (including transparency of benefit)	Documentation	Act	Implementation of Process
Differential incorporation Predictive categories differentiate by academic achievement	Potential for discrimination such as bias, labeling, and/or profiling	Application	Predict	Legality of Service
Centralization Institutions map at-risk categories to intervention strategies. If these strategies are too general, the intervention will not be effective	Lack of institutional best practices for using learning analytics	Application	Act	Implementation of Process
Standardization and Delegation Belief by the institution that the student is at-risk, does not meant the student is or feels at-risk	Student is unaware of data used in predictive model and therefore does not have context to interpret data	Application	Act	Interpretation of Data

In Table 11, a majority of the ethical concerns are application-focused, including differential access to services, the potential for discrimination, the absence of best practices, and a lack of context. In the documentation phase, an ethical concern is a lack of institutional principles or policies. In the absence of deeper discussions and reflection, unintentional consequences of learning analytics may include power moves. Thus, learning analytics can be viewed through a lens of social power and evaluated from the perspective of power moves.

Having highlighted Selber's power moves, which reveal how social power differentials can be created during the process of learning analytics, I turn to a framework that examines learning analytics from the perspective of social meaning, or semiotics.

Semiotics

From the perspective of semiotics, the learning analytics dashboard interface can be viewed as a "sign" that creates social meaning. In the study of semiotics, a sign is something that can be interpreted as having multiple meanings and, furthermore, that needs interpretation before communication can occur or meaning can be derived. Gunther Kress (2010) described how social meaning manifests through semiotics, viewing social semiotics as concerned "with meaning in all its appearances, social occasions, and cultural sites" (p. 2).

Kress defined three types of sign for creating social meaning as follows: (1) name, for that which would be too difficult to show; (2) color, to frame and highlight the message; and (3) image, for that which takes too long to read (p. 1). Kress specifically maintained that signs are a combination of form and meaning and based on the interests of the sign-maker and culturally available resources. His approach allowed him to theorize ethical communication using social semiotics in which community members have the resources to act, contribute, and understand the effect of their signs. However, Kress noted that cultural reality confounds the ideal situation, as do obstacles such as power, authority, authorship, social consequence, and personal choice (pp. 22-23).

From the perspective of Kress' (2010) approach, learning analytics can be viewed as a social semiotic process of making meaning. Returning to the dashboard as an artifact of learning analytics, we can view its interface as an image. The dashboard image shows what takes too long to read (data variables) and the at-risk label names something that is difficult to show (predictive model). Finally, the colors used on the dashboard (red, yellow, green) impart urgency to the overall message of at-risk. See Table 12.

Table 12. Learning Analytics and Social Signs

Meaning	Ethical Concern	Meta-category	Process Category	Ethical Category
Image Student "as data" displayed on visual dashboard	Student becomes objectified	Design	Act	Implementation of Process
Name Predictive model reduces student data to at-risk label	Potential for discrimination such as bias, labeling, and/or profiling	Design	Act	Legality of Service
	Institution does not give student an opportunity to question or correct data used in predictive model	Application		Implementation of Process
Color Urgency is imparted to message of at-risk by color and highlighted labels	Institutional users (faculty and staff) are unaware of data used in predictive model and therefore do not have context to interpret data	Design	Act	Interpretation of Data

Kress' (2010) social semiotic process would focus not only on the artifacts of visualizations and dashboards, but also on the data as originator of the at-risk label, and on both as signs that create meaning. When learning analytics is viewed as a social semiotic process, the majority of ethical concerns are design-focused (the visual object). Ethical concerns embedded in the dashboard design include viewing the "students as data," the potential for discrimination, and a lack of context for the student or institution. The last concern relates to the absence of the student voice, or the student's inability to provide feedback during the process of learning analytics.

Having highlighted Kress' social semiotic elements of learning analytics, the majority of which are related to design (visualizations and dashboards), I turn to social meaning as created by visual design.

Visual Design

The student dashboard, as a visual interface, has two potential audiences: the faculty members who suggest student intervention strategies and the students who receive the advice to engage in intervention strategies (some institutions do not use dashboards to engage; rather, students may be alerted of their need for intervention via email). Here, I discuss the effect of the visual design of the student dashboard as a sign. Visual design, as sign, also can be infused with social meaning. According to Nancy Allen (1996), contemporary rhetorical theory can help evaluate the persuasive nature of visual design elements. Correspondingly, she provided guidelines to begin the process of understanding how to create and analyze visuals rhetorically.

Allen proposed a framework for reviewing the conflicting legalities and differing moralities (cultural, religious, personal) that sensitize users to the rhetorical aspects of visuals, help users understand how a viewer might process visuals, and use rhetorical terms and language (p. 99). She rejected the traditional means of communicating ethics (e.g., journals, professional codes) as they often go unread, but, rather, supported a solution in which institutions establish an ethical culture (p. 100). As such, she outlined six dimensions of visual elements that might create ethical dilemmas:

- **Selection**. What the audience will and won't see
- **Emphasis**. Which details are removed or enhanced

- **Framing**. What is creating focus
- **Fonts**. How "tone" is set
- **Special Effects**. How meaning might be distorted, and what is a distraction
- **Enhancements**. How values are distorted (pp. 89-90)

Allen explained that, with new technologies, ethical concerns over visual design are increasing, a problem she views as two-fold. Visuals are altered simply because the practice has become easy to do using new software and hardware (a rhetorical practice in itself), and technical communicators are underprepared to understand the effect(s) that altered visuals may produce (p. 93).

Previous assessments treated the student as audience in order to describe the persuasive effects of the learning analytics process on the student. However, the student dashboard as a visual interface potentially has another audience: the faculty members who use the interface to suggest student intervention strategies. If we view faculty and staff as audiences, we can apply Allen’s (1996) six elements of visual rhetoric and ethical dilemmas to the learning analytics dashboard. Each dilemma has persuasive qualities when faculty uses the learning analytics dashboard as a tool to engage at-risk students in their education and suggest intervention strategies. Table 13 provides examples of “worst case scenarios” in response to the effect of persuasive elements on faculty.

Table 13. Learning Analytics and Visual Design

Dimension	Ethical Concern	Meta-category	Process Category	Ethical Category
Selection **Audience only sees at-risk label; personal assumptions lead to categorizing student**	Institutional users (faculty and staff) are unaware of data used in predictive model and therefore do not have context to interpret data	Design	Act	Interpretation of Data
Emphasis **Audience does not see details surrounding label; label "sticks" and student may be treated differently in the classroom**	Potential for discrimination such as bias, labeling, and/or profiling	Design	Act	Legality of Service
Framing and Enhancements **Attention is focused on student as data**	Student becomes objectified	Design	Act	Interpretation of Data
Fonts **Tone is set; relays professionalism or seriousness and leads to assumption of truth**	Institutional users (faculty and staff) are unaware of data used in predictive model and therefore do not have context to interpret data	Design	Act	Interpretation of Data
Special Effects **Meaning may be distorted; colors assign additional meaning to student via cultural norms (e.g. red, yellow, and green)**	Institutional users (faculty and staff) are unaware of data used in predictive model and therefore do not have context to interpret data	Design	Act	Interpretation of Data

Using Allen's framework with faculty as audience, we can identify ethical concerns related to the learning analytics dashboard. Ethical concerns are design-focused and relate to how data are interpreted, including a lack of context, the potential for objectifying a student, and the potential for discrimination.

Having highlighted Allen's six elements of visual design that can cause ethical dilemmas, I turn to the last ethical framework in Stage 2—that of new media literacy.

New Media Literacy

New media literacy is relevant to learning analytics in that it can define potential legal issues such as student privacy and informed consent. Heidi McKee (2008) described the technical communication researcher’s dilemma in addressing ethical concerns in new digital media as two-fold. The first problem concerns representation in term of reputation (ethos). How, for example, does a researcher build ethos, acknowledge contributing parties, and obtain permission? Second is the problem of informed consent. For example, how does one guide fair use or control the (re)mix of documents? For McKee, reflection is the key to adjusting to the convergences of new digital media and successfully addressing both ethical and legal concerns. Then, McKee (2008) would have institutions that are implementing learning analytics acknowledge student contributions, obtain permission for data use, and obtain informed consent.

Laura Gurak (2002) specifically highlighted how new media technologies have changed the concept of literacy. She described navigating the Internet as a form of digital literacy, what she terms “cyberliteracy,” and cyberliteracy as being about consciousness as literacy is to being about reading and writing (p. 16). Gurak expressed concerned over the rate with which information can be shared (**speed**), the lack of gatekeeping involved with information sharing (**reach**), the ability to use alternate identities when posting information or remixing documents not owned or authored by the poster (**anonymity**), and the overall ability to connect with those outside of an “inner circle” of friends (**interactivity**) (p. 44). Under Gurak’s four new features of the Internet, information travels more quickly and farther, and individuals can remain anonymous while conversing with more people than had previously been available. Gurak maintained that, while there are some positives resulting from the four features, such as increased globalness and community building, there are also negative results, including more casual, redundant, or repetitive communication; a lack of gatekeeping; problems of authorship and ownership; and the ability for businesses to gain customers without direct consent.

Gurak's (2002) work on cyberliteracy does not overtly highlight the ethical nature of these features and their consequences. However, viewing her framework through an ethical perspective, and then applying it to learning analytics' visualizations that have been harvested from social networks and posted to the Web or performance dashboards as presented to faculty, reveals ethical dilemmas for all four features. See Table 14.

Table 14. Learning Analytics and Features of the Internet

Feature	Ethical Concern	Meta-category	Process Category	Ethical Category
Speed Open-source modeling software allows for predictive modeling to occur without trained analysis by experts	Institutional users (faculty and staff) are unaware of data used in predictive model and therefore do not have context to interpret data	Application	Predict	Interpretation of Data
Reach Inaccurate or incomplete data may be used in predictive model	Inaccurate or incomplete data used in predictive model	Application	Gather	Statistical Methods
Anonymity Private data may be used without permission or de-anonymized by either party	Potential for revealing student status beyond "need to know" personnel (by student or institution)	Application	Act	Legality of Services
	Student not given an opportunity to opt-out	Documentation		Implementation of Process
Interactivity Information is pushed one-way (institution to student)	Student is not given an opportunity to question or correct data used in predictive model	Application	Act	Implementation of Process

As viewed through Gurak's four new features of the Internet, ethical concerns of learning analytics are application-based and include a lack of context, inaccurate or incomplete data, the potential for de-anonymization, and the absence of the student voice.

In Stage 2, I have identified and classified multiple ethical concerns by conducting a comparative analysis of existing ethical frameworks and learning analytics. The frameworks were chosen with the purpose of guiding research activities in the development of a matrix for understanding ethical concerns, with a focus on the design, application, and documentation of learning analytics. Furthermore, each ethical concern was assigned multiple categories (meta-, process, and ethical) for two reasons. First, assigning multiple categories allows for coding and organizing ethical concerns from multiple perspectives, a prerequisite of the framework methodology used in Stage 3. Second, assigning multiple categories allows for a richer and more in-depth deconstruction of the type and concentration of ethical concerns within each category, as well as validates concerns between the ethical frameworks used in Stage 2.

Stage 3. Deconstructing Ethical Concerns

In Stages 1 and 2 of this study, I explored the nature of learning analytics tools, practices, and methodology by means of genre theory, and then conducted a comparative analysis between ethical frameworks and learning analytics in order to identify ethical concerns. During the comparative analysis, I also classified the concerns using three categories (meta-, process, and ethical). In this stage, I use the categories to deconstruct the concerns using framework methodology and display them in tree diagrams and relational visuals. I do so in order to provide an in-depth review of the type and occurrence of ethical concerns of learning analytics from multiple perspectives.

Deconstructing the ethical concerns provides a rationale for the "why" of ethical concerns in the design, application, and documentation of learning analytics in post-secondary education. That is, many of the ethical concerns raised by learning analytics are intuitive—including (broadly) privacy, labeling, and accuracy of the model—however, this study vets the concerns using well-established ethical frameworks to help academia understand why it should be cautious when introducing learning analytics to campus.

According to Nicola Gale, Gemma Heath, Elaine Cameron, Sabina Rashid, and Sabi Redwood (2013), framework methodology has been used by social scientists since 1980 and was developed by Jane Ritchie and Liz Spencer, researchers at the National Center for Social Research in the United Kingdom (p. 2). The framework method is similar to, or a subset of, thematic analysis (content analysis), but is unique in its use of tree diagrams. The tree diagrams are particularly useful for analyzing qualitative data sets by (1) identifying similarities and differences in qualitative data and (2) finding descriptive relationships or explanatory themes between those similarities and differences. A tree diagram presents relationships between data sets visually and also facilitates the coding of data sets to develop a matrix (p. 118). For the purpose of this study, Stage 3 used a modified framework methodology, as fewer data variables were used than are typically associated with traditional framework methodology.

I develop the relational visuals to compare concerns across the ethical frameworks and within each category (meta-, process, and ethical), and to show the concentration of each concern. Relational visuals are used rather than a statistical figure with values (such as a pie chart), because the number of ethical concerns is not statistically relevant but, rather, an indication of the types of ethical concerns as revealed during the comparative analyses of selected frameworks. I use both size and color to provide a visual prompt to assess ethical concerns. For size, I use a formula to ensure that each concern is proportionally sized by the number of unique concerns within each category,[9] and I use progressive shading (light to dark) to indicate the number of ethical concerns within each category (more to fewer). The deconstruction process is shown in Figure 12.

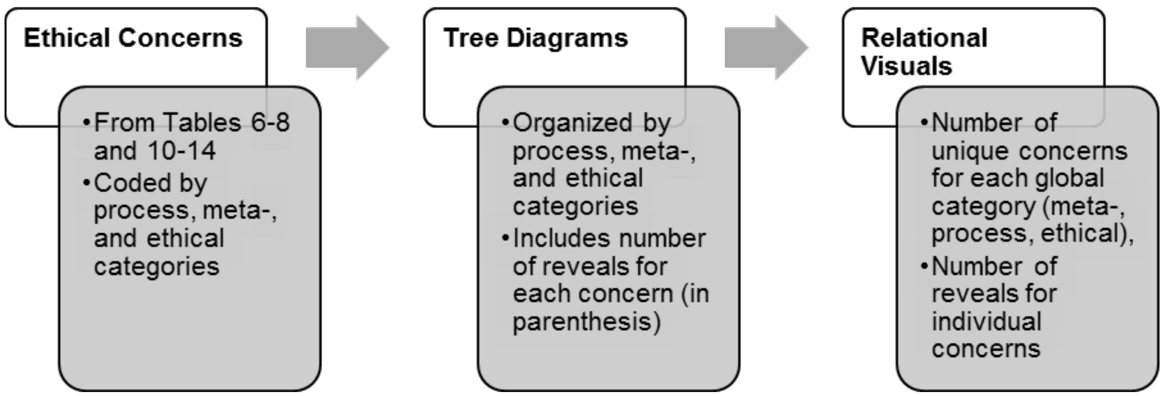

Figure 12. Deconstructing Ethical Concerns

Ultimately, I use the tree diagrams to organize the ethical concerns by their categories and the relational visuals to drill down to specific ethical concerns. I create both in order to facilitate developing context-specific responses for the final matrix of strategies and choices for understanding ethical concerns.

