# Implementing Data Analytics as an Organizational Innovation in Colleges and Universities

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# ABSTRACT

This study explores the question, How are individual adoption and organizational implementation of innovations in higher education related to the context of the organization, the characteristics of the innovation, and the attitudes of adopters? The study uses data collected from a survey of deans and department chairs from U.S. higher education institutions to examine the implementation of data analytics, or the extensive use of data, statistical analysis, data mining and modeling to drive organizational decisions, as an example of an organizational innovation. The findings indicate that individual adoption is associated with the adopter's perception of the usefulness of data analytics in practice and its legitimacy in solving organizational challenges. The usefulness of data analytics is related to the innovation characteristics of usability and functionality, which are in turn related to an organizational context that includes institutional and professional support for adoption, academic leaders engaged in implementation, data and information integrated into existing operations, and an organizational culture that is data-driven. Legitimacy is related to the functionality of data analytics and the existence of a data-driven culture but also the discipline of the adopter and institution type. The findings also indicate that organizational implementation of data analytics is associated with the alignment of data analytics to its organizational culture, the pressure exerted by the external environment, and the organization's dissatisfaction with current external methods or practices in use.

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# CHAPTER ONE

# INTRODUCTION

Data analytics has received significant attention over the last few years for its potential to enhance the productivity and success of higher education organizations. Data analytics is the extensive use of data, statistical analysis, and modeling to drive organizational decisions and actions (Davenport & Harris, 2007). Proponents contend that it has the potential to answer the increasing calls for accountability from those outside of the academy, improve student learning and success, reduce costs, improve effectiveness, and promote the innovation of individual institutions and the higher education industry (Grajek, 2011; Petersen, 2012; Rampell, 2008). Some have even called analytics the killer app or the universal decoder for education reform (Baer, 2011).

Within higher education, information technology professionals have taken the lead in developing analytic capabilities at their institutions and have written on its implementation and future possibilities. EDUCAUSE, an organization for information technology professionals in higher education, named data analytics one of its top three strategic initiatives (www.educause.edu). The *2012 Horizon Report*, a joint publication of EDCAUSE and the New Media Consortium, has identified "learning analytics" as one of the six technologies to watch, with a "time-to-adoption" horizon of the next two years (Johnson & Cummins, 2012).

Articles on analytics have been appearing with increasing regularity in higher education publications (Kolowich, 2012; Watters, 2011) but are largely limited to essays about the importance and opportunity of data analytics (Campbell, et al., 2007; Norris, et al., 2008; Oblinger, 2012) and self-reported case studies of applications of data analytics at a single institution (Cepull et al., 2012; Hrabowski et al., 2011; Wishon & Rome, 2012).

Within the current discussion, critics warn that data analytics is merely a bureaucratic intrusion upon institutional autonomy (Bollier, 2010; Petersen, 2012). They argue that data analysis is not new and that colleges and universities have been engaged in the collecting and reporting of data for years (Oblinger, 2012). Proponents counter that data analytics is different from data analysis and requires a shift of focus from applying analytical methods to solve individual problems to a broader view of developing analytical solutions characterized by the integrated use of data, processes, and systems (Liberatore & Luo, 2011). Freeman Hrabowski, president of University of Maryland, Baltimore County, states that in order to “address societal imperatives, higher education must begin by transforming its own culture, which is reflected in the questions we ask (and those we don’t), the achievements we measure and highlight (and those we ignore), and the initiatives we support (or don’t support)” (Hrabowski, et al., 2011, p16), and he sees data analytics as central to the transformation. It may be that data analytics represents a progression of the use of data in the management of higher education organizations – moving from the cataloging and reporting of historical data as institutional research to more dynamic and predictive modeling techniques that inform real-time decision making.

The interest in data analytics is well founded. Though data on the impact of analytics on higher education organizations are not available, a study of large corporations in the U.S. found that high-performing businesses are five times more likely to use analytics strategically than low-performing businesses (Davenport & Harris, 2007).

A recent study by McKinsey Global Institute found that U.S. health care could derive more than $300 billion in value every year from data analytics, two-thirds of which would be in the form of reducing national health care expenditures by about eight percent. They also estimate that in the developed economies of Europe, government administration could save more than $149 billion in operational efficiency improvements (Manyika, et al., 2011). Yet with all the interest in data analytics, it is not clear that all organizations have an existing practice of data-driven decision-making. One study found that 40 percent of major decisions in U.S. businesses are based not on facts but on a manager's instinct (Davenport & Harris, 2007). According to a survey by *Inside Higher Education*, only 36 percent of presidents, 31 percent of provosts, and 39 percent of financial officers said that their institutions were "very effective" at using data to aid and inform campus decision-making (Green, 2012).

Within higher education, there is little agreement on what data analytics is, and it appears that limited progress has been made in implementation. In 2005 and again in 2012, the EDUCAUSE Center for Applied Research (ECAR) surveyed chief information officers at institutions of higher education across the U.S. in an attempt to understand the state of the industry, highlight institutions that have made progress on analytics, and provide an overview of the opportunities for and challenges of implementing a data analytics program (Bichsel, 2012; Goldstein & Katz, 2005). The results indicate that, over the seven years between surveys, some movement has been made on expanding technology infrastructure to support data analytics and there has been a small increase in the percentage of institutions engaged in analytics efforts. At the same time, data analytics remains largely limited to the functional areas of admissions and enrollment management, business and finance, and student progression, with little movement into the core academic functions of student learning, faculty productivity, cost to degree, and research administration. Even as the data analytics literature outside of higher education calls for the engagement of the business owner and sponsorship separate from the information technology (IT) area as critical to success (Davenport & Harris, 2010; Redman, 2008), nationally in higher education, the IT function is still leading analytics efforts, and the attitudes of information technology leaders are still primarily informing the conversation about future development. In addition, academic leaders lag behind others in their organizations in use. In the 2005 EDUCAUSE survey, respondents reported that the least active analytics users were department chairs and their staffs (8 percent), deans and their staffs (15 percent), central research administration (3 percent), and central human resources (10 percent). The most active users were central business/finance (67 percent), admissions/ enrollment management (63 percent), and institutional research (57 percent) (Goldstein & Katz, 2005).

The results of the 2005 EDUCAUSE study are consistent with findings from the McKinsey Global Institute that looked at the potential for data analytics and big data to have positive impacts on productivity, competition, and innovation across different industries (Manyika, et al., 2011). They found that, while all sectors will have to overcome barriers to capture value from the use of big data, barriers are structurally higher for the public sector, including education, in part because of a lack of a data-driven mind-set and available data (Manyika, et al., 2011).

An important question then is, Why is the educational sector struggling to capitalize on data analytics and what could be done to improve the success and scope of data analytics in the future? EDUCAUSE identified a lack of investment and not enough analysts to do the work as the primary challenges to implementing data analytics (Bichsel, 2012). The McKinsey Group found that the educational sector is in the bottom quintile in IT investment, and all industries struggle to attract top analytical talent. They specifically called out the lack of data on critical operational processes and a lack of data-driven decision-making as being the substantial barriers to be overcome (Manyika, et al., 2011). The 2012 EDUCAUSE study agrees that an institutional culture in which administrators, faculty, and staff have a fear or mistrust of data, measurement and change can be a barrier to a successful analytics program (Bichsel, 2012).

A review of research on colleges and universities as organizations indicates that there may be more complex organizational, cultural, and political reasons for the lack of use of academic analytics in higher education, and until these issues are addressed in the approach, design, and functioning of data analytics systems, the promise of data analytics may be beyond what it can actually deliver. As individuals with substantial understanding of educational processes and operational decisions within higher education organizations, academic leaders (deans and department chairs) have been surprisingly silent on the role of data analytics in higher education organizations, including the questions we ask, the achievements we measure and highlight, and the initiatives we support. This study engages academic leaders, who are at the center of academic and student-learning processes, to understand their attitudes toward data analytics and to understand if and how their engagement in data analytics improves development, use, and implementation success.

## Background

The adoption and expansion of data analytics at colleges and universities can be viewed through the lens of theories on innovation diffusion. Colleges and universities face complex challenges to implementing and sustaining innovations because of their approach to organizing their work, resulting in failure more often than success (Bidwell, 2001; Zemsky, 2009).

An organization's framing of opportunities and challenges and the identification of a possible solutions or innovations is influenced by the structures, people, power, and culture of an organization (Bolman & Deal, 2008). A number of variables influence the process by which innovations are implemented successfully, including the characteristics of the organization and its professional staff, the nature of the innovation, and the external environment in which the innovation and organization exist. Significant research has occurred in the area of innovation, including the identification of variables that influence organizational innovativeness and innovation diffusion and descriptions of the process that appears to impact successful implementation. The development of an innovation-implementation model that speaks directly to the process within higher education organizations has the potential to inform the approach to implementing data analytics within colleges and universities.

## Statement of the Problem and Research Question

Many within and outside of higher education feel increasing pressure to engage more purposefully and deeply in data analytics (Bollinger, 2010; Lohr, 2012). Managers at large U.S. companies anticipate investing in data analytics extensively (Davenport &

Harris, 2007). Similarly, 86 percent of respondents in the 2012 EDUCAUSE survey believe data analytics will be more important for higher education's success in the future (Bischel, 2012). Interest and investments in implementing a data analytics program alone will not automatically lead to success. Leadership appears to be a key factor in data analytics deployment. Strong leaders committed to evidence-based decision-making is necessary to achieve a high level of data analytics implementation (Bischel, 2012; Davenport & Harris, 2010). A data-oriented culture that includes groups of people who share a belief that data and information play a critical role in organizational success is also important (Stiles, 2012). In fact, Stiles (2012) posits that imposing analytics on an organization that is not data oriented can result in ineffectual implementation or can lead to fundamentally misinformed, inaccurate decisions.

Academic leaders have an important role to play in understanding the academic processes that have the greatest potential to benefit from analytical applications. Recently both the American Council of Colleges and Universities (ACCU) and the Council of Graduate Schools (CGS) urged colleges and universities to engage in more robust data-driven assessment practices to improve student learning and success outcomes, but they also have identified "academic departments and faculty in particular as the key agents for how an institution changes its approach to implementing and evaluating intervention efforts to improve student success" (Hrabowski, et al, 2011, p18).

If higher education organizations are to navigate successfully the implementation of a data analytics initiative, especially one that touches the academic core, organizational leaders will need to develop a more data-driven culture and cultivate leaders with analytical skills. Engagement of academic leaders in the process is critical, because they have a detailed understanding of the academic processes and decision points that would benefit from data analytics. Yet, to date, discussions and research have been led primarily by information technology (IT) and institutional research (IR) staff. IT and IR have a critical role to play in institutional transformation through data analytics. IT has the technical capacity to align IT resources and IR has experience in defining, managing and reporting institutional data to internal and external stakeholders. Both are necessary to support both strategic initiatives and a culture of evidence-based decision-making and management. Unless the process, questions, and analysis engage academic leaders, the integration and impact of data analytics into the academic functions of colleges and universities will be limited. Research on the attitudes, engagement, and usage patterns of academic leaders at institutions who are currently engaged in data analytics will be an important step in developing an understanding of the unique challenges to data analytics implementation at colleges and universities and in designing a robust approach to implementation that fits the academic culture.

The purpose of this study is to investigate factors associated with the successful implementation of organizational innovations in U.S. colleges and universities. The research question that drives this analysis is, How are individual adoption and organizational implementation of innovations in higher education related to the context of the organization, characteristics of the innovation, and attitudes of adopters? This question is examined in relation to adoption and implementation of data analytics programs in U.S. higher education.

Based on the results of the study, recommendations will be made for how administrators, academic leaders and other educational change agents can improve the likelihood of success of the implementation of organizational innovations within their own context. In addition, specific recommendations for implementing data analytics systems will be made.

## Overview of the Method Used

This study uses a quantitative, cross-sectional research methodology. Data were collected through a survey of deans and department chairs from 255 U.S. higher education institutions that participated in the EDUCASE 2012 analytics survey or were identified as best-practice institutions through previous research on data analytics (Goldstein & Katz, 2005; Norris & Baer, 2012). Respondents provided information on the type and extent of data analytics activity at their institution, the features of their implementation process, and their attitude toward and personal use of data analytics. Analytical scales that measure the presence of the organizational context characteristics of collaboration, authenticity, institutional support, training and integrated use, the innovation characteristics of functionality and usability, and the adopter attitudes of usefulness and legitimacy were constructed from survey responses. Using questions derived from the DELTA framework (Davenport & Harris, 2010), the maturity level of data analytics at each institution was determined. Statistical analysis was completed to determine if the variables related to organizational context, innovation characteristics, and adopter attitudes have a significant impact on the extent of individual adoption and successful organizational implementation of a data analytics program at their institution.

# CHAPTER TWO
# REVIEW OF THE LITERATURE

In its most basic form, data analytics is the “extensive use of data, statistical and quantitative analysis, explanatory and predictive models, and fact-based management to drive decisions and actions” (Davenport & Harris, 2007, p7). Data analytics involves the integration, extraction, and transformation of data into actionable information so that specific decision points are identified. “Action” is an important element of the definition. Data analytics is more than analysis. It is a form of communication in which the analysis is transformed into a recommended action to guide decision-making. Within the field of data analytics, it is not enough to simply produce data and reports. The output of the work must transform multiple, disparate, and disconnected streams of organizational data into information upon which organizational leaders can build and implement strategies and substantially improve performance. As an organization moves from producing standard reports that document historical performance to conducting statistical analysis and predictive modeling around key organizational processes to explain what is occurring, why it is occurring, and what will happen next, organizations achieve increasing competitive advantage (Davenport & Harris, 2007). Once it begins to use data and information to inform strategy and predict future performance, an organization is moving into the realm of data analytics.

An important component of data analytics is a focus on process. Data analytics has the greatest potential when it is developed and embedded in normalized business processes (Petersen, 2012). A well-developed analytics program translates data into analysis, analysis into insight, and insight into managerial actions, such as improving operational decisions, redesigning or changing existing processes, formulating or adjusting strategies, or improving decision quality and speed (Liberatore & Luo, 2011).

Four key variables appear to be driving the current data analytics movement: the availability of increasing amounts of data and declining storage costs, improved and less expensive analytical software, the adoption of a process orientation by organizations to improve performance by focusing on value-added activities through process redesign, and the presence of more technically literate managers and executives (Liberatore & Luo, 2011). Critical to the new data analytics approach is the creation of analytics teams within the organization that include people with backgrounds in statistics and data analysis, process re-engineering and computer science, and professionals with industry knowledge (Liberatore & Luo, 2011).

## State of Data Analytics within Higher Education

Within higher education, terminology and definitions to describe analytics vary widely. Within EDUCAUSE, the working definition of data analytics is "the use of data, statistical analysis, and explanatory and predictive models to gain insights and act on complex issues" (www.educause.edu), or as "shorthand for the method of warehousing, organizing and interpreting massive amounts of data accrued by online learning platforms and student information systems in hopes of learning more about what makes students successful and by giving instructors (and the platforms themselves) the chance to adjust to improve learning outcomes" (Kolowich, 2010).

In 2005, EDUCAUSE coined the term "academic analytics," defined as "combining large data sets, statistical techniques and predictive modeling to produce actionable intelligence," in part to move the concept away from its original home in business operations and make it more palatable in the higher education industry (Campbell, et al., 2007). Other terms currently in use are "learning analytics," which refers to the interpretation of a wide range of data produced by and gathered on behalf of students in order to assess academic progress, predict future performance, and spot potential issues (Johnson & Cummins, 2012). Johnson and Cummins (2012) observe that learning analytics is limited in its implementation to a few institutions and is linked mostly to data generated from learning management systems and online interactions. Even though they indicate that implementation of learning analytics is on the mid-term horizon (next 2-3 years), the *Horizon Report* authors admit that broad adoption of a full-featured set of learning analytics tools is still some time away (Johnson & Cummins, 2012). An additional term is "action analytics," defined as "a process of data assessment and analysis that enables us to measure, improve, and compare the performance of individuals, programs, departments, institutions or enterprises, groups or organizations and/or entire industries" (Norris & Baer, 2012).

Across industries, most organizations begin their data analytics to build their customer base and enhance customer relationships by segmenting customers and understanding their behaviors, including identifying those at greatest risk of attrition so they can design interventions to keep them. Additional areas of focus are strategic business processes, human resource management, and finance (Davenport & Harris, 2010). Within higher education institutions, enrollment management, finance and budgeting, and student progress are the primary functional areas in which data analytics are employed. In 2012 between 55-65 percent of institutions reported engaging in data activity at the level defined as analytics in these areas (Bischel, 2012). In comparison, less than 20 percent of institutions reported data analytics activity in the functional areas of instructional management, central IT, student learning, strategic planning, alumni and advancement, research administration, library, cost to complete a degree, human resources, facilities, faculty promotion and tenure, faculty teaching performance, procurement, and faculty research performance (Bischel, 2012).

In contrast to the actual level of use, CIOs at higher education institutions consistently saw the benefit of analytics across all functional areas, with greater than 60 percent of respondents believing that analytics will help institutions understand student behavior, optimize use of resources, recruit students, and help students learn more effectively and graduate. Between 40 and 60 percent of respondents believe data analytics will create data transparency, demonstrate effectiveness and efficiency, improve administrative services, and contain or lower costs of education. Nearly 40 percent of respondents believe data analytics will improve faculty performance and reduce administrative costs (Bischel, 2012).

One area of progress is in the technology that is used for data storage and reporting. In 2005, approximately 30 percent of institutions had data warehouses (Goldstein & Katz, 2005). Seven years later, 62 percent of institutions reported using data warehousing and business intelligence systems as a way of integrating, organizing, and summarizing large data sets. What remains elusive is the use of these warehouses and tools to provide analysis and insight into strategic organizational decisions beyond enrollment management and finance. Closing the gap between the increase in technology and tools to manage and report data and the lack of expansion of use of data analytics by decision makers may require more extensive sponsorship for the deployment of data analytics outside of the information technology unit (Davenport & Harris, 2010) and expansive collaboration with academic leaders in order to develop a culture of evidence and inquiry throughout the institution (Bischel, 2012).

Progress on the development of data analytics also may be linked to some inherent data challenges within the educational environment. The McKinsey Global Institute examined data analytics and its potential application in five industries across the world. They report data are now an important part of every business and industry. Appropriate management and usage of data has the potential to create value by disrupting current business models and conferring strategic and operational advantage to those who engage in its use through five "transformative opportunities" to create competitive advantage and improve productivity and operations (Manyika et al., 2011). First, data analytics has the potential to enhance transparency simply by making data more easily accessible to relevant stakeholders in a timely manner. Second, providing meaningful data to managers and decision makers enables experimentation to discover client needs, expose unwanted variability in operations, and improve performance. Third, data can be used to segment client populations, identify and design customized actions, and tailor products and services precisely to meet their needs. Fourth, analytics derived from an understanding of the operational and decision processes can replace or support human decision-making with automated algorithms to substantially improve decision-making, minimize risks, and unearth valuable insights. Finally, data exploration and modeling can drive innovation by uncovering unseen opportunities to create new or enhance existing business models, products and services (Manyika et al., 2011).

While all industry sectors have the opportunity to capture value from data analytics, the researchers found that the public sector, including education, faces higher hurdles. When considering the overall ease with which an industry can capture value from data analytics, the educational sector was ranked in the bottom quintile of 20 industries evaluated. Ease of capture is a combination of the level of data, talent, and IT assets available to organizations and how receptive organizations in the industry are to using data. The educational services sector was in the second quintile for talent, but in the bottom quintile for IT assets, having a data-driven mind-set, and data availability (Manyika et al., 2011).

In addition, McKinsey analyzed the value potential or how well a sector can benefit from one of the five transformative opportunities from data analytics. Value potential was determined by considering how much data is available to the organization and the intensity of transactions that generate data. The larger the amount of data available, the more likely the sector can benefit from the use of automated algorithms to augment or replace human decision-making. Value potential also includes customer intensity. The more customers an organization has, the greater its potential to apply segmentation to tailor programs and services. Finally, value potential includes the level of turbulence or the potential for innovative disruptions and variability of performance within the sector. The higher the variability in performance, the more it indicates organizations can benefit from the use of data and experimentation to expose variability and improve performance. The educational services sector scored in the fourth quintile overall, but was in the bottom quintile for the amount of data per firm, transaction intensity, and turbulence. Importantly, education was in the top quintile for customer intensity and variability in performance.

The McKinsey Global Institute assessment paints a challenging but promising picture. While the impediments faced by the education sector in developing analytics capabilities (limited IT assets, data availability, and data orientation) are substantial, the potential benefits of unleashing the talent available in colleges and universities to develop data analytics that address the performance variability and better serve the large and diverse student and client population also are substantial.

The McKinsey analysis highlights the growing importance of data analytics across industry sectors, including education, but it also highlights why the implementation of data analytics in the education sector will require thoughtful design, development, and implementation in order to address the unique challenges of higher education so the industry can take full advantage of the “transformative” opportunities data analytics presents. The implementation approach will require an understanding of the academic process and the role of shared governance and collaboration in higher education organizations. Yet little research has been done to understand how the unique nature of higher education organizations may impact the development and implementation of data analytics and how academic leaders’ attitudes and understanding of academic processes and operations to which data analytics may be applied impact successful implementation of innovations in general and data analytics specifically.

## Defining Mature Analytical Organizations

A discussion of the development and progression of a data analytics program within a particular organization raises the question of what a mature analytical organization looks like. Davenport and Harris (2010) created the DELTA Framework to describe the progression of data analytics within a specific organization. DELTA is an acronym for the five critical variables that indicate a mature data analytics program. The variables are *data* that are accessible, high quality, consistent, and integrated; an e*nterprise orientation* in which the organization owns important data and analytical software and talent, and management across the enterprise is motivated to cooperate on analytical initiatives; *leaders* who consistently manage by fact and are committed to the success of specific analytical projects; *targets* focused on strategic activities and operations; and *analysts* with expertise in building, applying and maintaining models that help the business hit its analytical targets. The authors argue that the five DELTA elements work together to improve success and that the lack of progress on any single element can be a roadblock. The DELTA matrix describes five stages of development across each of the five variables (Table 1), moving from “Stage 1: Analytically Impaired” to “Stage 5: Analytical Competitors.”

Progression across the matrix indicates increasing levels of leadership for and use of analytics at the enterprise or organizational level to the point at which data analytics is a key feature of organizational strategy, capacity, and leadership focus. Key variables for success that higher education may need to address to progress to Stage 5 include the identification of critical organizational and operational data even though education ranks at the bottom for data availability (Manyika et al., 2011); an engaged discussion of the organizational responsibility for data analytics even though the current discussion is still focused primarily within IT; a purposeful cultivation of senior leaders with analytical capabilities even though presidents and provosts indicate that their organizations are not particularly effective at using data to make decisions (Green, 2012); the application of data analytics to the central strategy of the organization even though it is currently limited to administrative and student support functions (Bichsel, 2012); and the cultivation of "analytical amateurs" across the organization, specifically among academic leaders, even though they appear to be the least engaged in its use (Goldstein & Katz, 2005).

**Table 1: DELTA Framework (Davenport and Harris 2010)**

| Success Factor | Stage 1 Analytically Impaired | Stage 2 Localized Analytics | Stage 3 Analytical Aspirations | Stage 4 Analytical Companies | Stage 5 Analytical Competitors |
|---|---|---|---|---|---|
| Data | Inconsistent, poor quality and organization; difficult to do substantial analysis; no groups with strong data orientation | Much data useable, but in functional or process silos; senior executives don't discuss data management | Identifying key data domains and creating central data repositories | Integrated, accurate, common data in central warehouse; data still mainly an IT matter; little unique data | Relentless search for new data and metrics; organization separate from IT oversees information; data viewed as strategic asset |
| Enterprise | No enterprise perspective on data or analytics. Poorly integrated systems | Islands of data, technology, and expertise deliver local value | Process or business unit focus on analytics. Infrastructure for analytics beginning to coalesce | Key data, technology and analysts managed from an enterprise perspective | Key analytical resources focused on enterprise priorities and differentiatio n |
| Leadership | Little awareness of or interest in analytics | Local leaders emerge but have little connection | Senior leaders recognizing importance of analytics and developing analytical capabilities | Senior leaders developing analytical plans and building analytical capabilities | Strong leaders behaving analytically and showing passion for analytical competition |
| Targets | No targeting of opportunities | Multiple disconnected targets, typically not of strategic importance | Analytical efforts coalescing behind a small set of important targets | Analytics centered on a few key business domains with explicit and ambitious outcomes | Analytics integral to the company's distinctive capability and strategy |
| Analysts | Few skills and those attached to specific functions | Unconnected pockets of analysts; unmanaged mix of skills | Analysts recognized as key talent and focused on important business areas | Highly capable analysts explicitly recruited, developed, deployed and engaged | World-class professional analysts; cultivation of analytical amateurs across the enterprise |

## Data Analytics: An Innovation for Higher Education Organizations

Data analytics is an example of an organizational innovation and as such may best be investigated through the theoretical framework of innovation adoption and diffusion. Innovation research began in the 1940s in the area of rural sociology and has expanded over the last seven decades to include such diverse disciplines as communication, public health marketing, and education. Throughout the extensive history of the study of innovation, many definitions have been developed. Most include the identification of an idea that is new to an individual, group, or organization and the implementation of that idea with the goal of organizational improvement (Dill & Friedman, 1979; Rogers, 2003; White & Glickman, 2007). Van de Ven, et al. (2008) add that an organizational innovation "entails a collective effort of considerable duration and requires greater resources than are held by the people undertaking the effort" (p22). Organizational innovations exclude lone-worker innovations and those that emerge primarily by chance. An idea is not required to be new to the world in order to be defined as an innovation. It must simply be new to the organization that is attempting to implement it, even if others outside of the organization perceive it as an imitation of an existing idea (Rogers, 2003).

Innovations can come from any place and any direction. Innovations can be developed by professionals based on their experiences and engagement in the core work of the organization, introduced to the organization through implementation by other competitive organizations, or forced upon the organization because of a change in the political or regulatory environment. To become an organization-level innovation, internal ideas must achieve awareness and momentum among enough and the right people to reach organizational importance and attention (Van de Ven, 1986). Innovations that are introduced to the organization from the external environment require organizational responses that must be framed and refined to align with organizational values and identity (Clark, 1968; Rogers, 2003) before they can be adopted successfully.

A primary focus in innovation research is diffusion. Through the diffusion process, individuals make an adoption choice, not in a vacuum, but within the larger social system of which they are a part. The social system is greater than the organization and includes personal and professional networks. People subjectively evaluate an innovation based on information from others. Early adopters of an innovation share their experiences (good or bad) with others through interpersonal networks. The experiences of early adopters and the extent to which those experiences are shared determine the rate of adoption of others in the social system (Bidwell, 2001; Rogers, 2003). The norms of the social system affect the innovation decision, rate of diffusion, and the role and influence of opinion leaders and change agents in the adoption process. Once the rate of adoption reaches a critical mass, the innovation implementation becomes self-sustaining (Rogers, 2003).

