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Data Analytics and the Imperatives for Data-Informed Decision-Making in Higher Education

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Chapter 1

Data Analytics and the Imperatives for Data-Informed Decision Making in Higher Education

Karen L. Webber and Henry Y. Zheng[1]

Introduction

Higher education decision makers are keen to utilize the vast and still growing volumes of data on students, faculty, staff, and institutions themselves. More data, it may be reasoned, will produce better decisions. On the surface that can be true, and yet the larger volume of data does not necessarily ensure better decision making. Along with more data come the need to use contextualized knowledge of the higher education organization, analytics strategies that account for the unique situation or population under study, and must be mindful of privacy, ethical, and overall responsible use of the data. While the allure of vast quantities of data offer the possibility of greater student success and more effectively-managed institutions, higher education leaders must consider how data analytics can be most effectively harnessed, how strategies for good data governance and organizational strategies can support informed decision making, and how and where issues of privacy and security must be addressed.

In the article entitled “Data to Knowledge to Results: Building an Analytics Capability,” Davenport, Harris, DeLong, and Jacobson (2001) foresaw the impact of the data tsunami on organizational decision making and lamented that “In the rush to use computers for all transactions, most organizations have neglected the most important step in the data transformation process: the human realm of analyzing and interpreting data and then acting on the insights. According to Davenport et al. (2001), companies have emphasized important technology and data infrastructures, but they have not attended to the organizational, cultural, and strategic changes necessary to leverage their investments. In other words, having the data but not using it to generate actionable insights to achieve better organizational outcomes was the problem. Eighteen years later, that message has been heard loud and clear among organizations across the world. Intel Corporation CEO Brian Kzanich (in Gharib 2018) called data the ‘new oil’ that is essential to organizational agility and survival. He further surmised that data and its use in analytics will have a fundamental impact to most industries across the board.

Like the business community, the higher education sector is feeling similar pressures from the data analytics movement. Facing growing competitions, rising education costs, and shifting demographic trends, the highly pressurized and competitive higher education environment today has shown the importance of a deep commitment to data-informed decision support (Gagliardi and Turk 2017; Swing and Ross 2016). Data analytics has featured prominently in recent years of Educause’s Top 10 IT Issues. For example, in the 2019 list (Grajek, 2019), issue #3 concerns privacy, issue #6 addresses the data-enabled institution, and issue #8 speaks to data management and governance. In a recent interview, Michael Crow, President of Arizona State University (ASU) and a nationally known innovator in higher education, commented on how data analytics informs decision making at ASU: “For us, to be a public university means engaging the demographic complexity of our society as a whole. It means understanding that demographic complexity. It means designing the institution to deal with that demographic complexity. And it means accepting highly differentiated types of

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[1] Webber, K.L. and Zheng, H.Z. (Eds.) *Data Analytics in Higher Education* (in press, 2019). Baltimore, MD: Johns Hopkins University Press.

intelligence: analytical intelligence, emotional intelligence. Students are not of one type but are of many, many types. Taking all of that and overlaying it with hundreds of degree programs results in so many variables and so many dimensions of complexity that you actually can't operate the institution unless you make a fundamental switch and say to yourself that, at the end of the day, it is just about analytics." (Bischel 2012, 16).

Despite some newfound emphasis on data analytics, higher education officials are not yet adept at using analytics to support decision making. In a recent survey of provosts and chief academic officers among US colleges, *Inside Higher Education* analysts (2019) found that only 16% of private university provosts and 19% public university provosts believe that their universities use data very effectively to inform campus decision making. This predicament is often described as being "data rich but information poor" (Reinitz 2015), and precisely how Davenport et al. described the industry almost 18 year ago. Clearly, for data-informed decision making to take root in higher education, we must have conceptual clarity on what defines data-informed decision making and how it can be practiced. This and the subsequent chapters in this book seek to explain and illustrate how data analytics can support a data-informed decision-making culture in higher education. While the focus of discussions in this book relate to data analytics that affect student success and institutional administration, we heartily acknowledge that Big Data and techniques such as predictive analyses are being used in faculty member research. The creation of new knowledge is indeed a vital endeavor, and Big Data labs and advanced computing centers with high capacity computing are enabling researchers to investigate important questions such as changing weather patterns and its current and predicted impact on living conditions, food sources, and energy consumption. Data analytics have the potential to help researchers move society forward in many ways. Further, the discussions in this book focus on data analytics in U.S. higher education, but we fully acknowledge similar trends and activities are happening in higher education around the world. Although the examples provided herein are from US institutions, data analytics poses similar challenges and opportunities in higher education across the globe.