Process Category: Tree Diagram and Relational Visuals

The first tree diagram and set of relational visuals focus on the **process categories** of gather, predict, act, measure, and refine (the five stages of learning analytics). From

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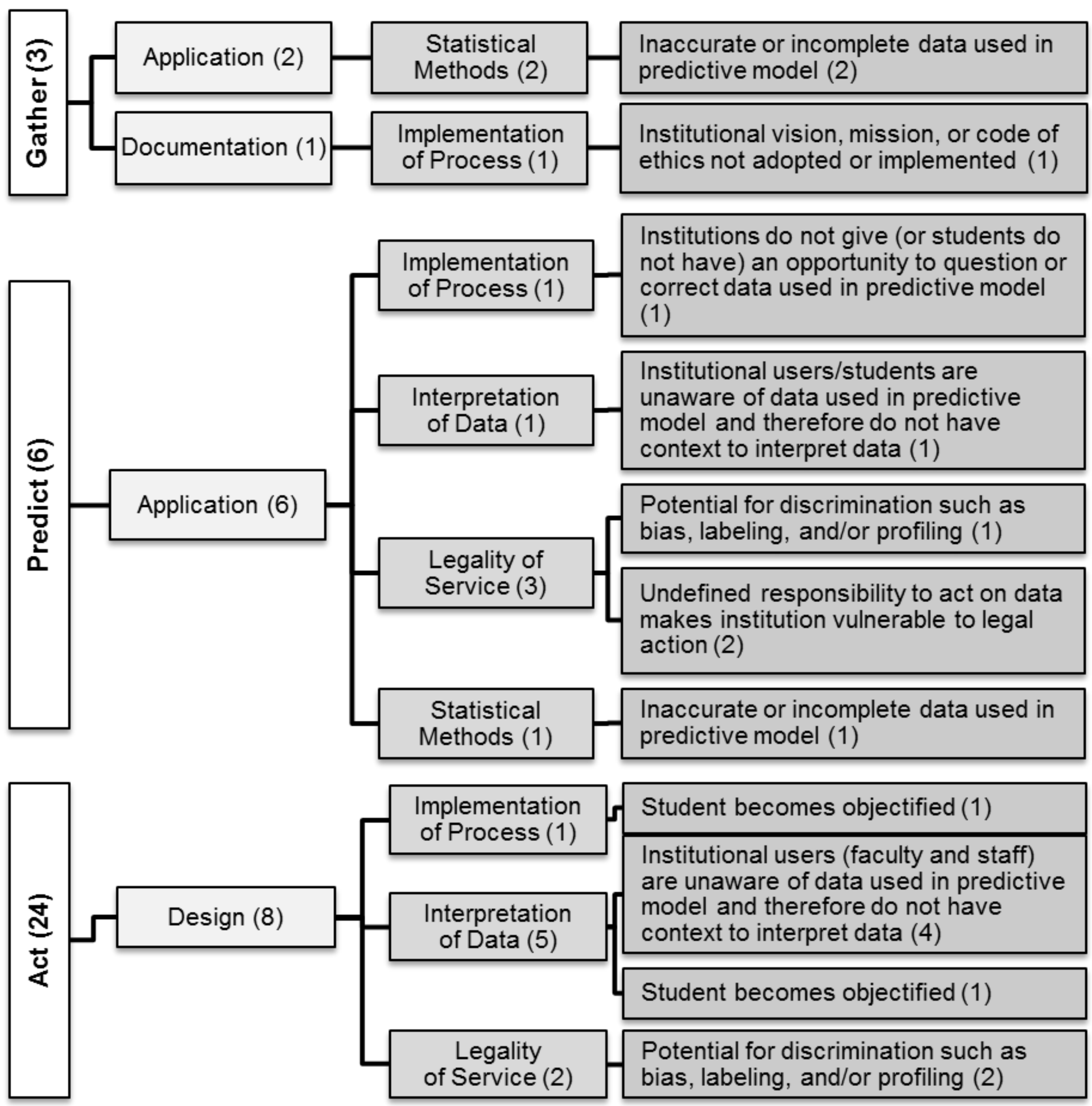
[9] This formula was necessary due to formatting constraints within Microsoft Word. Using a percentage of individual ethical concerns as compared to all ethical concerns within a category, I first moved the decimal to the left by one, divided the result by two, and then added the number one. For example, if an ethical concern comprised 18% of the total concerns within a category, the resulting size would be 1.9 inches in Microsoft Word [**(1.8 / 2) + 1 = 1.9 inch**].

the base of the diagram (process categories), the tree branches out to meta-categories and ethical categories. In the final branch, individual ethical concerns from the comparative analysis in Stage 2 are listed. The number of times the ethical concern was revealed during the comparative analysis is also indicated (in parentheses). See Figure 13.



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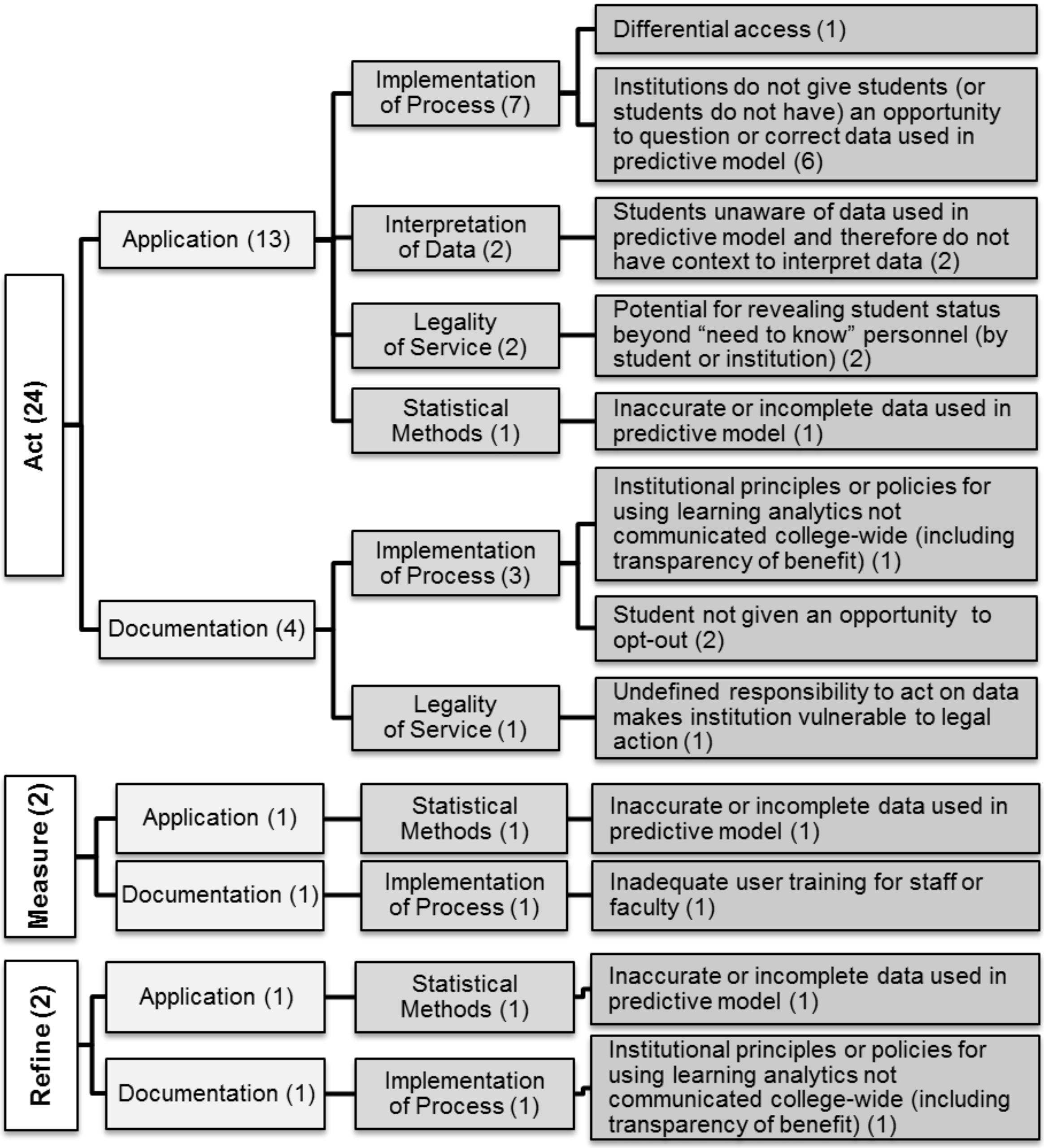


Figure 13. Process Category: Tree Diagram

Figure 13 reveals the distribution of ethical concerns across the stages of learning analytics (gather, predict, act, measure, refine). The majority of concerns occur during the **act** stage of learning analytics (24). Within this stage, the application of learning analytics reveals the largest number of concerns (13), followed by design (8) and documentation (4). Furthermore, the **act** stage of learning analytics is the only stage that raises concerns in all three meta-categories (design, application, and documentation) and in all four ethical categories (implementation of process, interpretation of data, legality of service, and statistical methods).

Figure 13 also shows that the **predict** stage of learning analytics reveals six potential ethical concerns. All of the concerns in the predict stage are raised during the application of learning analytics. The **gather** stage of learning analytics reveals three ethical concerns: two during application and the third concern during documentation. Finally, the **measure** and **refine** stages of learning analytics each reveal two ethical concerns: one each during the application and documentation of learning analytics.

Alternatively, ethical concerns can be viewed using a relational visual that shows the number of unique concerns identified by process category (gather, predict, act, measure, refine). The proportional size of each category is determined by the number of times a unique ethical concern was revealed during the comparative analysis. See Figure 14.

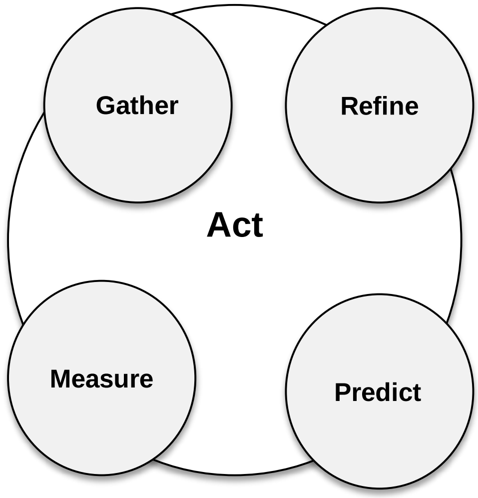
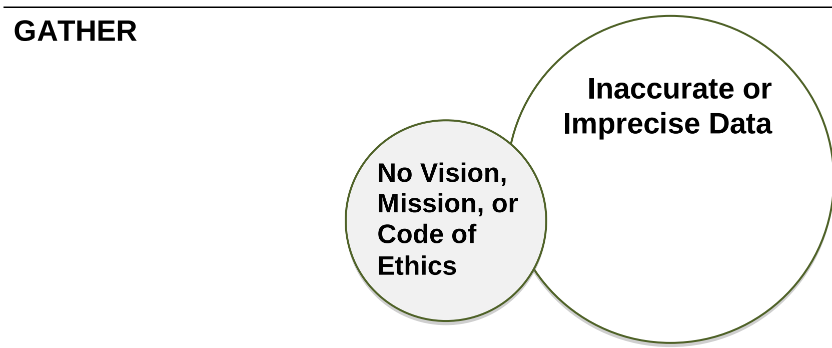


Figure 14. Process Category: Distribution of Ethical Concerns

Figures 13 and 14 reinforce the finding that the act stage of learning analytics is the process category most susceptible to ethical concerns, with ten unique concerns identified. The four other stages have two concerns each. Individual relational visuals for each **process category** (gather, predict, act, measure, and refine) are provided in Figure 15, followed by a discussion of each. These relational visuals differ from Figure 14 in that each indicates the number of times a concern was revealed during the comparative analysis rather than the unique number of concerns. The concerns have also been given generalized labels to accommodate the visual size.



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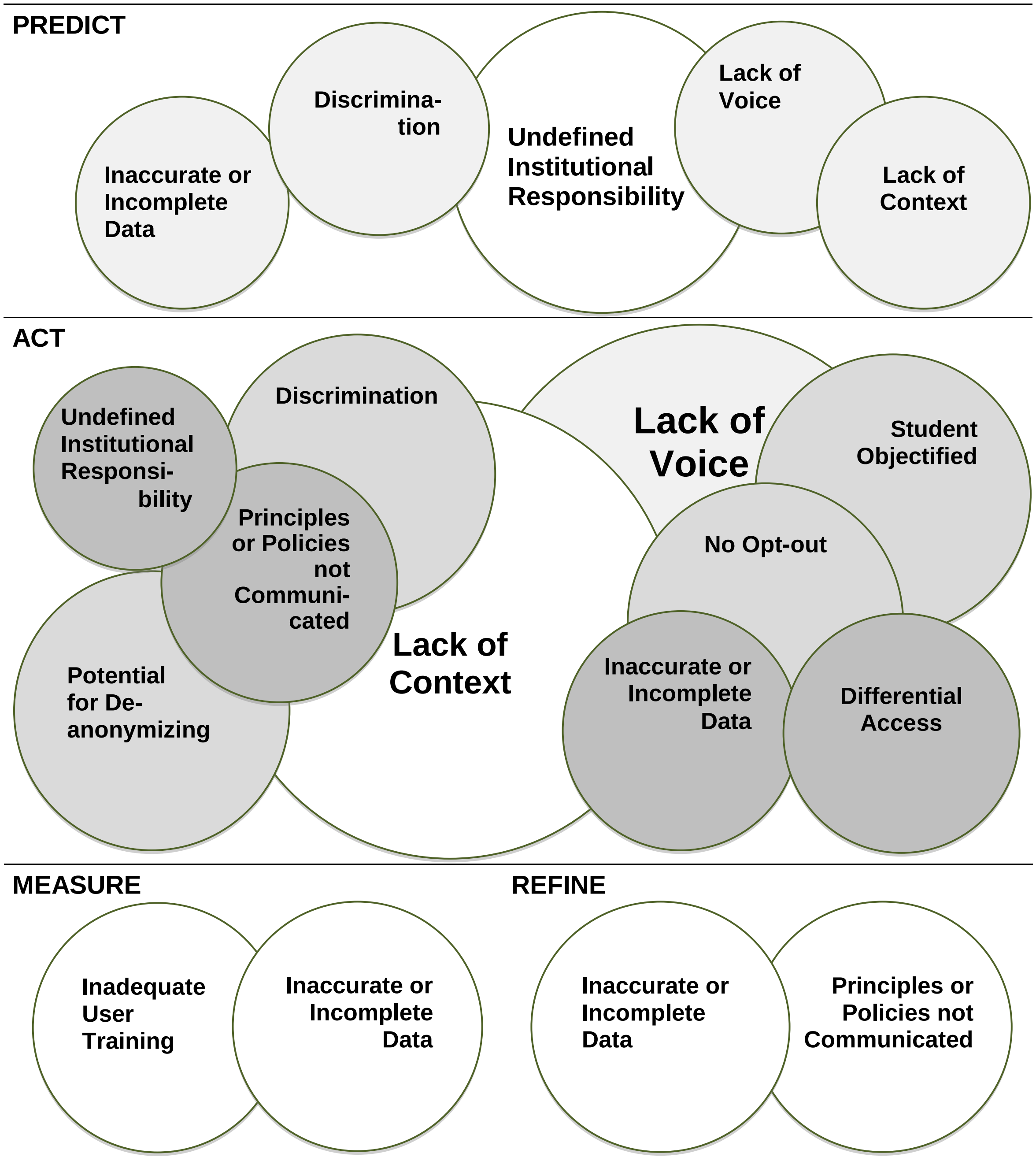


Figure 15. Process Category: Relational Visuals

During the **gather** stage of learning analytics, ethical concerns (2) are related to the use of inaccurate or incomplete data in the predictive model (which and how data are collected). Non-adoption or non-implementation of an institutional vision, mission, or code of ethics (why data are collected) comprises the rest of the ethical concerns revealed during the gather stage (1).