Rogers (2003) proposes a five-stage model to describe the innovation process within organizations. The model is split between the initiation phase and the implementation phase. During initiation, the organization moves through an agenda-setting stage, in which a general organizational problem is identified, and a matching stage, in which the organization fits a problem from the organization's agenda with an innovation to address it. At the point when the organization decides to adopt a specific innovation, the implementation phase begins. Implementation contains three stages. The first is the redefining stage, in which the innovation is modified and reinvented to fit the organization and organizational structures are altered. The second is the clarifying stage, in which the relationship between the organization and the innovation is defined more clearly. Third is the routinizing stage, in which the innovation becomes an ongoing element in the organization's activities and loses its separate identity. Though the process appears linear, the implementation of innovations is highly organic and non-linear (Rogers, 2003; Van de Ven et al., 2008) and requires organizational as well as individual change and a continual reframing to fit the local context and priorities. It is adaptive, meaning the organization adapts to the innovation and the innovation is adapted to the organization (Fonseca, 2002).

Beyond the general innovation implementation process, different types of organizations, including service organizations, may experience the process differently (Greenhalgh et al., 2004). Educational organizations have unique ways of organizing that may influence the process by which they implement organizational innovations and their ability to routinize or sustain them over time (Clark, 1968). The study of change in colleges and universities is informed by the general theories change and innovation (Van de Ven & Poole, 1985). Peterson's (2008) analysis of the diverse approaches to the study of colleges and universities as organizations since 1950 found that research on universities as organizations mirrors organizational theory development overall. He also found that the conceptualization of higher education organizations has changed as major shifts in the environment and related challenges have resulted in changes in educational approach and structure.

Individual colleges and universities also have a unique history and organizational characteristics that impact their ability to implement and routinize innovations successfully. An understanding of how structures, people, politics, and culture influence the implementation process would be useful, especially as it relates to specific innovations, such as data analytics. Following are key organizational theories that should inform the investigation into innovation implementation processes within higher education organizations.

Colleges and universities have *professional bureaucratic structures* that rely on a departmentalized organization and professional discretion to deliver their programs and services and govern performance (Mintzberg, 1979; Weber, 1922). As such, the implementation of innovations is challenging because professionals work relatively independently and have considerable control over their own work and their own decisions, including discretion over which innovations to incorporate into their professional practice. In addition, colleges and universities and their faculty and staff exist in *highly institutionalized fields* (DiMaggio & Powell, 1983; Meyer et al., 2008; Scott, 2001) in which broader institutional meanings and rules limit the innovations that can be legitimately introduced to the organization and influence how, when, and at what level of success they will be implemented. Next, colleges and universities have characteristics of *loosely-coupled organizations* (Cameron, 1984; Hallett & Vantresca, 2006; Weick, 1976) that provide opportunities for localized innovations to find their way into segments of the organization but limit the ability to implement and routinize innovations at the organizational level. Colleges and universities develop *organizational cultures* that define acceptable ways for the organization to address opportunities and challenges through innovative activities and limit attempts to do things differently (Clark, 1972; Schein, 2004; Tierney, 1988). Finally, colleges and universities can be seen as *collaborative communities* that organize and manage their activities through networks of professionals focused on common values and purposes (Heckscher & Adler, 2006), which limit the effectiveness of more goal-rational, hierarchical forms of organizational innovation implementation. Together, these characteristics influence the type and number of legitimate innovations recognized by the organization, how they move through the organization, and who within the organization engages with the innovation and actually adopts it.

## Organizational Innovation Adoption and Diffusion

Significant work has been completed over the last 50 years to study the product and process of innovation. The research questions investigated have evolved over time from a consideration of how organizational variables such as size and complexity impact levels of innovativeness (Davis et al., 1982; Dill & Friedman, 1979; Rogers, 2003; Wood, 1981) to work that attempts to develop a detailed understanding of the process by which organizations innovate (Kozma, 1985; Van de Ven et al., 2008). The predominant focus of innovation research has been on understanding the variables that impact innovation adoption choices among individuals and groups and individual and organizational innovativeness. Research indicates that different variables have different levels of impact at different points in the process (Davis, et al., 1982; Kozma, 1985; Van de Ven et al., 2008).

Organizational adoption decisions are more complex than simply a series of individual adoption decisions and involve organizational variables that also influence adoption choice (Rogers, 2003; Van de Ven, 1986). Implementation generally involves many individuals, including proponents and opponents of the adoption decision, which through negotiation alter the innovation and the organization over time and influence implementation success (Van de Ven, 1986). An affirmative adoption decision by an organization does not necessarily lead to successful implementation, so the dependent variable in organizational innovation research is often implementation rather than adoption (Zaltman, et al., 1973). Argyris and Schön (1996) argue that change at the individual level must precede changes at other levels, including organizational. Since the decision to adopt an innovation is a personal one, each new adopter goes through a similar filtering process of alignment with values and previous experience (Kozma, 1985) prior to the adoption choice.

Greenhalgh, et al. (2004) conducted a meta-analysis of innovation research in health care organizations and found that innovation implementation is not straightforward and that many of the standard variables are necessary but not sufficient to explain successful implementation of innovations in complex organizations. Overall, they found that attributes are neither stable features of the innovation nor sure determinants of successful implementation. Rather, it is the interaction among the innovation, the intended adopter(s), and a particular context that determines success. Finally, the researchers found that most innovation research has addressed centrally developed and driven innovations, but many innovations in service organizations are developed organically and spread informally.

Overall, Greenhalgh et al. (2004) found that the preponderance of empirical innovation research was based on product-based innovations, and there may be limited generalizability to an understanding of innovation processes in service organizations.

They also noted that there is almost a complete absence of research studies that focus primarily on the sustainability or routinization of complex service innovations. In the research that did focus on the service sector, the reseachers found little recognition or analysis of the issue of internal politics.

Easterby-Smith (1987), in an overview of change and innovation in higher education literature, found that there are four levels at which innovations occur. The first is innovations to the content of subjects and disciplines. Innovation occurs readily at this level, and it is the level at which academic professionals are expected to innovate as part of their regular routine. The second level is the educational processes by which these subjects are communicated. Innovation at this level involves professional practice that informs much of the day-to-day activity of teaching and learning. A third level is the overall balance of subjects, courses, projects, and disciplines within an organization. Most of the research has been focused on the appropriate allocation of resources. The fourth level is the institutional structures and systems within which the three previous levels take place. Little to no research has been completed at this level. It could be argued that a fifth level exists that is not addressed in Easterby-Smith’s typology. A consideration of the innovation processes that occur at the field or industry level would provide important insight into the ways in which certain innovations receive legitimacy and best-practice status and are adopted by multiple organizations. The field or industry level would be particularly important to explore because much of the change and innovation that is being called for by external stakeholders is directed at the higher education industry and not at any one particular organization. Higher education innovation research has primarily occurred at the first two levels. Specifically lacking are studies that focus on organizational innovation processes. The literature gap was recognized years ago (Baldridge and Burnham, 1975) and continues today.

Most of the empirical research on innovation done in higher education settings is focused on instructional or disciplinary innovations and primarily on variables that impact innovativeness. Within these studies, a few theoretical frameworks have been developed to attempt to describe the variables that impact the implementation process. Davis, et al. (1982) studied 21 faculty who were implementing a teaching technology innovation in their classroom. From their findings, the research team developed a process model of innovation for higher education. The model identifies an innovation with four stages (consideration, design and development, implementation, and continuation) and four critical variables (organizational support, innovation characteristics, innovator activities, and innovator motivation) that must occur at appropriate stages for the innovation to be implemented successfully. The proposed four stages are consistent with Rogers' (2003) five stages of organizational innovation: agenda-setting, matching, redefining, clarifying, and routinizing. The researchers argue for a true stage model in that the adopters must complete each stage successfully in order to move on to the next one. The four variables are hypothesized to be differentially effective at the different stages in the process because the requirements for the successful completion of each stage depend upon unique and changing conditions. The research was based on a case study of one institution, and the authors recognized the limitation and call for future research that involves a number of institutions of higher education using the same (or similar) innovations in order to increase sample size and analyze the effects of organizational variables. In addition, recent research on innovation process contradicts these findings, in that no evidence was found to support a stage-wise process for innovation development and implementation (Van de Ven et al., 2008).

Kozma (1985) developed a process theory of innovation implementation in higher education using grounded theory methodology. He was particularly interested in the involvement of others beyond the original innovator in the implementation process. He found that differences in successful implementation could not be accounted for by characteristics of the innovation or the innovator but by the process used to implement them. He found no evidence of clear stages, and a clear point of adoption or implementation was difficult to identify. He argued that instructional innovation is evolutionary because new practices are built on previous practices.

## Variables that Influence Innovation Implementation in Higher Education Organizations

From a review and analysis of existing literature, it seems that successful implementation of innovations is associated with both the process an organization uses to redefine and clarify the innovation to fit a particular organizational context and the support structures it provides to encourage individual adoption and integration of the innovation into ongoing, regular activities. During the process, individual adoption may occur through the adaptation of the innovation to align with professional practice. At the same time, adoption of the innovation may change professional practice, which leads to changes in organizational routines and culture over time. Regardless of source, it appears the innovation must gain currency with the professionals in the organization as appropriately addressing a particular problem or organizational need before it will be adopted, or the innovation fails to integrate with the culture and practice and remains separate and irrelevant, resulting in implementation failure.

Over time, though the length of time can vary considerably, the innovation may build momentum as more and more professionals absorb the innovation into their professional practice until a point is reached in which the innovation is no longer seen as separate from the day-to-day routines of the organization or its professionals. The innovation has been transformed from something that is done in addition to regular functions to something that is seen as integral to regular practices and operations of the organization. In this context, the successful implementation of a data analytics program may be related to a shift to a more data-oriented organizational culture, which Stiles (2012) identifies a critical to the success of any data analytics program.

Innovation implementation is not straightforward. Attributes of the innovation are neither stable nor sure determinants of successful implementation. Rather, it is the interaction among the innovation, the intended adopter(s), and a particular context that determines success (Greenhalgh et al., 2004). Through an analysis of previous research on innovation implementation within and outside higher education, nine variables have been identified that describe the critical dimensions of the organizational context in which the innovation is implemented (collaboration, authenticity, institutional support, training, and integrated use), the characteristics of the innovation (functionality and usability) and the attitude of the potential adopter (usefulness and legitimacy) (Table 2).

**Table 2: Innovation Implementation Research Variables**

| Concept | Conceptual Definition | Authors |
|---|---|---|
| Collaboration | Collaborative innovation development and adoption across the organization with decentralized and transparent decision-making responsibilities regarding implementation | *Baldridge (1975)*<br>Van de Ven & Poole (1985)<br>Van de Ven (1986)<br>*Easterby-Smith (1987)*<br>*Green (2003)*<br>Rogers (2003)<br>Greenhalgh, et al. (2004)<br>Hargrave & Van de Ven (2006)<br>Heckscher & Adler (2006)<br>Klein (2010) |
| Authenticity | Shared understanding and agreement among members of the organization of purpose of the innovation and the outcomes it is designed to achieve; consistency between the innovation and the organizational culture and values | *Eraut (1975)*<br>*Cannon & Lonsdale (1987)*<br>Van de Ven (1996)<br>Argyris & Schon (1996)<br>*Van Driel et al. (1997)*<br>Rogers (2003)<br>Greenhalgh, et al. (2004)<br>Schein (2004)<br>*Kezar (2006)* |
| Institutional Support | Organizational leaders who actively support the innovation and recognize and reward adoption; organizational resources available to support the innovation and implementation | *Eraut (1975)*<br>*Baldridge (1980)*<br>*Davis, et al. (1982)*<br>*Kozma (1985)*<br>*Savenije & Van Rosmalen (1988)*<br>Van de Ven (1986)<br>Rogers (2003)<br>Greenhalgh, et al. (2004)<br>*Kezar (2003)*<br>*Kezar (2006)* |
| Training | Mechanisms to address employee development and increase employee knowledge of the innovation and expand usage | *Eraut (1975)*<br>*Van Driel, et al. (1997)*<br>Rogers (2003)<br>Greenhalgh, et al. (2004)<br>*Kezar (2003)*<br>*Kezar (2006)* |
| Integrated Use | Integration of the innovation into existing organizational systems and structures | *Rutherford & Fleming (1985)*<br>*Gioia & Thomas (1996)*<br>Rogers (2003)<br>Greenhalgh, et al. (2004)<br>*Kezar (2006)*<br>*White & Glickman (2007)* |
| Functionality | Meets an organizational need as defined by the user and provides a relative advantage to the idea it supersedes | *Cohen, March & Olsen (1972)*<br>*Eraut (1975)*<br>*Baldridge (1980)*<br>*Kozma (1985)*<br>Van de Ven (1996)<br>Rogers (2003) |

| | | |
|---|---|---|
| Usability | Ease to which an innovation can be incorporated into professional practice. | Van de Ven (1996)<br>Fonseca (2002)<br>Rogers (2003)<br>Greenhalgh, et al. (2004)<br>Wixom & Todd (2005) |
| Usefulness | Extent to which innovation assists adopter in completing organizational responsibilities | Wixom & Todd (2005) |
| Legitimacy | Perception the innovation is appropriate for the organization and consistent with professional values and practices | DiMaggio & Powell (1983)<br>Meyer & Rowan (1991)<br>Rogers (2003)<br>Hargrave & Van de Ven (2006)<br>*Meyer et al. (2008)* |
| External Pressure | Physical, technological, cultural and social elements outside of the organization that influence its ability to function and achieve its goals | Pfeffer & Salancik (2003)<br>Scott & Davis (2007) |

*Note: Italics indicates study was completed within an educational organization.*

**Collaboration.** The implementation of an innovation is a collective activity that requires attention, expertise, resources, and efforts from multiple individuals and groups (Heckscher & Adler, 2006; Rogers, 2003; Van de Ven, 1986). The relative autonomy of professionals within higher education organizations and the political nature of the organizational environment make collaboration and decentralized decision-making important characteristics of the implementation process (Baldridge, 1980; Green, 2003; Greenhalgh et al., 2004; Rogers, 2003). Innovations in universities are often locally developed (Kozma, 1985) and begin with an individual or a small group of individuals. The innovation is altered through a dialectical process of negotiation and compromise as groups seek to modify the innovation to address their own unique needs and interests (Klein, 2010; Van de Ven & Poole, 1985). It evolves gradually through debate at all levels of the organization, improving quality and encouraging acceptance by increasing numbers of professionals within the organization. As a result, an innovation's eventual acceptance may have less to do with the particular innovation and more to do with the collaborative process by which it was developed and implemented (Heckscher & Adler, 2006; Kozma, 1985). As a result, the idea or innovation itself changes over time in a recursive fashion (Hargrave & Van de Ven, 2006). When successful, the collaborative mode is cooperative rather than confrontational and emerges from shared previous experience and values (Kozma, 1985).

**Authenticity.** An organization's openness and ability to adopt specific innovations is tied to the culture of the organization, especially if the organization has a significant number of professionals (Schein, 2004). The norms of the organization affect which innovations are selected, the rate of diffusion, and the role of opinion leaders and change agents in the adoption process (Rogers, 2003). An organization's culture can support the adoption of an innovation if the change aligns with its culture (Xiao & Tsui, 2007). Organizational culture also can limit the adoption of potential innovations, which is positive if the innovation is inappropriate for the organization, but pressure to behave in culturally acceptable ways may constrain innovation or attempts to do things differently (Schein, 2004). The authenticity of the innovation evolves as the members of the organizational community develop a shared understanding and agree on the purpose of the innovation and the outcomes that it is designed to achieve (Eraut ,1975; Kezar, 2006; Rogers, 2003; Van de Ven, 1986). Innovations that radically differ from an organization's values have been found to be difficult to implement successfully (Rogers, 2003).

**Institutional support.** As something new being introduced into the organization, innovations begin as separate from the established systems, structures and processes of the organization. Institutional supports are distinctive from ongoing resources and create the bridge between the introduction of the innovation to the point where it is part of regular operations. Institutional support includes resources, both financial and personnel (Baldridge, 1980; Eraut, 1975; Rogers, 2003; Savenjie & Van Rosmalen, 1988), including a champion or change agent with the ability to navigate the political dynamics of the organization (Baldridge, 1980; Kozma, 1985; Van de Ven, 1986). Support also can take the form of senior leaders who actively and visibly support an innovation, are engaged in its use and implementation, and recognize and publicly reward adoption (Baldridge, 1980; Davis et al., 1982; Greenhalgh et al., 2004; Kezar, 2003; Kezar, 2006). An important component of institutional support is accountability or the level at which organizational leaders are held accountable for organizational outcomes related to the innovation (Kezar, 2003).

**Training.** The adoption of an innovation may involve a change in practice because something new is being introduced into regular routines. Organizations need to provide mechanisms to build employee knowledge and capacity not only to use the specific technology but also to adapt their own practice in order to best utilize it (Eraut, 1975; Greenhalgh et al., 2004; Kezar, 2003; Kezar, 2006; Rogers, 2003). In the case of data analytics, academic leaders may need to receive training on how to use the specific technology to access information from the system, but they also may need professional development in how to understand the data and metrics and how to incorporate them into their own decision-making processes.

**Integrated use.** The purposeful use of integrating structures and systems may be particularly important to higher education organizations because of their loosely coupled nature (Weick, 1976). Loose coupling is critical to the initiation of innovative ideas because the organization needs to be open to its changing environment and flexible enough to consider novel adaptations. The difficulty is that implementing an innovation requires a tight coupling around a best solution and singleness of purpose (Cameron, 1984). Loose coupling means it is likely that novel solutions will remain local even if it is desirable for them to be standardized across the organization (Bidwell, 2001). Thoughtful integration of an innovation into existing organizational systems provides opportunities for the innovation to move across formal structural boundaries and allow for knowledge transfer about an innovation, its implementation, and success (Greenhalgh et al., 2004; Kezar, 2006; Rogers, 2003). Kezar (2006) found that one of the biggest obstacles in implementing innovative academic programs is the siloed bureaucratic departmental and administrative structures on most campuses. New structures, processes, and rewards need to be established that enhance group and cross-divisional work, including integrating mechanisms, such as feedback loops and data and information about the innovation, the organization, and the changing external environment (Greenhalgh et al., 2004; Kezar, 2006; White & Glickman, 2007) that reinforce the importance of adoption. Communication networks are critical in the management of perceptions and information about the innovation and implementation process and in guiding the organization's interpretation of appropriateness and success (Gioia & Thomas, 1996; Rutherford et al., 1985).

**Functionality.** An innovation, by definition, is an idea that is being introduced with the goal of organizational improvement. Key to successful implementation is that the innovation actually solves a problem. A challenge to successful implementation is that the innovation must solve the problem as defined by the user in a way that is better than what the professional is currently doing (Rogers, 2003; Van de Ven, 1986). The cause-and-effect relationship between the problem and the innovation is often reversed (Van de Ven, 1986). Innovations are introduced without a problem to solve or when no dissatisfaction with the current solution exists (Eraut, 1975). Colleges and universities have a reputation for minimal problem assessment prior to an adoption decision (Baldridge, 1980) or identifying solutions first and then looking for problems to solve (Cohen, March, & Olsen, 1972). In addition, faculty and professional staff members have explicit and tacit knowledge gained through education and disciplinary affiliations that inform and influence what they see as an appropriate definition of the problem and acceptable solutions (Eraut 1975; Kozma, 1985). As a result, functionality may be defined differently by professionals within an organization from the way the organization itself defines it, requiring flexibility as a key component of the innovation.

**Usability.** Professionals manage their work by matching standardized solutions to client or student needs, using regular routines in order to minimize the complexity of their work (Mintzberg, 1979). The introduction of new program, service, or technology innovations, even if designed to reduce workload, changes the established routines and can be disruptive for the professional during the early adoption stages. The usability of the innovation captures how easily the potential adopter can incorporate an innovation into his or her practice. Usability has two dimensions: the innovation must be easy to use, meaning it is easy to operate (Davis, 1989; Wixom & Todd, 2005), and must be easy to manipulate so that it can be used for multiple purposes (Wixom & Todd, 2005). The ability to manipulate the innovation creates flexibility that allows innovations, particularly those that come from outside the organization, to be altered to address the specific needs of the potential adopter (Fonseca, 2002; Greenhalgh, et al., 2004; Van de Ven, 1996). Usability is the companion to functionality. The better an innovation is at addressing a particular problem and the easier it is to use, the more likely individuals are to adopt and to continue to use an innovation.

**Usefulness.** The usefulness of an innovation as a factor in adoption choice and continued use has been primarily investigated in technology adoption research but likely has broader application in general innovation research (Davis, 1989; Wixom & Todd, 2005). Usefulness is not a characteristic inherent in the innovation but is linked to the attitude that adopters develop as they put the innovation into practice. The perception of usefulness is related to the extent that the innovation actually improves the ability to complete organizational responsibilities and increases effectiveness in day-to-day responsibilities (Wixom & Todd, 2005).

**Legitimacy.** While an innovation must align with an organization's ideals, in complex professional organizations it also must align with the professional values and knowledge of the adopters (Van Driel et al, 1997). Professional knowledge exerts a major influence on the ways in which professionals respond to innovations. It appears they are rarely open to all possible innovations and will consider only those for which their basic disciplinary assumptions hold (Van Driel et al., 1997; Cannon & Lonsdale, 1987). An innovation becomes relevant to a potential adopter when the innovation achieves both cognitive legitimacy (I think it's okay to change) and social-political legitimacy (others think it's okay to change) (Hargrave & Van de Ven, 2006). Since colleges and universities are embedded in highly institutionalized fields (Meyer et al., 2008), with the influence of regional and specialized accrediting agencies, professional associations, and state and federal governments to spread coercive, mimetic, and normative change (DiMaggio & Powell, 1983), the legitimacy of an innovation can be influenced by external forces but also by professional norms and expectations. As a result, innovations identified to solve real organizational problems may be viewed as illegitimate, while innovations that are adopted at the organizational level may not necessarily be designed to solve specific organizational problems (Meyer & Rowan, 1991).

# CHAPTER THREE

# CONCEPTUAL FRAME AND METHODS

Forces within and outside of higher education are positioning data analytics as an organizational innovation that has the potential to improve institutional and student performance and reduce costs, but successfully implementing innovations like data analytics at colleges and universities has been a challenge for many institutions. Existing research on implementing organizational innovations in colleges and universities in general and on data-analytics development and implementation specifically does not yet provide a useful framework or guidance for organizational leaders on how to structure and manage the implementation process in a way that increases the likelihood of success.

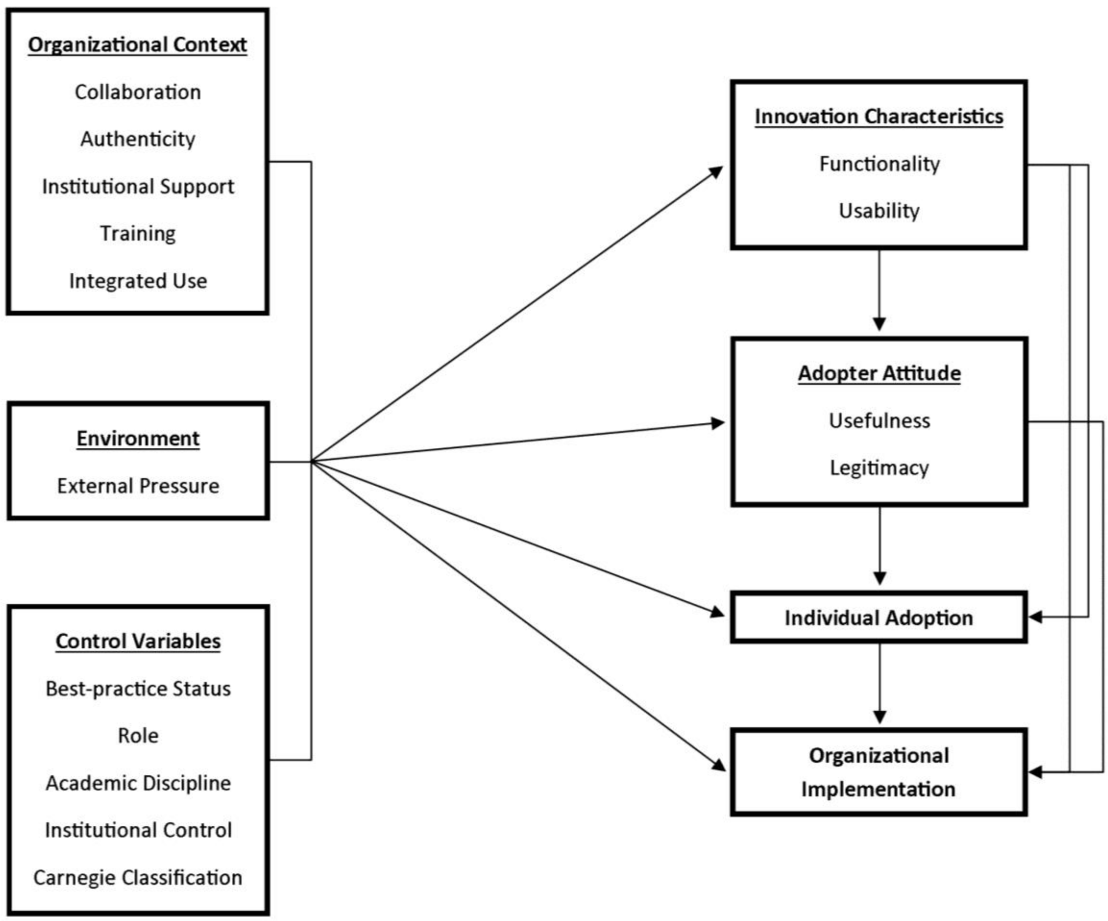
The purpose of this study is to investigate factors associated with the successful implementation of organizational innovations in U.S. colleges and universities. The research question that drives this analysis is, How are individual adoption and organizational implementation of innovations in higher education related to the context of the organization, characteristics of the innovation, and attitudes of adopters? This question is examined in relation to adoption and implementation of data analytics programs in U.S. higher education.

## Conceptual Framework

The conceptual framework for implementing innovations in higher education organizations (Figure 1) on which this study is based is built upon existing research and models for implementing organizational innovations. Rogers (2003) identified that the implementation of innovations is influenced both by the process an organization uses to redefine and adapt the innovation to fit its context and by the support structures it provides to encourage individual adoption and integration of the innovation into ongoing, regular activities. Greenhalgh, Robert, MacFarlane, Bate, and Kyriakidou (2004) conducted a meta-analysis of innovation research in health-care organizations and found that innovation implementation is not straightforward and that standard characteristics of the innovation and organization are not sufficient to explain successful implementation of complex innovations in professional organizations. Rather, it is the combination of the innovation, the intended adopter(s), and a particular context that determines successful implementation.

The conceptual framework integrates Roger's (2003) three-stage model which describes the structured process by which innovations are implemented within an organization with Greenhalgh, et al.'s (2004) findings that it is the combination of the innovation, the context, and the intended adopter that influences individual adoption choice, which in turn influences the extent of implementation achieved by the organization. The variables in the conceptual framework were identified from a review of the extensive literature on innovation diffusion and implementation so their relationship to individual adoption and organizational implementation could be measured.