Data-Informed Decision Making (DIDM) vs. Data-Driven Decision Making (DDDM)

In higher education and other industries, the terms *data-informed* and *data-driven* are often used interchangeably in describing how data analytics supports organizational decision making. However, these two terms carry different meanings and therefore it is important to discuss their differences and similarities so that there is a conceptual clarity as we move on to discuss data-informed decision making in the remainder of this book.

- **Data-Driven Decision Making**, **(DDDM)** gained strength in the 1980s, focuses on decision algorithms, heuristics, and decision rules that empower decision processes and minimize human factors (let data speak for itself);
- **Data-Informed Decision Making**, **(DIDM)** more recently introduced, focuses on leveraging data to generate insights to provide the contexts and evidence base for formulating decisions (let us figure out what data tell us).

According to Heavin and Power (2017), Data-Driven Decision Making (DDDM) refers to the collection and analysis of data to make decisions. Data "drive" the decision-making and conclusions are made using verifiable data or facts. It is "the practice of basing decisions on the analysis of data rather than purely on intuition." (Provost and Fawcett 2013) DDDM is a decision process that is guided by a set of algorithms supported by both historical and current data elements. These algorithms can be a set of mathematical formulas, an engineering model, or a machine learning module. The decisions - typically routine and operational in nature – are supported and even suggested by the algorithms so that human decision makers do not need to add input; most algorithms produce decisions that are automatically accepted by the computer systems. For example, when student academic records are read and processed by a degree audit program, the algorithm built in to that program will evaluate the students' eligibility for degree completion. The program can generate a set of courses that need to be taken by each student and may even suggest different pathways for degree completion. When a student has completed all degree requirements and is eligible for graduation, an automated procedure may alert the student to file application for graduation and for inclusion in the next commencement.

While a number of articles or other written documents use the terms DIDM and DDDM interchangeably, we argue that the "drive" in DDDM implies that data determine the direction of the decision-making process and decision-makers typically accept the decision recommendations. Many of the decisions made in business organizations are DDDM even though we may not even realize it. For example, Walmart stores nationally re-stock its shelves when inventory tracking systems detect low inventory and an order will be automatically placed for the suppliers to re-stock. In higher education, when students miss a deadline to pay fee or exceed the credit hours limit for the semester, an email will be automatically generated to remind the students and the system will block the students' ability to enroll for the semester. While DDDM systems exist and can provide some advantages in ensuring some proactive prompts (when decision logic is fully implemented), we believe that Data-Informed Decision-Making (DIDM) is more helpful and robust in most decision situations when human intelligence and flexibility are required. Therefore, the focus of this book is more about DIDM and less on DDDM.

Data-Informed Decision-Making (DIDM) recognizes that human judgement is a key element in complex, dynamic, and strategic decision-making. Because of the complexities, DIDM involves many more variables than a set of algorithms may be able to effectively address. Politics, human sensitivity, organizational values, and timing considerations are just some examples as why computer programs cannot fully be incorporated to make "data-driven" decisions for many dynamic decision situations.

We define DIDM as the process of organizing data resources, conducting data analysis, and developing data insights to provide the contexts and evidence base for formulating organizational decisions. In DIDM, data are just the evidence base, while the decision context is very much as important, if not more important than the data alone. Higher education leaders, even when equipped with sufficient data and excellent analysis, will need to draw on their professional experience, intuition, political acumen, ethical practice, and strategic considerations in making their decisions. Data are the important part of the decision equation but not the only part that drive the decision (Knapp et al. 2007). According to Maycote (2015) "Being data-informed is about striking a balance in which your expertise and understanding of information plays as great a role in your decisions as the information itself. In the analogy of flying an airplane--no matter how sophisticated the systems onboard are, a highly trained pilot is ultimately responsible for making decisions at critical junctures. The same is true in a business organization" (p. 1). Given the recent tragic loss of two Boeing 737 Max airplanes, seemingly due to faulty control algorithms, Maycotte's (2015) analogy is appropriate yet disquieting.