The ethical concerns revealed during the **predict** stage of learning analytics (modeling of gathered data) are equally distributed (1 each) with the exception of an undefined institutional responsibility to act on data, which makes the institution vulnerable to legal action (2). The equally distributed concerns during the predict stage include the following (1 each):

- Institution does not give, or student does not have, an opportunity to question or correct data used in predictive model (lack of voice)
- Institutional users/students are unaware of data used in predictive model and therefore do not have context to interpret data (lack of context)
- Potential for discrimination such as bias, labeling, and/or profiling
- Inaccurate or incomplete data used in predictive model

Multiple ethical concerns are revealed during the **act** stage of learning analytics, in which institutions suggest intervention strategies to increase student success. A majority of these concerns (6) are related to institutional users and/or students not having an opportunity to question data used in the predictive model. Concerns revealed twice during the act stage include the potential for discrimination such as bias, labeling, and/or profiling; students not having the context to interpret data or an option to opt-out; and the potential for revealing data beyond "need to know" personnel. Other concerns include the following:

- Student becoming objectified

- Differential access
- Inaccurate or incomplete data used in the predictive model
- Institutional principles or policies for using learning analytics not communicated college-wide (including transparency of benefit)
- Undefined responsibility to act on data making institution vulnerable to legal action

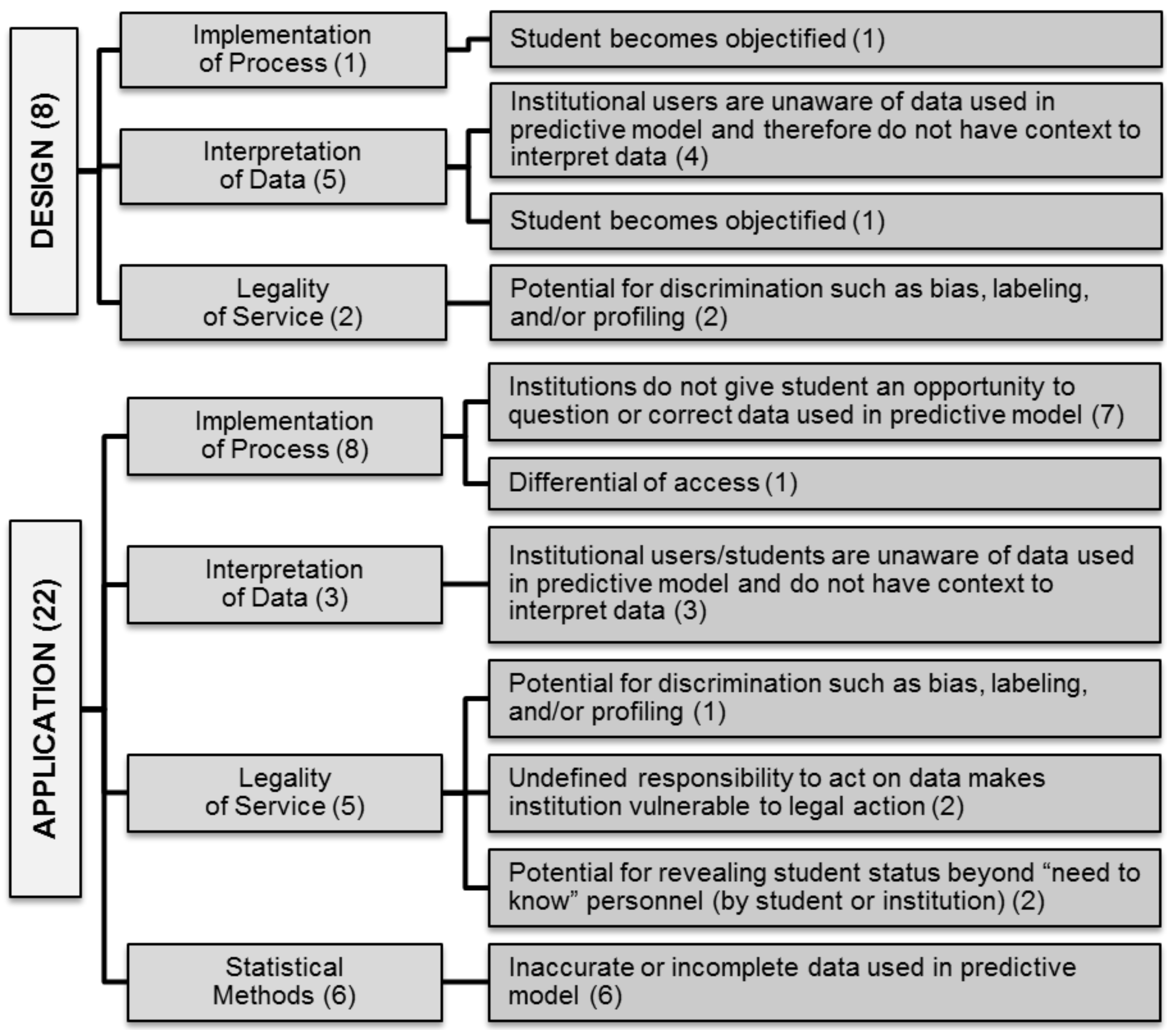
During the **measure** stage of learning analytics, in which the outcome of a student intervention strategy is assessed, inaccurate or incomplete data use in the predictive model (how data are collected) and inadequate user training for faculty or staff are of equal concern.

Finally, ethical concerns related to the **refine** stage of learning analytics (continuous improvement modeling) are balanced between inaccurate or incomplete data used in predictive model and institutional principles/policies not communicated college-wide (including transparency of benefit).

To summarize, with respect to the process categories of learning analytics (gather, predict, act, measure, and refine), the majority of ethical concerns are raised during the act stage. This result shows that the process of identifying students as at-risk and of implementing and suggesting intervention strategies for them warrants paying attention to numerous ethical concerns, including giving the student an opportunity to question or correct his or her own data.

Meta-Category: Tree Diagram and Relational Visuals

The second tree diagram and set of relational visuals focus on **meta-categories**, that is, on the design, application, and documentation of learning analytics. From the base of the diagram (meta-categories), the tree branches out to ethical categories. In the final branch, individual ethical concerns from the comparative analysis in Stage 2 are listed. The number of times the ethical concern was revealed during the comparative analysis is also indicated (in parentheses). See Figure 16.



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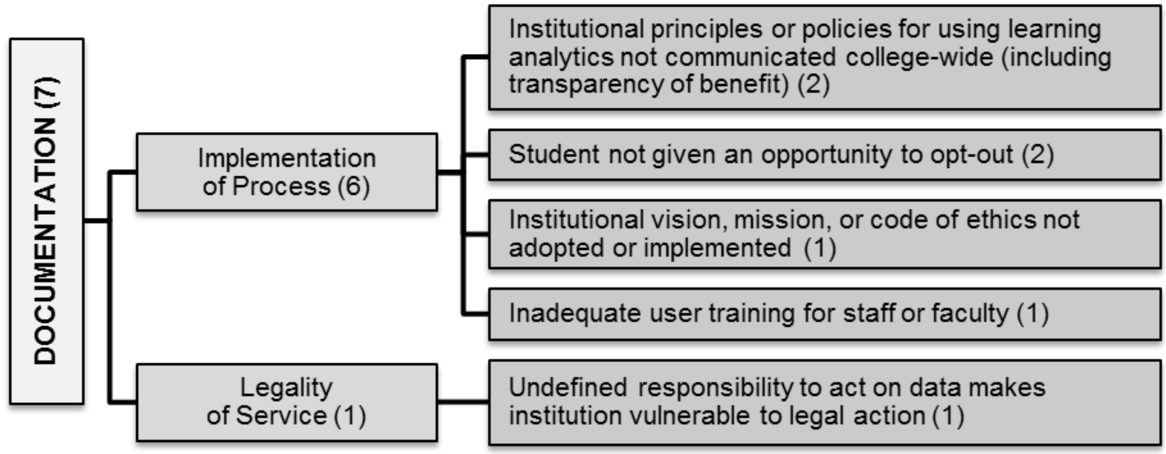


Figure 16. Meta-category: Tree Diagram

Figure 16 reveals the distribution of ethical concerns across the meta-categories of learning analytics. A majority of these concerns are raised during the **application** of learning analytics (22), that is, during the processes of learning analytics. Furthermore, all four meta-categories are represented during the application of learning analytics, in which concerns are raised with respect to implementation of process (8), statistical methods (6), legality of service (5), and interpretation of data (3). Fewer ethical concerns are revealed during the **design** of learning analytics (8), a majority of which relate to interpretation of data (5), followed by legality of service (2), and implementation of process (1). Ethical concerns raised during the **documentation** of learning analytics follow closely behind with seven concerns revealed, raised with respect to the implementation of process (6) and legality of service (1).

Alternatively, ethical concerns may be viewed using a relational visual that shows the number of unique concerns identified by meta-category (design, application, and documentation). The proportional size of each category is determined by the number of times a unique ethical concern was identified. See Figure 17.

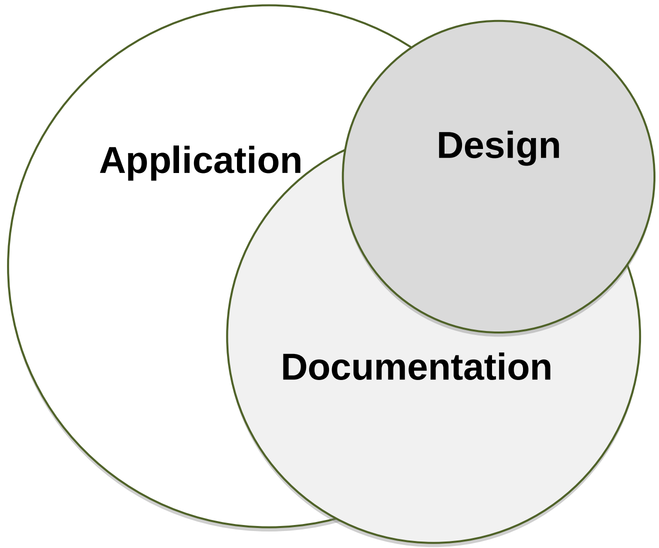
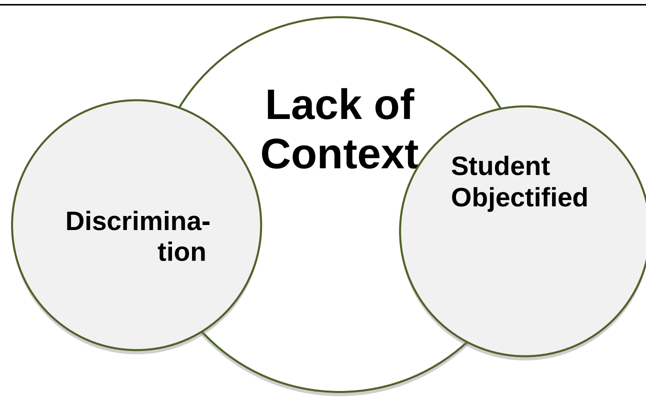


Figure 17. Meta-category: Distribution of Ethical Concerns

Figures 16 and 17 reinforce the finding that the application of learning analytics is the meta-category most susceptible to ethical concerns. Individual relational visuals for each meta-category (design, application, and documentation) are provided in Figure 18, followed by a discussion of each. These relational visuals differ from Figure 17 in that each indicates the number of times a concern was identified rather than the number of unique concerns. The concerns have also been given generalized labels to accommodate the visual size.

DESIGN



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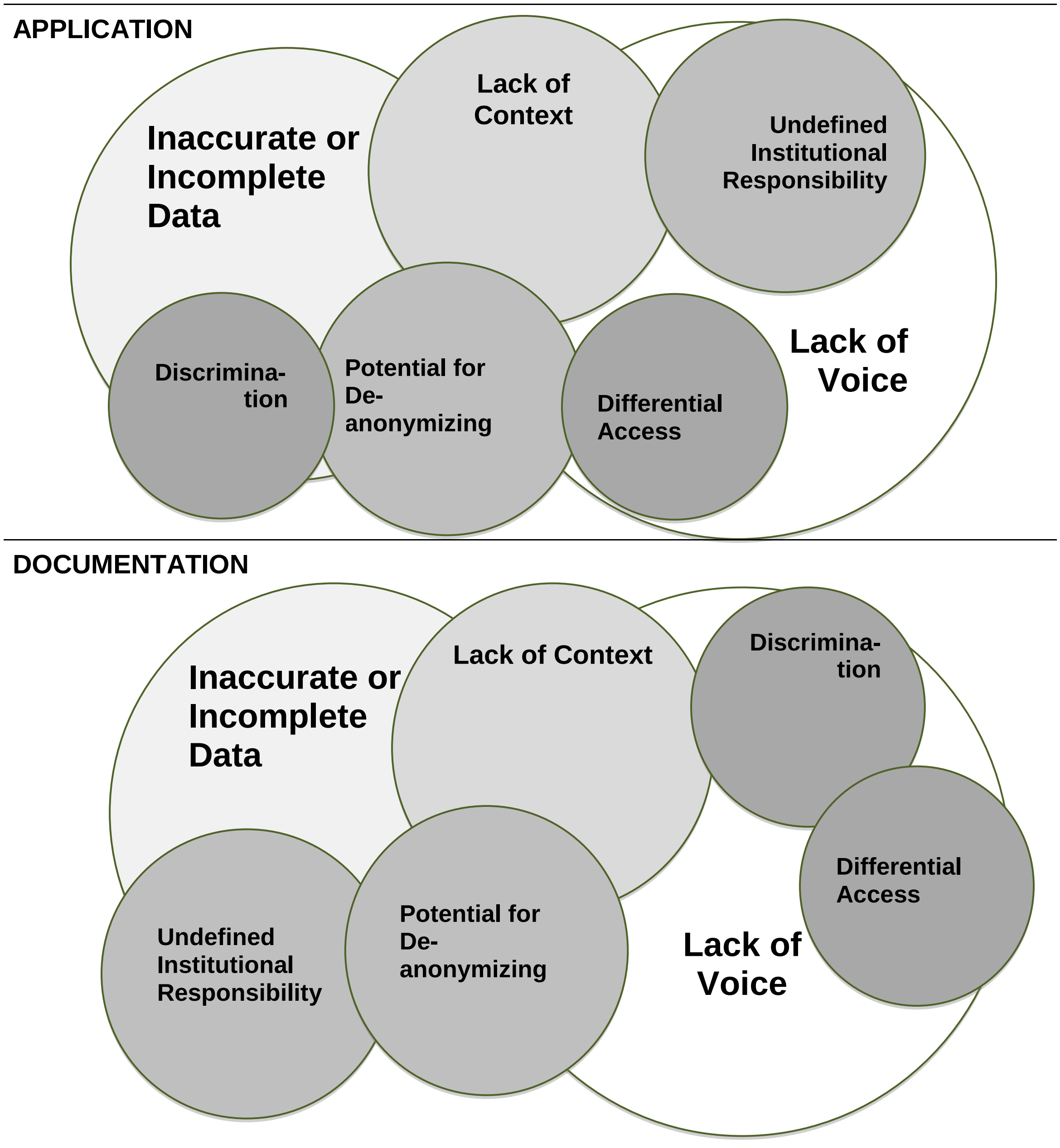


Figure 18. Meta-category: Relational Visuals

During the **design** of learning analytics, when visual objects are created, a majority of ethical concerns (4) are related to the institutional users or students not having context to interpret the data. Other ethical concerns identified include objectifying the student and the potential for discrimination such as bias, labeling, and/or profiling (2 each).