**Figure 1: Conceptual Framework for Implementing Innovations in Higher Education Organizations**



The conceptual framework proposes that four major components are related to the extent of individual adoption and organizational implementation of a particular innovation. First is the organizational context in which the innovation is implemented and the strategies that leaders or change agents use to support the implementation. Variables within the organizational context are: collaboration, authenticity, institutional support, training, and integrated use. Second is the external environment in which the organization is situated and the level of external pressure that exists to adopt the innovation. Third are the characteristics of the innovation itself, which are not inherent in the innovation but are acquired through the organizational environment and the success of the strategies used by the organization to support implementation. Innovation characteristics investigated are functionality and usability. Fourth is the attitude of the individual adopter toward the innovation, that is, the adopter's perceptions of the innovation's usefulness and legitimacy. These conceptual framework elements are now reviewed in greater detail.

The first component of the conceptual framework is organizational context, which includes five variables that previous research indicates may influence individual adoption and organizational implementation. First is *collaboration*, or a shared responsibility for the redefinition and implementation of an innovation between senior leaders and the faculty and professional staff (Clark, 1968; Greenhalgh, et al., 2004; Kozma,1985; Rogers, 2003). Second is *authenticity*, or the fit between the innovation and the organization, the development of a shared understanding and agreement across the organization of the purpose of the innovation, and the consistency between the innovation and the organizational culture and values (Baldridge, 1980; Clark, 1968; Eraut, 1975; Greenhalgh, et al., 2004; Kezar, 2006; Rogers, 2003; Van de Ven, 1996). Third is *institutional support,* or the recognition and clear communication from organizational leaders that the adoption of the innovation is important for organizational success, including direct advocacy, reward, recognition, and financial support for ongoing implementation (Baldridge, 1980; Clark, 1968; Davis, et al., 1982; Greenhalgh, et al., 2004; Kezar, 2006; Rogers, 2003). Fourth is *training,* or professional development and education directed toward adoption and use of the innovation within the organization (Eraut, 1975; Greenhalgh, et al., 2004; Kezar, 2006; Kozma, 1985; Rogers, 2003; Van Driel, et al., 2004). Fifth is *integrated use,* or the purposeful integration of an innovation into existing organizational systems that provides opportunities for the innovation to move across formal structural boundaries and allows for knowledge transfer about an innovation and its implementation (Eraut, 1975; Greenhalgh, et al., 2004; Kezar, 2003; Kezar, 2006; Kozma, 1985; Rogers, 2003).

The second component of the conceptual framework is the influence of the external environment on the adoption of organizational innovations. Organizations exist in a specific environment to which they must adapt in order to acquire resources to survive (Pfeffer & Salancik, 2003; Scott & Davis, 2007). Within highly institutionalized fields, such as higher education, the external environment can influence which innovations can be legitimately introduced to the organization and influence how, when, and at what level of success they will be implemented (DiMaggio & Powell, 1983; Meyer et al., 2008).

The third component of the conceptual framework is the acquired characteristics of the innovation itself. The influence of two variables will be investigated as part of this study. The first is *functionality,* or the extent to which an innovation solves a problem and is perceived as better than existing practices (Rogers, 2003; Van de Ven, 1996). The second is *usability*, or the ease with which a potential adopter can incorporate an innovation into his or her practice because it is easy to use and can be adapted to fit specific needs of the adopter (Davis, 1989; Fonseca, 2002; Greenhalgh, et al. 2004; Wixom & Todd, 2005).

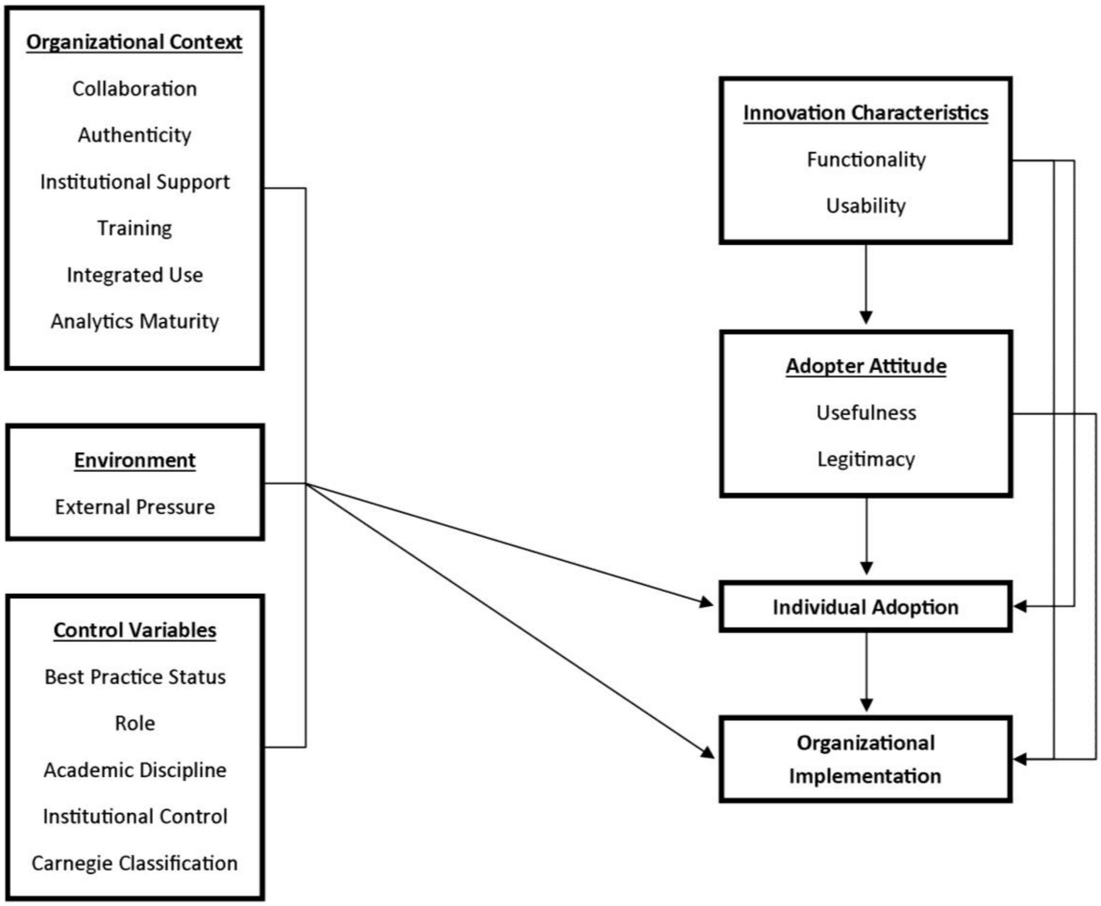
The fourth component of the conceptual framework is adopter attitude toward the innovation. The influence of two variables will be investigated as part of this study. The first variable is *usefulness,* or the extent adopters believe the innovation improves their ability to complete organizational responsibilities (Davis, 1989; Wixom & Todd, 2005). The second variable is *legitimacy,* or the extent adopters believe the innovation is appropriate for the organization and consistent with their professional values and practices (Cannon & Lonsdale, 1987; DiMaggio & Powell, 1983; Hargrave & Van de Ven, 2006; Rogers, 2003; Van Driel et al., 1997)

A set of five control variables are used in the analysis to investigate if organizational and adopter characteristics influence innovation adoption and implementation. The control variables investigated are 1) status as a best-practice institution in the area of data analytics, as recognized by previous research on the topic; 2) role of the respondent within the organization (dean or department chair); 3) academic discipline of the respondent (biology, management, English, nursing, political science, or education); 4) institutional control of the organization as defined by IPEDS (public or private, not-for-profit); and 5) Carnegie Classification as defined by IPEDS (Research, Masters, Baccalaureate, or Associates).

It is possible that successful organizational implementation is not linear, but circular and reinforcing. As individual academic leaders become engaged in innovation adoption and use, they become recognized and supported through the integration process and serve as role models for others in the organization (Kozma, 1985; Van de Ven, 1996). As additional adopters become engaged, the organizational culture begins to shift, which in turn encourages additional engagement and use. New adopters reinforce the choice of existing adopters and positively impact the attitude of intended adopters, increasing levels of individual adoption and organizational implementation (Argyris & Schön, 1996; Hargrave & Van de Ven, 2006).

The primary conceptual framework for implementing innovations in higher education organizations (Figure 1) provides a generic frame for investigating the implementation of innovations within higher education organizations. This study investigates specifically the individual adoption and organizational implementation of data analytics by academic leaders within higher education institutions. The primary conceptual framework has been adapted to include specific structural elements that have been shown to enhance data analytics implementation within organizations in general, but that have not been investigated within higher education organizations. A modified conceptual framework (Figure 2) includes all ten variables included in the original framework but has been expanded to include the variable of *analytics maturity*, or the structures and systems available to implement and maintain a data analytics program successfully, as part of the organizational context.

**Figure 2: Conceptual Framework for Implementing Data Analytics in Higher Education Organizations**



Analytics maturity is based on the DELTA framework (Davenport & Harris, 2010), which indicates that as organizations expand to a more centralized and strategic use of data and enterprise systems, develop leaders and targets focused on strategic results, and leverage highly skilled analysts across the organization, they increase their capacity to deploy data analytics successfully and benefit from its use. Both conceptual frameworks (original and modified) will be used in this study.

Table 3 presents the conceptual and operational definitions of the variables that appear in the conceptual frameworks (Figures 1 and 2). These definitions supported the development of survey items to measure the study's variables.

**Table 3: Conceptual and Operational Definitions of Research Concepts**

| **Concept** | **Conceptual definition** | **Operational definition** |
|---|---|---|
| Collaboration | Collaborative innovation development and adoption across the organization with decentralized and transparent decision-making responsibilities regarding implementation | Involvement of academic leaders in the development and implementation of data analytics |
| Authenticity | Shared understanding and agreement among members of the organization of the purpose of the innovation and the outcomes it is designed to achieve; consistency between the innovation and the organizational culture and values | Data-driven organizational culture |
| Institutional Support | Organizational leaders who actively support the innovation and recognize and reward adoption; organizational resources available to support the innovation and implementation | Funding, tools and staff to support and maintain data analytics |
| Training | Mechanisms to address employee development and increase employee knowledge of the innovation and expand usage | Training and professional development for the end user to use data analytics successfully |
| Integrated Use | Integration of the innovation into existing organizational systems and structures | Integration of data analytics with other information within the institution |
| Analytics Maturity | Structures and systems available to implement and maintain a data analytics program successfully | Level of data, enterprise systems, leadership, talent and analysts as part of a data analytics programs |
| External pressure | Physical, technological, cultural and social elements outside of the organization that influence its ability to function and achieve its goals | Extent of pressure from external entities to adopt data analytics |
| Functionality | Meets an organizational need as defined by the user and provides a relative advantage to the idea it supersedes | Perception data and information available from data analytics is accurate and the right kind of data to make decisions |
| Usability | Ease to which an innovation can be incorporated into professional practice | Perception data analytics is flexible and easy to use |
| Usefulness | Extent to which innovation assists adopter in completing organizational responsibilities | Perception data analytics is improving professional performance |
| Legitimacy | Perception the innovation is appropriate for the organization and consistent with professional values and practices | Perception analytics is appropriate for higher education |
| Individual adoption | Level of use of the innovation by the user | Extent of individual use of the data analytics system |
| Organizational implementation | Extent of use of the innovation by the organization | Depth of organizational use of data analytics across functional areas |

## Method

The study uses a quantitative, cross-sectional methodology. Data were collected through a survey of deans and department chairs from institutions that a) participated in the EDUCAUSE 2012 analytics survey, or b) have been identified as best-practice institutions through previous research on data analytics (Goldstein & Katz, 2005; Norris & Baer, 2012). The survey collected responses to questions related to the status of data analytics, activities related to implementation and personal use, perceptions of effectiveness of data analytics, and potential and problems of using data analytics in higher education. Respondents also were asked to assess the maturity of data analytics at their institution using the DELTA framework (Davenport & Harris, 2010).

## Participant Selection

In 2012 the EDUCAUSE Center for Applied Research (ECAR) conducted a study to examine the state of data analytics in U.S. higher education. Survey respondents were chief information officers and institutional researchers at EDUCAUSE member institutions. The survey in the present analysis uses the same institutional population, but targets academic leaders, defined as deans and department chairs or heads. The survey in the present analysis includes a subset of questions that were originally asked in the EDUCAUSE administered survey but were modified to fit the conceptual framework and the language of academic leaders.

The EDUCAUSE Center for Applied Research provided a list of the institutions that responded to their 2012 analytics survey. The original file contained 339 records. Within the file, 288 records included both the organization name and the Integrated

Postsecondary Education Data System (IPEDS) identification number, 47 records included the organization name but not the IPEDS identification number, and four records had an IPEDS identification number but no organization name. An IPEDS search was conducted to attempt to identify the missing information. Most of the institutions without an IPEDS identification number were international institutions; one institution was a preparatory high school; one institution could not be found; and one search resulted in multiple institutions with the same name identified so it was not possible to determine the specific institution. These 47 records were excluded from the study. Of the four records with an IPEDS identification number but no organization name, a search of the IPEDS database failed for three of the records and resulted in the identification of one institution.

After the first round of data validation, the file was reduced to 289 records. The 289 records with both an IPEDS identification number and institution name were entered into the IPEDS Data Tool. During this process, three of the IPEDS identification numbers were returned as invalid. An associated name search failed for two of the institutions, and one was identified and the IPEDS identification number was corrected. This process resulted in 287 validated IPEDS identification numbers with associated institutional names. Through review of the list, five records were identified as system offices or board offices and not campuses. These were eliminated from the file, resulting in a final list of 282 U.S. colleges and universities that participated in the original EDUCAUSE Analytics Survey.

In addition to the validated EDUCAUSE 2012 institutional respondents, unique additional institutions were identified as best-practice or leading institutions in the area of data analytics. The institutions were identified through the EDUCAUSE 2005 report (Goldstein & Katz, 2005) and through a study of analytics in higher education funded through the Bill & Melinda Gates Foundation (Norris & Baer, 2012). Three institutions appeared on both best-practice lists. In addition, 11 institutions from the EDUCAUSE 2012 Analytics Survey respondent list also were included in the Gates or EDUCAUSE 2005 best-practice list. The survey sample was expanded to include the additional 38 best-practice institutions, resulting in a total survey sample of 320 institutions with a subset of 49 best-practice institutions.

A sub-set of 20 institutions was randomly selected from the total sample to determine common disciplines from which the distribution list was developed. Through a Web search, the academic disciplines at each institution were identified and compared, and the three most common pure and applied disciplines were selected for the study: biology, management, English, nursing, political science and education.

A Web search was conducted to identify names and email addresses of deans and department chairs from the six academic disciplines at the 320 institutions in the sample. Institutions with fewer than three of the identified academic disciplines were eliminated from the survey population, as were institutions that did not publicly disclose email addresses of their employees. As a result, the final survey population was 255 institutions, with a subset of 37 best-practice institutions, which yielded 1910 deans and department chairs with valid email addresses.

## Survey Construction and Data Collection

The survey “Attitude and Usage of Data and Analytics” (Appendix A) is an original instrument that was constructed to collect data on the variables in the conceptual framework as defined by the operational definitions (Table 3). The instrument was created from modified versions of a sub-set of questions from the 2005 and 2012 EDUCAUSE surveys on data analytics in higher education (Goldstein & Katz, 2005; Bischel, 2012) and published instruments from previous research on adoption of technological innovations (Barki & Hartwick, 1994; Davis, 1989; Wixom & Todd, 2005). Questions designed to measure data analytics maturity were based on the DELTA framework (Davenport & Harris, 2010). Questions from the existing instruments or literature were selected based on their relevance to the conceptual framework and alignment with the operational definitions and were modified to fit the specific constructs under investigation and the academic environment. Additional original questions were written to measure variables in the conceptual framework that were not adequately addressed in the existing instruments.

The draft instrument was pre-tested on a total of ten deans and department chairs from the sample disciplines at a public, Masters-level university. Pre-test participants completed the survey in the presence of the researcher and commented on the instrument as they completed the survey. After completion of the survey, the researcher interviewed the pre-test participant to discover areas of confusion with language, question sequencing, and response categories. The instrument was revised, based on pre-test participant feedback, before final distribution.

The final survey was submitted to the University of Minnesota Institutional Review Board (IRB) and was determined to be exempt (Appendix C). After receiving IRB approval, the survey was distributed electronically to 1,910 chairs or heads of departments of biology, management, English, nursing, political science and education, as well as the deans who oversee those departments at each of the 255 U.S. higher education institutions in the sample. Potential respondents received an initial email on May 7, 2013, describing the purpose of the study and asking for their participation. The email contained a link to the electronic survey instrument. Potential participants received three reminder emails asking them to complete the survey. The survey was open through May 31, 2013, to allow enough time for respondents to complete the survey based on their availability. In all, 364 individuals started the survey, leading to 313 usable surveys, for a total individual response rate of 313/1910 or 16.4 percent. The respondents represent 179 different higher education institutions for an institutional response rate of 179/255 or 70.2 percent.

Individual and institutional characteristics that were recorded include the role and discipline of the respondent and the following institutional characteristics: status as a best-practice institution in data analytics, institutional control, and Carnegie Classification. The institutional characteristics were collected through IPEDS.

## Variables and Measures

Questions in the “Attitude and Usage of Data and Analytics” survey (Appendix B) were developed to measure the variables included in the conceptual framework. Scales were constructed from survey questions to measure the variables of collaboration, authenticity, training, institutional support, integrated use, analytics maturity, functionality, usability, usefulness, legitimacy, external pressure, individual adoption, and organizational implementation. Items associated with each scale are displayed in Chapter 4.

Exploratory factor analysis using principal axis factoring of survey questions related to organizational context, innovation characteristics, and usefulness variables suggested seven unique factors. Separate factor analyses were completed for survey questions from the DELTA framework used to analytics maturity, the blocks of questions from the EDUCAUSE survey used to measure legitimacy and external pressure, and the dependent variables of individual adoption and organizational implementation.

*Collaboration Scale:* Involvement of potential adopters in the design and execution of an organizational innovation is believed to influence implementation success (Greenhalgh, et al., 2004; Hargrave & Van de Ven, 2006; Heckscher & Adler, 2006; Klein, 2010). The survey included five questions intended to capture different opportunities for involvement of academic leaders in the development and implementation of data analytics at their institution. Using the five involvement questions identified through factor analysis, the first iteration of the collaboration scale was tested for reliability. While the collaboration scale achieved a high Cronbach's Alpha (0.908), two items in the scale were highly correlated, indicating they might be measuring the same dimension. The most highly correlated question was removed from the scale, and scale reliability was retested. The remaining four questions were combined to create the final collaboration scale which achieved a Cronbach's Alpha of 0.880. Scores for the collaboration scale generated from the survey responses have a positive skew (0.852), with a mean of 7.7 (*n*=234; *SD*=2.92) with a range of four to 16.

*Authenticity Scale:* Aligning an innovation with the organizational culture or redefining the organizational culture to align with the purpose of an innovation is important for implementation success (Argyris & Schön, 1996; Kezar, 2006; Schein, 2004; Van de Ven, 1996). Similarly, successful deployment of data analytics benefits from a data-driven culture (Bischel, 2012; Davenport & Harris, 2010). Respondents were asked six questions designed to capture different dimensions of their campus culture related to attitude toward and use of data. Factor analysis supported the inclusion of the six questions in a single scale. The authenticity scale was created using the six questions and achieved a Cronbach's Alpha of 0.732. Scores generated from the survey responses for the authenticity scale are normally distributed with a slight negative skew (-0.247) and have a mean of 8.9 (*n*=283; *SD*=2.23) with a range of four to 16.

*Institutional Support:* The type and level of resources an organization provides to support the implementation and adoption of an innovation are indicated to improve the likelihood of success (Baldridge, 1980; Davis, et al., 1982; Greenhalgh, et al., 2004; Kezar, 2003). Respondents were asked five questions designed to identify the mechanisms provided to support the implementation of data analytics. Factor analysis supported inclusion of the five questions in a single scale, and the scale was tested for reliability. The first iteration of the scale achieved a Cronbach's Alpha of 0.861 but violated Tukey's assumption of additivity. The question related to IT staff support was removed because it was highly correlated with the remaining questions. The final institutional support scale achieved a Cronbach's Alpha of 0.838 and no longer violated the additivity assumption. Scores generated from the survey responses for the institutional support scale are normally distributed with a slight negative skew (-0.140) and have a mean of 8.9 (*n*=209; *SD*=2.43) with a range of four to 16.

*Training:* The extent to which an organization provides opportunities for employee professional development and training to support their use of an innovation has been demonstrated to have a positive impact on individual adoption and use (Greenhalgh, et al., 2004; Kezar, 2006; Van Driel, et al., 1997). Respondents were asked three questions designed to capture the extent to which the institution provides training and professional development for the end user to use data analytics successfully. Factor analysis supported inclusion of the three questions in a single scale, and the scale was tested for reliability. The three questions were combined to create the training scale which achieved a Cronbach's Alpha of 0.801. Scores generated from the survey responses for the training scale are normally distributed and have a mean of 6.4 (*n*=242; *SD*=1.75) with a range of three to 12.

*Integrated Use:* Integration of an innovation into the existing organizational and operational systems is critical because it supports knowledge transfer about the innovation across organizational silos and highlights the importance of use of the innovation across systems within and outside the institution (Gioia & Thomas, 1996; Greenhalgh, et al., 2004; White & Glickman, 2007). Three questions were asked to determine the extent to which data and information from data analytics is integrated with institutional systems and processes. Factor analysis supported inclusion of the questions in a single scale, and the scale was tested for reliability. The three questions were combined to create the integrated use scale, and the resulting scale achieved a Cronbach's

Alpha of 0.755. Scores generated from the survey responses for the integrated use scale are normally distributed and have a mean of 7.6 (*n*=201; *SD*=1.95) with a range of three to 12.

*Analytics Maturity:* Within the field of data analytics, Davenport and Harris (2010) developed the DELTA framework as a way to understand the level of maturity an organization has achieved in data analytics. DELTA is an acronym for the five elements that Davenport and Harris (2010) believe must be addressed by an organization to implement and maintain a data analytics program successfully: data, enterprise approach, leadership, targets, and analytical talent. Five questions were included in the survey of academic leaders to capture their perceptions of where their organization is on each of the five DELTA elements. Each of the five questions has five levels of response, with each level representing a step forward in analytical maturity. Together, the five questions and five response levels allow for the creation of a 5x5 matrix to indicate an organization's data analytics maturity level. Using the five DELTA framework questions, an analytics maturity scale was created to provide a measure of data analytics maturity at the responding institutions. The resulting analytics maturity scale achieved a Cronbach's Alpha of 0.825. Scores generated from the survey responses for the analytics maturity scale are normally distributed, with a slight positive skew (0.118) and have a mean of 15.2 (*n*=266; *SD*=3.99) with a range of five to 25.

*Functionality:* Functionality is an important concept in innovation implementation because it speaks to the extent that the potential adopter believes the innovation being suggested for adoption actually addresses an organizational problem or provides a way to take advantage of an organizational opportunity (Kozma, 1985; Rogers, 2003; Van de

Ven, 1996). Respondents were asked four questions designed to capture the extent that academic leaders perceive the data and information available from data analytics addresses their professional and organizational needs. Factor analysis supported inclusion of the questions in a single scale, and the scale was tested for reliability. The four questions were combined to create the functionality scale, which achieved a Cronbach's Alpha of 0.789. Scores generated from the survey responses for the functionality scale are normally distributed with a slight negative skew (-0.267) and have a mean of 10.0 (*n*=192; *SD*=2.22) with a range of four to 16.

*Usability:* Previous research indicates that the easier an innovation is to use and to incorporate into existing practices, the more likely the user will be to adopt it (Barki & Hartwick, 1994; Wixom & Todd, 2005). Respondents were asked five questions to gauge the extent to which academic leaders perceive the data analytics system as flexible and easy to use. Factor analysis supported inclusion of the questions in a single scale, and the scale was tested for reliability. The five questions were combined to create the usability scale, which achieved a Cronbach's Alpha of 0.879. Scores generated from the survey responses for the usability scale are normally distributed with a slight negative skew (-0.206) and have a mean of 10.8 (*n*=215; *SD*=2.80) with a range of five to 20.

*Usefulness:* How useful an innovation is, or the extent to which individual adopters believe it improves their job performance, influences the extent to which professionals will adopt the innovation into their own practice. Respondents were asked three questions designed to capture the perception of academic leaders that the data analytics system and tools are useful in their professional role and aid them in decision-making. Factor analysis supported inclusion of the questions in a single scale, and the scale was tested for reliability. The initial scale achieved a Cronbach's Alpha=0.866, but two questions were highly correlated with each other (0.811) and had a significant result for Tukey's test for non-additivity. The mostly highly correlated question was removed from the scale, and the scale was re-tested. The two remaining questions in the final usefulness scale have a correlation of 0.601. Scores generated from the survey responses for the usefulness scale are normally distributed with a slight negative skew (-0.191) and have a mean of 4.9 ($n$=243; $SD$=1.30) with a range of two to eight.

*Legitimacy:* An innovation is seen as legitimate when potential adopters believe it to be appropriate for the organization and consistent with their professional values and practices. As legitimacy increases, so does adoption (DiMaggio & Powell, 1983; Hargrave & Van de Ven, 2006; Meyer et al., 2008; Rogers, 2003). In order to gauge the extent to which academic leaders perceive data analytics as beneficial to higher education, participants were asked to indicate the level of benefit the use of data analytics would provide in nine areas: containing or lowering the cost of education, recruiting students, helping students learn more effectively, helping students graduate on time, improving faculty performance, optimizing the use of resources, demonstrating higher education's effectiveness to external audiences, improving administrative performance, and informing strategic investments. In order to gauge their concern with the adoption of data analytics, participants were asked to indicate the level of concern with the use of data analytics in six areas: current models of measuring quality could be inadequate, current models of measuring productivity could be inadequate, governing bodies may mandate the use of data, wrong conclusions may be drawn about our institution, data will be misused, and using data analytics may be the wrong model for higher education.

Factor analysis of the benefit and concern questions suggested three different legitimacy variables: 1) benefit, 2) concern with data usage, and 3) concern with current models. The legitimacy/benefit scale gauges the extent to which academic leaders perceive data analytics to be beneficial to their organization and higher education. The legitimacy/concern with data use scale measures the extent to which academic leaders are concerned with the overall use of data analytics and how it may impact the organization. The legitimacy/concern with models scale gauges the extent to which academic leaders are concerned with the current models that are being used to judge the quality and productivity of higher education institutions.

Based on the results from the factor analysis, the nine benefit questions were combined to create the legitimacy/benefit scale, which achieved a Cronbach's Alpha of 0.880. Scores generated from the survey responses for the legitimacy/benefit scale are negatively skewed (-0.857) and have a mean of 21.7 ($n$=238; $SD$=3.98) with a range of nine to 27. The four concern questions regarding data use were combined to create the legitimacy/concern with data use scale, which achieved a Cronbach's Alpha of 0.744. Scores generated from the survey responses for the legitimacy/concern with data use scale are normally distributed with a slight negative skew (-0.108) and have a mean of 8.7 ($n$=269; $SD$=2.14) with a range of four to 12. Finally, the two concern questions regarding current models in use were combined to create the legitimacy/concern with models scale, which have a correlation of 0.792. Scores generated from the survey responses for the legitimacy/concern with models scale are negatively skewed (-0.973) and have a mean of 5.1 ($n$=284; $SD$=1.10) with a range of two to six.

*External Pressure:* Pressure from the external environment may impact an institution's adoption of data analytics. Survey respondents were asked to report the extent to which they feel each of the following will drive expanded use of data at their institution: reporting requirements of accrediting bodies, reporting requirements of their board of trustees, external competition, public accountability, pressure to identify cost savings, pressure to improve student learning, and pressure to improve student completion rates. In order to test the total influence external pressure has on individual adoption and organizational implementation, a scale that combines each driver into an external pressure scale was created. The question regarding reporting requirements of accrediting bodies was excluded from the scale, because it did not factor with the remaining questions under factor analysis and inclusion made the scale unreliable. The remaining six questions were combined to create the final external pressure scale, which achieved a Cronbach's Alpha of 0.799. Scores generated from the survey responses for the external pressure scale are negatively skewed (-0.786) and have a mean of 18.8 ($n$=287; $SD$=3.16) with a range of six to 24.

*Individual Adoption:* The conceptual framework developed from previous research on innovation implementation posits that individual adoption and organizational implementation may be different processes influenced by different variables. Three questions were asked to capture the extent to which academic leaders had incorporated data analytics into their professional practice in different decision settings: use of data analytics in formal meetings, use of data analytics in informal conversations, and use of data analytics to guide decision-making. The three use questions were combined to create the individual adoption scale, which achieved a Cronbach's Alpha of 0.884. Scores generated from the survey responses for the Individual Adoption Scale are negatively skewed (-0.626) and have a mean of 9.3 (*n*=262; *SD*=2.08) with a range of three to 12. The resulting individual adoption scale is used in later regression analysis as the dependent variable to examine variables associated with individual adoption of data analytics.

*Organizational Implementation:* A clear definition of the organizational implementation of an innovation is difficult to identify. As Rogers (2003) found, organizational implementation of an innovation is not a specific action or outcome that can be clearly identified but a process that moves from the decision to implement to a point at which the innovation is routinized. Implementation of data analytics is more complex than the implementation of the software or system to manage the data and report the analysis. It includes the use of data from the system in increasingly complex and sophisticated ways that move the organization toward enhanced, data-driven decision-making in strategic business processes that result in improved organizational performance. For this study, organizational implementation is measured by combining responses to the questions regarding depth of data usage across seven operational areas: course scheduling and staffing, enrollment management, student retention and graduation, strategic planning, student learning assessment, cost to deliver programs, and grants and research administration. The resulting organizational implementation scale provides an indication of both the extent of use of data analytics across different functions in the organization and the level at which data is used to support those functions. The organizational implementation scale achieved a Cronbach's Alpha of 0.867. Scores generated from the survey responses for the organizational implementation scale are negatively skewed (-0.743) and have a mean of 25.1 ($n$=212; $SD$=5.69) with a range of seven to 35. The organizational implementation scale is used in later regression analysis as the dependent variable to better understand variables that influence organizational implementation of data analytics.

Correlation analysis of the dependent scales suggests that they are distinct measures, though the correlations between functionality and usefulness (.795), functionality and usability (.761), and training and institutional support (.781) were strong (Appendix A).

## Analytical Approach

In the first stage of the analysis, the responses collected through surveys of deans and department chairs were analyzed using multiple regression analysis to determine to what extent the variables in the conceptual framework (Figure 1) are associated with individual adoption and organizational implementation of data analytics. In the first step of the analysis, the relationship between the organizational context variables (collaboration, authenticity, institutional support, training and integrated use) and the dependent variables of functionality and usability was investigated. In the second step of the analysis, the relationship between the organizational context and innovation characteristics variables and the dependent variables of usefulness and legitimacy was investigated. In the third step of the analysis, the relationship between the organizational context, innovation characteristics, and adopter attitude variables and the dependent variable of individual adoption was investigated. Finally the relationship between organizational context, innovation characteristics, adopter attitudes variables, and individual adoption and the dependent variable of organizational implementation was investigated.

In the second stage of the analysis, survey responses were analyzed using multiple regression analysis to determine to what extent the variables described in the modified conceptual framework (Figure 2), including the variable of analytics maturity, are associated with individual adoption and organizational implementation of data analytics.

# CHAPTER FOUR

# RESULTS

Based on previous research on the implementation of organizational innovations (see Chapter 2), ten variables have been identified that may have a significant impact on individual adoption and organizational implementation (see Figure 1 in Chapter 3). The ten independent variables describe the organizational context, external environment, innovation characteristics, and adopter attitudes that may influence success. In this chapter, the ten variables are examined using survey data gathered during May 2013 from deans and department chairs from the disciplines of biology, management, English, nursing, political science and education from a cross-section of U.S. higher education institutions. Analytical scales were created from survey questions that represent different dimensions of each variable. The contribution of these independent variables on the dependent variables of individual adoption and organizational implementation is examined using multiple regression analysis.

## Survey Respondents

Table 4 shows that, of the 313 individuals who responded to the survey, the majority of respondents were from institutions that had not been recognized as best-practice institutions in the area of data analytics (84 percent). More than half of respondents were department chairs (57 percent). The largest numbers of respondents were from the disciplines of nursing (20 percent) and English (20 percent) with the fewest respondents coming from biology (13 percent) and political science (14 percent). Two-thirds of respondents were from public institutions. Masters institutions had the greatest representation (35 percent) with baccalaureate institutions having the smallest (14 percent).

## Institutional Priority of Data Analytics

The rhetoric on the emerging importance of data analytics is somewhat supported by respondents' reports of its priority status at their institutions (Table 5). Respondents indicated that data analytics is a topic that is receiving increasing attention and prioritization on college campuses across the United States: 65 percent of survey respondents identified data analytics as a priority, either for their institution as a whole or for some units on their campus, and only 5 percent responded that it is not a priority or interest at their institution. The results are consistent with the 2012 EDUCAUSE survey, which found that 69 percent of chief information officers and institutional research professionals at the same institutions reported similar levels of prioritization (Bischel, 2012).

**Table 4: Survey Respondent Characteristics (n=313)**

| Characteristic | Total | Percent of Respondents |
|---|---|---|
| **Best-practice Institution** | | |
| Best-practice Institution | 51 | 16.3 |
| Not Best-practice Institution | 262 | 83.7 |
| **Role** | | |
| Dean | 134 | 42.8 |
| Department Chair | 179 | 57.2 |
| **Academic Discipline** | | |
| Biology | 42 | 13.4 |
| Management | 46 | 14.7 |
| English | 63 | 20.1 |
| Nursing | 64 | 20.4 |
| Political Science | 45 | 14.4 |
| Education | 53 | 16.9 |
| **Institutional Control** | | |
| Public | 210 | 67.1 |
| Private, not-for-profit | 103 | 32.9 |
| **Carnegie Classification** | | |
| Research | 96 | 30.7 |
| Masters | 108 | 34.8 |
| Baccalaureate | 44 | 14.1 |
| Associates | 65 | 20.8 |

The perception of prioritization of data analytics is not significantly different across respondent roles, institutional control or Carnegie Classification (Table 6). The perception of prioritization was significantly different across academic discipline. No significant difference was found based on best-practice status, which is surprising given that recognition as a best-practice institution in data analytics would seem to indicate a higher level of institutional or unit priority.

**Table 5: Status of Data Analytics at the Institution (n=313)**

| Status of data analytics at the institution | Responses |
|---|---|
| A major priority institution-wide | 23.5% |
| A major priority for some units, but not the entire institution | 41.8 |
| An interest for some units | 26.9 |
| Not a priority or interest | 5.4 |
| Don’t know | 2.4 |

**Table 6: Status of Data Analytics by Individual and Organizational Characteristics**

| Characteristic | Mean/SD | F |
|---|---|---|
| **Best-practice Institution** | | |
| Overall Mean | 2.9 (0.85) | 0.019 |
| Best-practice Institution | 2.9 (0.69) | |
| Not Best-practice Institution | 2.9 (0.88) | |
| **Role** | | |
| Overall Mean | 2.9 (0.85) | 2.386 |
| Dean | 2.9 (0.80) | |
| Department Chair | 2.8 (0.89) | |
| **Academic Discipline** | | |
| Overall Mean | 2.9 (0.85) | 2.996* |
| Biology | 2.6 (0.77) | |
| Management | 2.6 (0.97) | |
| English | 2.7 (0.91) | |
| Nursing | 3.1 (0.77) | |
| Political Science | 2.9 (0.76) | |
| Education | 3.1 (0.80) | |
| **Institutional Control** | | |
| Overall Mean | 2.9 (0.85) | 0.770 |
| Public | 2.9 (0.81) | |
| Private, not-for-profit | 2.8 (0.92) | |
| **Carnegie Classification** | | |
| Overall Mean | 2.9 (0.85) | 2.445 |
| Research | 2.9 (0.82) | |
| Masters | 2.8 (0.83) | |
| Baccalaureate | 2.6 (0.86) | |
| Associates | 3.1 (0.89) | |

*Response categories: 1=not a priority or interest; 2=an interest for some units; 3=a major priority for some units but not the entire institution; 4=a major priority institution wide; Significance:* $p<.05$; ** $p<.01$;*** $p<.001$*

**Survey Response Frequencies and Analysis**

This study investigates how individual adoption and successful implementation of an innovation may be driven by the organizational context in which the program is implemented, the external environment in which the organization exists, the acquired characteristics of the innovation, and academic leaders' attitude toward the innovation. Successful implementation also may be influenced by the experience and background of the adopters and the type of institution at which they are employed. The response frequencies to survey questions used to construct the analytical scales are analyzed in this section.

The hypothesized conceptual framework for implementing innovations in higher education organizations (Figure 1) is an extension of Roger's (2003) theory of organizational innovation and is described in significant detail in Chapter 3. The conceptual framework includes five variables that describe the organizational context in which the innovation is being implemented (collaboration, authenticity, institutional support, training and integrated use), two variables that describe the acquired characteristics of the innovation (functionality and usability), and two variables that describe the individual adopter's attitude toward the innovation (usefulness and legitimacy). It is hypothesized that these variables, along with pressure from the external environment, combine to positively influence both individual adoption and organizational implementation.

**Collaboration: Involvement of Academic Leaders in Data Analytics Development**

Overall, academic leaders report limited involvement in the implementation of data analytics at their institutions (Table 7). Fewer than 35 percent of respondents report that academic leaders at their institution were very or somewhat involved in any of the aspects of development or implementation. Their most significant area of involvement appears to be in the defining of data and metrics that are used in the system, with 9 percent reporting academic leaders were very involved and 23 percent reporting they were somewhat involved. The area of least involvement was in experimenting with the analytics system before full implementation (with 2 percent reporting academic leaders were very involved and 14 percent reporting they were somewhat involved) and designing screen layouts or data presentations, with more than half of the respondents saying academic leaders were not at all involved (51 percent).

**Table 7: Descriptive Analysis: Collaboration Scale Items (n=234)**

| *How engaged have deans and department chairs, heads, or directors at your institution been in the following aspects of data analytics?* | Very | Some what | A little | Not at all | Don't know |
|---|---|---|---|---|---|
| Defining data and metrics | 8.8% | 23.3% | 44.3% | 20.2% | 3.4% |
| Overall planning of the analytics system for tools | 6.9 | 21.4 | 42.7 | 24.8 | 4.2 |
| Designing screen layouts or data presentations | 3.1 | 13.4 | 26.0 | 50.8 | 6.9 |
| Experimenting with the analytics tools before full implementation | 2.3 | 13.8 | 30.7 | 43.3 | 10.0 |

*Cronbach's Alpha = 0.880*

## Authenticity: Organizational Culture Related to Data Analytics and Data Usage

A majority of respondents report that their institutions are moving toward a more data-driven culture (Table 8). More than 86 percent strongly agree or agree that their administration largely accepts the use of data in measuring performance. Nearly 72 percent strongly agree or agree that their institution has a culture that supports the use of data to make decisions. Respondents also report that their faculty largely accepts the use of data in measuring performance (65 percent), but not at the same levels as their administration.

Respondents were less positive about activities at their institution that directly link data to actions. More than half of respondents report that their institution has clearly defined performance outcomes (57 percent strongly agree or agree), consistently make changes based on data (57 percent strongly agree or agree), and direct resources to units where decisions are data driven (51 percent strongly agree or agree). Interestingly, 10 percent of respondents said they “don’t know” if resources flow to units that are data driven, indicating a possible lack of visibility in the connection between data use and resource distribution.

**Table 8: Descriptive Analysis: Authenticity Scale Items (n=283)**

| *To what extent do you agree with the following statements about your institution?* | Strongly agree | Agree | Disagree | Strongly disagree | Don't know |
|---|---|---|---|---|---|
| Our administration largely accepts the use of data in measuring performance | 27.7% | 58.5% | 10.9% | 1.6% | 1.3% |
| We have a culture that supports the use of data to make decisions | 16.7 | 55.0 | 20.6 | 5.5 | 2.3 |
| Our faculty largely accept the use of data in measuring performance | 12.8 | 52.6 | 26.3 | 5.4 | 2.9 |
| We have clearly defined performance outcomes | 14.5 | 42.8 | 34.1 | 7.4 | 1.3 |
| We consistently make changes based on data | 8.0 | 49.0 | 35.6 | 5.1 | 2.2 |
| Resources flow to units where decisions are data driven | 4.5 | 46.9 | 29.1 | 9.4 | 10.0 |

*Cronbach's Alpha = 0.831*

## Institutional Support: Organizational Backing for Implementing Data Analytics

From the perspective of academic leaders, their organizations have not done a particularly good job of supporting data analytics at their institution (Table 9). Fewer than half of respondents agree their institution has provided appropriate tools and software (43 percent). Approximately one-third agree their institution has provided timely information about changes to the data analytics system (35 percent) or has provided well-trained staff to develop models and provide analysis (33 percent). Less than one-quarter agree their institution has provided adequate funding for data analytics (24 percent).

## Training: Individual Support for Data Analytics Adoption

Academic leaders indicate that their institutions have not provided adequate support to them so they could more successfully use data analytics in their own practice (Table 10). Fewer than one-third of respondents agreed that their organization provided clear definitions of data used for data analytics (32 percent). Fewer than one-quarter agreed that their organization provided effective training for users (23 percent) or provided professional development in using data in decision-making (21 percent). The finding is important because academic leaders are reporting that they have not received sufficient professional development on how to use data, even as higher education institutions are experiencing growing pressure to increase the use of data in decision-making.

**Table 9: Descriptive Analysis: Institutional Support Scale Items (n=209)**

| *For data analytics, my institution has provided:* | Strongly agree | Agree | Disagree | Strongly disagree | Don't know |
|---|---|---|---|---|---|
| Appropriate tools and software for data analytics | 2.3% | 40.2% | 38.6% | 9.8% | 9.1% |
| Timely information about changes to the system | 2.7 | 32.7 | 44.5 | 14.1 | 6.1 |
| Well-trained staff to develop models and provide analysis | 2.3 | 30.2 | 47.3 | 15.6 | 4.6 |
| Adequate funding | 1.9 | 22.3 | 45.8 | 19.3 | 10.6 |

*Cronbach's Alpha = 0.838*

**Table 10: Descriptive Analysis: Training Scale Items (n=242)**

| *For data analytics, my institution has provided:* | Strongly agree | Agree | Disagree | Strongly disagree | Don't know |
|---|---|---|---|---|---|
| Clear definitions of data used | 2.7% | 29.2% | 50.8% | 12.9% | 4.5% |
| Effective training for users | 1.5 | 21.6 | 57.2 | 15.5 | 4.2 |
| Appropriate professional development on how to use data in decision-making | 2.3 | 19.0 | 58.9 | 17.5 | 2.3 |

*Cronbach's Alpha = 0.810*

### Integrated Use: Incorporating Data Analytics into the Institution

Survey respondents report that data analytics is somewhat integrated with other systems and operations at their institution (Table 11). Fifty-five percent of respondents report that their data analytics tools report data linked to their strategic goals to at least some extent. Fewer than half said their data analytics systems provide data to external stakeholders (46 percent) or integrate data from different sources (37 percent). With more than half of respondents reporting that their institution's data analytics systems integrate data from different sources very little or not at all, it is not surprising that many higher education organizations struggle to implement data analytics successfully.

### Analytics Maturity: Systems and Structures to Support Data Analytics

The frequency of responses for each of the DELTA framework questions provides a picture of the overall level of data analytics maturity of the responding institutions (Table 12). The largest percentage of respondents report that their organization has Level 2 Data "usable data but in silos" (39 percent), Level 2 Enterprise Systems, "unconnected data systems" (35 percent), Level 4 Leadership, "most administrators usually use data" (33 percent), Level 3 Targets, "a small set of goals linked to our strategic plan" (38 percent), and Level 3 Analytical Talent, "skilled analysts in a few key areas" (43 percent).

**Table 11: Descriptive Analysis: Integrated Use Scale Items (n=201)**

| *To what extent do your institution's data analytics tools:* | Great extent | Some extent | Very little | Not at all | Don't know |
|---|---|---|---|---|---|
| Report data linked to your strategic goals | 11.5% | 43.5% | 33.8% | 7.3% | 3.8% |
| Provide data to external stakeholders | 10.7 | 35.2 | 27.6 | 7.7 | 18.8 |
| Integrate data from different sources | 5.0 | 32.2 | 42.9 | 10.0 | 10.0 |

*Cronbach's Alpha = 0.755*

**Table 12: Analytics Maturity Scale Construction (n=266)**

| | |
|---|---|
| **Data Quality: Which phrase best describes the quality of data available to you for decisions?** | |
| Integrated, accurate and accessible data with new data incorporated regularly | 7.0% |
| Integrated, accurate and accessible institutional data | 11.0 |
| Usable data that is centrally stored | 30.2 |
| Usable data but in silos | 38.9 |
| Unintegrated, poor quality data | 11.3 |
| Don't know | 1.7 |
| **Enterprise Systems: Which phrase best describes your institution's data systems?** | |
| Central data system for analysis | 11.6% |
| Central data system for standard reporting | 30.6 |
| Central data system in development | 16.6 |
| Unconnected data systems | 35.2 |
| No real data system | 1.0 |
| Don't know | 5.0 |
| **Leadership: Which phrase best describes the use of data in decision-making at your institution?** | |
| All administrators regularly use and promote the use of data | 17.1% |
| Most administrators usually use data | 32.9 |
| Many administrators are beginning to use data | 25.8 |
| A few administrators use data | 19.5 |
| Administrators are uninterested in using data | 2.3 |
| Don't know | 2.3 |
| **Targets: Which phrase best describes the use of performance goals at your institution?** | |
| A comprehensive set of strategic goals with ongoing data analysis | 15.3% |
| A comprehensive set of goals linked to our strategic plan | 31.7 |
| A small set of goals linked to our strategic plan | 38.0 |
| A few disconnected goals | 12.0 |
| No strategic or operational goals | 2.0 |
| Don't know | 1.0 |
| **Analysts: Which phrase best describes the availability of staff to conduct data analysis at your institution?** | |
| Highly skilled analysts available to all areas | 2.6% |
| Skilled analysts available to all areas | 7.3 |
| Skilled analysts in a few key areas | 43.4 |
| Some with basic skills in data analysis | 22.8 |
| A few skills in data analysis | 21.9 |
| Don't know | 2.0 |

*Cronbach's Alpha = 0.825*

On average, institutions are between Level 2 and Level 3 on the Analytics Maturity Scale, which is defined by Davenport and Harris (2010) as being somewhere between "Localized Analytics" and having "Analytical Aspirations," but the range of maturity across institutions is surprising. Many institutions report characteristics of their data analytics program that would place them at "Level 1: Analytically Impaired." Especially striking is the percentage of respondents who report they have "unintegrated, poor quality data" (11 percent) and "a few [people] with skills in data analysis" (22 percent). On the other end of the spectrum are respondents who report characteristics of "Stage 5: Analytical Competitors." Seven percent of respondents said their organizations have "integrated, accurate and accessible data with new data incorporated regularly"; 15 percent said they have a comprehensive set of performance goals with ongoing data analysis; 17 percent said "all administrators regularly use and promote the use of data"; 12 percent report having a "central data system for analysis"; but only 3 percent report having "highly skilled analysts available to all areas."

Consistent with both the McKinsey Group study (Manyika et al., 2011) and the EDUCAUSE Analytics 2012 report (Bischel 2012), access to highly trained analysts to conduct data analytics appears to be a significant challenge facing higher education organizations in implementing a data analytics program.

## Functionality: Addressing Organizational Needs through Data Analytics

Academic leaders are having a mixed experience with the functionality of data and reporting available to them through the analytics system (Table 13). Just over two-thirds of respondents said the data analytics tools available to them provide accurate data, to some or a great extent (69 percent), but just over one-third said they allow for adaptations (36 percent) to at least the same extent. Fewer than 40 percent agree that the system provides the right kind of data (39 percent) or has significantly improved decision-making at their institution (37 percent). These results indicate that there may be a disconnect between the data available to academic leaders and the type of data they need to make organizational decisions.

**Table 13: Descriptive Analysis: Functionality Scale Items (n=192)**

| *To what extent do your institution's data analytics tools:* | Great extent | Some extent | Very little | Not at all | Don't know |
|---|---|---|---|---|---|
| Provide accurate data | 10.4% | 58.5% | 19.6% | 3.1% | 8.5% |
| Allow for adaptations to meet different needs | 3.8 | 32.2 | 41.4 | 11.5 | 11.1 |

| *In my experience, my institution's data analytics tools:* | Strongly agree | Agree | Disagree | Strongly disagree | Don't know |
|---|---|---|---|---|---|
| Provide the right kind of data | 1.1% | 38.2% | 45% | 9.2% | 6.5% |
| Have significantly improved decision-making at my institution | 3.8 | 33.5 | 38.8 | 9.5 | 14.4 |

*Cronbach's Alpha = 0.789*

## Usability: Ease of Incorporating Data Analytics into Professional Practice

Overall, academic leaders do not find the data analytics tools available to them to be particularly usable (Table 14). Fewer than one-third of respondents agree that their institution's data analytics tools provide reports in the right format (32 percent), make information easy to access (30 percent), or do what they want them to do (28 percent). Only one-quarter of respondents agree that their data analytics tools are versatile in addressing needs as they arise (26 percent) or were easy to operate (23 percent). In fact not a single respondent strongly agreed that their institution's data analytics tools were easy to operate.

## Usefulness: Using Data Analytics to Improve Professional Practice

Academic leaders report that data analytics are having a limited impact on their own decision-making (Table 15). More than 60 percent of respondents said that data analytics has improved their ability to make good decisions to a great or some extent (60 percent), while just over one-third agree that data analytics enables them to make decisions more quickly (36 percent).

**Table 14: Descriptive Analysis: Usability Scale Items (n=215)**

| *In my experience, my institution's data analytics tools:* | Strongly agree | Agree | Disagree | Strongly disagree | Don't know |
|---|---|---|---|---|---|
| Provide data in the right format | 1.1% | 30.7% | 50.8% | 12.5% | 4.9% |
| Make information easy to access | 1.1 | 29.2 | 53.4 | 13.6 | 2.7 |
| Do what I want them to do | 1.1 | 27.3 | 52.3 | 12.5 | 6.8 |
| Are versatile in addressing needs as they arise | 1.9 | 24.0 | 51.7 | 12.2 | 10.3 |
| Are easy to operate | 0.0 | 23.2 | 51.3 | 16.3 | 9.1 |

*Cronbach's Alpha = 0.879*

**Table 15: Descriptive Analysis: Usefulness Scale Items (n=243)**

| *In my experience, my institution's data analytics tools:* | Strongly agree | Agree | Disagree | Strongly disagree | Don't know |
|---|---|---|---|---|---|
| Enable me to make decisions quickly | 1.1% | 35.1% | 47.7% | 11.1% | 5.0% |
| *To what extent do your institution's data analytics tools:* | Great extent | Some extent | Very little | Not at all | Don't know |
| Improve my ability to make good decisions | 10.7 | 49.6 | 30.5 | 6.9 | 2.3 |

*Correlation = 0.601*

## Legitimacy: Perception of Benefits of Data Analytics

Respondents were asked to indicate the level of potential benefit from the use of data analytics. Academic leaders report the greatest benefits of data analytics to be in the areas of optimizing resources, recruiting students, demonstrating higher education's benefit to external audiences, and informing strategic investments, with more than 50 percent of respondents indicating they believe data analytics could provide a "major benefit" in these areas. Academic leaders anticipated lower levels of benefit from data analytics in improving administrative and faculty performance and containing or lowering the cost of education, with 35 percent or fewer of respondents indicating they saw data analytics providing a major benefit in these areas (Table 16).

**Table 16: Descriptive Analysis: Legitimacy/Benefit Scale Items (n=283)**

| *What kind of benefit do you think data analytics will yield in the following areas?* | Major benefit | Minor benefit | No benefit | Don't know |
|---|---|---|---|---|
| Optimizing use of resources | 60.5% | 33.0% | 3.7% | 2.7% |
| Recruiting students | 57.0 | 35.8 | 3.4 | 3.8 |
| Demonstrating higher education's effectiveness to external audiences | 54.4 | 36.4 | 5.8 | 3.4 |
| Informing strategic investments | 50.3 | 33.2 | 5.5 | 11.0 |
| Helping students learn more effectively | 49.7 | 41.5 | 6.1 | 2.7 |
| Helping students graduate on time | 46.6 | 42.1 | 8.9 | 2.4 |
| Containing or lowering the cost of education | 35.0 | 46.3 | 9.9 | 8.8 |
| Improving administrative performance | 35.0 | 45.9 | 13.6 | 5.4 |
| Improving faculty performance | 27.9 | 56.8 | 12.9 | 2.4 |

*Cronbach's Alpha = 0.880*

## Legitimacy/Concerns with Data Use

As in the case of perception of benefit, respondents were asked to indicate their level of potential concern with the use of data analytics (Table 17). Their greatest areas of concern are that wrong conclusions will be drawn about their institution, with 94 percent reporting a major or minor concern, and that data will be misused, with more than 80 percent of respondents reporting a concern. Respondents were split about concern that governing bodies may mandate the use of data, with 44 percent reporting a major concern, 32 percent reporting a minor concern and 24 percent reporting no concern. They also were split on the appropriateness of data analytics as a model for higher education, with 29 percent of respondents reporting a major concern, 35 percent reporting a minor concern, and 32 percent saying it was no concern.

## Legitimacy/Concerns with Current Models

The greatest concern among all respondents is that current models of measuring both quality and productivity could be inadequate, with 64 percent and 53 percent respectively reporting a major concern (Table 18). Only 4 percent and 6 percent respectively indicated that they had “no concern” with these issues.