During the **application** of learning analytics, of the processes of learning analytics, a majority of concerns (7) raised relate to the inability of students to question or correct data used in the predictive model. Other concerns include inaccurate or inaccurate data (6) and the institution or student not having context to interpret the data (3). The following concerns were raised less frequently during the application of learning analytics:

- Undefined responsibility to act on data making institution vulnerable to legal action (2)
- Potential for revealing student status beyond "need to know" personnel (by student or institution) (2)
- Differential access (1)
- Potential for discrimination such as bias, labeling, and/or profiling (1)

Finally, during the **documentation** of learning analytics, in which evidence is produced, a majority of ethical concerns are related to a lack of communication of institutional principles or policies for using learning analytics (2), including transparency of benefits to the institution, as well as no opportunity to opt-out for students (2). Other ethical concerns raised during the documentation of learning analytics (1 each) include the following:

- Undefined responsibility to act on the data making the institution vulnerable to legal action,

- Inadequate user training for faculty and staff, and
- An institutional vision, mission, or code of ethics not implemented.

To summarize, the majority of ethical concerns for the meta-categories of learning analytics (design, application, and documentation) are revealed during the application category of learning analytics. This finding indicates that the processes of learning analytics warrant attention, including giving students an opportunity to question or correct their data (7) and carefully reviewing the data used in the predictive model (6).

Ethical Category: Tree Diagram and Relational Visuals

The final tree diagram and set of relational visuals focus on the **ethical categories**, that is, on the implementation of process, interpretation of data, legality of service, and statistical methods categories. This tree diagram contains ethical categories at the base, followed by individual ethical concerns from the comparative analysis in Stage 2. The number of times the ethical concern was revealed during the comparative analysis is also indicated (in parentheses). See Figure 19.

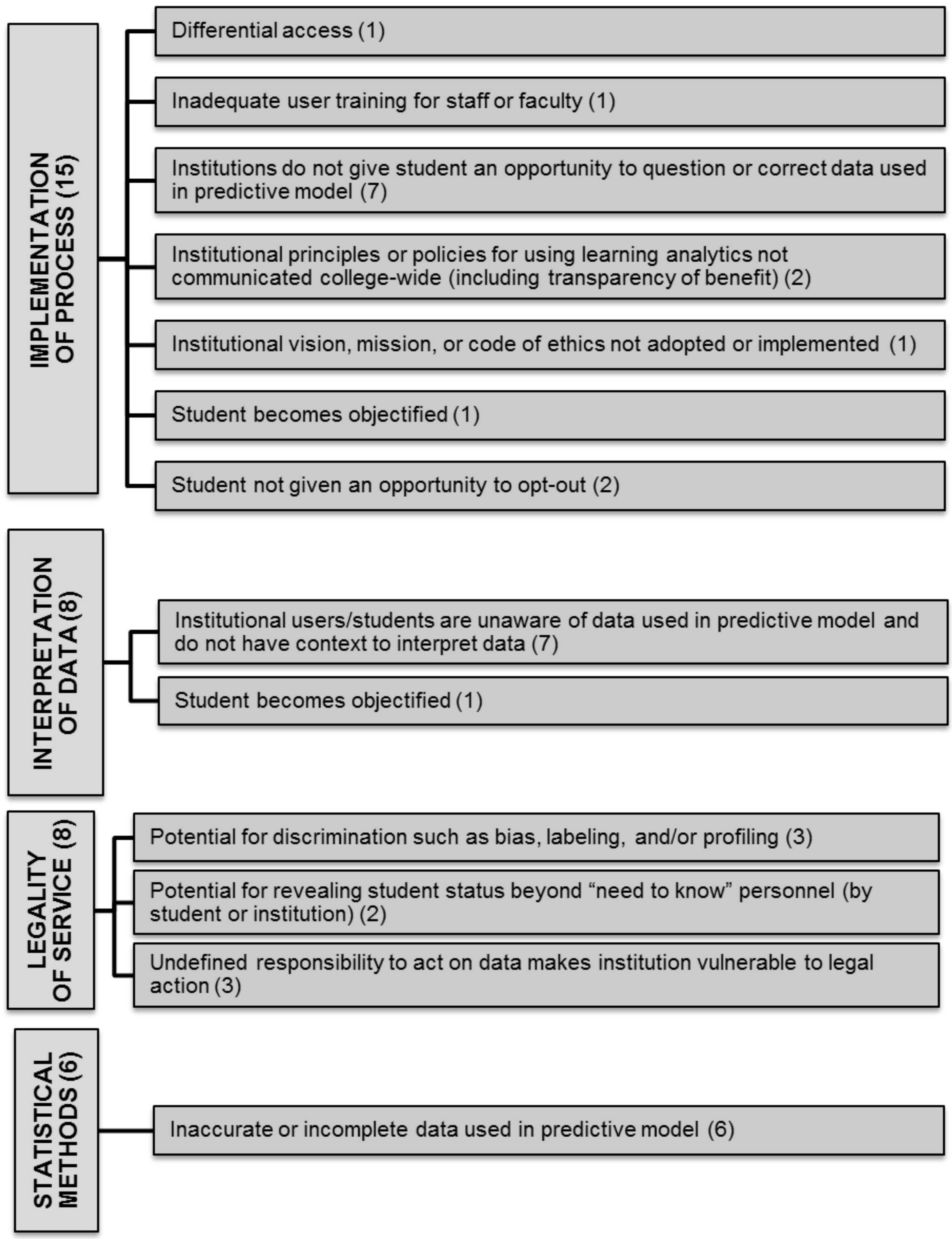


Figure 19. Ethical Category: Tree Diagram

Figure 19 reveals that a majority of concerns are raised during the **implementation of process** (15). Both **interpretation of data** and **legality of service** raise 8 ethical concerns, while **statistical methods** raises 6.

Alternatively, the ethical concerns can be viewed using a relational visual that shows the number of unique concerns identified by ethical-category (implementation of process, interpretation of data, legality of service, and statistical methods). The proportional size of each category is determined by the number of times a unique ethical concern was identified. See Figure 20.

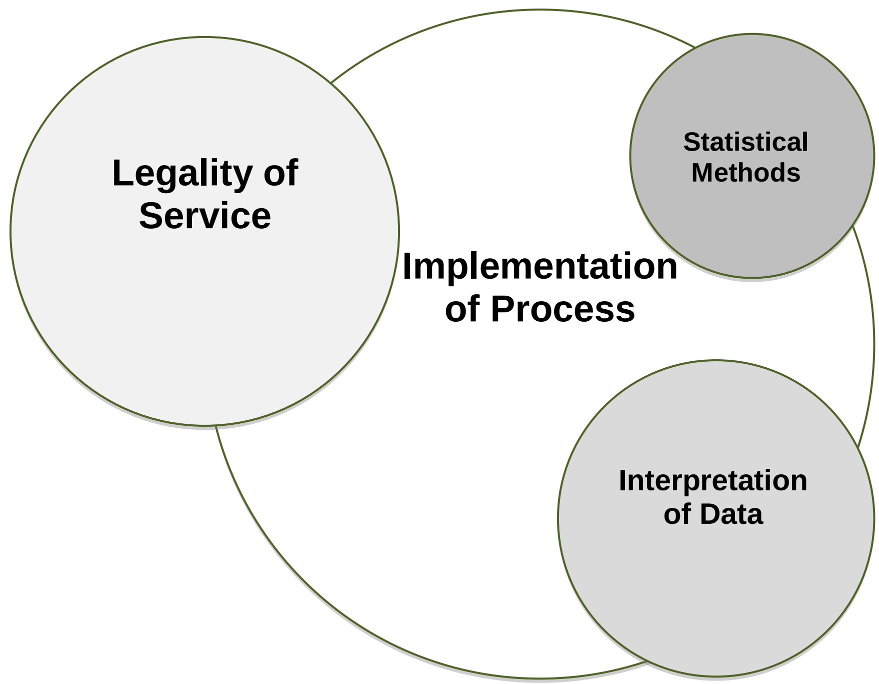
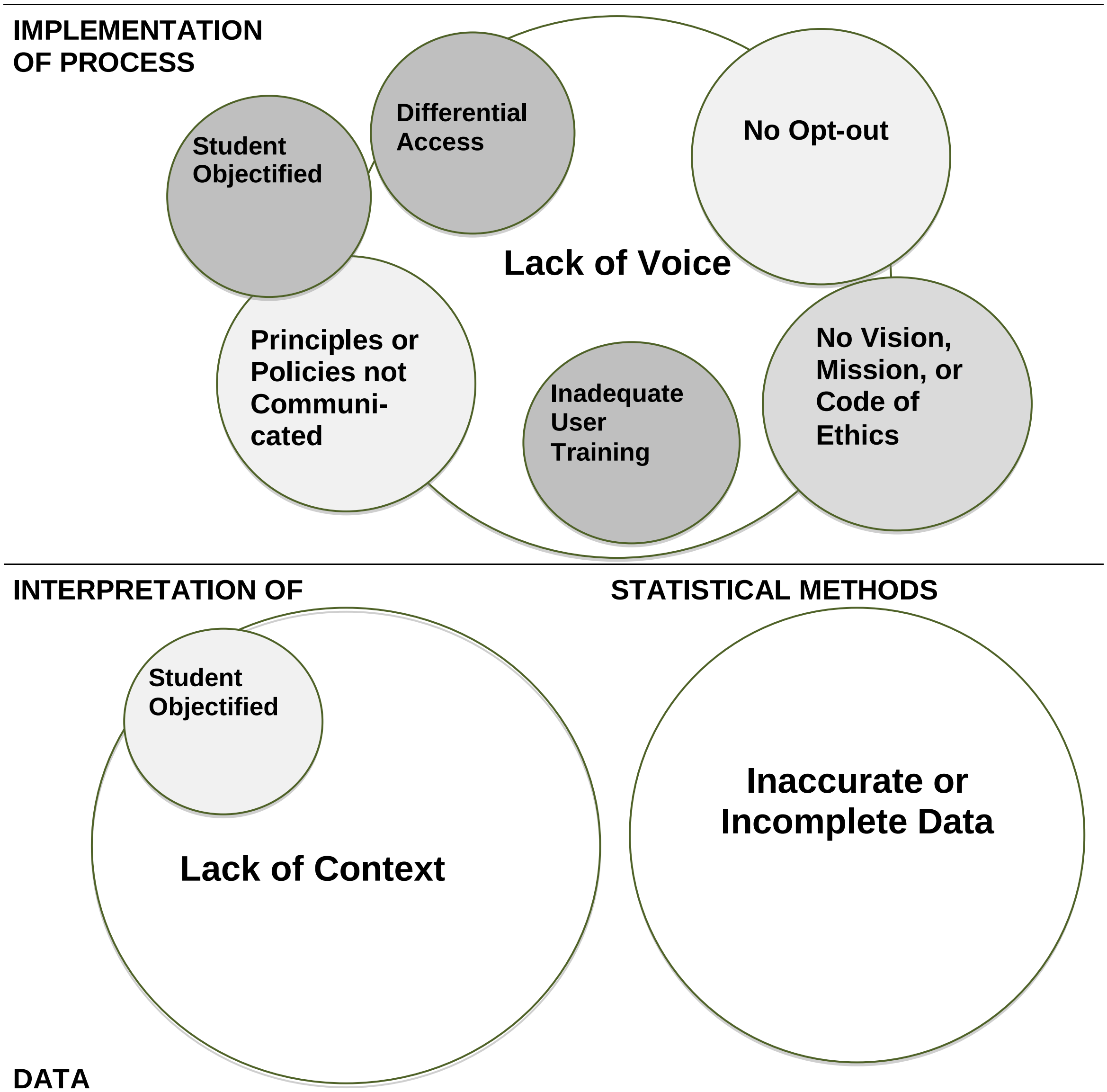


Figure 20. Ethical Category: Distribution of Ethical Concerns

Figures 19 and 20 above reinforce the conclusion that implementation of process is the ethical category most susceptible to ethical concerns. Individual relational visuals for each ethical-category (implementation of process, interpretation of data, legality of service, and statistical methods) are provided in Figure 21 below, followed by a discussion of each. These relational visuals differ from Figure 20 in that each indicates the number of times a concern was identified rather than the number of unique concerns. The concerns have also been given generalized labels to accommodate the visual size.