When taken together, responses to concern with use and concern with current models may indicate that academic leaders are not necessarily concerned that data analytics is the wrong approach for higher education, but they believe that the current models in use are inadequate and do not serve them well.

**Table 17: Descriptive Analysis: Legitimacy/Concern with Data Use Scale Items (n=269)**

| *What kind of concern, if any, do you have about the use of data analytics?* | Major concern | Minor concern | No concern | Don't know |
|---|---|---|---|---|
| Governing bodies may mandate the use of data | 44.0% | 31.7% | 23.5% | 0.7% |
| Wrong conclusions may be drawn about our institution | 38.6 | 55.3 | 5.5 | 0.7 |
| Data will be misused | 30.1 | 51.7 | 17.1 | 1.0 |
| Using data analytics may be the wrong model for higher education | 28.6 | 34.8 | 32.4 | 4.2 |

*Cronbach's Alpha = 0.744*

**Table 18: Descriptive Analysis: Legitimacy/Concern with Model Scale Items (n=284)**

| *What kind of concern, if any, do you have about the use of data analytics?* | Major concern | Minor concern | No concern | Don't know |
|---|---|---|---|---|
| Current models of measuring quality could be inadequate | 63.7% | 31.2% | 3.8% | 1.4% |
| Current models of measuring productivity could be inadequate | 53.2 | 38.6 | 5.5 | 2.7 |

*Correlation = 0.792*

## External Pressure: Environmental Drivers for Data Analytics Adoption

Academic leaders report experiencing widespread external pressure to adopt more extensive use of data analytics (Table 19). When the response categories of "great extent" and "some extent" are combined, at least 70 percent of respondents reported that each category will drive expanded data use. Respondents hold an almost universal view that accrediting bodies are a driver for the expanded use of data and data analytics. More than 97 percent of respondents said that the reporting requirements of accrediting bodies will drive expanded use of data, to a great or to some extent. Not a single respondent answered "not at all." Reporting requirements of accrediting bodies is the only potential driver for which a majority of respondents indicated it will drive adoption to a great extent.

After the influence of accrediting bodies, the next three most important external drivers are pressure to improve student learning and student completion rates and to identify cost savings. Each of the areas involves more specific analysis of internal operations, which are likely driven by external pressure for performance.

**Table 19: Descriptive Analysis: External Pressure Scale Items (n=287)**

| *To what extent do you think the following will drive expanded use of data at your institution?* | Great extent | Some extent | Very little | Not at all | Don't know |
|---|---|---|---|---|---|
| Reporting requirements of accrediting bodies | 67.7% | 29.4% | 2.2% | 0.0% | 0.6% |
| Pressure to improve student learning | 37.2 | 53.5 | 7.1 | 1.9 | 0.3 |
| Pressure to improve student completion rates | 45.5 | 41.0 | 10.0 | 1.9 | 1.6 |
| Pressure to identify cost savings | 39.6 | 45.4 | 12.5 | 0.6 | 1.9 |
| External competition | 21.5 | 55.4 | 17.6 | 3.2 | 2.2 |
| Public accountability | 24.9 | 49.5 | 19.2 | 4.8 | 1.6 |
| Reporting requirements of your board of trustees | 29.6 | 42.8 | 20.6 | 4.5 | 2.6 |

*Cronbach's Alpha = 0.796*

## Individual Adoption of Organizational Innovations

An examination of the frequencies of responses to each question that makes up the individual adoption scale indicates that most respondents use data analytics to some extent (Table 20), with more than 83 percent reporting they use data analytics to a great or some extent to guide their decision-making in the last year. Nearly 83 percent said they used data analytics in discussions at college or department meetings, and nearly 76 percent used data analytics during informal conversations with colleagues in the last year.

A separate survey question assessed respondents' future use of data analytics (Table 21). Not only do academic leaders report relatively strong usage of data analytics within the last year, they also report anticipating increased use over the next year. Nearly 80 percent said their usage of data analytics will increase either substantially or slightly.

**Table 20: Descriptive Analysis: Individual Adoption Scale Items (n=262)**

| *To what extent have you used data analytics for the following in the last year?* | Great extent | Somewhat | Very little | Not at all |
|---|---|---|---|---|
| Used data analytics to guide your own decision-making in the last year | 37.4% | 46.2% | 14.5% | 1.9% |
| Used data analytics in discussions at college or department meetings in the last year | 35.9 | 46.9 | 13.4 | 3.8 |
| Used data analytics during informal conversations with colleagues in the last year | 23.7 | 51.9 | 21.0 | 3.4 |

*Cronbach's Alpha = 0.884*

**Table 21: How do you anticipate your usage of data analytics will change in the next year? (n=262)**

| Response | Percentage |
|---|---|
| Increase substantially | 37.4% |
| Increase slightly | 42.4 |
| Stay about the same | 19.1 |
| Decrease slightly | 0.4 |
| Decrease substantially | 0.8 |

**Organizational Implementation: Depth of Data Usage Across Operational Functions**

As originally indicated in the 2012 EDUCAUSE study (Bischel 2012), data usage varies across institutions and across operational functions within institutions. A question format similar to that of the 2012 EDUCAUSE survey asked academic leaders to indicate the level of data usage within their own unit across seven functional categories: grants and research administration, enrollment management, student retention and graduation, course scheduling and staffing, cost of delivering programs, student learning assessment, and strategic plan implementation. Respondents were asked to indicate the highest level of data usage within their unit for each functional category: use data to forecast performance, use data to inform planning, use data to monitor progress, collect data but it is rarely used, and don't collect data.

The fourth and fifth categories (use data to inform planning and use data to forecast performance) traditionally define entrance into the realm of data analytics. When these two categories are combined, it appears that higher education institutions have made the most progress in the more operations-centric functions of course staffing and scheduling (69 percent) and enrollment management (68 percent), with nearly 70 percent of respondents indicating they use data to inform planning or forecast performance in these areas. The functional categories in which data analytics is least utilized is in managing the cost to deliver programs (44 percent) and grants and research administration (35 percent). Surprising is the moderate use of data analytics in the area of student learning assessment (52 percent) and student retention and graduation (60 percent), given the high profile these operational areas have achieved among accrediting bodies and public accountability reports (Table 22).

**Table 22: Descriptive Analysis: Organizational Implementation Scale Items (n=212)**

| *What is the highest level at which data is used in your unit?* | Use data to forecast performance | Use data to inform planning | Use data to monitor progress | Collect data but it is rarely used | Don't collect data | Don't know |
|---|---|---|---|---|---|---|
| Course schedules and staffing | 18.2% | 50.8% | 15.7% | 7.0% | 6.7% | 1.6% |
| Enrollment management | 30.4 | 37.7 | 17.3 | 5.4 | 3.2 | 6.1 |
| Student retention and graduation | 26.0 | 34.0 | 26.6 | 7.4 | 3.2 | 2.9 |
| Strategic planning | 17.6 | 41.3 | 17.9 | 9.6 | 6.4 | 7.1 |
| Student learning assessment | 16.6 | 35.1 | 34.5 | 10.5 | 2.6 | 0.6 |
| Cost to deliver programs | 11.3 | 32.8 | 14.1 | 17.0 | 11.6 | 13.2 |
| Grants and research administration | 9.7 | 25.5 | 25.8 | 9.7 | 10.0 | 19.4 |

*Cronbach's Alpha = 0.884*

Within each functional category, academic leaders are using data at different levels depending on their role and academic discipline. The mean level of data usage for strategic plan implementation is 3.6, which means the average academic unit is moving from using data to monitor the progress of their strategic plan to using data to inform changes to their strategic plan. The mean level of usage is similar across all individual and organizational characteristics, with the exception of academic discipline (Table 25).

The mean level of data usage for student learning assessment is 3.5, which means the average academic unit is moving from monitoring student learning to using data to inform curricular planning. Again, the mean level of usage is similar across all individual and organizational characteristics, with the exception of academic discipline (Table 25). Academic leaders in nursing and education report using data at higher levels in the area of student learning assessment.

The mean level of data usage related to student retention and graduation is 3.7 but varies considerably across individual and institutional characteristics. A statistically significant difference exists based on status as a best-practice institution, but it is academic leaders from institutions that have not been recognized as best-practice institutions that report a higher level of data usage in this area (Table 23). Statistically significant differences are reported based on role, with deans reporting higher usage (Table 24), and institutional control, with private institutions reporting higher usage (Table 26). Within academic disciplines, biology and nursing report higher usage levels (Table 25).

The mean level of data usage for managing the cost of delivering programs is 3.2, with little variability across individual and organizational characteristics. The one exception is academic discipline (Table 25).

The mean data usage for enrollment management is 3.9, which means institutions are consistently using data to inform enrollment planning. Usage does vary based on role within the institution, institutional control and Carnegie Classification. Deans report their units engage in higher levels of data usage for enrollment management than department chairs (Table 24); private institutions report higher levels than public institutions (Table 26); and baccalaureate institutions report higher levels than the other Carnegie Classifications (Table 27).

Academic leaders report mean data usage in the area of grants and research administration of 3.2, which can be interpreted as the average institution is using data to monitor progress of their grants and research activity. Mean data usage for grants and research administration varied significantly based on the following: role within the institution, with deans reporting higher levels of usage than department chairs (Table 24); academic discipline, with nursing and education reporting higher levels of usage (Table 25); institutional control, with public institutions reporting significantly higher levels of usage than private, not-for-profit institutions (Table 26); and Carnegie Classification, with research institutions reporting higher levels of usage than baccalaureate institutions (Table 27).

**Table 23: Mean Data Usage by Best Practice Status**

| | Overall Mean | Best-Practice Institution | Not Best-Practice Institution | F |
|---|---|---|---|---|
| Course Scheduling and Staffing | 3.7 (1.07) | 3.7 (1.06) | 3.7 (1.07) | 0.117 |
| Enrollment Management | 3.9 (1.02) | 3.9 (1.14) | 3.9 (1.00) | 0.268 |
| Student Retention and Graduation | 3.7 (1.04) | 3.5 (1.22) | 3.8 (0.99) | 4.482* |
| Strategic Plan Implementation | 3.6 (1.12) | 3.5 (1.31) | 3.6 (1.08) | 0.698 |
| Student Learning Assessment | 3.5 (0.98) | 3.5 (1.05) | 3.5 (0.96) | 0.404 |
| Cost of Delivering Programs | 3.2 (1.27) | 3.1 (1.32) | 3.2 (1.26) | 0.047 |
| Grants and Research Administration | 3.2 (1.18) | 3.3 (1.26) | 3.2 (1.16) | 0.172 |

*Response categories: 1=Don't collect data; 2=Collect data but it is rarely used; 3=Use data to monitor progress; 4=Use data to inform planning; 5=Use data to forecast performance. Significance: * p<.05; ** p<.01;*** p<.001*

**Table 24: Mean Data Usage by Role at Institution**

| | Overall Mean | Dean | Department Chair | F |
|---|---|---|---|---|
| Course Scheduling and Staffing | 3.7 (1.07) | 3.8 (0.96) | 3.6 (1.14) | 2.529 |
| Enrollment Management | 3.9 (1.02) | 4.1 (0.97) | 3.8 (1.05) | 3.912* |
| Student Retention and Graduation | 3.7 (1.04) | 3.9 (0.96) | 3.6 (1.08) | 5.032* |
| Strategic Plan Implementation | 3.6 (1.12) | 3.6 (1.02) | 3.5 (1.19) | 0.803 |
| Student Learning Assessment | 3.5 (0.98) | 3.6 (0.99) | 3.4 (0.96) | 3.309 |
| Cost of Delivering Programs | 3.2 (1.27) | 3.3 (1.19) | 3.0 (1.32) | 3.029 |
| Grants and Research Administration | 3.2 (1.18) | 3.4 (1.00) | 3.0 (1.31) | 6.535* |

*Response categories: 1=Don't collect data; 2=Collect data but it is rarely used; 3=Use data to monitor progress; 4=Use data to inform planning; 5=Use data to forecast performance.*
*Significance: * p<.05; ** p<.01;*** p<.001*

**Table 25: Mean Data Usage by Academic Discipline**

| | Overall Mean | Biology | Management | English | Nursing | Political Science | Education | F |
|---|---|---|---|---|---|---|---|---|
| Course Scheduling and Staffing | 3.7 (1.07) | 3.8 (0.89) | 3.7 (1.14) | 3.6 (1.12) | 3.7 (1.02) | 3.8 (1.06) | 3.6 (1.18) | 0.253 |
| Enrollment Management | 3.9 (1.02) | 3.9 (1.00) | 3.7 (1.21) | 3.9 (0.99) | 4.0 (1.00) | 3.8 (1.06) | 4.2 (0.84) | 1.320 |
| Student Retention and Graduation | 3.7 (1.04) | 4.1 (0.73) | 3.6 (1.26) | 3.4 (0.90) | 4.0 (1.02) | 3.4 (1.27) | 4.1 (0.78) | 5.318*** |
| Strategic Plan Implementation | 3.6 (1.12) | 3.5 (0.99) | 3.2 (1.35) | 3.6 (1.05) | 3.8 (1.09) | 3.4 (1.18) | 3.8 (0.97) | 2.371* |
| Student Learning Assessment | 3.5 (0.98) | 3.4 (0.94) | 3.5 (1.04) | 3.3 (0.93) | 3.8 (1.07) | 3.4 (0.94) | 3.7 (0.85) | 2.411* |
| Cost of Delivering Programs | 3.2 (1.27) | 3.4 (1.20) | 2.8 (1.26) | 3.0 (1.27) | 3.5 (1.16) | 2.9 (1.46) | 3.3 (1.18) | 2.427* |
| Grants and Research Administration | 3.2 (1.18) | 3.1 (1.18) | 2.9 (1.12) | 3.2 (1.19) | 3.5 (1.03) | 2.8 (1.43) | 3.4 (1.08) | 2.387* |

*Response categories: 1=Don't collect data; 2=Collect data but it is rarely used; 3=Use data to monitor progress; 4=Use data to inform planning; 5=Use data to forecast performance. Significance: * p<.05; ** p<.01;*** p<.001*

**Table 26: Mean Data Usage by Institutional Control**

| | Overall Mean | Public | Private, not-for-profit | F |
|---|---|---|---|---|
| Course Scheduling and Staffing | 3.7 (1.07) | 3.7 (1.01) | 3.5 (1.17) | 2.603 |
| Enrollment Management | 3.9 (1.02) | 3.8 (1.01) | 4.1 (1.01) | 6.376* |
| Student Retention and Graduation | 3.7 (1.04) | 3.6 (1.07) | 3.9 (0.95) | 5.809* |
| Strategic Plan Implementation | 3.6 (1.12) | 3.6 (1.14) | 3.6 (1.07) | 0.457 |
| Student Learning Assessment | 3.5 (0.98) | 3.6 (0.99) | 3.5 (0.95) | 0.672 |
| Cost of Delivering Programs | 3.2 (1.27) | 3.2 (1.25) | 3.1 (1.30) | 0.969 |
| Grants and Research Administration | 3.2 (1.18) | 3.3 (1.10) | 2.8 (1.27) | 9.786** |

*Response categories: 1=Don't collect data; 2=Collect data but it is rarely used; 3=Use data to monitor progress; 4=Use data to inform planning; 5=Use data to forecast performance. Significance: * p<.05; ** p<.01;*** p<.001*

**Table 27: Mean Data Usage by Carnegie Classification**

| | Overall Mean | Research | Masters | Baccalaureate | Associates | F |
|---|---|---|---|---|---|---|
| Course Scheduling and Staffing | 3.7 (1.07) | 3.8 (1.00) | 3.7 (1.00) | 3.6 (1.32) | 3.5 (1.10) | 0.657 |
| Enrollment Management | 3.9 (1.02) | 3.8 (1.10) | 4.1 (0.93) | 4.2 (1.02) | 3.8 (1.01) | 2.698* |
| Student Retention and Graduation | 3.7 (1.04) | 3.6 (1.11) | 3.8 (1.01) | 3.9 (1.07) | 3.7 (0.96) | 0.949 |
| Strategic Plan Implementation | 3.6 (1.12) | 3.4 (1.24) | 3.6 (1.09) | 3.8 (0.96) | 3.7 (1.01) | 1.984 |
| Student Learning Assessment | 3.5 (0.98) | 3.5 (1.03) | 3.6 (0.95) | 3.5 (0.90) | 3.6 (1.01) | 0.277 |
| Cost of Delivering Programs | 3.2 (1.27) | 3.2 (1.35) | 3.2 (1.27) | 2.7 (1.22) | 3.4 (1.08) | 2.064 |
| Grants and Research Administration | 3.2 (1.18) | 3.4 (1.12) | 3.1 (1.07) | 2.7 (1.42) | 3.3 (1.23) | 2.849* |

*Response categories: 1=Don't collect data; 2=Collect data but it is rarely used; 3=Use data to monitor progress; 4=Use data to inform planning; 5=Use data to forecast performance.*
*Significance: * p<.05; ** p<.01;*** p<.001*

Understanding the differing levels of data usage across operational categories and individual and organizational characteristics is important because previous research indicates that successful innovation adoption requires that the innovation be legitimate and useful. The findings from this section seem to support this position. The level of data usage by an institution appear to be influenced by the following: business need, such as the increased level of usage of enrollment management and student retention analytics by private institutions because of their need to strategically manage tuition revenue; or organizational mission, such as the increased level of usage for research and grants administration analytics by research institutions. The level of data usage also appears to be influenced by the discipline of the adopters and the type of institution at which they are employed.

## Relationships between Scale Variables and Control Variables

To see if significant differences in experiences with and attitudes toward data analytics exist across groups, the mean scores for the independent and dependent variable scales were analyzed by the control variables of best-practice status, role, academic discipline, institutional control, and Carnegie Classification. No significant differences in scales were found between best-practice and other institutions (Table 28).

**Table 28: Mean Score of Analytical Scales by Best-practice Status**

| | Overall Mean | Best-practice Institution | Not Best-practice Institution | F |
|---|---|---|---|---|
| Collaboration | 7.7 (2.92) | 7.2 (2.99) | 7.8 (2.91) | 1.002 |
| Authenticity | 16.4 (3.28) | 16.6 (3.25) | 16.4 (3.30) | 0.209 |
| Institutional Support | 8.9 (2.43) | 9.3 (2.02) | 8.8 (2.49) | 1.101 |
| Training | 6.4 (1.75) | 6.3 (1.61) | 6.4 (1.78) | 0.034 |
| Integrated Use | 7.6 (1.95) | 7.2 (1.89) | 7.7 (1.95) | 1.889 |
| Analytics Maturity | 15.2 (3.99) | 15.6 (3.80) | 15.1 (4.02 | 0.553 |
| Functionality | 10.0 (2.22) | 9.3 (2.57) | 10.1 (2.14) | 2.475 |
| Usability | 10.8 (2.80) | 10.7 (2.93) | 10.8 (2.79) | 0.073 |
| Usefulness | 4.9 (1.30) | 4.7 (1.49) | 5.0 (1.25) | 1.749 |
| Legitimacy/ Benefit | 21.7 (3.98) | 21.6 (4.51) | 21.7 (3.88) | 0.037 |
| Legitimacy/ Concern with Data Use | 8.7 (2.14) | 8.7 (2.06) | 8.7 (2.17) | 0.011 |
| Legitimacy/ Concern with Model | 5.1 (1.10) | 5.1 (1.17) | 5.1 (1.09) | 0.006 |
| External Pressure | 18.8 (3.16) | 18.9 (3.61) | 18.8 (3.08) | 0.013 |
| Individual Adoption | 9.3 (2.08) | 9.0 (2.21) | 9.4 (2.05) | 0.899 |
| Organizational Implementation | 25.1 (5.69) | 24.6 (6.27) | 25.1 (5.58) | 0.236 |

*Significance: * p<.05; ** p<.01;*** p<.001*

Significant differences by role were found to exist, with deans reporting higher levels of analytics maturity, functionality, usefulness, individual adoption, and organizational implementation of data analytics at their institution (Table 29). There appears to be a relationship based on role between an academic leader's perception of the usefulness of data analytics, their concern with the use of data analytics and individual adoption. It may be that as individuals begin to use analytics, its usefulness becomes more apparent (or not), which begins to impact their concern with how the data is used. Deans may experience higher levels of use, both individually and organizationally, because their role provides a broader organizational view and greater opportunity for use.

Significant differences also exist across academic disciplines (Table 30). Academic leaders in education report higher levels of collaboration in the development of data analytics, while those from English report lower levels. There are also significant differences in the extent to which campuses are data-driven, with nursing and education reporting higher levels than management and political science. Academic leaders from political science report the lowest levels of usefulness and benefit of data analytics compared to their peers from the remaining disciplines. It appears academic leaders are experiencing different levels of external pressure to adopt data analytics, with nursing reporting greater amounts of pressure, especially compared to management who report experiencing lower levels of pressure. Finally, respondents report a small but significant difference in individual adoption, with academic leaders in education reporting the higher levels of adoption and those in English and political science reporting lower levels.

**Table 29: Mean Score of Analytical Scales by Role**

| | Overall Mean | Dean | Department Chair | F |
|---|---|---|---|---|
| Collaboration | 7.7 (2.92) | 7.6 (2.56) | 7.7 (3.25) | 0.053 |
| Authenticity | 16.4 (3.28) | 16.5 (3.17) | 16.3 (3.39) | 0.315 |
| Institutional Support | 8.9 (2.43) | 9.2 (2.31) | 8.5 (2.52) | 3.533 |
| Training | 6.4 (1.75) | 6.6 (1.58) | 6.2 (1.87) | 2.931 |
| Integrated Use | 7.6 (1.95) | 7.6 (1.64) | 7.7 (2.24) | 0.193 |
| Analytics Maturity | 15.2 (3.99) | 15.7 (3.90) | 14.6 (4.01) | 5.135* |
| Functionality | 10.0 (2.22) | 10.3 (2.01) | 9.6 (2.35) | 6.138* |
| Usability | 10.8 (2.80) | 11.1 (2.63) | 10.6 (2.94) | 1.849 |
| Usefulness | 4.9 (1.30) | 5.2 (1.08) | 4.7(1.42) | 10.829** |
| Legitimacy/ Benefit | 21.7 (3.98) | 22.2 (3.20) | 21.2 (4.58) | 3.353 |
| Legitimacy/ Concern with Data Use | 8.7 (2.14) | 8.1 (1.91) | 9.2 (2.21) | 18.988*** |
| Legitimacy/ Concern with Models | 5.1 (1.10) | 5.1 (1.07) | 5.1 (1.13) | 0.068 |
| External Pressure | 18.8 (3.16) | 19.2 (2.76) | 18.6 (3.43) | 2.284 |
| Individual Adoption | 9.3 (2.08) | 9.7 (1.89) | 8.9 (2.15) | 10.495** |
| Organizational Implementation | 25.1 (5.69) | 25.9 (5.10) | 24.0 (6.23) | 5.708* |

*Significance: * p<.05; ** p<.01;*** p<.001*

**Table 30: Mean score of Analytical Scales by Academic Discipline**

| | Overall Mean | Biology | Management | English | Nursing | Political Science | Education | F |
|---|---|---|---|---|---|---|---|---|
| Collaboration | 7.4(2.86) | 7.4(2.86) | 7.5(2.28) | 6.7(2.32) | 7.8(3.15) | 7.8(3.52) | 8.7(2.97) | 2.437* |
| Authenticity | 16.4(3.28) | 16.1(3.20) | 14.9(3.46) | 16.0(2.65) | 17.7(3.16) | 15.8(3.40) | 17.4(3.37) | 4.666*** |
| Institutional Support | 8.9(2.43) | 8.9(2.77) | 9.0(2.20) | 8.8(2.62) | 8.7(2.20) | 8.2(2.67) | 9.3(2.33) | 0.728 |
| Training | 6.4(1.75) | 6.6(1.79) | 6.4(1.94) | 6.0(1.64) | 6.3(1.55) | 6.1(1.95) | 6.8(1.71) | 1.462 |
| Integrated Use | 7.6(1.95) | 7.5(1.61) | 6.7(1.86) | 7.6(1.98) | 7.8(2.39) | 7.8(1.59) | 8.0(1.77) | 1.712 |
| Analytics Maturity | 15.2(3.99) | 15.0(4.38) | 13.8(4.18) | 15.1(3.46) | 15.2(3.70) | 15.0(4.37) | 16.4(3.93) | 1.933 |
| Functionality | 10.0(2.22) | 10.0(2.43) | 10.1(1.32) | 10.1(2.26) | 10.0(2.18) | 9.0(2.55) | 10.3(2.26) | 1.089 |
| Usability | 10.8(2.80) | 10.7(3.18) | 10.4(1.64) | 10.7(2.84) | 10.8(2.79) | 10.4(3.07) | 11.6(2.91) | 0.979 |
| Usefulness | 4.9(1.30) | 5.2(1.36) | 5.1(0.92) | 4.9(1.33) | 5.0(1.24) | 4.3(1.41) | 5.0(1.29) | 2.362* |
| Legitimacy/Benefit | 21.7(3.98) | 21.8(3.71) | 21.7(3.31) | 21.0(4.23) | 23.7(2.91) | 18.6(5.08) | 22.3(3.23) | 7.505*** |
| Legitimacy/Concern with Data Use | 8.7(2.14) | 7.9(1.92) | 8.6(2.13) | 9.1(2.18) | 8.0 (1.71) | 9.3(2.46) | 8.9(2.15) | 3.451** |
| Legitimacy/Concern with Current Models | 5.1(1.10) | 4.9(1.12) | 4.9(1.19) | 5.3(0.95) | 5.2 (0.93) | 5.2(1.39) | 5.0(1.11) | 1.086 |
| External Pressure | 18.8(3.16) | 17.9(2.53) | 16.8(3.85) | 19.0(3.18) | 20.7(3.17) | 18.5(3.08) | 19.2(2.77) | 9.750*** |
| Individual Adoption | 9.3(2.08) | 9.5(2.06) | 9.5(1.79) | 8.9(2.02) | 9.4(2.15) | 8.5(2.17) | 9.8(2.03) | 2.335* |
| Organizational Implementation | 25.1(5.69) | 25.4(3.15) | 23.6(6.55) | 24.4(5.81) | 25.8(6.07) | 23.6(6.54) | 26.6(5.03) | 1.606 |

*Significance: * $p<.05$; ** $p<.01$;*** $p<.001$*

From the previous analysis, it appears that external pressure may play a catalyzing role in the adoption of data analytics. Those disciplines that report higher levels of external pressure to adopt data analytics also report that their units are more data-driven and report greater benefit from use.

When institutional control is considered, little significant difference exists in the experiences and attitudes of academic leaders from public and private, not-for-profit institutions except in the area of external pressure (Table 31). Academic leaders from public institutions report higher levels of external pressure to adopt data analytics than their peers at private, not-for-profit institutions.

When mean responses to the scales are compared across Carnegie Classification, four areas of significant difference are identified (Table 32). Academic leaders from Associates-degree institutions have a more data-driven culture (authenticity) and report that data analytics is more integrated into their plans and operations (integrated use). They perceive data analytics as having a greater potential benefit to their organization and the higher education industry (legitimacy/benefit) and are feeling greater pressure to adopt data analytics (external pressure).