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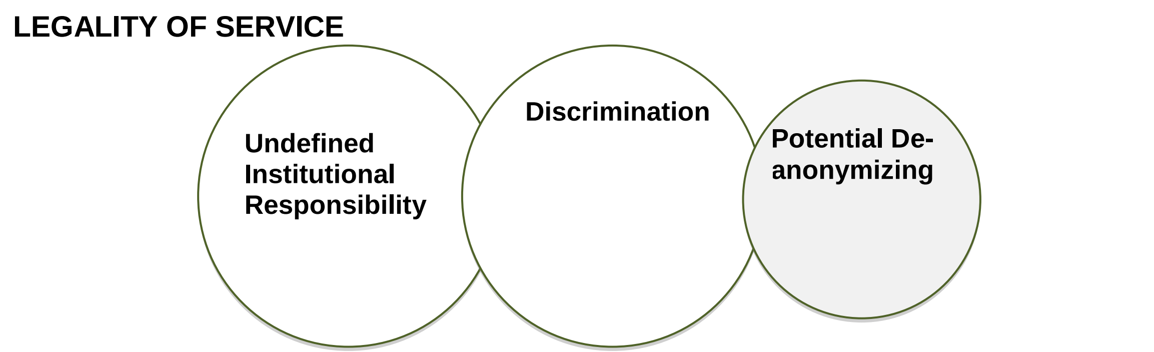

Figure 21. Ethical Category: Relational Visuals

During **implementation of process**, institutions are not giving (or the students do not have) an opportunity to question or correct the data used in the predictive model. Therefore, a lack of voice clearly stands out as the concern most often raised during implementation. Other ethical concerns raised during implementation of process include the following:

- Students not given an opportunity to opt-out (2)
- Institutional principles or policies for using learning analytics not communicated college-wide (including transparency of benefit) (2)
- Differential access (1)
- Inadequate user training for staff or faculty (1)
- Institutional vision, mission, or code of ethics not adopted or implemented (1)
- Student becomes objectified (1)

When **interpreting data**, a lack of context for the institution or student is of most concern (7). Student objectification (students as data) also raises concern. Ethical concerns raised with respect to **legality of service** during learning analytics are almost evenly distributed. The ethical concerns include the following:

- Undefined responsibility to act on data making institution vulnerable to legal action (3)
- Potential for revealing student status beyond “need to know” personnel (by student or institution) (2)
- Potential for discrimination (2)

Finally, all of the ethical concerns related to the **statistical methods** used in learning analytics are due to the use of inaccurate or incomplete data in the predictive model.

To summarize, the majority of ethical concerns raised with respect to the ethical categories of learning analytics (implementation of process, interpretation of data, legality of service, and statistical methods) relate to implementation of process, interpretation of data, and statistical methods. The concerns that warrant attention include giving students an opportunity to question or correct the data used in the predictive model (7), making sure that students understand the learning analytics model within the context of learning (7), and reviewing the data sources for accuracy (6).

The final relational visual includes ALL categories of concern revealed during Stage 2 of the research (meta-, process, or ethical), and supports the finding that ethical concerns related to a lack of voice, a lack of context, and inaccurate or incomplete data were the concerns most revealed during the comparative analysis in Stage 2. See Figure 22.

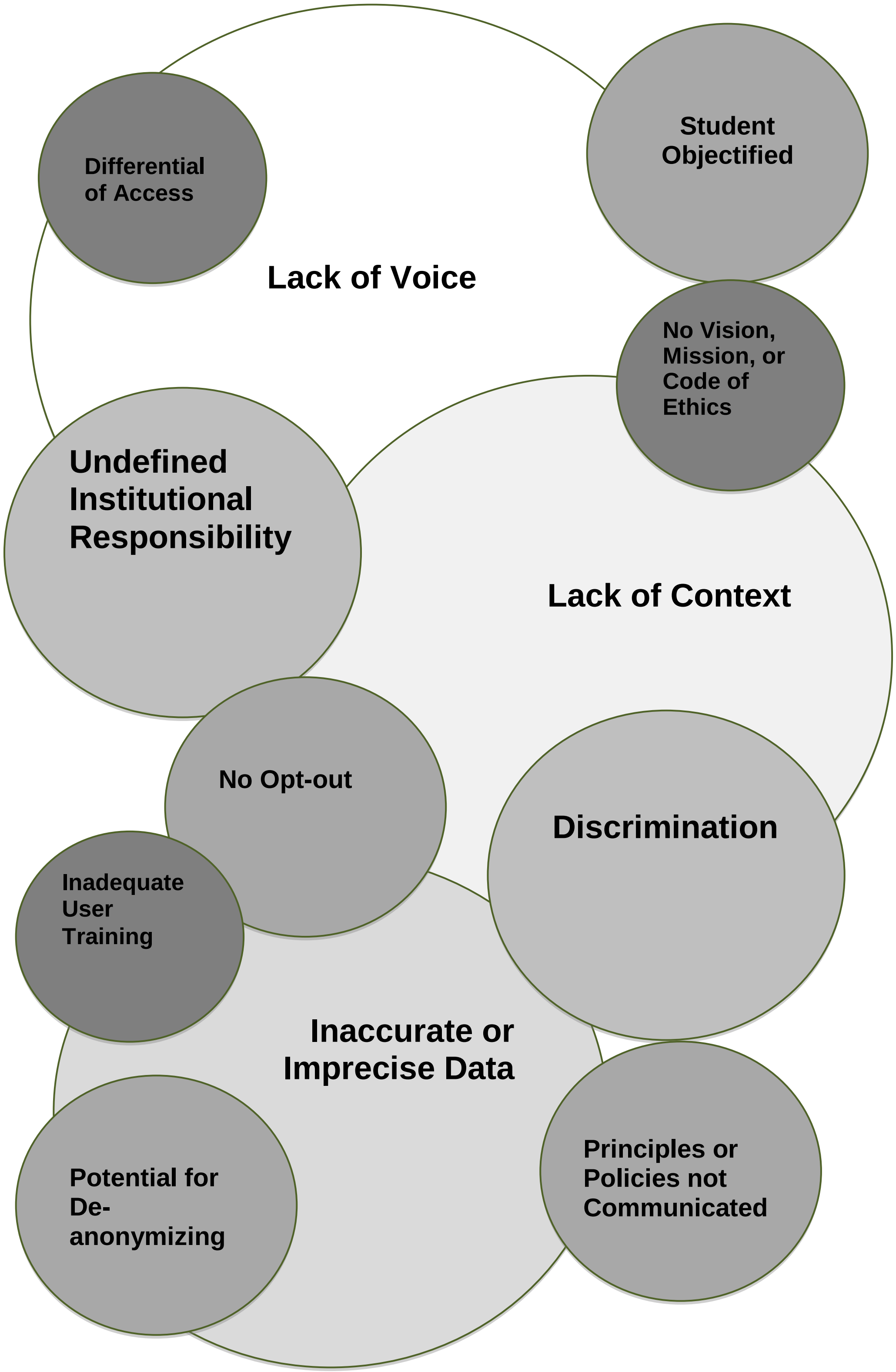

Figure 22. Summary of Ethical Concerns Revealed during Study

Figure 22 above presents all of the ethical concerns cited during Stage 2 of the research, regardless of category (meta-, process, or ethical). The percentage attributed to each ethical concern is not statistically relevant but, rather, indicates the number of times a concern was revealed through the analysis of ethical frameworks in rhetorical theory, visual design, semiotics, human-computer interaction, social power, and new media literacy.

From the overall deconstruction of ethical concerns, it is clear that the inability of students to provide input into the learning analytics process is the concern most often revealed during the comparative analysis, followed by a lack of context for interpreting the data by both institutional users and students, and the potential inaccuracies in the predictive model caused by inaccurate or incomplete data. Secondary concerns include an undefined institutional responsibility to act on data, which could put the institution at risk for legal action, as well as the possibility for discrimination to occur during the learning analytics process. Concerns identified less frequently include the potential for students to become objectified (student viewed as data), no option for students to opt-out of the process, a potential for de-anonymizing the student as at-risk, and college principles and policies not developed or not communicated college-wide. The final concerns identified include inadequate user training (for both students and institutional users), the potential for differential access, and a lack of a vision or mission statement, or code of ethics, created and communicated by the institution.

For the final step in deconstructing ethical concerns, I developed a coding system to organize and sort concerns while retaining the identity of the multiple categories assigned in Stage 2, as the categories provided the rich discussion afforded by the tree diagrams and relations visuals above.

Coding Ethical Concerns

In order to sort and organize ethical concerns, I developed a unique coding system. Using the first two letters of the meta- and ethical categories and the first letter in the process category, I created the alphanumeric coding system shown in Table 15. Each code consists of three alpha identifiers in the order of meta-, process, and ethical categories, separated by dots, and followed by the number of times the concern was revealed.

Table 15. Alphanumeric Coding Scheme for Ethical Concerns

Meta-category	Process Category	Ethical Category	Example Code
Design (De)	Gather (G)	Implementation of Process (Ip)	De.G.Ip2
Application (Ap)	Predict (P)	Interpretation of Data (Id)	Ap.P.Id
Documentation (Do)	Act (A)	Legality of Service (Ls)	Do.A.Ls3
	Measure (M)	Statistical Methods (Sm)	
	Refine (R)		

Table 16 provides the unique code for each concern listed in Tables 6-8 and Tables 10-14 from Stage 2. I also list the specific table in which each concern originated, the author, the concept behind the concern, and the concern itself. I carry this information forward to Stage 4, in which I develop responses to the concerns, so that the responses are created within the context of how the concerns were identified. I also do not collapse concerns at this point for the same reason. Therefore, while there may be duplicate concerns in this step based on the assigned code, the response to each concern may be different. One exception to this rule is a concern from Table 13 (Allen, 1996) regarding

Selection, Fonts, and Special Effects in which institutional users (faculty and staff) are unaware of data used in predictive model and therefore do not have context to interpret data. This table is the only one in which three concepts raise the same concern and are represented using the same code (De.A.Id3) and, therefore, I felt comfortable collapsing the concern at this stage.

Table 16. Coded Ethical Concerns

Table#, Author	Concept	Concern	Code
6, Aristotle	Ethos: Ulterior Motive	Institutional vision, mission, or code of ethics not adopted or implemented	Do.G.Ip
6, Aristotle	Ethos: No Expertise	Inadequate user training for staff or faculty	Do.M.Ip
6, Aristotle	Ethos: Receiving Benefit	Institutional principles or policies for using learning analytics not communicated college-wide (including transparency of benefit)	Do.R.Ip
7, Aristotle	Pathos: Frustration or Resentment	Students are unaware of data used in predictive model and therefore do not have context to interpret data	Ap.A.Id
7, Aristotle	Pathos: Helplessness	Institutions do not give student an opportunity to question or correct data used in predictive model	Ap.A.Ip
7, Aristotle	Pathos: Resignation	Lack of institutional best practices for using learning analytics	Ap.A.Ip
7, Aristotle	Pathos: Concern or Embarrassment	Potential for revealing student status beyond “need to know” personnel (by student or institution)	Ap.A.Ls
7, Aristotle	Pathos: Concern or Embarrassment	Student not given an opportunity to opt-in/opt-out	Do.A.Ip
7, Aristotle	Pathos: Resignation	Undefined responsibility to act on data makes institution vulnerable to legal action	Do.A.Ls
7, Aristotle	Pathos: Frustration or Resentment	Inaccurate or incomplete data used in predictive model	Ap.A.Sm
8, Aristotle	Logos	Institutions do not give student an opportunity to question or correct data used in predictive model	Ap.P.Ip
8, Aristotle	Logos	Undefined responsibility to act on data makes institution vulnerable to legal action	Ap.P.Ls
8, Aristotle	Logos	Inaccurate or incomplete data used in predictive model	Ap.P.Sm
10, Katz & Rhodes (2009)	Means-end Frame	Lack of institutional best practices for using learning analytics	Ap.A.Ip
10, Katz & Rhodes (2009)	Tool Frame	Inaccurate or incomplete data used in predictive model	Ap.G.Sm
10, Katz & Rhodes (2009)	Tool Frame	Inaccurate or incomplete data used in predictive model	Ap.M.Sm

Table#, Author	Concept	Concern	Code
10, Katz & Rhodes (2009)	False Frame	Undefined responsibility to act on data makes institution vulnerable to legal action	Ap.P.Ls
10, Katz & Rhodes (2009)	Tool Frame	Inaccurate or incomplete data used in predictive model	Ap.R.Sm
11, Selber (2004)	Exclusion, Compartmentaliza-tion, Segregation	Differential \access	Ap.A.Ip
11, Selber (2004)	Centralization	Lack of institutional best practices for using learning analytics	Ap.A.Ip
11, Selber (2004)	Differential Incorporation	Potential for discrimination such as bias, labeling, and/or profiling	Ap.P.Ls
11, Selber (2004)	Deflection	Institutional principles or policies for using learning analytics not communicated college-wide (including transparency of benefit)	Do.A.Ip
11, Selber (2004)	Standardization, Delegation	Students are unaware of data used in predictive model and therefore do not have context to interpret data	Ap.A.Id
12, Kress (2010)	Color	Institutional users (faculty and staff) are unaware of data used in predictive model and therefore do not have context to interpret data	De.A.Id
12, Kress (2010))	Image	Student becomes objectified	De.A.Ip
12, Kress (2010)	Name	Potential for discrimination such as bias, labeling, and/or profiling	De.A.Ls
12, Kress (2010)	Name	Institutions do not give student an opportunity to question or correct data used in predictive model	Ap.A.Ip
13, Allen (1996)	Framing and Enhancements	Student becomes objectified	De.A.Id
13, Allen (1996)	Selection, Fonts, Special Effects	Institutional users (faculty and staff) are unaware of data used in predictive model and therefore do not have context to interpret data	De.A.Id3
13, Allen (1996)	Emphasis	Potential for discrimination such as bias, labeling, and/or profiling	De.A.Ls
14, Gurak (2006)	Interactivity	Institutions do not give student an opportunity to question or correct data used in predictive model	Ap.A.Ip
14, Gurak (2006)	Anonymity	Potential for revealing student status beyond “need to know” personnel (by student or institution)	Ap.A.Ls
14, Gurak (2006)	Reach	Inaccurate or incomplete data used in predictive model	Ap.G.Sm
14, Gurak (2006)	Speed	Institutional users (faculty and staff) are unaware of data used in predictive model and therefore do not have context to interpret data	Ap.P.Id
14, Gurak (2006)	Anonymity	Student not given an opportunity to opt-in/opt-out	Do.A.Ip

In summary, the motive for assigning multiple categories to ethical concerns in Stage 3 was to explore, in-depth, the relationships between and among ethical concerns. The code assignment needed to precede any collapse of categories or combination of duplicate concerns, as the response to a concern may differ depending on the context in which it was identified. With Stages 1-3 complete, in the next section I review frameworks in ethical pedagogy to serve as a guide for developing responses to the ethical concerns of learning analytics (Stage 4). Once Stage 4 is completed, the matrix of strategies and choices for understanding the design, application, and documentation of learning analytics in post-secondary education can be built (Stage 5).

Stage 4. Combining Pedagogical Frameworks

In this stage, I review pedagogical frameworks that focus on teaching students in rhetoric and scientific and technical communication how to respond to ethical dilemmas. The frameworks are appropriate to this study as, ultimately, the matrix for understanding ethical concerns can serve as a pedagogical tool for the ethical design, application, and documentation of learning analytics, both within rhetoric and scientific and technical communication as well as for the learning analytics community. Frameworks chosen for review include Mark Ward's (2010) non-foundational questions regarding ethical behavior; Heather Canary's (2007) teaching ethical actions; Aristotle's ethical characteristics of goodwill, practical skills, and practical wisdom; and Stuart Selber's (2004) ethical literacies (rhetorical, critical, and functional). Other authors are cited to round out the discussion on ethical pedagogy.

Ethical Questions

Scientific and technical communication changed with the publication of Steven Katz's (1992) landmark essay "The Ethic of Expediency: Classical Rhetoric, Technology, and the Holocaust." In his article, Katz explained the necessity of integrating ethics into technical communication education by describing the dangers of a rhetoric based solely on the ethic of expediency (convenient but immoral). By examining Hitler's rhetoric, he uncovered how the ethic of expediency, in combination with science and technology, allowed Hitler to create a "moral" warrant for Nazi action (p. 201). The final question Katz posed to rhetoricians is how do we "contribute to this *ethos* by our writing theory, pedagogy, and practice when we consider techniques of document design, audience adaptation, argumentation, and style without also considering ethics?" (p. 208).

Ward (2010) also reviewed the ethics of technical writing pedagogy in terms of design, and provided an alternative to Katz's ethic of expediency: the ethic of exigency, or a situation demanding action. Ward described the ethic of exigency as "social knowledge—a mutual constructing of objects, events, interests, and purposes," viewing the community as rhetorical and the rhetorical community as a genre (p. 63). As such, ethics in information design questions the effect that an arrangement of text and graphics has on a particular culture. Ward conducted his own review of the literature on technical communication ethics and found that the literature focused on one single moment in decision-making, leaving two questions unanswered:

- By what principles can we design information to encourage co-construction of life-affirming meaning with our audiences, and

- How can designers resist bowing to an ethic of exigence when they have concerns about the meaning systems that are being legitimized by their work? (p 78)

To answer these questions, Ward discussed the difference between foundational and non-foundational approaches to teaching ethics. A foundational approach suggests a course of action when faced with an ethical dilemma (a call to action—the ethics of exigency). However, for Ward this approach did not explain why concerns become ethical dilemmas to begin with, how we determine trivial versus obviously unethical questions, and how we identify the cultural influences on an individual when faced with ethical choices. Ward believed that the second approach to ethics, non-foundational, answers these ethical questions, citing Foucault's belief that "individuals could cultivate the power to denaturalize and subvert institutionalized influences by asking these types of questions" (p. 83):

- Why do I want to be ethical? (ethical substance)
- What must I do to become ethical in this situation? (ethical work)
- Do I agree with this? (ethical goal)

Ward believed that a two-part approach is needed for understanding ethics. The first part relies on a foundational approach that is prescription focused (solution-based) and the second part relies on a non-foundational approach that is description focused (rationale-based).

Katz stressed the importance of incorporating ethics into technical communication. In response, I use Ward's non-foundational questions to provide a rationale for the design (ethical substance), application (ethical work), and documentation (ethical goal) of learning analytics by addressing his questions while developing responses to ethical concerns. For example, to have ethical substance in **design**, a designer would consider, “Why do we want to develop ethical design in learning analytics?” During the **application** of learning analytics, ethical work by all users (students, faculty, staff, and institutions) would consider, “What must we do to use learning analytics applications ethically?” Finally, when **documenting** learning analytics, institutions would have an ethical goal of providing overall guidance for learning analytics by considering, “Do we agree with all aspects of design and application of learning analytics on campus?”

Ethical Actions

Paul Dombrowski’s (2009) framework for defining ethics for technical communication pedagogy raised concerns that ethics “overlap[s] with moral, legal and religious” beliefs and that these concerns make ethical pedagogy confusing (p. 306). He cited the H-Bomb and Challenger/Columbia disasters as watershed events that changed technical communication from an individualized activity to one that considered “social context and historical circumstances” (p. 307). Dombrowski proposed that students be taught to consider rhetoric *and* ethics in “[how] technology is designed, the way it is actually used, and to some degree even the [societal impacts on the] shape of the technology itself” during the course of instruction (p. 315).

Canary (2007) looked beyond the conceptual idea of identifying ethical concerns for technical communication pedagogy to a more detailed approach to teaching ethics in the classroom. She viewed a student's ability to respond appropriately to ethical problems as a principle concern for ethics educators, defining ethics education as not only learning concerns but also as "learning how to identify, evaluate, and respond to ethical dilemmas" (p. 195). She introduced the "dual aspect theory" of moral development, one that included not only "individual attitudes toward ethical principles such as honesty, respect, trust, and fairness" but also the ability of students to be able "to reason through situations using one's principles and then acting on that reason" (p. 196). Canary described a model for measuring moral behavior that includes the following aspects:

- Sensitivity, to understand effect of one's actions on others;
- Motivation, to choose appropriate action out of many; and
- Character, to execute action. (p. 197)

Canary's model maps (broadly) to Dombrowski's design, use, and shape of technology (respectively). If Dombrowski's social aspect of ethical pedagogy is combined with Canary's proposed model of action and applied to learning analytics, the latter can assume a social aspect, especially with regards to equity of service. Specifically, considering the social aspect consists of understanding the effect of **design** on learning analytics (sensitivity); choosing appropriate **applications** of learning analytics for the predictive model, intervention strategies, and subsequent assessment of success (motivation); and properly implementing learning analytics with thorough **documentation** (character).

Returning to traditional rhetoric, I also consider Aristotle's characteristics of ethos as a form of action. Aristotle described ethics as virtue and as "providing and preserving good things; or… conferring many great benefits, and benefits of all kinds on all occasions" (1991, 1366a29-13). Previously, I connected Aristotle's persuasive element of ethos to the institution (as speaker) and as perceived by users of learning analytics. That is, the institution should gather accurate and complete student data (show goodwill), measure intervention strategies to student success (use practical wisdom and skills), and refine student records accurately and completely (virtue). For learning analytics then, if the institution fulfills these criteria, it could be considered to have exhibited ethical characteristics.

Further, as pathos is connected to a student's condition as invoked by an institutional action, attending to failures of pathos could also be considered an ethical action. For example, pathos can be repurposed as ethos if the institution (as the object of the student's condition) is empathetic towards the student and responds to any negative conditions that the student may have while engaging in the learning analytics process (showing good will). As well, an institution can repurpose logos (as predictive model) if it attends to the accuracy and completeness of the data record as well as implements learning analytics with transparency and equity (using practical skills and wisdom). This action would provide another opportunity for an institution to increase ethos. However, achieving Aristotle's concept of virtue would most likely not be feasible, as an institution clearly benefits from implementing learning analytics and, while it can be transparent in its endeavors, benefitting from increased retention and tuition is a fixed failure of ethos (ulterior motive).

Therefore, Aristotle's ethos can be consider ethical action for learning analytics when designers consider good will towards the student in the **design** of learning analytics (eunoia), when users implement practical skills in developing appropriate **applications** for learning analytics (phronesis/skills), and when the institution uses practical wisdom while **documenting** the design and application of learning analytics (phronesis/wisdom).

Ethical Literacy

In *Multiliteracies for a Digital Age*, Selber (2004) proposed an ethical, defined as useful and professionally responsible, approach to teaching computer literacy. He objected to contemporaneous practices in literacy programs of overemphasizing technology, failing to recognize design bias, ignoring the forces shaping technology development and use, and being too decontextualized. To address these concerns, Selber recommended teaching three categories of literacy (functional, critical, rhetorical), aligning each with an objective. Functional literacy is the use of technology with the goal of effective employment; critical literacy is the ability to understand technology with the goal of informed critique; and rhetorical literacy is the ability to produce artifacts using technology with the goal of reflective production. He described these categories as creating an "ideal multi-literate student" (p. 25). Selber's work on literacy can be applied to learning analytics by **designing** visualizations and dashboards with reflective production (rhetorical literacy), **applying** learning analytics processes effectively (functional literacy), and **documenting** the design and application of learning analytics with informed critique (critical literacy).

Having reviewed four different pedagogy frameworks for teaching ethics in rhetoric and scientific and technical communication, in the next section, I propose a combined ethical framework using all of the frameworks.

Proposed Ethical Framework to Guide Responses

The goal of a combined ethical framework is to provide an overarching guide for responding to ethical concerns in learning analytics. In Table 17, I summarize Ward's (2010) non-foundational questions regarding ethical behavior; Canary's (2007) teaching ethical actions; Aristotle's ethical characteristics of goodwill, practical skills, and practical wisdom (ethos); and Selber's (2004) ethical literacies (rhetorical, critical, and functional) as each applies to the design, application, and documentation of learning analytics.

Table 17. Combined Pedagogy Framework

Author Framework	Design	Application	Documentation
Ward's Ethical Questions (2010)	**Ethical Substance**: Why do I want to be ethical?	**Ethical Work**: What must I do to become ethical in this situation?	**Ethical Goal:** Do I agree with this?
Aristotle's Ethical Character	***Eunoia***: Good will toward audience	***Phronesis***: Practical skills	***Phronesis***: Practical wisdom
Canary's Ethical Actions *(2007)*	**Sensitivity**: Understand effect of one's actions on others	**Judgment**: Envision courses of action	**Character**: Able to execute an action
Selber's Ethical Literacy (2004)	**Rhetorical Literacy**: Produce with reflection	**Functional Literacy**: Use effectively	**Critical Literacy**: Understand with informed critique

In Stage 3, the ethical concerns most revealed during the **design** of learning analytics included a lack of context for interpreting data, the objectification of students, and the potential for discrimination towards students. These concerns all relate to the effect of learning analytics artifacts on the student; therefore, the design phase corresponds to Selber's rhetorical literacy because it requires creating artifacts using reflective production. Guidance would also be provided by Ward's non-foundational question "Why do I want to be ethical?" (ethical substance), the answers to which are provided by Aristotle's ethical characteristics (good will toward audience) and Canary's ethical action in the form of sensitivity (understanding the effect of one's actions on others).

Also in Stage 3, the ethical concerns most cited during the **application** of learning analytics included a lack of input from students to correct or question their data and the potential for an inaccurate or incomplete predictive model. Selber's functional literacy would apply in that it requires effective usage. Responses and strategies for the application of learning analytics would be guided by Ward's non-foundational question "What must I do to become ethical in this situation?" (ethical work). Answers to this question are provided by Aristotle's ethical characteristics (practical skills) and Canary's ethical action in the form of motivation (choosing an appropriate action out of many).

Finally, in Stage 3, the ethical concerns most cited during the **documentation** of learning analytics included implementation and regulation of learning analytics by institutions. Therefore, Selber's critical literacy would apply, as institutions and institutional users must implement learning analytics with informed critique. Responses and strategies for the documentation of learning analytics would be guided by Ward's non-foundational question, "Do I agree with this?" (ethical goal). Answers to this question are provided by Aristotle's ethical characteristics (practical wisdom) and Canary's ethical actions in the form of character (able to execute an action).

There was a fine line between the ethical frameworks assigned to application and documentation; therefore, I settled on distinguishing between users of learning analytics who are more focused on applying learning analytics (action, skills-based, and how-to) and institutions that need to engage in a broader and more critical perspective of how learning analytics will affect the entire institution, especially from a legal standpoint and regarding equity of service. Table 18 summarizes this combined pedagogical framework for the purpose of addressing ethical concerns, providing the questions, rationale, and literacy for developing ethical responses in the design, application, and documentation of learning analytics.

Table 18. Guide for Developing Responses to Ethical Concerns

Meta-category	**Question**	**Rationale**	**Literacy**
Design	Why do we want to develop ethical design in learning analytics?	To ensure that users understand the rhetorical aspects of visualizations in terms of unequal social power, lack of context to interpret data, and discriminatory aspects of learning analytics (requires goodwill and sensitivity).	Rhetorical
Application	What must we do to use learning analytics applications ethically?	Ensure that processes are in place to acknowledge student voice, to provide adequate services, and to conduct adequate training in order to implement learning analytics accurately with the motivation of increasing student success (requires practical skills and motivation).	Functional
Documentation	Do we agree with all aspects of design and application of learning analytics on campus?	Agreement involves developing sound policies and procedures for learning analytics processes, and establishing a mission, vision, and code of ethics to serve as an infrastructure for conducting learning analytics campus-wide and, thereby, allowing students to engage with transparency while protecting student privacy (requires practical wisdom and character)	Critical

An unexpected outcome of combining the pedagogical frameworks is the table above for guiding responses to ethical concerns in learning analytics. This guide provides another framework in addition to the matrix that can be used as a tool for teaching ethics in scientific and technical communication. It also can be used by the learning analytics community to guide future work in responding to ethical concerns in the design, application, and documentation of learning analytics.

In conclusion, I summarized and combined four existing frameworks in ethical pedagogy to serve as a guide for developing responses to ethical concerns of learning analytics that were identified in Stage 2 and deconstructed (and coded) in Stage 3. The combined framework describes ethical questions, ethical characteristics, ethical actions, and ethical literacies to consider while designing, applying, or documenting learning analytics. In Stage 5, I incorporate the components of the combined framework from Table 18 into the matrix design, and review the combined framework as a guideline for developing strategies and choices for responding to ethical concerns of learning analytics.

Stage 5. Building the Matrix

In this final stage, I explain the matrix design, build the matrix, and then populate it with strategies and choices for responding to ethical concerns using the combined framework from Table 18. With the exception of the responses (yet to be developed), all elements are available to design and build the matrix including ethical concerns, categories (meta-, process, and ethical), and ethical questions and rationales to serve as guides for developing ethical responses (questions, actions, and literacies).

Matrix Design

I incorporated multiple components into the design of the matrix (see Figure 23). First, I divided the matrix into the three over-arching themes of this study: design, application, and documentation, displayed as a header. For each of these three categories, a sub-header poses both the ethical question (bold) and the rationale for action (italicized). Finally, the matrix lists the type of literacy (left column), the process categories and ethical categories (right column), and the individual responses to ethical concerns in the center.

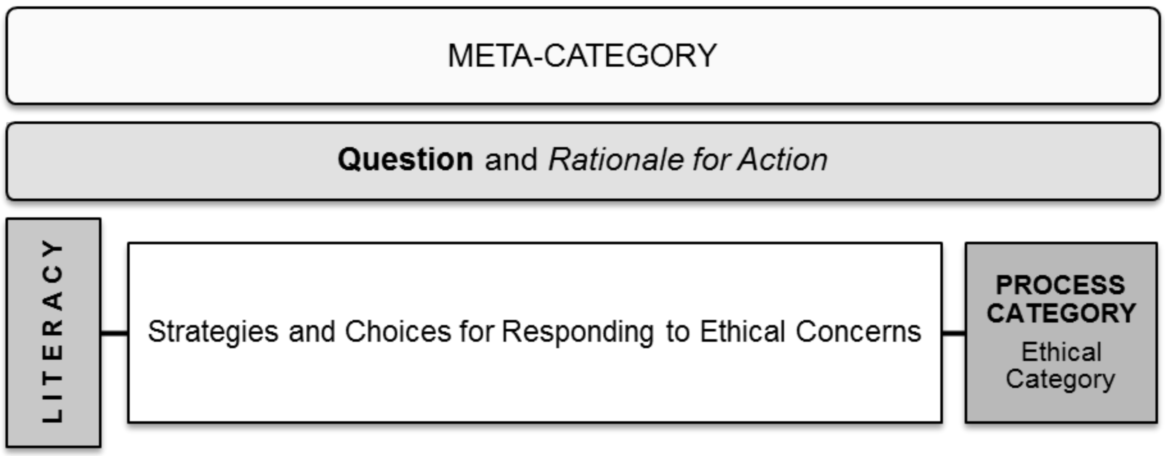

Figure 23. Matrix Format and Design

I chose this format with the intention of providing multiple viewpoints of strategies and choices for responding to ethical concerns in learning analytics. For example,

- Designers of learning analytics visualizations or dashboards can focus on design responses (meta-category);
- Legal counsel can assess ramifications of implementation by surveying the legality of service responses (ethical category);
- Tutoring centers can adopt best practices by reviewing all responses during the act stage (process category); or
- Diversity officers can advise all facets of learning analytics by addressing rhetorical and discriminatory aspects of learning analytics (individual ethical concerns).