**Table 31: Mean Score of Analytical Scales by Institutional Control**

| | Overall Mean | Public | Private, not-for-profit | F |
|---|---|---|---|---|
| Collaboration | 7.7 (2.92) | 7.5 (2.84) | 8.0 (3.08) | 1.235 |
| Authenticity | 16.4 (3.28) | 16.7 (3.12) | 15.9 (3.56) | 3.384 |
| Institutional Support | 8.9 (2.43) | 8.8 (2.33) | 8.9 (2.64) | 0.053 |
| Training | 6.4 (1.75) | 6.4 (1.72) | 6.2 (1.82) | 0.891 |
| Integrated Use | 7.6 (1.95) | 7.6 (2.02) | 7.7 (1.83) | 0.128 |
| Analytics Maturity | 15.2 (3.99) | 15.3 (4.02) | 14.8 (3.94) | 0.993 |
| Functionality | 10.0 (2.22) | 10.0 (2.28) | 10.0 (2.11) | 0.004 |
| Usability | 10.8 (2.80) | 10.8 (2.78) | 10.8 (2.87) | 0.017 |
| Usefulness | 4.9 (1.30) | 4.9 (1.28) | 4.9 (1.34) | 0.206 |
| Legitimacy/ Benefit | 21.7 (3.98) | 22.0 (3.93) | 21.1 (4.03) | 2.574 |
| Legitimacy/ Concern with Data Use | 8.7 (2.14) | 8.6 (2.05) | 8.8 (2.35) | 0.504 |
| Legitimacy/ Concern with Model | 5.1 (1.10) | 5.1 (1.07) | 5.0 (1.16) | 1.120 |
| External Pressure | 18.8 (3.16) | 19.3 (2.95) | 17.8 (3.35) | 15.223*** |
| Individual Adoption | 9.3 (2.08) | 9.3 (2.04) | 9.2 (2.16) | 0.199 |
| Organizational Implementation | 25.1 (5.69) | 25.2 (5.52) | 24.8 (6.15) | 0.148 |

*Significance: * p<.05; ** p<.01;*** p<.001*

**Table 32: Mean Score of Analytical Scales by Carnegie Classification**

| | Overall Mean | Research | Masters | Baccalaureate | Associates | F |
|---|---|---|---|---|---|---|
| Collaboration | 7.7 (2.92) | 7.3 (2.90) | 7.5 (2.85) | 8.3 (3.18) | 8.1 (2.89) | 1.254 |
| Authenticity | 16.4 (3.28) | 16.1 (3.20) | 16.3 (3.31) | 15.6 (3.51) | 17.5 (3.04) | 2.872* |
| Institutional Support | 8.9 (2.43) | 8.4 (2.41) | 8.8 (2.28) | 9.6 (2.68) | 9.3 (2.47) | 2.195 |
| Training | 6.4 (1.75) | 6.1 (1.71) | 6.4 (1.82) | 6.6 (1.74) | 6.6 (1.71) | 0.797 |
| Integrated Use | 7.6 (1.95) | 7.0 (1.97) | 7.8 (1.64) | 7.4 (2.01) | 8.4 (2.07) | 5.095** |
| Analytics Maturity | 15.2 (3.99) | 14.7 (3.99) | 15.3 (3.78) | 15.0 (3.77) | 15.7 (4.52) | 0.753 |
| Functionality | 10.0 (2.22) | 9.5 (2.61) | 10.1 (2.03) | 10.0 (2.09) | 10.4 (1.98) | 1.385 |
| Usability | 10.8 (2.80) | 10.1 (2.96) | 11.3 (2.61) | 11.0 (2.51) | 10.8 (2.96) | 2.325 |
| Usefulness | 4.9 (1.30) | 4.7 (1.28) | 5.0 (1.24) | 4.7 (1.38) | 5.1 (1.35) | 1.275 |
| Legitimacy/ Benefit | 21.7 (3.98) | 21.8 (4.15) | 21.8 (3.90) | 19.8 (3.76) | 22.8 (3.62) | 3.795* |
| Legitimacy/ Concern with Data Use | 8.7 (2.14) | 8.6 (1.99) | 8.6 (2.13) | 8.8 (2.53) | 8.8 (2.53) | 0.099 |
| Legitimacy/ Concern with Model | 5.1 (1.10) | 5.2 (1.11) | 5.2 (0.95) | 4.7 (1.33) | 5.1 (1.16) | 1.634 |
| External Pressure | 18.8 (3.16) | 18.6 (3.73) | 19.2 (2.59) | 17.2 (3.16) | 19.5 (2.82) | 5.189** |
| Individual Adoption | 9.3 (2.08) | 9.1 (2.13) | 9.5 (1.91) | 9.1 (2.14) | 9.4 (2.22) | 0.651 |
| Organizational Implementation | 25.1 (5.69) | 24.7 (5.93) | 25.5 (5.21) | 25.1 (5.43) | 24.9 (6.37) | 0.262 |

*Significance: * p<.05; ** p<.01;*** p<.001*

## Testing Relationships in the Conceptual Framework

With the dependent and independent scales that represent the variables in the conceptual framework, multiple regressions were conducted to test the relationships in the model. As suggested by the conceptual framework, adoption of data analytics by academic leaders may be associated with: 1) the organizational context in which the data analytics program is being implemented; 2) the characteristics of the data analytics program itself; 3) and the attitude of the individual toward data analytics.

The first analysis tested the relationship between the organizational context variables of collaboration, authenticity, institutional support, training and integrated use and the innovation characteristics of functionality and usability. Based on the findings from the multiple regression analysis (Table 33), academic leaders' perceptions of the innovation characteristics of usability and functionality are influenced by different sets of variables within the organizational context.

The variables of collaboration, authenticity, training, and integrated use are significant in a model that explains over 60 percent of the variability in an academic leader's perception that the data analytics program is functional. When an institution has a data-driven culture (authenticity), involves academic leaders in the collaborative development of the program (collaboration), successfully integrates data analytics with other information and operations within the institution (integrated use), and provides appropriate training (training), academic leaders perceive data analytics as more functional.

**Table 33: Regression of Innovation Characteristics on Organizational Context**

| | Functionality | Usability |
|---|---|---|
| *Organizational Context* | | |
| Collaboration | 0.207** | 0.152 |
| Authenticity | 0.185* | 0.101 |
| Institutional Support | 0.118 | 0.229* |
| Training | 0.256** | 0.275** |
| Integrated Use | 0.242** | 0.131 |
| External Pressure | 0.093 | 0.025 |
| *Control Variables* | | |
| Best-practice Institution: Yes[1] | 0.014 | 0.046 |
| Role: Dean[2] | 0.074 | -0.037 |
| Discipline: Biology[3] | -0.083 | 0.013 |
| Discipline: Management[3] | 0.066 | 0.010 |
| Discipline: Political Science[3] | -0.075 | -0.036 |
| Discipline: Nursing[3] | -0.087 | 0.001 |
| Discipline: Education[3] | -0.095 | 0.087 |
| Control: Private Institution[4] | 0.032 | -0.086 |
| Carnegie: Masters[5] | -0.030 | 0.095 |
| Carnegie: Baccalaureate[5] | -0.042 | 0.097 |
| Carnegie: Associates[5] | -0.033 | 0.000 |
| $R^2$ | 0.609*** | 0.534*** |

*Significance: * p<.05; ** p<.01;*** p<.001*
*(1) Referent is not a best-practice institution (2) Referent is chair; (3) Referent is English; (4) Referent is public institution; (5) Referent is research institution*

The variables of institutional support and training are significant in a model that explains over 50 percent of the variability in an academic leaders' perception that data analytics were usable (Table 33). When academic leaders find their institution provides appropriate funding, tools, and staff to support and maintain data analytics (institutional support) and provides training and professional development for use (training), they are more likely to perceive that the data analytics program at their institution is usable within their own practice.

Next adopter attitudes (usefulness, legitimacy/benefit, legitimacy/concern with data use, and legitimacy/concern with models) were regressed on the innovation characteristics and organizational context variables (Table 34). It may be that usefulness and legitimacy are not inherent characteristics of an innovation but are acquired through the actions of the organization and the experiences of individual adopters as an innovation is implemented and supported within a specific organization.

The perception of the usefulness of data analytics is influenced by both the characteristics of the data analytics program and by the organizational context in which the program is implemented. Functionality, usability, authenticity, training, and integrated use are significant in a model that explains over 73 percent of the variability in the academic leaders' perception that data analytics is useful.

**Table 34: Regression of Adopter Attitudes on Innovation Characteristics and Organizational Context**

| | Usefulness | Legitimacy/ Benefit | Legitimacy/ Concern with Data Use | Legitimacy/ Concern with Models |
|---|---|---|---|---|
| *Innovation Characteristics* | | | | |
| Functionality | 0.520*** | 0.510** | -0.313* | -0.024 |
| Usability | 0.284** | -0.134 | 0.164 | -0.245 |
| *Organizational Context* | | | | |
| Collaboration | -0.048 | 0.007 | -0.119 | 0.067 |
| Authenticity | 0.182** | -0.083 | -0.107 | -0.106 |
| Institutional Support | 0.036 | -0.157 | 0.024 | -0.212 |
| Training | -0.228** | 0.033 | 0.012 | 0.232 |
| Integrated Use | 0.194** | -0.063 | -0.059 | -0.150 |
| External Pressure | 0.031 | 0.045 | 0.164 | 0.309** |
| *Control Variables* | | | | |
| Best-practice Institution: Yes[1] | 0.021 | 0.014 | -0.029 | -0.047 |
| Role: Dean[2] | 0.083 | -0.046 | -0.150 | 0.048 |
| Discipline: Biology[3] | -0.045 | 0.145 | 0.023 | 0.074 |
| Discipline: Management[3] | 0.091 | 0.067 | -0.096 | -0.164 |
| Discipline: Political Science[3] | 0.012 | -0.043 | 0.047 | -0.125 |
| Discipline: Nursing[3] | -0.056 | 0.306* | -0.199 | -0.061 |
| Discipline: Education[3] | -0.104 | 0.155 | 0.017 | 0.020 |
| Control: Private Institution[4] | -0.008 | 0.115 | 0.166 | 0.087 |
| Carnegie: Masters[5] | -0.074 | -0.049 | 0.063 | 0.117 |
| Carnegie: Baccalaureate[5] | -0.132 | -0.307* | 0.008 | 0.145 |
| Carnegie: Associates[5] | -0.080 | 0.081 | 0.240 | 0.199 |
| $R^2$ | 0.736*** | 0.329** | 0.220 | 0.203 |

*Significance: * p<.05; ** p<.01;*** p<.001*
*(1) Referent is not a best-practice institution (2) Referent is chair; (3) Referent is English;*
*(4) Referent is public institution; (5) Referent is research institution*

When academic leaders experience their institution as having a data-driven culture (authenticity), they are more likely to perceive data analytics as useful to them personally. In addition, when available data are accurate and appropriate (functional), easy to incorporate into their practice (usability), and integrated with other systems and data within the organization (integrated use), academic leaders perceive data analytics as more useful. There is a negative relationship between usefulness and training. Training has a positive relationship with both functionality and usability, but when all three variables are included in the model for usefulness, training has a negative association with usefulness.

The drivers of the perception of legitimacy are more difficult to interpret. Functionality, academic discipline, and Carnegie Classification made significant contributions to a model that explains 33 percent of the variability in the respondent's perception that data analytics was legitimately beneficial (Table 34). High levels of functionality are associated with greater perceived benefits. Respondents in nursing report higher levels of benefit than those in the referent group (English), and those in Baccalaureate institutions see less benefit than those in Research institutions.

Even though the overall models for the variables of legitimacy/concern with data usage and legitimacy/concern with models were not significant, functionality was negatively associated with respondents' level of concern with how data analytics will be used (legitimacy/concern with data use). As functionality increases, respondents' concern with how the data in the system is being used decreases. External pressure to adopt data analytics (external pressure) is positively associated with respondents' level of concern with the current data analytics models (legitimacy/concern with model). As external pressure to adopt data analytics increases, respondents’ concerns with the current models in use also increase. It may be that backgrounds, professional experiences, and theories in use influence the level of concern with data usage and models, which are not easily changed by actions of the organization.

A final multiple regression tests relationships among organizational context, innovation characteristics, adopter attitudes, and individual adoption (Table 35). The variables of usefulness and legitimacy/benefit are significant in a model that explains nearly 50 percent of the variability in the level of individual adoption. From the perspective of academic leaders, data analytics must be both useful, meaning that use enhances their ability to do their job, and it must be legitimate, meaning academic leaders must believe that use of data analytics is the right tool to improve or address different challenges facing their organization, in order for them to adopt the use of data analytics into their own practice.

**Table 35: Regression of Individual Adoption on All Predictor Variables**

| | Individual Adoption |
|---|---|
| *Adopter Attitudes* | |
| Usefulness | 0.414** |
| Legitimacy/Benefit | 0.223* |
| Legitimacy/Concern with Data Use | -0.181 |
| Legitimacy/Concern with Models | -0.120 |
| *Innovation Characteristics* | |
| Functionality | -0.059 |
| Usability | -0.098 |
| *Organizational Context* | |
| Collaboration | -0.126 |
| Authenticity | 0.075 |
| Institutional Support | 0.095 |
| Training | 0.024 |
| Integrated Use | 0.047 |
| External Pressure | 0.021 |
| *Control Variables* | |
| Best-practice Institution: Yes[1] | -0.075 |
| Role: Dean[2] | 0.085 |
| Discipline: Biology[3] | 0.000 |
| Discipline: Management[3] | 0.009 |
| Discipline: Nursing[3] | -0.202 |
| Discipline: Political Science[3] | 0.012 |
| Discipline: Education[3] | 0.051 |
| Control: Private Institution[4] | 0.029 |
| Carnegie: Masters[5] | 0.045 |
| Carnegie: Baccalaureate[5] | -0.104 |
| Carnegie: Associates[5] | -0.097 |
| $R^2$ | 0.486*** |

*Significance: * p<.05; ** p<.01;*** p<.001*
*(1) Referent is not a best-practice institution (2) Referent is chair; (3) Referent is English;*
*(4) Referent is public institution; (5) Referent is research institution*

**Organizational Implementation of Data Analytics at Higher Education Institutions**

The previous section focused on variables that contribute to the extent of individual adoption of data analytics by academic leaders. This section investigates the second component of the conceptual framework – the variables that contribute to organizational implementation. The conceptual framework includes the possibility that the dependent variables that influence individual adoption also influence organizational implementation. A multiple regression analysis was completed to test the association of organizational context, innovation characteristics and adopter attitudes, individual adoption, and the control variables of best-practice status, role, academic discipline, institutional control, and Carnegie Classification (Table 36).

The variables of authenticity, external pressure and legitimacy/concern with models are significant in a regression model that explains over 54 percent of the variability in the level of organizational implementation. When the campus culture is data-driven (authenticity), the external environment exerts pressure to adopt data analytics (external pressure), and there is increasing concern with the effectiveness of the current models used in data analytics (legitimacy/concern with models), institutions are more likely to expand their implementation of data analytics. Noteworthy is that the level of individual adoption was not significant in the organizational implementation model.

**Table 36: Regression of Organizational Implementation on All Predictor Variables and Individual Adoption**

| | Organizational Implementation |
|---|---|
| Individual Adoption | 0.112 |
| *Adopter Attitude* | |
| Usefulness | -0.287 |
| Legitimacy/Benefit | -0.103 |
| Legitimacy/Concern with Data Use | -0.050 |
| Legitimacy/Concern with Model | 0.243* |
| *Innovation Characteristics* | |
| Functionality | 0.040 |
| Usability | 0.036 |
| *Organizational Context* | |
| Collaboration | -0.070 |
| Authenticity | 0.603*** |
| Institutional Support | -0.136 |
| Training | 0.252 |
| Integrated Use | 0.050 |
| External Pressure | 0.226* |
| *Control* | |
| Best-practice Institution: Yes[1] | 0.004 |
| Role: Dean[2] | -0.051 |
| Discipline: Biology[3] | 0.030 |
| Discipline: Management[3] | 0.040 |
| Discipline: Nursing[3] | -0.127 |
| Discipline: Political Science[3] | -0.088 |
| Discipline: Education[3] | 0.039 |
| Control: Private Institution[4] | 0.094 |
| Carnegie: Masters[5] | -0.040 |
| Carnegie: Baccalaureate[5] | 0.025 |
| Carnegie: Associates[5] | -0.072 |
| $R^2$ | 0.547*** |

*Significance: * p<.05; ** p<.01;*** p<.001*
*(1) Referent is not a best-practice institution (2) Referent is chair; (3) Referent is English; (4) Referent is public institution; (5) Referent is research institution*

The finding that having a data-driven culture supports organizational implementation of data analytics is somewhat circular. It appears an organization needs a data-driven culture to support implementation of data analytics yet needs implementation of data analytics to develop a data-driven culture. It is possible the level of organizational implementation of data analytics and the extent to which the organization is data-driven reinforce each other. As data are put into use in some segments of the organization, the culture of the organization begins to shift toward more data-driven practices. As data-driven practices increase, opportunities to expand implementation increase. Also not surprising is the role external pressure plays in implementation. The influence of the external environment on the behavior of organizations is well-documented (Pfeffer & Salancik 2003). As higher education institutions experience increasing pressure to adopt innovative practices, leaders pursue methods to incorporate them into the organization in order to continue to receive support from the external environment.

A more surprising finding is that concern with the current models in use may drive implementation. It may be that pressure to use and report increasing levels of data coupled with the dissatisfaction with the status quo or existing models drives an institution to develop and adopt systems in pursuit of better models. Though not significant, the negative relationship between usefulness, which was a significant predictor for individual adoption, and organizational implementation warrants further investigation. Davenport and Harris (2010) speak to the importance of focusing on a few key business processes in order to achieve the greatest benefit from data analytics. It may be that as institutions press to adopt data analytics across an increasing number of functional areas, the implementation moves away from key business processes and therefore the usefulness of the overall system decreases. Another possible explanation may be that as senior leaders press to adopt organizational innovations that are driven from outside the organization, the usefulness of the innovation to individuals within the organization declines because the innovation is not driven by actual organizational need.

## Testing the Impact of Analytics Maturity on Individual Adoption and Organizational Implementation

The conceptual framework analyzed in the previous section (Figure 1) was designed to explain the generalized process by which organizational innovations are adopted within higher education institutions. The modified conceptual framework that was adapted to investigate the individual adoption and organizational implementation of data analytics (Figure 2) is now investigated.

A regression analysis was completed for individual adoption and organizational implementation that includes organizational context, including the analytics maturity variable, external pressure, innovation characteristics, and adopter attitudes, and the control variables, as described in the modified conceptual framework (Figure 2). Inclusion of analytics maturity in the regression model for individual adoption of data analytics increases the explanatory power of the model slightly. The regression model for individual adoption is significant and explains nearly 50 percent of the variability in individual adoption. As was the case with the regression model for individual adoption that did not include the analytics maturity variable, the variables of usefulness and legitimacy/benefit remain significant, while analytics maturity is not significant in the model (Table 37).

**Table 37: Regression of Individual Adoption on All Predictor Variables and Analytics Maturity**

| | Individual Adoption |
|---|---|
| *Adopter Attitudes* | |
| Usefulness | 0.442** |
| Legitimacy/Benefit | 0.263* |
| Legitimacy/Concern with Data Use | -0.134 |
| Legitimacy/Concern with Models | -0.145 |
| *Innovation Characteristics* | |
| Functionality | -0.131 |
| Usability | -0.170 |
| *Organizational Context* | |
| Collaboration | -0.059 |
| Authenticity | -0.025 |
| Institutional Support | 0.134 |
| Training | -0.066 |
| Integrated Use | -0.018 |
| Analytics Maturity | 0.210 |
| External Pressure | 0.042 |
| *Control Variables* | |
| Best-practice Institution: Yes[1] | -0.086 |
| Role: Dean[2] | 0.077 |
| Discipline: Biology[3] | -0.011 |
| Discipline: Management[3] | 0.003 |
| Discipline: Political Science[3] | -0.033 |
| Discipline: Nursing[3] | -0.227 |
| Discipline: Education[3] | 0.068 |
| Control: Private Institution[4] | -0.020 |
| Carnegie: Masters[5] | 0.025 |
| Carnegie: Baccalaureate[5] | -0.079 |
| Carnegie: Associates[5] | -0.153 |
| $R^2$ | 0.492*** |

*Significance: * p<.05; ** p<.01;*** p<.001*
*(1) Referent is not a best-practice institution (2) Referent is chair; (3) Referent is English; (4) Referent is public institution; (5) Referent is research institution*

The relationship between analytics maturity and organizational implementation is not clear. Inclusion of analytics maturity increases the explanatory power of the regression model for organizational implementation. The regression model for organizational implementation is significant and explains nearly 60 percent of the variability in organizational implementation (Table 38). Analytics maturity has a positive impact on the organizational implementation $R^2$ value, but it was not significant in the model. Also, the inclusion of analytics maturity offsets some of the influence of other variables in the model. The variables of legitimacy/concern with models and external pressure remain significant. Authenticity also remained significant in the model but the level of significance decreased. In addition, the negative relationship between usefulness and organizational implementation increased and became significant.

The increase in predictive value is not surprising since the analytics maturity score represents the organizational systems and structures that should be in place in order for data analytics to develop and be successful. The findings from the regression analysis may indicate that the organizational systems and structures are not sufficient for successful organizational implementation. Implementation of data analytics in higher education organizations is more complex than simply acquiring a new software program or system. Successful implementation may be more directly influenced by the existence of a data-driven culture and pressure from the external environment.

**Table 38: Regression of Organizational Implementation on All Predictor Variables and Analytics Maturity**

| | Organizational Implementation |
|---|---|
| Individual Adoption | 0.124 |
| *Adopter Attitudes* | |
| Usefulness | -0.356* |
| Legitimacy/Benefit | -0.135 |
| Legitimacy/Concern with Data Use | -0.049 |
| Legitimacy/Concern with Models | 0.284** |
| *Innovation Characteristics* | |
| Functionality | 0.093 |
| Usability | -0.055 |
| *Organizational Context* | |
| Collaboration | -0.054 |
| Authenticity | 0.481** |
| Institutional Support | -0.215 |
| Training | 0.219 |
| Integrated Use | -0.015 |
| Analytics Maturity | 0.307 |
| External Pressure | 0.244* |
| *Control Variables* | |
| Best-practice Institution: Yes[1] | 0.021 |
| Role: Dean[2] | -0.023 |
| Discipline: Biology[3] | 0.032 |
| Discipline: Management[3] | 0.024 |
| Discipline: Political Science[3] | -0.108 |
| Discipline: Nursing[3] | -0.113 |
| Discipline: Education[3] | -0.013 |
| Control: Private Institution[4] | 0.082 |
| Carnegie: Masters[5] | -0.078 |
| Carnegie: Baccalaureate[5] | 0.010 |
| Carnegie: Associates[5] | -0.063 |
| $R^2$ | 0.584*** |

*Significance: * p<.05; ** p<.01;*** p<.001*
*(1) Referent is not a best-practice institution (2) Referent is chair; (3) Referent is English; (4) Referent is public institution; (5) Referent is research institution*

# CHAPTER FIVE
# DISCUSSION OF RESULTS

The results of this study of the implementation of data analytics at U.S. colleges and universities suggest that the successful implementation of innovations in higher education organizations is more complex than simply introducing a new technology, program, or service into the organization. Adoption of an organizational innovation is associated with the interaction between: 1) the organizational context in which the innovation is implemented; 2) the characteristics of the innovation itself; and 3) the attitude of the individual adopter toward the innovation.

Individual adoption of an organizational innovation is related to two critical elements that define adopters' attitudes. From the perspective of academic leaders, an innovation must be useful, meaning that its use enhances their own ability to do their job, and it must be legitimate, meaning they must believe that the innovation is the right tool for addressing challenges facing the organization. Usefulness and legitimacy are not inherent characteristics of an innovation but are acquired through actions of the organization and individual adopters as the innovation is implemented and supported within a specific context. When academic leaders experience the innovation as being consistent with their organizational culture and purpose, they are more likely to perceive the innovation as useful to them personally. In addition, when they experience the innovation as functional and easy to integrate into their practice and with other systems within the organization, their perception that the innovation is useful is enhanced. Academic leaders do not consider an innovation in isolation but through the lens of their academic discipline and the type of organization at which they work. Over time, as a specific innovation is implemented within a specific organizational context, the innovation may take on a greater degree of legitimacy if the organization manages implementation successfully.

Functionality is a critical variable in the process of individual adoption. As adopters engage with the innovation and experience it as functional, their perception of both its usefulness and legitimacy increases and their concern with use decreases. The results of the study indicate that academic leaders' perception of functionality is positively associated with the alignment of the innovation with the purpose and culture of their organization (authenticity), the engagement of academic leaders in its development (collaboration), the availability of training and professional development related to use (training), and the integration with strategies and operations in the institution (integrated use). Usability is the second critical innovation characteristic that leads to increased perception of usefulness. The perception of the usability of an innovation increases when institutions provide appropriate funding, tools, and staff to support and maintain the innovation and training and professional development for the end user to use an innovation successfully in their own practice.

The findings indicate that the variables that support the introduction of an innovation into an organization are not the same variables that drive individual academic leaders to incorporate the innovation into their own practice. Successful organizational implementation is associated with the alignment of the innovation with organizational culture and purpose, by the pressure exerted on the organization by the external environment, and with the dissatisfaction with the current methods or practices in use.

## Discussion

Higher education does not lack good ideas for improvement. What institutions may lack is an implementation approach that allows organizational leaders to select those innovations that best align with the strategic and operational needs and culture of their organization and that support the redefinition and clarification of the innovation to match the needs of the academic leaders who will be expected to incorporate it into their everyday practices.

This study of the implementation of data analytics provides empirical support for a model of innovation implementation that recognizes the critical connection between the specific context in which an innovation is introduced and how potential adopters perceive the usefulness and legitimacy of the innovation in their own practice (Greenhalgh et al., 2004). The findings of the study may serve as a challenge for organizational leaders and change agents who are given responsibility to bring new practices, programs, or technologies to a campus community. It is not enough to identify and acquire a new innovation and introduce it into a campus by touting its success at other institutions or as answering calls for accountability from the external environment. The implementation process may also need to involve an individual-adoption process, which is more personal and directed toward building confidence among academic professionals that the innovation is right for them and right for the organization. This study provides a number of new insights into the process of implementation of organizational innovations in U.S. colleges and universities that increases the likelihood of engagement and support from the academic professionals and provides a number of cautionary notes for how to avoid implementation pitfalls that may limit implementation success.

*First, organizations should be selective in the innovations introduced into the campus environment, with organizational need as the driver for adoption.* One of the more surprising findings in this study is that even academic leaders within what the industry has identified as best-practice institutions did not report higher levels of use of data analytics for themselves or the organization, nor were they more likely to perceive data analytics as legitimate compared to their colleagues at institutions that were not recognized as best-practice schools. Simply introducing an innovative best practice into an organization is not sufficient to implement the innovation and engage academic professionals in its use. Innovations do not have a set of inherent characteristics that drive adoption but instead acquire those characteristics through the implementation process.