Developing Responses

Using Table 18 as a reference, I created responses to the ethical concerns based on the context in which they were identified and then sorted the responses by the unique identifiers. Once the responses were sorted by the three meta-categories—design, application, and documentation—I was able to collapse duplicate responses having the same unique code within those meta-categories (although I indicated when I did so with the numeric digit at the end of the code). In the next section, I indicate the unique code for each concern—sorted by meta-category—and the associated response that I developed.

Design: Choices and Strategies for Learning Analytics

Responses and strategies for the **design** of learning analytics focus on financially investing in the adequate training of faculty and staff in order to raise awareness of the rhetorical and discriminatory aspects of learning analytics, and on elevating the students over their data rather than viewing them as data. An additional recommendation would be to employ a data designer to guide and train the institution to address the concerns as well as help provide context to minimize the above concerns. See Table 19.

Table 19. Design: Responses for the Final Matrix

Code	Response to Concern
De.A.Id	Employ data designer to guide the application of learning analytics with the goal of providing context to data, elevating students over data rather than viewing students as data; of raising awareness of the rhetorical aspects of learning analytics; and of the ethical concerns related to the discriminatory aspects of learning analytics (bias, labeling, profiling)
De.A.Id **De.A.Ip**	Invest financially to provide adequate training of faculty and staff to properly raise awareness of ethical concerns related to elevating students over data rather than viewing students as data
De.A.Id3	Invest financially to provide adequate training of faculty and staff to properly raise awareness of the rhetorical aspects of learning analytics
De.A.Ls2	Invest financially in adequate training of faculty and staff to properly raise awareness of the discriminatory aspects of learning analytics (bias, labeling, profiling)

Application: Choices and Strategies for Learning Analytics

Responses and strategies for the **application** of learning analytics focus on deep and broad intervention strategies and resources for ensuring student success, including acknowledging student contributions outside of academia, providing opportunities for student feedback, and recognizing the importance of measuring success. Application of learning analytics would also demand that institutions develop best practices for using learning analytics for all stakeholders. See Table 20.

Table 20. Application: Responses for Final Matrix

Code	Response to Concern
Ap.A.Id	Be transparent as to how at-risk categories are assigned to provide context to labels
Ap.A.Id	Use informed consent to obtain permission for data and be transparent with all instances of data manipulation
Ap.A.Ip	Create institutional best practices for using learning analytics and train faculty and staff on best practices
Ap.A.Ip	Provide a network of advisors, counselors, and other staff to support any non-academic issues that are preventing students from academic success
Ap.A.Ip	Provide intervention strategies in a variety of delivery methods including online, by phone, in the evening, weekends, or off campus so that students are not denied access
Ap.A.Ip	Use data intensive analytics (such as disposition and context analytics) and real-time data gathering to decentralize the process and allow institutions to focus intervention strategies on individual student needs
Ap.A.Ip3	Provide students with an opportunity to update their data records through direct feedback in order to provide context and/or explain why their label does not reflect their academic performance (give students a voice)
Ap.A.Ls	Merge at-risk intervention strategies with ongoing campus intervention strategies (tutoring, learning center, etc.) to prevent student from being singled out (identified as at-risk)
Ap.A.Ls	Provide data privacy training to faculty and staff and minimize access to private student data to “need to know” personnel
Ap.A.Sm	Be transparent as to how at-risk categories are assigned to provide context to labels
Ap.G.Sm2	Review initial student data record and data variables for accuracy
Ap.M.Sm	Invest financially in staffing and financial resources to adequately measure success and continually refine the student data record and predictive model data variables
Ap.P.Id	Employ data designer to guide the design of visualizations and dashboards with the goal of providing context to data, elevating students over data rather than viewing students as data; of raising awareness of the rhetorical aspects of learning analytics; and of the ethical concerns related to the discriminatory aspects of learning analytics (bias, labeling, profiling)
Ap.P.Ip	Provide students with an opportunity to update their data records through direct feedback in order to provide context and or explain why their label does not reflect their academic performance (give students a voice)
Ap.P.Ls	Acknowledge student contributions outside of academia such as personal, social, and other

Code	Response to Concern
	extra-curricular activities
Ap.P.Ls2	Provide an opt-in that includes a “release from harm” using transparent language to describe data capture, predictive modeling variables, and probability of inaccuracies
Ap.P.Sm	Change or increase data variables, or use real-time data for more accurate predictions
Ap.R.Sm	Invest financially in staffing and financial resources to adequately measure success and continually refine the student data record and predictive model data variables

Documentation: Choices and Strategies for Learning Analytics

Responses and strategies for the **documentation** of learning analytics focus on developing an infrastructure of policies and procedures that supports the implementation of learning analytics, including an opt-out option, a mission or vision statement specifically addressing learning analytics, and a code of ethics for using learning analytics. Documentation of learning analytics would hold institutions accountable for overarching goals, outcomes, and measurement of learning analytics, including legal obligations. See Table 21.

Table 21. Documentation: Responses for Final Matrix

Code	Response to Concern
Do.A.Ip	Be transparent in terms of who benefits from learning analytics
Do.A.Ip2	Provide an opt-in that includes a “release from harm” using transparent language to describe data capture, predictive modeling variables, and probability of inaccuracies
Do.A.Ls	Provide intervention strategies in a variety of delivery methods including online, by phone, in the evening, weekends, or off campus so that students are not denied access
Do.G.Ip	Develop and implement institutional mission, vision, and code of ethics for learning analytics and communicate campus-wide
Do.M.Ip	Invest financially in training of faculty and staff to ensure both expertise and time is allocated to properly implement all stages of learning analytics
Do.R.Ip	Develop principles and polices for implementing learning analytics including transparency of benefit to institution and communicate campus wide

Having developed responses by meta-category and collapsed all duplicate concerns, I was able to populate the matrix. The culminating matrix is shown in Figure 24, which lists the strategies and choices for understanding the ethical concerns raised by the design, application, and documentation of learning analytics in post-secondary education.

Populating the Matrix

The below matrix, which facilitates understanding ethical concerns in the design, application, and documentation of learning analytics in post-secondary education, completes the five-stage methodology of this study.

DESIGN OF LEARNING ANALYTICS

Why do we want to develop ethical design in learning analytics?

To ensure that users understand the rhetorical aspects of visualizations in terms of unequal social power, lack of context to interpret data, and discriminatory aspects of learning analytics (requires goodwill and sensitivity).

RHETORICAL LITERACY

- Invest financially in adequate training of faculty and staff to properly raise awareness of the discriminatory aspects of learning analytics (bias, labeling, profiling) (2) — **ACT** Legality of Service
- Invest financially to provide adequate training of faculty and staff to properly raise awareness of the rhetorical aspects of learning analytics (3) — **ACT** Interpretation of Data
- Invest financially to provide adequate training of faculty and staff to properly raise awareness of ethical concerns related to elevating students over data rather than viewing students as data (1 Id, 1 Ip) — **ACT** Interpretation of Data/ Implementation of Process
- Employ a data designer to guide the design of learning analytics with the goal of providing context to data, elevating students over data rather than viewing students as data; of raising awareness of the rhetorical aspects of learning analytics; and of the ethical concerns related to the discriminatory aspects of learning analytics (bias, labeling, profiling) — **ACT** Interpretation of Data

APPLICATION OF LEARNING ANALYTICS

What must we do to use learning analytics applications ethically?

Ensure that processes are in place to acknowledge student voice, to provide adequate services, and to conduct adequate training in order to implement learning analytics accurately with the motivation of increasing student success (requires practical skills and motivation).

FUNCTIONAL LITERACY

- Review initial student data record and data variables for accuracy (2) — **GATHER** Statistical Methods
- Employ data designer to guide the design of visualizations and dashboards with the goal of providing context to data, elevating students over data rather than viewing students as data; of raising awareness of the rhetorical aspects of learning analytics; and of the ethical concerns related to the discriminatory aspects of learning analytics (bias, labeling, profiling) — **PREDICT** Interpretation of Data

Figure continues…

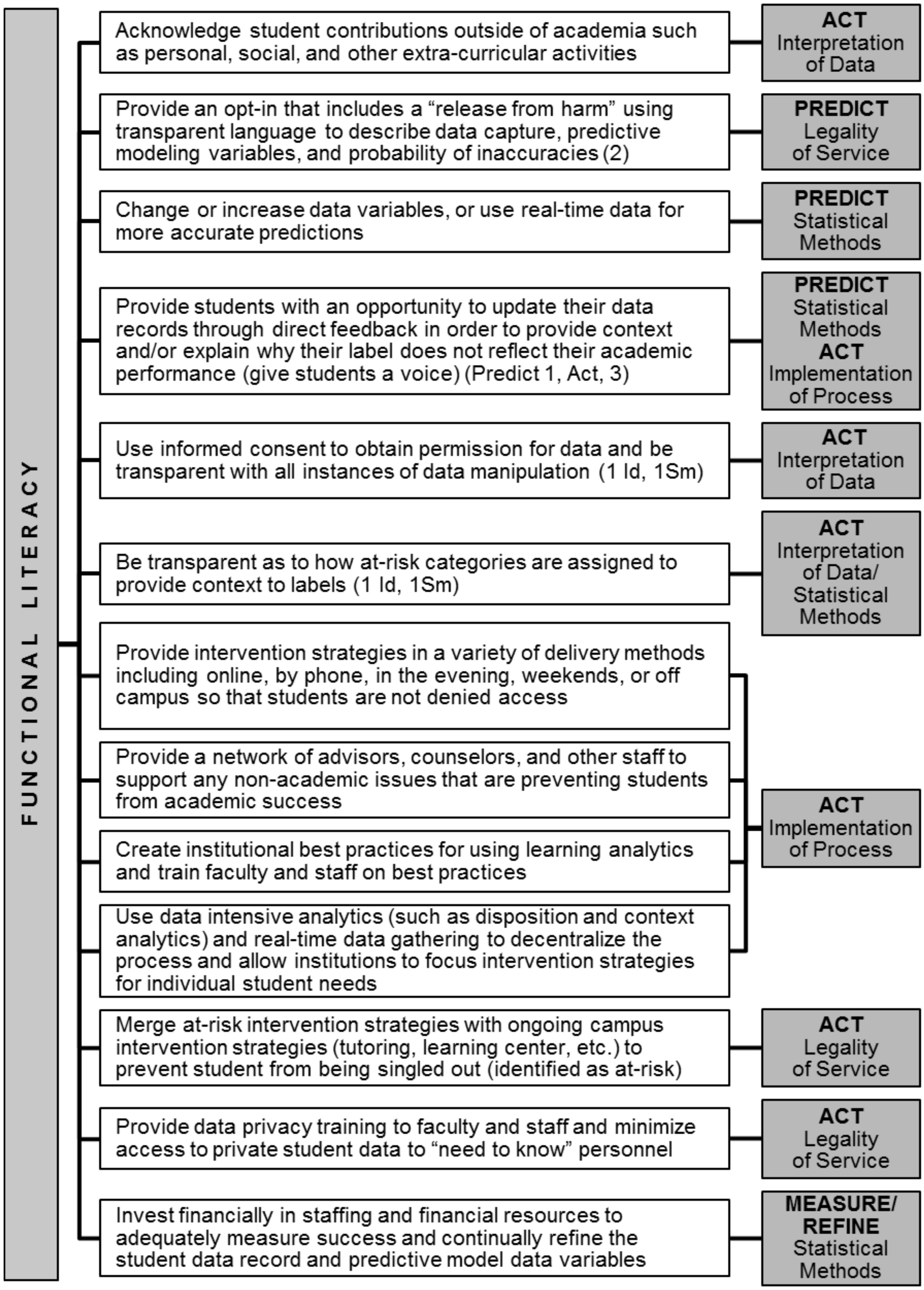

Figure continues…

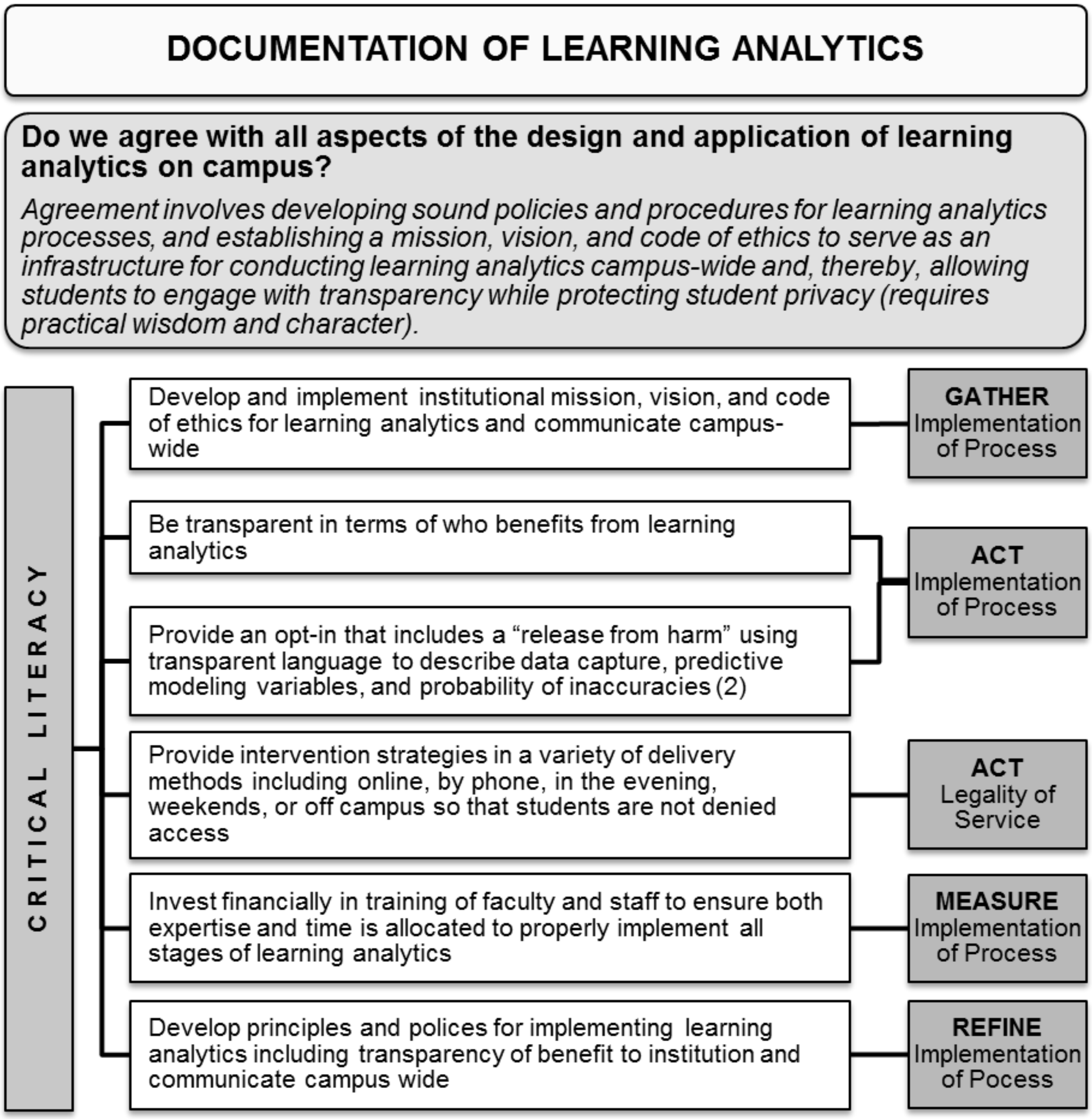

Figure 24. *Matrix for Understanding Ethical Concerns in the Design, Application, and Documentation and of Learning Analytics in Post-Secondary Education*

By reviewing Big Data as a precursor to analytics in academia, I provided a glimpse into the potential ethical concerns of learning analytics. Using genre theory to understand the nature of learning analytics tools, practices, and methodology of learning analytics (Stage 1), as well as conducting a comparative analysis using frameworks from rhetoric and scientific and technical communication in persuasion, human-computer interaction, social power, semiotics, visual design, and new media literacy, I identified and categorized ethical concerns using three classification systems (meta-, process, and ethical) (Stage 2). Using the categories to deconstruct ethical concerns using framework methodology (tree diagrams and relational visuals), I revealed where ethical concerns occurred in the leaning analytics process and examined the relationships between and the concentration of ethical concerns in each category (Stage 3). During Stage 3, I also developed a coding system to help organize the concerns. I then reviewed pedagogical frameworks that focus on teaching students in rhetoric and scientific and technical communication how to respond to ethical dilemmas, creating a guiding framework for developing responses for each ethical concern (Stage 4). Finally, with the ethical concerns identified and coded and a framework developed to guide ethical responses, I designed and built a matrix for understanding ethical concerns in the design, application, and documentation of learning analytics in post-secondary education (Stage 5).

The goal for providing a matrix of strategies and choices for understanding ethical concerns in learning analytics was two-fold. First, the matrix will allow the learning analytics community to help educational institutions view learning analytics research and practice using an ethical lens and to guide them towards using new learning analytics tools with an ethical viewpoint. Second, for rhetoric and scientific and technical communication researchers and practitioners specifically, such a matrix will be useful as a means of continuing long-standing efforts of analyzing the ethical concerns raised by both the tools (scientific and technical communication) and the effects of artifacts (rhetorical theory) within a genre. Both of these objectives will inform future scholarship and practice in deploying learning analytics across education.

CHAPTER 5. DISCUSSION

In this final chapter, I use the matrix to provide global recommendations for addressing ethical concerns in the design and documentation of learning analytics, and targeted recommendations for using the matrix in the application of all five categories of learning analytics: social network, discourse, content, disposition, and context. I follow these recommendations with a discussion of potential future research and study limitations.

Applying the Matrix

In general, the strategies and responses in the design and documentation of learning analytics should constitute a minimum level of ethical action. This minimal implementation would ensure that students are shown goodwill by the institution and users (design) and that those institutions are properly implementing learning analytics in terms of transparency and equality of benefit to students (documentation).

For design, the guiding question becomes, **Why do we want to develop ethical design in learning analytics?** The overall goal of ethical design should be to understand the rhetorical effects of learning analytics visualizations. This goal would include investing financially in the adequate training of faculty and staff in order to raise awareness of the rhetorical and discriminatory aspects of learning analytics and elevating students over their data rather than viewing them as data. An additional recommendation would be to employ a data designer to guide and train institutions to address the above concerns as well as to help provide context to the data in order to minimize the concerns.

For documentation, the guiding question becomes, **Do we agree with all aspects of the design and application of learning analytics on campus?** The overall goal of ethical documentation should be to envision ethical actions, including establishing policies and procedures; communicating a mission, vision, and code of ethics; providing adequate funds for both equipment and staff training; and giving student options for engaging in success.

Addressing the strategies and responses in the application of learning analytics would be more complex for each situation and type of learning analytics used, but should always consider student engagement and success as the priority. Examples of addressing ethical concerns in the application of all five types of learning analytics follows.

Social network analytics uses data harvested from social platforms to investigate the relationships between networked individuals and the concentration of those relationships. This type of analytics identifies students who are disconnected from other students in the classroom or those who are at the center of receiving and delivering information. Most likely, an application would involve faculty or students creating social network visualizations for a course and, by doing so, having access to personal data harvested from students' social network accounts. Focusing on the application of social network analytics, ethical responses and strategies could include providing students with opportunities to provide context for the relationships and the concentration of those relationships as portrayed through their social network accounts. That is, faculty members and students must acknowledge that social network relationships are not an indication of relationship strength outside of that medium.

Discourse analytics gathers data from student discussion boards to view the quality of dialogue as well as to map the knowledge constructed through student language and interactions. Discourse analytics follows the same model as social network analytics, but differs in that analysis occurs within the course management system and within each course discussion board rather than externally, through social networked data. Instructors are usually the creators of visualizations for discourse analytics. Focusing on the concerns raised by discourse analytics, ethical responses and strategies could include creating and implementing institutional best practices for using discourse analytics as well as training faculty interested in using it.

Content analytics uses data harvested from user-generated hashtags (within social networks) to catalogue resources as identified by each student. Content analytics tracks student progress by documenting if (and how) they construct knowledge. Again, instructors would be the most likely to use content analytics. Focusing on the concerns of content analytics, ethical responses and strategies could include full transparency with respect to how at-risk labels are assigned to provide context to students.

Disposition analytics uses a self-reporting tool to gather personal behavioral information. Results of these inventories are used to suggest intervention strategies that better fit a student’s personality or behaviors. Collection of this data would most likely occur at the institutional level. Focusing on concerns of disposition analytics, ethical responses and strategies could include providing data privacy training for faculty and staff to ensure that personal student data are kept private.

Context analytics uses sophisticated models of learning analytics and gathers data such as biological feedback, daily activities (both type and location), and environmental data through mobile computing apps. For context analytics, students may or may not be required to share personal self-quantifying data. Focusing on concerns of context analytics, ethical responses and strategies could include providing a network of advisors, counselors, and other staff to support any non-academic issues that are preventing students from academic success.

These examples, although brief, provide a glimpse into the possibilities of using the proposed matrix for the design, application, and documentation of learning analytics in post-secondary education.

Current and Future Research

Since the completion of this study, the fifth International Conference on Learning Analytics and Knowledge occurred in March of 2015 at Marist College in Poughkeepsie, New York (LAK15, 2015a). A review of the LAK15 abstracts revealed only one abstract related to ethics: "Ethical and privacy issues in the application of learning analytics," authored by Hendrik Drachsler, Adam Cooper, Tore Hoel, Rebecca Ferguson, Alan Berg, Maren Scheffel, Gabor Kismihók, Jocelyn Manderveld, and Weigin Chen (2015). In a workshop session, these authors led a conversation focused on "ethical and privacy concerns regarding potential harm to individuals," with the "aim to understand the issues with greater clarity, and to find ways of overcoming the issues and research challenges related to ethical and privacy aspects of learning analytics practice."

In January of 2015, Niall Sclater conducted a thorough examination of ethical concerns. In his guide, “Effective learning analytics: Using data and analytics to support students,” Sclater categorized and examined eight separate areas related to ethical and legal issues within learning analytics: responsibility, transparency and consent, privacy, validity, access, enabling positive interventions, minimizing adverse impacts, and stewardship of data. Within these eight areas, Sclater identified 86 separate issues and posed a question for each, presumably for institutions to consider when implementing learning analytics.

These two examples complement and reinforce this study’s findings with respect to the **application** and **documentation** of learning analytics, but still lacked a focus on ethical concerns that arise with respect to the **design** of learning analytics. This omission validates using rhetorical and scientific and technical communication perspectives, as these frameworks clearly uncovered ethical concerns in the design of learning analytics visualizations that are less intuitive.

Future research could start with **globally** validating the matrix by expanding the choice of frameworks for identifying ethical concerns. My focus included frameworks from rhetoric and scientific and technical communication; however, the variety of disciplines engaged in learning analytics work could introduce ethical perspectives not covered here. Specifically, the fields of statistics, behavioral science, cognitive psychology, education, and computer science could have much to offer. The strategies and choices that I chose for responding to ethical concerns could also be validated, as could re-visiting the initial categories (meta-, process, and ethical) that I chose for deconstructing ethical concerns, or even proposing a new classification system.

Additional research could examine the matrix in depth to review how to implement the responses and strategies. For example, with respect to the **design** of learning analytics, strategies would include identifying specific attributes of the student dashboard or visualizations that may be discriminatory. That is, instead of concluding that color or font could be an ethical concern, a future study could identify which colors or fonts raise an ethical concern and why. Other questions could include identifying the best options for elevating students over data to reduce objectification and for presenting visual artifacts in context in order to clarify the process and outcomes for students.

With respect to the **application** of learning analytics, future studies could focus on deriving best practices for intervention strategies to ensure student success or developing a process to solicit student feedback (giving students a voice). Student and institutional user training, including privacy training, would be key for the application of learning analytics. In addition, a shared predictive model among institutions would help the overall leaning analytics community establish a baseline of effective data sets, which they could then easily modify for individual campuses.

Future studies focusing on the **documentation** of learning analytics could include examples of a code of ethics (potentially shared), a mission and vision statement, and policies and procedures for institutions (including an opt-out option). I consider these documents crucial to successfully implementing learning analytics, and facilitating the creation of well-thought out documentation can only benefit the learning analytics community as a whole.

Additionally, I focused on learning analytics at the post-secondary level and therefore on adults who can advocate for their education and who are responsible for their own success. While learning analytics is occurring in K-12, the set of practices and concerns related to using learning analytics at this educational level are different from those discussed in this study and include, for example, attention to parental consent and advocacy and engagement with parents on intervention strategies. The consideration of K-12 brings a complexity to ethical concerns in learning analytics that falls outside the scope of this study, but that has potential for future research.

Finally, future research could prepare the community for new technology in learning analytics. Daniel Burrus (2014) describes *The Internet of Things* as including physical objects—such as clothing, smart homes, health monitors, transportation (vehicles and roads)—that are embedded with sensors that send and receive data. These technologies could raise context analytics' use of personal and behavioral data to a new level and, with that, increase concerns over safety and privacy as well. The Federal Trade Commission (FTC) estimates that the number of networked objects will reach 20 billion in the next five years (FTC, 2013).

In terms of future pedagogy, there is no doubt that rhetoric and scientific and technical communicators need to include ethical data design to their growing list of essential knowledge and tools. Teaching students how to respond to ethical dilemmas in information design is the work of practitioners in rhetoric and scientific and technical communication. Therefore, the matrix can serve as a pedagogical tool for ethical design, application, and documentation of learning analytics within both rhetoric and scientific and technical communication as well as within the learning analytics community as others look to them for guidance.

Study Limitations

The most critical limitation of this study is the choice of frameworks used to analyze ethical concerns. I focused on literature that would guide the development of a matrix for understanding ethical concerns, focusing on the design, application, and documentation of learning analytics. The frameworks selected were well-established in the literature and, often, seminal works by well-known researchers and practitioners within the disciplines of rhetoric and scientific and technical communication. However, despite the careful selection of frameworks, the ethical concerns identified were limited in type and amount by the chosen frameworks. For example, the statistical category could be much better developed if specific types of statistical errors were considered (I only considered accuracy or completeness of data).

A second limitation to this study lies in the categories used to deconstruct the ethical concerns. The process (gather, predict, act, measure, refine) and meta-categories (design, application, documentation) may be the most intuitive. However, the ethical categories (implementation of process, interpretation of data, legality of service, statistical methods), while not completely arbitrary as they were based on global concerns identified in the review of Big Data, were limiting. An example of a different set of ethical categories would be Sclater's recent work, which examined 8 areas of concern and 86 separate issues.

A third limitation to this study may pertain to the development of responses and strategies for the ethical concerns. The pedagogical frameworks I used included both foundational approaches to ethical actions and non-foundational questions regarding ethical behavior. However, even within these frameworks, other researchers may interpret a response or strategy differently than I, identify new responses and strategies to the ethical concerns, or even choose different frameworks to guide the development of responses and strategies. Ultimately, the responses and strategies relied on my interpretation of approaches that would address the ethical concerns in the design, documentation, and application of learning analytics.

Finally, Dr. Donald Ross (personal communication, July 18, 2015), Graduate Advisor in the Department of Writing Studies at the University of Minnesota, pointed out that raising awareness of the discriminatory aspects of learning analytics is not enough. I agree. All responses should serve as a platform to begin identifying, discussing, and addressing discrimination embedded in the design, application, and documentation of learning analytics. After conducting this study and observing the extent of discrimination that is possible—especially in the design of learning analytics—I would add one more recommendation: a mandatory next step for institutions should be to consult diversity experts.

Conclusion

Learning analytics is a young, rapidly evolving discipline, as evidenced by its progress from the more static academic analytics to the more dynamic and diversified learning analytics. The ethical concerns of learning analytics have not been thoroughly discussed within the discipline nor has there been an extensive study that reviews the ethical concerns of learning analytics from the perspective of rhetoric and scientific and technical communication.

When I attended the second Learning Analytics and Knowledge Conference in 2012, I found there to be a lack of discussion about ethics—people spoke about quantifying students, quantifying their behavior, their relationships, their daily activities… without questioning the practice. There was also a lack of transparency in data use—students often did not know the quantification was occurring. Finally, I found a lack of consistency in data modeling—researchers and practitioners were not necessarily sharing their data elements or predictive models, in part, because successful predictive models have monetary value and would be considered proprietary. For me, these factors culminated in an absence of language for identifying, speaking to, and understanding ethical concerns in learning analytics. Which brought me to my research question: **How can we use rhetorical, scientific, and technical communication perspectives to understand ethical concerns in the design, application, and documentation of learning analytics in post-secondary education**?

I believe that I have answered this question for three reasons. First, the matrix validates the use of rhetoric and scientific and technical communication perspectives as a means to understand ethical concerns in the design, application, and documentation of learning analytics. The frameworks I chose were indeed helpful, as I identified ethical concerns and as I developed responses to those concerns. Second, the matrix will serve rhetoric and scientific and technical communication as a potential pedagogical tool for the ethical design, application, and documentation of learning analytics. Preparing students to respond to ethical dilemmas is one focus of rhetoric and scientific and technical communication practitioners and one of their strengths. Finally, there is no doubt that rhetoric and scientific and technical communication should continue their work in ethical data design. As such, the matrix provides an additional option for rhetoric and scientific and technical communication to guide multiple disciplines when conducting learning analytics through an ethical lens.

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