Organizations may need to consider more carefully the types of innovations and change programs they attempt to bring to their organization, even as the external environment is creating pressure to engage at greater levels. The process of matching between organizational problems and possible innovations may be more critical to successful implementation than previously thought. Higher education's tendency to identify an innovation first and then go looking for a problem to solve makes the purposeful matching process more critical and challenging (March, Cohen & Olsen, 1972). Introducing innovations that closely match the organizational culture and specific needs are likely to be more successful than innovations that lack close alignment.

Davenport and Harris (2010) speak to the importance of strategic choice in data analytics. They argue that organizations cannot be equally analytical about everything, and those that are successful focus on a few key business processes in order to achieve organizational success. This study provides some support for their position. Academic leaders consistently reported higher levels of benefit for certain types of analytics that were aligned with particular business needs of the organization. Academic leaders at private institutions perceived greater benefit of analytics that focused on enrollment management and student recruitment, likely because they are aware of the importance of achieving enrollment goals because of their tuition-driven business model. Similarly, academic leaders at public institutions reported higher levels of potential benefit of data analytics to improve student learning and improve graduation rates, likely because they are feeling increasing pressure from state legislatures and the general public to show performance improvement in those areas.

*Second, innovations should be adapted to a particular organizational context and not simply adopted from the outside.* Within the higher education industry, innovation options are often introduced from outside the organization, through accrediting bodies, professional conferences, sponsored studies, trade publications, and private consultants and vendors, in a type of mimetic change process. Results achieved from implementing an innovation at one organization are publicized as holding the promise for similar results if implemented at another organization. Findings from this study indicate that this may not always be the case. Implementation of innovations in higher education organizations, especially those originally developed from the outside, is more complex than simply deciding to acquire a new technology, practice or program that was successful elsewhere.

For example, a recent study by the Gardner Institute (Drake 2010) found that not all colleges and universities experience the same level of change in first-year retention rates as a result of implementing First Year Experience programs. When investigating the differences in performance, they found that the level of implementation was the driving factor. The present study provides additional empirical support for the position that adoption choice alone is not sufficient to change organizational performance but requires adaptation of the innovation to a specific organization. The analytics maturity score, which was developed by data analytics scholars outside of higher education, provides a proxy for the systems and structures that should be in place in order for data analytics to develop and be successful. The data analytics maturity scale was not significant in the regression model for individual adoption of data analytics in higher education institutions. Academic leaders were less influenced by the technical infrastructure that their organization had put in place to deploy data analytics than by how useful and legitimate the data was to their own practice. Technically solid systems might be in place, but, unless they are designed and delivered in such a way that the data and information that comes out of the systems are useful and legitimate, use is diminished.

Findings were consistent when the analytics maturity score was applied to organizational implementation. Though the predictive value of the model increased slightly, the analytics maturity score did not contribute significantly to the regression model for organizational implementation. The authenticity of the innovation (in this case, the existence of a data-driven culture) and external pressure continued to play a significant, positive role in organizational implementation. Analytics maturity, which was developed outside of higher education, includes an emphasis on centralization, an enterprise view, and standardization that is critical for business environments but may be seen as inappropriate by academic leaders who see the centralization as limiting their own program or discipline. The findings may suggest that as higher education organizations have moved to centralized data systems, standardized reporting, and organization-oriented metrics, academic leaders within departments and colleges find the output from the systems less useful and grow increasingly concerned with the metrics being used. Simply adopting an analytics model using a best-practice approach from outside higher education was not sufficient for success.

*Third, once an innovation is identified, redefinition should focus on aligning the systems and structures of the innovation with the culture of the organization.* Authenticity, the development of a shared understanding of the purpose of the innovation and the creation of consistency between the innovation and the organization's culture and values, is critical to both individual adoption and organizational implementation. Authenticity was the major predictor for organizational implementation and was significantly associated with the perception that data analytics was both functional and useful. It is the only factor significantly related to both individual adoption and organizational implementation. As an innovation is introduced into an organizational context, either because of pressure for adoption from outside the organization or because of dissatisfaction with institutional performance, it is important that a specific innovation be selected so that it has the greatest potential to align or at least not directly conflict with the culture and purpose of the organization.

In order for the realignment to occur, academic leaders should be directly engaged in altering the systems and structures of the innovation so they more closely fit the organizational context, and in integrating the innovation with other systems and structures, so it becomes incorporated into the regular operations of the organization. In the present study, the level of involvement of academic leaders in the design and implementation of data analytics was significantly related to their perception of the functionality of data analytics system. Their involvement in the redefinition of data analytics through the design of the data, metrics, and reports available increased the likelihood that they would see the resulting information was accurate and right for the organization.

As academic leaders choose to adopt the innovation into their practice, the extent to which they are supported and rewarded for the adoption may communicate to the rest of the academic community the commitment of organization leaders to the innovation, encouraging others to adopt the practice as well. As increasing numbers within the campus community incorporate the innovation into their own practice, the campus culture may continue to shift as the innovation is continually adapted to align with the work of a greater number of academic professionals within the organization. In this way, the innovation and the culture of the organization may change together, with academic professionals central to the transformation effort.

*Fourth, as the purpose of the innovation is clarified, the functionality and usefulness of the innovation to academic professionals should remain central to its ongoing development.* The fact that colleges and universities are staffed by autonomous, highly educated professionals is important when considering the implementation of organizational innovations. Academic professionals have substantial discretion in the work they do and how they do it. In this study, the usefulness of data analytics showed a significant association with the extent of adoption by academic leaders. Usefulness is related to a number of variables, including the functionality and usability of the system.

Though it was not significant in individual adoption, the importance of functionality in the model is apparent. The functionality of the innovation, meaning the extent to which it delivers on its promise of solving a problem, was significant in an academic leader’s perception that the data analytics system was both useful and legitimate. Functionality both increased their perception that data analytics could be beneficial to the organization and reduced their concern with how the data from the system will be used. As mentioned previously, however, functionality is defined by the end user and is not an inherent characteristic of the innovation. It must be purposely cultivated through the implementation process – a process that should include a close partnership with academic professionals if they are to be expected to embed the innovation in their practice.

Functionality, use, and usefulness might be reinforcing phenomena. Academic leaders who reported increased levels of use of data analytics also reported decreasing levels of concern with how data are used at their institution. It may be that as individuals begin to use analytics, the functionality of the analytics system to the end user becomes apparent (or not). If academic professionals find that the system produces accurate, adaptable data that assist them in making decisions, they perceive the system to be more useful and begin to experience the potential benefits and become less concerned with use.

It is the importance of usefulness and functionality that may make ongoing, institution-wide implementation challenging. In the study, there was a negative relationship between organizational implementation and usefulness. The finding is intriguing. It may be that as institutions press to adopt data analytics across an increasing number of functional areas, the implementation moves away from key business processes of concern to academic leaders or becomes more standardized and centrally focused, and therefore the functionality and usefulness of the overall system decreases. The finding is counter-intuitive and unexpected, so it is unclear if the negative relationship is true for organizational adoption of innovations in general or if the relationship is idiosyncratic and specific to data analytics. The relationship between usefulness and organizational implementation warrants further investigation.

*Fifth, the implementation process should be adaptable within the organization to address the legitimacy concerns of academic leaders.* The study of the adoption of data analytics provides further evidence of the relationship between legitimacy and adoption choice and provides additional insight into the challenge that the need for legitimacy brings. Individual adoption choice, while most significantly related to usefulness, was also significantly related to the perception of benefit of data analytics. Complicating the implementation process is the finding that legitimacy is related to the academic leader's own background and discipline. Throughout the analysis, academic leaders from disciplines of political science and English reported lower levels of use and perceived benefit and higher levels of concern with data analytics, while nursing and education consistently reported higher levels of use and perceived benefit and lower levels of concern. These findings may indicate that college and university cultures are not monolithic but multiple and pluralistic. The task may not be alignment of the innovation with the organizational culture but the ongoing alignment of the innovation with many cultures, including various and sometimes conflicting norms and values that exist within an academic community.

## Implications for Theory

The conceptual framework used to guide data collection and analysis was based on findings from previous research on implementing organizational innovations. Results from the present study provide additional support for and extend existing theories of organizational innovation but also provide evidence for the need to reconsider elements of the theories, especially as they are applied to higher education organizations or professional organizations with a substantial professional employee population.

Scott and Davis (2007) distinguish between the concepts of organizations and organizing. They argue that organizations are not static but are in a continual state of organizing as they change to respond to ongoing pressures to adapt to internal and external exigencies. The same could be said for implementing service innovations in professional organizations. Service innovations are not implemented with a finite end date and outcome, but instead organizations may be implementing continuously as the external environment changes, as ideas central to the innovation evolve, as additional professionals incorporate new routines into old, and as new professionals join the organization.

Innovations in service organizations are not adopted independently but in connection to key processes and systems in order to improve service delivery or performance outcomes. For example, in higher education organizations, new instructional design approaches are not adopted in isolation but as an approach to improve existing processes of teaching and learning and to improve student performance and outcomes. Similarly, data analytics is not adopted for its own sake but to improve decision-making, resource allocation or other critical outcomes of the organization. As a result, adoption does not occur separately from existing processes. Innovations are incorporated into them (Fonseca, 2002; Kozma, 2005). Previous models represent implementation as a single process. Findings here point to the possibility of multiple implementation streams that are experienced and recognized by different individuals within the organization.

It may be that, before innovations can be implemented, organizations need to understand the organizational processes into which the innovations are being inserted. The close connection between organizational process and the successful deployment of data analytics (Davenport & Harris, 2007; Manyika et al., 2011) may also exist for other types of service innovations. The redefinition and clarification of the innovation within the organization and the adaptation of organizational structures to align with the innovation (Rogers 2003) may actually be connected to the underlying organizational processes at work. Adaptation of the innovation and the organization to each other (Fonseca, 2002; Van de Ven et al., 2008) may be most closely related to changing the organizational processes that drive the performance or the outcome that the innovation is designed to address. The development of an understanding and disaggregation of the organizational processes into which the innovation is being introduced may be a component of the implementation process that needs to be incorporated into future models.

The models for the implementation of organizational innovations represent the organization as the adopting unit (Rogers, 2003). While there has been recognition that individual adoption plays an important role in organizational implementation (Argyris & Schön, 1996; Fonseca, 2002; Kozma, 1985; Van de Ven et al, 2008), the relationship between individual adoption and organizational implementation has not been well addressed by previous models. The results of the present study indicate that individual adoption and organizational implementation are not the same, nor are they influenced by the same variables. Progress on organizational implementation appears to be driven by the more macro-level variables of external pressure and organizational culture that provide attention and traction for a particular innovation within a particular organization. Individual adoption of organizational innovations appears to be driven by more micro-level variables that influence the framing of the innovation within an organizational context that influences the perceptions and attitudes of the individual adopters. Future models should consider how the organizational implementation and individual adoption processes diverge from and converge with each other in the process of implementing over time.

Previous models of the innovation implementation process point to the importance of functionality of the innovation to the adoption choice (Kozma, 1985; Rogers, 2003; Van de Ven, 1996). Findings here indicate that, while functionality plays an important role, it may not alone be sufficient. Models of the individual adoption process may need to be expanded to include the concepts of usability and usefulness, both closely tied to the end-user's experience with and personal benefit from an innovation. The concepts of usability and usefulness are most closely aligned with individual technology adoption (Barki & Hartwick, 1994; Davis, 1989; Wixom & Todd, 2005), but findings from the study suggest that these concepts could be extended to more generalized innovation implementation models. The importance of usability and usefulness in individual adoption choices provides additional support for the need for organizations to understand organizational processes prior to identifying and implementing an innovation to ensure a close alignment between the two.

The tight integration of the innovation with the underlying organizational process that it is designed to impact – in conjunction with the importance of usability and usefulness of the innovation to the end user – points to the need to revisit the role of collaborative development (Heckscher & Adler, 2006) in the implementation process. Collaborative development of data analytics is related to the end user's perception of the functionality of data analytics. Academic leaders who reported higher levels of involvement of their colleagues in the development of data analytics on their campus reported higher levels of functionality of the system. Professionals within the organization have a unique perspective on how the organization delivers its programs and services, as well as the decision points that are embedded in each of the processes. A revised model of the implementation of organizational innovations may need to include the disaggregation of the organization into its underlying operational process and include the points of intersection between the organizational process to be improved, the innovation designed to improve it, and the individual adopter's role in the process as the innovation is redesigned and deployed.

Finally, the role of the external environment in individual adoption and organizational implementation of innovations appears to be complex. In the study, external pressure did increase the level of organizational implementation. Academic leaders who reported higher levels of pressure to adopt data analytics also reported their organization had implemented data analytics to a greater extent across more operational categories. Increased levels of external pressure also are related to academic leaders' concern that the current models in use were inadequate. This finding is noteworthy because concern with current models in use was significant in organizational implementation. It may be that dissatisfaction with current models in use and with the type of pressure received from the external environment may move organizations to implement innovative practices that they feel are more appropriate for their organization. In this way, some organizations may be attempting to manage their environments by identifying and implementing innovations to replace sub-optimal programs or practices received from the outside.

## Implications for Practice

As senior administrators implement an organizational innovation at their own institutions, they should give careful consideration to the technical aspects of implementation, such as tools, training and resources. These elements are significant in the implementation process and are positively associated with the perceived characteristics of the innovation at their institution. Senior administrators also should consider the personal components of implementation. Variables such as the level of collaborative development that engages professional employees in the design, testing, and ongoing improvement of the innovation and the integration of the innovation into existing processes and routines also are significant in the implementation process. It may be the quality of the experience with the implementation process and the consistency with the organization culture that is related to the perception of, attitudes toward, and eventual use of an innovation by adopters.

Also important is the translation of the pressures for adoption from the external environment. External pressure is universal and is felt at similar levels across different institution types and disciplines, but external calls for an innovation are not sufficient to drive adoption. Senior leaders may play a critical role in the translation of external pressure into institution-specific needs and actions that compel academic leaders to integrate innovative practices into their daily routines. If not appropriately translated, external pressure may be associated with increased levels of concern about adoption, which is negatively related to adoption choice.

Finally, an innovation should be implemented in a way that gives consideration to the specific institution in which it is being developed. The higher education sector is not homogeneous. Institutional cultures and professional norms vary substantially across institutions based on mission, constituencies served, and mix of academic programs. Similarly, individual institutions are not homogeneous. Deans, department chairs, and faculty members within a particular institution come from various disciplines and work and educational experiences that may influence their perception of what is legitimate and appropriate for their programs and students. Any strategy to implement an innovation must be technically excellent, but equally critical is the strategy to engage a diverse set of academic leaders fully in the idea the innovation represents. When campuses reach a consensus on the purpose and need for deploying the innovation and create a shared responsibility for its development and use, they will begin to experience the improved effectiveness, efficiencies, and student success that are promised.

Within the specific area of data analytics, a number of implications for practice were identified. It is clear that while data analytics is receiving attention and is seen as a priority on many college campuses, organizations need to build capacity in deploying data analytics and in behaving analytically before the benefits can accrue.

Senior leaders need to consider carefully the data analytics technology and methods they choose to deploy within their own institution. McKinsey (Manyika et al., 2011) recommends that organizations invest in technology and develop analytical techniques that fit their own business need. From the research findings, it appears that institutions may be adopting technology and analytical techniques from the outside that do not fit their own organization. Academic leaders do not necessarily object to the idea of using data analytics in higher education, but they do see the current models used to measure both productivity and quality to be inadequate. In fact, the dissatisfaction with current models pushed from the outside might be used as an impetus for local developments and adaptations. Consistent with the McKinsey recommendation, the analytical techniques used need to be developed to fit within the specific organizational context to provide insight into specific academic processes and strategies. Before deploying data analytics, organizations will need to collect and analyze relevant data to understand better the underlying operational processes.

A key component of deploying analytics is leaders acting analytically and using data to inform decisions. Senior leaders cannot assume that those in management positions come into their roles equipped with the knowledge and competencies to use data in their own decision-making processes. They must cultivate the skills and competencies required in all members of the institution who are responsible for organizational processes and actions. Academic leaders report needing more support and training in the use data analytics, especially as it relates to incorporating data-based decision-making into their own practices. This finding is important, because academic leaders are reporting that they have not received sufficient professional development on how to use data, even as higher education institutions are experiencing growing pressure to increase the use of data in managing the institution.

Dissatisfaction with current models in use might be related to the dissatisfaction with both the functionality and usability of information available from the current systems. While two-thirds of respondents said the data available to them were accurate, fewer than 40 percent believe they have the right kind of data or that the current systems improve decision-making at the institution. Current systems fare even worse when it comes to usability. Fewer than one-third of respondents said that the data system is easy to operate or that data are presented in the right format or are easy to access. As senior leaders pursue implementation of data analytics at their own institution, they should assess whether the current data systems in use are tools and technologies that have been repurposed from existing business environments or are systems that have been designed specifically with the analytical needs of higher education organizations in mind.

Finally, academic leaders report that current data analytics systems in use are not well integrated. McKinsey (Manyika et al., 2011) identified the need for organizations to pursue access to data from multiple sources and develop the capacity to integrate the multiple data sources into actionable information as critical to capturing the full potential of data analytics. With more than half of respondents reporting that their institution's data analytics systems integrate data from different sources very little or not at all, it is not surprising that many higher education organizations struggle to implement data analytics successfully. Higher education organizations have been recognized as siloed, loosely-coupled organizations. Data systems that treat data in isolation from other organizational data or that serve only a particular organizational function reinforce the silos and diminish the functionality and usability of organizational data because the decision-maker can get only a partial view of any organizational decision. Senior leaders should move away from single-purpose analytics tools toward an integrated approach to data management, analysis, and reporting that allows for a full organizational view and an understanding of business, student, and academic processes from beginning to end and across strategic and operational areas.

## Limitations of the Study

The sampling methodology for the survey respondents was not random across the entire population of U.S. higher education organizations. The institutions selected to participate in the survey had already responded to an initial survey on analytics. As a result, the findings regarding level of implementation may not be representative of all higher education institutions in the US. In addition, the individual response rate to the survey was low (16.4 percent), which could negatively impact generalizability.

Data analytics is the “innovation” studied here. As a service innovation, data analytics is not just a specific technology but an approach to interacting with and using data to manage decisions and operations. As a result, identification of the presence of the innovation and the level of implementation on the campus was based on the respondent’s own awareness. Using individual awareness could lead to under or over reporting of extent of implementation within the organization. Overall the extent of prioritization of data analytics was consistent across two groups: 69 percent of CIOs and 65 percent of academic leaders reported data analytics as a priority at their institution. The similarity of reported prioritization by two different groups within the same set of organizations could indicate that respondents had the ability to identify the innovation and its level of implementation within the organization regardless of their own level of use.

Finally, the conceptual framework attempts to describe a generalized process for the implementation of innovations within higher education organizations, and data analytics is the specific innovation used to test the model. The findings from the study of the implementation of data analytics support the conceptual framework, but it is unclear if the specific findings are generalizable to other types of technological or service innovations. Additional research of the conceptual framework using other types of innovations will need to be completed before any claims of generalizability can be made.

## Directions for Future Research

In this exploratory study, the intent of the research is to develop and test an initial set of variables related to innovation adoption and implementation in higher education. The study represents a first attempt at operationalizing the conceptual framework for the individual adoption and organizational implementation of innovations in higher education institutions. The conceptual framework, including the variables upon which the survey instrument was created, was developed from previous theory and research but had not yet been tested in an empirical setting. Additional research must be completed before more generalizable findings can be claimed. Data analytics, as the specific innovation studied, may have unique features that are not directly applicable to other types of innovations. Future research that applies the conceptual framework to different types of organizational innovations will be needed to understand if the innovation implementation process is generalizable beyond data analytics. In addition, findings from the study raised a number of questions that could not be answered with the current data set and will require additional research.

The concept of legitimacy is well-documented in innovation research and played an important role in influencing an academic leader’s adoption patterns in this study, but the context and innovation variables investigated in the study provided little insight into what influences academic leaders’ perception of the legitimacy of the innovation. In the study, the functionality of the innovation was related to the respondents’ perceptions of legitimacy – both increasing the perception that the innovation will benefit their organization and decreasing their level of concern with data use. The control variables of academic discipline and Carnegie Classification are related to the perception that data analytics are legitimately beneficial. External pressure also is related to legitimacy but in an unexpected way. Increasing levels of external pressure are related to increasing levels of concern with current models in use. This finding is consistent with earlier research in that innovations that come from outside of the organization have a greater difficulty in being adopted or at least need to be modified to fit the culture of the organization. It may be that if academic leaders perceive adoption is being driven from the outside as opposed to from organizational need, their concern with its appropriateness for their organization increases. A more comprehensive understanding of what drives an academic leader’s perception of legitimacy is an important area of future research, especially as it relates to how an innovation acquires legitimacy over time.

A closely related topic for future research is the differing role the external environment plays in individual adoption and organizational implementation. In the regression model, external pressure to adopt an innovation was positively related to organizational implementation. Academic leaders who reported higher levels of external pressure to adopt data analytics also reported higher levels of organizational implementation. External pressure did not have the same impact on individual adoption. In fact, as academic leaders perceived increasing pressure to adopt data analytics, they reported increasing levels of concern with the current models in use. This finding may mean that external pressure from accrediting bodies, the public, and boards may be a double-edged sword. While these external pressures are pushing senior leaders to adopt innovations within their organization, they may be alienating academic leaders from incorporating the innovations into their own practice. Simply adopting an innovation from the outside, without proper translation to the organizational culture or to align with internal purposes, may result in implementation failure. An area for future research is how the translation of external pressure occurs and its impact on both individual adoption rates and organizational implementation.

Another closely related topic is the role of academic discipline. Academic discipline was shown throughout the study to be related to the attitudes toward and the adoption of data analytics. In developing the sampling strategy, it was anticipated disciplines without programmatic accreditation (biology, English, and political science) would behave differently from applied disciplines with programmatic accreditation (management, nursing, and education). Results did not support this assumption. In fact, in a number of the operational areas, academic leaders from biology reported usage levels more similar to nursing and education, and management reported usage levels more in line with English and political science. Could the difference be explained by their disciplinary orientation toward data usage, by other types of external pressure or by their career experiences? These questions were not addressed in the study and could be fruitful areas for future research.

The methodology used in the previous study was cross-sectional and based on point-in-time experiences of academic leaders. The conceptual framework attempts to describe a process of implementation that plays out over time. A longitudinal study of the process of the implementation of organizational innovations would provide additional insight into the nature of the variables and how they impact implementation over time. Case studies of higher education institutions implementing data analytics or other organizational innovations would provide additional insight into the model.

Finally, the previous study focused on the innovation implementation process within a specific organization and the role organizational context, innovation characteristic, and adopter attitude variables played on individual adoption and organizational implementation. A different but related line of research would be the variables that influence innovation adoption by the industry or sector. Attitudes and adoption patterns were different based on organizational type with different experiences being reported by academic leaders depending on the type of organization in which they worked. A consideration of the innovation processes that occur at the level of industry or sector would provide important insights into the ways in which certain innovations receive legitimacy and best-practice status and are adopted by multiple organizations within a sector or across the higher education industry. The field or industry level would be particularly important to explore because much of the change and innovation that is being called for by external stakeholders is directed at the higher education industry and not at any one particular organization.

# REFERENCES


Argyris, C. & Schon, D.A. (1996). *Organizational Learning II: Theory, Method and Practice*. Reading, MA: Addison-Wesley Publishing Company.

Baldridge, J. V. (1980). Managerial Innovation: Rules for Successful Implementation. *The Journal of Higher Education*, 51 (2), 117-134.

Baldridge, J.V. & Burnham, R. (1975). Organizational Innovation: Individual, organizational, and environmental impacts. *Administrative Science Quarterly*, 20(2), 165-176.

Barki, H. & Hartwick, J. (1994). Measuring user participation, user involvement and user attitude. *MIS Quarterly*, 18:1, 59-82.

Bichsel, J. (2012). *Analytics in Higher Education: Benefits, Barriers, Progress, and Recommendations* (Research Report). Loiusville, CO: EDUCAUSE Center for Applied Research, August 2012, available from http://www.educause.edu/ecar.

Bidwell, C. (2001). Analyzing Schools as Organizations: Long-term permanence and short-term change. *Sociology of Education*, 74(Extra Issue), 100-114.

Bollier, D. (2010). *The Promise and Peril of Big Data* (Research Report). The Aspen Institute: Communications and Society Program. Washington, D.C., 2010, available from: http://www.thinkbiganalytics.com/uploads/Aspen-Big_Data.pdf

Bolman, L. & Deal, T. (2008). *Reframing Organizations: Artistry, Choice and Leadership*. San Francisco, CA: John Wiley & Sons, Inc.

Cameron, K. S. (1984). Organizational adaptation and higher education. *Journal of Higher Education*, 55 (2), 122-144.

Campbell, J.P., DeBlois, P.B. and Oblinger, D.G. (2007). Academic Analytics: A New Tool for a New Era. *EDCAUSE Review*, July/August 2007, 41-57.

Cannon, R.A. and Lonsdale, A.J. (1987). A "muddled array of models": Theoretical and organizational perspectives on change and development in higher education. *Higher Education*, 16, 21-32.

Cepull, J.C., Radhakrishnan, R. and Widder, D.R. (2012). Building a Performance Analytics Environment. *EDUCAUSE Review Online*. Published July 18, 2012: available from www.educause.edu/ero/article/building-performance-analytics-environment

Clark, B. (1972). The organizational saga in higher education. In C. Brown (Ed.) *Organization & Governance in Higher Education* (5th Edition). (pp. 153-159). Boston, MA. Pearson Custom Publishing.

Clark, T. N. (1968). Institutionalization of Innovations in Higher Education: Four Models. *Administrative Science Quarterly*, 13(1), 1-25.

Cohen, M.D., March, J.G. & Olsen, J.P. (1972). A garbage can model of organizational choice. *Administrative Science Quarterly*, 17(1), 1-25.

Davenport, T.H. and Harris, G.H. (2007). *Competing on Analytics: The New Science of Winning*, Harvard Business School Press: Boston, MA.

Davenport, T.H., Harris, G.H. and Morrison, R. (2010). *Analytics at Work: Smarter Decisions, Better Results*, Harvard Business School Publishing Corporation: Boston, MA.

Davis, F.D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13:3, 319-340.

Davis, R. H., Strand, R., Alexander, L. T., & Hussain, M. N. (1982). The Impact of Organizational and Innovator Variables on Instructional Innovation in Higher Education. *The Journal of Higher Education*, 53 (5), 568-586.

Dill, D. D., & Friedman, C. P. (1979). An analysis of frameworks for research on innovation and change in higher education. *Review of Educational Research*, 49(3), 411-435.

DiMaggio, P.J. & Powell, W.W. (1983). The iron cage revisited: institutional isomorphism and collective rationality in organizational fields. *American Sociological Review*, 48(2), 147-160.

Drake, B. (2010). *Foundations of Excellence in the First College Year: 2010 Retention Analysis.* Unpublished report. John N. Gardner Institute for Excellence in Undergraduate Education.

Easterby-Smith, M. (1987). Change and innovation in higher education: A role for corporate strategy? *Higher Education*, 16, 37-52.

Eraut, M. (1975). Promoting innovation in teaching and learning: Problems, processes and institutional mechanisms. *Higher Education*, 4, 13-26.

Fonseca, J. (2002). *Complexity and Innovations in Organizations*. New York: Routledge.

Gioia, D.A. and Thomas, J.B. (1996). Identity, image and issue interpretation: Sensemaking during strategic change in academia. *Administrative Science Quarterly*, 41:3, 370-403.

Goldstein, P.J. & Katz, R.N. (2005) *Academic Analytics: The uses of management information and technology in higher education*. (Research Report). Boulder, CO: EDUCAUSE Center for Applied Research, available from http://www.educause.edu/ecar.

Grajek, S. (2011, November/December). Research and Data Services for Higher Education Information Technology: Past, present, and future. *EDUCAUSE Review*, pp46-60.

Green, K.C. (2012). (Not) Using Data for Decisions, Blog: Digital Tweed, *Inside Higher Ed*, January 25, 2012, available from: www.insidehighered.com/blogs/not-using-data-decisions

Green, K.C. (2012). Actionable Analytics. Blog: Digital Tweed, *Inside Higher Ed*, February 15, 2012, available from: www.insidehighered.com/blogs/digital-tweed/actionable-analytics

Green, R. (2003). Markets, management and "reengineering" higher education. *Annals of the American Academy of Political and Social Science*, 585, 196-210.

Greenhalgh, T., Robert, G., MacFarlane, F., Bate, P. & Kyriakidou, O. (2004). Diffusion of innovations in service organizations: Systemic review and recommendations. *The Milbank Quarterly*, 82(4), 581-629.

Hallett, T. & Ventresca, M.J. (2006). How institutions form: Loose coupling as mechanism in Gouldner's Patterns of Industrial Bureaucracy. *American Behavioral Scientist*, 49(7), 908-924.

Hargrave, T.J. & Van de Ven, A.H. (2006). A collective action model of institutional innovation. *Academy of Management Review*, 31(4), 864-888.

Heckscher, C. & Adler, P. (2006). *The Firm as a Collaborative Community*. Oxford: Oxford University Press.

Hrabowski, F.A., Suess, J. and Fritz, J. (2011). Assessment and Analytics in Institutional Transformation. *EDUCAUSE Review*, Sept/Oct 2011, p15-28.

Johnson, L., Adams, S., and Cummins, M. (2012). *The NMC Horizon Report: 2012 Higher Education Edition*. Austin, Texas: The New Media Consortium.

Jones, L.R. (1978). Fiscal strategies to stimulate instructional innovation and change. *The Journal of Higher Education*, 49(6), 588-607.

Julius, D.J., Baldridge, J.V. & Pfeffer, J. (1999). A memo from Machiavelli. *The Journal of Higher Education*, 70(2), 113-133.

Kegan, R., & Lahey, L.L. (2009). *Immunity to Change: How to overcome it and unlock the potential in yourself and your organization*. Boston, MA: Harvard Business Press.

Kezar, A. (2003). Enhancing innovative partnerships: Creating a change model for academic and student affairs collaboration. Innovative Higher Education, 28(2), 137-156.

Kezar, A. (2006). Redesigning for collaboration in learning initiatives: An examination of four highly collaborative campuses. *The Journal of Higher Education*, 77(5), 804-838.

Klein, J.T. (2010). *Creating Interdisciplinary Campus Cultures: A Model of Strength and Sustainability*. San Francisco, CA: John Wiley & Sons, Inc.

Kolowich, S. (2010). “Technology and the Completion Agenda.” *Inside Higher Ed*, Nov. 9, 2010, available from http://www.insidehighered.com/news/2010/11/09/completion

Kozma, R.B. (1985). A grounded theory of instructional innovation in higher education. *The Journal of Higher Education*, 56(3), 300-319.

Lederman, D. (2010). Using data to drive performance. *Inside Higher Ed*, May 12, 2010, available from http://www.insidehighered.com/news/2010/05/12/analytics#sthash.UeU1YdsC.dpbs.

Liberatore, M.J. and Luo, W. (2011). The Analytics Movement: Implications for Operations Research. *Interfaces*, 40(4), pp313-324.

Lohr, S. (2012). “The Age of Big Data.” *The New York Times*, Feb. 12, 2012. Sunday Review Section.

Manyika, J., Chui, M., Brown, B., Bughin, J., Dobbs, R., Roxburgh, C., and Byers, A.H. (2011). *Big Data: The Next Frontier for Innovation, Competition, and Productivity*. (Research Report). McKinsey Global Institute, June 2011, available from http://www.mckinsey.com/insights/mgi/research/technology_and_innovation/big_data_the_next_frontier_for_innovation

Meyer, J.W. & Rowan, B. (1991). Institutionalized Organizations: Formal structure as myth and ceremony. In W.W. Powell & P.J. DiMaggio (Ed.), *The New Institutionalism in Organizational Analysis*, (pp. 41-62). Chicago: University of Chicago Press.

Meyer, J.W., Ramirez, F.O., Frank, D.J. & Schofer, E. (2008). Higher Education as an Institution. In P. Gumport (Ed.) *Sociology of Higher Education: Contributions and their Contexts*. Baltimore, MD: The Johns Hopkins University Press.

Mintzberg, H. (1979). The professional bureaucracy. In C. Brown (Ed.) *Organization & Governance in Higher Education* (5th Edition). (pp. 50-70). Boston, MA. Pearson Custom Publishing.

Norris, D., Baer, L. (2012). Building Organizational Capacity for Analytics: Preliminary Report. Nov. 28, 2012 draft provided by author.

Norris, D., Baer, L., Leonard, J., Pugliese, L., and Lefrere, P. (2008). "Action Analytics: Measuring and Improving Performance that Matters in Higher Education," *EDUCAUSE Review*, January/February 2008, pp42-67.

Norris, D., Baer, L. and Offerman, M. (2010). A National Agenda for Action Analytics: Insights from the Second National Symposium on Action Analytics, available from: http://www.edu1world.org/ClientFiles/b96d05b1-f1af-449c-a337-3694447df939/NAtional%20Agenda%20for%20Action%20Analytics%2006242010[1].pdf

Oblinger, D.G. (2012). Let's Talk… Analytics. *EDUCAUSE Review*, July/August 2012, p10-13.

Petersen, R.J. (2012). Policy Dimensions of Analytics in Higher Education. *EDUCAUSE Review* July/August 2012, pp44-49.

Peterson, M.W. (2008). The Study of Colleges and Universities as Organizations. In P. Gumport (Ed.) *Sociology of Higher Education: Contributions and their Contexts*. Baltimore, MD: The Johns Hopkins University Press.

Pfeffer, J., & Salancik, G.R. (2003). *The External Control of Organizations: A Resource Dependence Perspective.* Stanford, CA: Stanford University Press.

Rampell, C. (2008). Colleges Mine Data to Predict Dropouts. *The Chronicle of Higher Education*, 54:38, May 30, 2008, pA1.

Redman, T.C. (2008). *Data Driven: Profiting from Your Most Important Business Asset.* Boston, MA: The Harvard Business School Publishing Corporation.

Rogers, E. (2003). *Diffusion of Innovations* (5th Edition). New York: Free Press.

Rutherford, D. & Fleming, W. (1985). Strategies for change in higher education: Three political models. *Higher Education*, 14, 433-445.

Savenjie, B. & Van Rosmalen, K. (1988). Innovation in a professional organization. *Higher Education,* 17, 683-698.

Schein, E.H. (2004). *Organizational Culture and Leadership* (3rd ed.), San Francisco, CA: Jossey-Bass.

Scott, W.R. (2001). *Institutions and Organizations* (2nd ed.), Thousand Oaks, CA: Sage Publications.

Scott, W.R. & Davis, G.F. (2007*). Organizations and Organizing: Rational, Natural and Open System Perspectives*. Upper Saddle River, NJ: Pearson Prentice Hall.

Stiles, R. J. (2012) Understanding and Managing the Risks of Analytics in Higher Education: A Guide. EDUCASE Report, available from http://net.educause.edu/ir/library/pdf/EPUB1201.pdf

Tierney, W.G. (1988). Organizational culture in higher education: Defining the essentials. The *Journal of Higher Education*, 59(1), 2-21.

Van de Ven, A. H. (1986). Central problems in the management of innovation. *Management Science*, 32 (5), 590-607.

Van de Ven, A. H., Polley, D. E., Garud, R., & Venkataraman, S. (2008). *The Innovation Journey*. New York: Oxford University Press.

Van de Ven, A.H. & Poole, M.S. (1985). Explaining development and change in organizations. *Academy of Management Review*, 20(3), 510-540.

Van Driel, J.H., Verloop, N., Van Werven, H. I., & Dekkers, H. (1997). Teachers' craft knowledge and curriculum innovation in higher engineering education. *Higher Education*, 34, 105-122.

Watters, A. (2011). What are your plans for all that student data? Inside Higher Ed, Nov. 22, 2011, available from http://www.insidehighered.com/blogs/hack-higher-education/what-are-your-plans-all-student-data#sthash.rktBy850.dpbs.

Weber, M. (1922). Bureaucracy. In J. Shafritz, J.S. Ott, Y.S. Jang (Eds.) 2005, *Classics of Organization Theory* (6th ed.), (pp. 73-78). Belmont, CA; Wadsworth.

Weick, K. E. (1976). Educational Organizations as Loosely Coupled Systems. *Administrative Science Quarterly*, 21(1), 1-19.

White, S. C., & Glickman, T. S. (2007). Innovation in Higher Education: Implications for the Future. *New Directions for Higher Education*, 137, 97-104.

Wishon, G. and Rome, J. (2012). Enabling the Data-driven University. *EDUCAUSE Review Online*. Published August 13, 2012, available from: www.educause.edu/ero/article/enabling-data-driven-university.

Wixom, B.H. & Todd, P.A. (2005). A theoretical integration of user satisfaction and technology acceptance. *Information Systems Research*, 16:1, 85-102.

Wood, D.J. (1981). Academic women's studies programs: A case of organizational innovation. *The Journal of Higher Education*, 52(2), 155-172.

Xiao, Z. & Tsui, A.S. (2007). When Brokers May Not Work: The cultural contingency of social capital in Chinese high tech firms. *Administrative Science Quarterly*, 52, 1-31.

Zaltman, G., Duncan, R. & Holbek, J. (1973). *Innovations and Organizations*. New York: John Wiley & Sons.

Zemsky, R. (2009). *Making Reform Work: The Case for Transforming American Higher Education*. New Brunswick, NJ: Rutgers University Press.

# APPENDIX A: Correlation Matrix of Dependent Scales

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| (1) Usefulness | 1.0 | | | | | | | | | | | | |
| (2) Legitimacy/Benefit | .298 *** | 1.0 | | | | | | | | | | | |
| (3) Legitimacy/ Concern with Data Use | -.342 *** | -.297 *** | 1.0 | | | | | | | | | | |
| (4) Legitimacy/Concern with Models | -.249 *** | -.073 | .410 *** | 1.0 | | | | | | | | | |
| (5) Functionality | .795 *** | .288 *** | -.311 *** | -.199 ** | 1.0 | | | | | | | | |
| (6) Usability | .672 *** | .169 * | -.179 ** | -.254 *** | .761 *** | 1.0 | | | | | | | |
| (7) Collaboration | .403 *** | .156 * | -.112 | -.090 | .451 *** | .410 *** | 1.0 | | | | | | |
| (8) Authenticity | .524 *** | .240 *** | -.276 *** | -.148 * | .576 *** | .494 *** | .329 *** | 1.0 | | | | | |
| (9) Institutional Support | .546 *** | .091 | -.177 * | -.242 *** | .655 *** | .634 *** | .424 *** | .482 *** | 1.0 | | | | |
| (10) Training | .488 *** | .152 * | -.172 ** | -.161 ** | .620 *** | .632 *** | .425 *** | .499 *** | .781 *** | 1.0 | | | |
| (11) Integrated Use | .524 *** | .112 | -.116 | -.096 | .607 *** | .488 *** | .506 *** | .435 *** | .527 *** | .433 *** | 1.0 | | |
| (12) Analytics Maturity | .569 *** | .174 ** | -.185 ** | -.171 ** | .668 *** | .613 *** | .275 *** | .685 *** | .585 *** | .551 *** | .499 *** | 1.0 | |
| (13) External Pressure | .329 *** | .319 *** | -.094 | .111 | .336 *** | .254 *** | .147 * | .446 *** | .191 ** | .224 ** | .325 *** | .368 *** | 1.0 |

*Significance: * p<.05; ** p<.01;*** p<.001*

# APPENDIX B: Survey of the Attitude and Usage of Data and Analytics

**Informed Consent**

Participation in the following survey will pose little risk to you as a participant. I will not be asking for personal or sensitive information and your responses will be confidential. While there are no direct benefits to you as a participant, the results will advance knowledge in the area of change management and decision-making that will be useful for academic leaders across the country. Participation in the study is completely voluntary. Your decision whether or not to participate will not affect your current or future relationship with the University of Minnesota. If you decide to participate, you are free to not answer any question or to withdraw at any time without affecting those relationships. There is no compensation for your participation in the study. If you agree to be in this study, you will be directed to an electronic survey that will take you approximately 10 minutes to complete. Confidentiality: Responses to this survey will be anonymous. No individual identifiers will be used to connect your responses to you. Your email address will be recorded to track completion and will be deleted at the close of the survey prior to analysis. Results from the survey will be published in aggregate categories and will not identify individuals or institutions who participated in the study. Research records will be stored securely and only researchers will have access to the records.

Contacts and Questions: If you have questions regarding this study, please contact the researcher: Lisa Foss: 320-241-0186 or fossx105@umn.edu or her advisor Prof. Melissa S. Anderson: 612-624-5717 or mand@umn.edu. If you have any questions or concerns regarding this study and would like to talk to someone other than the researcher(s), you are encouraged to contact the Research Subjects’ Advocate Line, D528 Mayo, 420 Delaware St. Southeast, Minneapolis, Minnesota 55455; (612) 625-1650. Thank you in advance for your participation.

Statement of Consent: I have read the above information and consent to the study.

- ❍ Yes (1)
- ❍ No (2)

*If No Is Selected, Then Skip To End of Survey*

**Q1: To what extent do you agree with the following statements about your institution?**

| | Strongly agree | Agree | Disagree | Strongly disagree | Don't know |
|---|---|---|---|---|---|
| We have a culture that supports the use of data to make decisions. | ❍ | ❍ | ❍ | ❍ | ❍ |
| We consistently make changes based on data. | ❍ | ❍ | ❍ | ❍ | ❍ |
| Access to data for decision-making is better today than it was two years ago. | ❍ | ❍ | ❍ | ❍ | ❍ |
| We have clearly defined performance outcomes. | ❍ | ❍ | ❍ | ❍ | ❍ |
| Our faculty largely accept the use of data in measuring performance. | ❍ | ❍ | ❍ | ❍ | ❍ |
| Our administration largely accepts the use of data in measuring performance. | ❍ | ❍ | ❍ | ❍ | ❍ |
| Broader access to data at my institution increases internal competition among units for resources. | ❍ | ❍ | ❍ | ❍ | ❍ |
| Resources flow to units where decisions are data driven. | ❍ | ❍ | ❍ | ❍ | ❍ |

**Q2: What is the highest level for which data is used in your unit in the following areas?**

| | Don't collect data | Collect data but it is rarely used | Use data to monitor progress | Use data to inform planning | Use data to forecast performance | Don't know |
|---|---|---|---|---|---|---|
| Strategic plan implementation | ❍ | ❍ | ❍ | ❍ | ❍ | ❍ |
| Student learning assessment | ❍ | ❍ | ❍ | ❍ | ❍ | ❍ |
| Student retention and graduation | ❍ | ❍ | ❍ | ❍ | ❍ | ❍ |
| Enrollment management | ❍ | ❍ | ❍ | ❍ | ❍ | ❍ |
| Course scheduling and staffing | ❍ | ❍ | ❍ | ❍ | ❍ | ❍ |
| Cost of delivering programs | ❍ | ❍ | ❍ | ❍ | ❍ | ❍ |
| Faculty promotion and tenure | ❍ | ❍ | ❍ | ❍ | ❍ | ❍ |
| Faculty scholarship | ❍ | ❍ | ❍ | ❍ | ❍ | ❍ |
| Grants and research administration | ❍ | ❍ | ❍ | ❍ | ❍ | ❍ |

**Q3: To what extent do you think the following will drive expanded use of data at your institution?**

| | Great extent | Some extent | Very little | Not at all | Don't know |
|---|---|---|---|---|---|
| Reporting requirements of accrediting bodies | ❍ | ❍ | ❍ | ❍ | ❍ |
| Reporting requirements of your board of trustees | ❍ | ❍ | ❍ | ❍ | ❍ |
| External competition | ❍ | ❍ | ❍ | ❍ | ❍ |
| Public accountability | ❍ | ❍ | ❍ | ❍ | ❍ |
| Pressure to identify cost savings | ❍ | ❍ | ❍ | ❍ | ❍ |
| Pressure to improve student learning | ❍ | ❍ | ❍ | ❍ | ❍ |
| Pressure to improve student completion rates | ❍ | ❍ | ❍ | ❍ | ❍ |
| Other | ❍ | ❍ | ❍ | ❍ | ❍ |

**Q4: Which phrase best describes the quality of data available to you for decisions? (Select one)**

❍ unintegrated, poor quality data
❍ usable data but in silos
❍ usable data that is centrally stored and managed
❍ integrated, accurate and accessible common data
❍ integrated, accurate and accessible data with new data incorporated regularly
❍ don't know

**Q5: Which phrase best describes your institution's data systems? (Select one)**

❍ no real data system
❍ unconnected data systems
❍ central data system in development
❍ central data system for standard reporting
❍ central data system for analysis
❍ don't know

**Q6: Which phrase best describes the use of data in decision-making at your institution? (Select one)**

- ❍ adminstrators uninterested in using data
- ❍ a few administrators use data
- ❍ many administrators are beginning to use data
- ❍ most administrators usually use data
- ❍ all administrators regularly use and promote the use of data
- ❍ don't know

**Q7: Which phrase best describes the use of performance goals at your institution? (Select one)**

- ❍ no strategic or operational goals
- ❍ a few disconnected goals
- ❍ a small set of goals linked to our strategic plan
- ❍ a comprehensive set of goals linked to our strategic plan
- ❍ a comprehensive set of strategic goals with ongoing data analysis
- ❍ don't know

**Q8: Which phrase best describes the availability of staff to conduct data analysis at your institution? (Select one)**

- ❍ few with skills in data analysis
- ❍ some analysts but they are unconnected
- ❍ skilled analysts in a few key areas
- ❍ skilled analysts available to all areas
- ❍ highly skilled analysts and we purposefully develop analytical skills in all decision makers
- ❍ don't know

*Data analytics is the extensive use of data, statistical analysis, data mining and modeling to drive organizational decisions. It involves the integration and transformation of data into information to monitor progress, build and implement strategies and improve performance. It usually involves a technical reporting environment that involves dashboards, scorecards, or reports that are available directly to decision makers.*

**Q9: What kind of benefit do you think data analytics will yield in the following areas?**

| | Major benefit | Minor benefit | No benefit | Don't know |
|---|---|---|---|---|
| containing or lowering the cost of higher education | ❍ | ❍ | ❍ | ❍ |
| recruiting students | ❍ | ❍ | ❍ | ❍ |
| helping students learn more effectively | ❍ | ❍ | ❍ | ❍ |
| helping students graduate on time | ❍ | ❍ | ❍ | ❍ |
| improving faculty performance | ❍ | ❍ | ❍ | ❍ |
| optimizing use of resources | ❍ | ❍ | ❍ | ❍ |
| demonstrating higher education's effectiveness to external audiences | ❍ | ❍ | ❍ | ❍ |
| improving administrative performance | ❍ | ❍ | ❍ | ❍ |
| informing strategic investments | ❍ | ❍ | ❍ | ❍ |
| other | ❍ | ❍ | ❍ | ❍ |

**Q10: What kind of concern do you have about the use of data analytics?**

| | Major concern | Minor concern | No concern | Don't know |
|---|---|---|---|---|
| data will be misused | ❍ | ❍ | ❍ | ❍ |
| wrong conclusions may be drawn about our institution | ❍ | ❍ | ❍ | ❍ |
| governing bodies may mandate the use of data | ❍ | ❍ | ❍ | ❍ |
| implementing and maintaining the system could be expensive | ❍ | ❍ | ❍ | ❍ |
| current models of measuring productivity are inadequate | ❍ | ❍ | ❍ | ❍ |
| current models of measuring quality are inadequate | ❍ | ❍ | ❍ | ❍ |
| using data analytics is the wrong model for higher education | ❍ | ❍ | ❍ | ❍ |
| other | ❍ | ❍ | ❍ | ❍ |

**Q11: Which of the following statements best describes the status of data analytics at your institution?**

- ❍ a major priority institution-wide
- ❍ a major priority for some units, but not the entire institution
- ❍ an interest for some units
- ❍ not a priority or interest
- ❍ I don't know

*If "not a priority or interest" is selected, then skip to end of survey. If "I don't know" is selected, then skip to end of survey.*

*To what extent do you agree with the following statements?*

**Q12: For data analytics, my institution has provided:**

| | Strongly agree | Agree | Disagree | Strongly disagree | Don't know |
|---|---|---|---|---|---|
| adequate funding | ❍ | ❍ | ❍ | ❍ | ❍ |
| appropriate tools and software | ❍ | ❍ | ❍ | ❍ | ❍ |
| well-trained staff to develop models and provide analysis | ❍ | ❍ | ❍ | ❍ | ❍ |
| effective training for users | ❍ | ❍ | ❍ | ❍ | ❍ |
| clear definitions of data used | ❍ | ❍ | ❍ | ❍ | ❍ |
| IT staff who know how to support the technology | ❍ | ❍ | ❍ | ❍ | ❍ |
| timely information about changes to the system | ❍ | ❍ | ❍ | ❍ | ❍ |
| appropriate professional development on how to use data in decision-making | ❍ | ❍ | ❍ | ❍ | ❍ |

**Q13: In my experience, my institution's data analytics tools**

| | Strongly agree | Agree | Disagree | Strongly disagree | Don't know |
|---|---|---|---|---|---|
| provide the right kind of data | ❍ | ❍ | ❍ | ❍ | ❍ |
| provide reports in the right format | ❍ | ❍ | ❍ | ❍ | ❍ |
| are versatile in addressing needs as they arise | ❍ | ❍ | ❍ | ❍ | ❍ |
| have eliminated any single unit's ability to control access to information | ❍ | ❍ | ❍ | ❍ | ❍ |
| enable me to make decisions more quickly | ❍ | ❍ | ❍ | ❍ | ❍ |
| have significantly improved decision-making at my institution | ❍ | ❍ | ❍ | ❍ | ❍ |
| do what I want them to do | ❍ | ❍ | ❍ | ❍ | ❍ |
| make information easy to access | ❍ | ❍ | ❍ | ❍ | ❍ |
| are easy to operate | ❍ | ❍ | ❍ | ❍ | ❍ |

**Q14: How engaged have deans and department chairs, heads or directors at your institution been in the following aspects of data analytics?**

| | Very | Somewhat | A little | Not at all | Don't know |
|---|---|---|---|---|---|
| overall planning of the analytics system or tools | ❍ | ❍ | ❍ | ❍ | ❍ |
| defining data and metrics | ❍ | ❍ | ❍ | ❍ | ❍ |
| designing report formats | ❍ | ❍ | ❍ | ❍ | ❍ |
| designing screen layouts or data presentation | ❍ | ❍ | ❍ | ❍ | ❍ |
| experimenting with the analytics tools before full implementation | ❍ | ❍ | ❍ | ❍ | ❍ |

**Q15: To what extent does your institution's data analytics tools:**

| | Great extent | Some extent | Very little | Not at all | Don't know |
|---|---|---|---|---|---|
| allow for adaptations to meet different needs | ❍ | ❍ | ❍ | ❍ | ❍ |
| provide accurate data | ❍ | ❍ | ❍ | ❍ | ❍ |
| improve your ability to make good decisions | ❍ | ❍ | ❍ | ❍ | ❍ |
| enhance your effectiveness on the job | ❍ | ❍ | ❍ | ❍ | ❍ |
| provide data to external stakeholders | ❍ | ❍ | ❍ | ❍ | ❍ |
| report data linked to your strategic goals | ❍ | ❍ | ❍ | ❍ | ❍ |
| integrate data from different sources | ❍ | ❍ | ❍ | ❍ | ❍ |

**Q16: To what extent have you used data analytics for the following in the last year?**

| | Great extent | Some what | Very little | Not at all |
|---|---|---|---|---|
| in discussions at college or department meetings | ❍ | ❍ | ❍ | ❍ |
| during informal conversations with colleagues | ❍ | ❍ | ❍ | ❍ |
| to guide my own decision-making | ❍ | ❍ | ❍ | ❍ |

**Q17: How do you anticipate your usage of data analytics will change in the next year?**

❍ Increase substantially
❍ Increase slightly
❍ Stay about the same
❍ Decrease slightly
❍ Decrease substantially

**Q18: Please explain the reason for your response above.**

**Q19: Is there anything else you would like to add or comment on?**

# APPENDIX C: IRB APPROVAL

4/8/13

The IRB: Human Subjects Committee determined that the referenced study is exempt from review under federal guidelines 45 CFR Part 46.101(b) category #2 SURVEYS/INTERVIEWS; STANDARDIZED EDUCATIONAL TESTS; OBSERVATION OF PUBLIC BEHAVIOR.

**Study Number:** 1304E30861

**Principal Investigator:** Lisa Foss

**Title(s):**
Perception and Usage of Data and Analytics by Deans, Chairs and Directors at US Colleges and Universities

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This e-mail confirmation is your official University of Minnesota HRPP notification of exemption from full committee review. You will not receive a hard copy or letter.

This secure electronic notification between password protected authentications has been deemed by the University of Minnesota to constitute a legal signature.

The study number above is assigned to your research. That number and the title of your study must be used in all communication with the IRB office.

Research that involves observation can be approved under this category without obtaining consent.

SURVEY OR INTERVIEW RESEARCH APPROVED AS EXEMPT UNDER THIS CATEGORY IS LIMITED TO ADULT SUBJECTS.

This exemption is valid for five years from the date of this correspondence and will be filed inactive at that time. You will receive a notification prior to inactivation. If this research will extend beyond five years, you must submit a new application to the IRB before the study's expiration date.

Upon receipt of this email, you may begin your research. If you have questions, please call the IRB office at (612) 626-5654.

You may go to the View Completed section of eResearch Central at http://eresearch.umn.edu/ to view further details on your study.

The IRB wishes you success with this research.