The Importance of Clearly Delineating Between DDDM and DIDM

DIDM has its roots in the organizational learning theories in organizational management literature (Goldring and Berends 2009; Winkler and Fyffe 2016). Organizational learning is the process by which members of an organization acquire and use information to change and implement action (Beckhard 1969). Organizations that have knowledge systems distributed across functional units and individuals as well as embedded in the culture, values, and routines of the organizations are undergoing the process of organizational learning. In this way, data can serve as a catalyst to propel organizational learning. Leaders can use data to put into place mechanisms to support individual and collective learning surrounding data (Pfeffer 1998). A few more comments may help examine the differences between these two forms of decision making:

- DIMM is a more relevant and useful concept in the context of higher education because the decision context is very dynamic;
- DIDM acknowledges that data are not perfect in the sense that not all data are available and not all available data are accurate;
- DIDM acknowledges that analyses and algorithms are not perfect; models and algorithms are based on information available and human interpretation is needed;
- Organizational decision making is more nuanced than most algorithms can predict; and
- Human interactions and environmental factors are not as routine and more likely to change.

No doubt, data are invaluable and critical sources of decision insights for higher education organizations today. However, data analytics alone do not drive decisions, especially those strategic and operational decisions that have complex and dynamic contextual factors. For example, many universities employ predictive models to help them identify and recruit students and make admissions decisions. However, these predictive models do not replace the careful review and reading of the admission files and supporting documents by the admissions counselors. Many intangible factors need to be accounted for in such decisions. It would be callous and arbitrary if admissions offices rely entirely on quantifiable data and decision algorithms to make decisions.

In order to fulfill the missions of higher education that include teaching and learning, research and discovery, and public and community services, higher education officials engage in the human interactions with constituents or stakeholders. The idea of having super-algorithms to drive decisions and actions may have some appeal in the routinized and stable decision situations such as degree audit. However, we believe that DIDM is a better paradigm and concept to embrace, particularly in strategic and operational decision-making processes that involve human judgment, political sensitivity, and ethical considerations. For DDDM to work well, data need to be clean, stable and consistent, and regularly updated. Such an ideal situation is not often available in higher education.

Many institutions, even those equipped with the best data warehouses and business intelligence systems, face many challenges in data management. Due to inconsistent data standards and definitions, varying efforts in data quality control, and lack of strong data governance practices, it is not unusual that different numbers are produced for a seemingly identical question. A classic example is the calculation of faculty FTEs. The Offices of Institutional Research, Human Resources, Faculty Affairs, and academic departments may all be able to produce their own FTE numbers. Depending on what data definition is used, it is possible that all answers are technically correct but each is derived for a different context (Zheng 2015).

Additionally, in the age of Internet of Things (IoT)[2], the speed, volume, and variety of data available for decision analysis are overwhelming and they limit decision-makers' ability to process all available data quickly enough to use pre-determined algorithms to drive decisions. Chin and Shih (2017) point out that there is a growing belief that sophisticated algorithms can explore huge databases and find relationships independent of any preconceived theory and hypotheses. The assumption is: The bigger the data, the more powerful and precise are the findings. However, this belief may be misguided and potentially risky. There is high potential for more data sources and new data elements for which the current algorithms cannot account. Algorithms have the potential to include small biases in data that may be compounded. Because many machine learning applications do not offer a transparent way to see the algorithms or logic behind recommendations (O'Neil 2016), some business leaders call for 'explainable algorithms.' Despite all the hype about Big Data, data cannot be very useful unless they can be analyzed in a timely way to develop contextualized meaning (Lane and Finsel 2014).

In their 2012 report *Analytics in Higher Education: Benefits, Barriers, Progress, and Recommendations*, Educause formally defined analytics as "the use of data, statistical analysis, and explanatory and predictive models to gain insight and act on complex issues" (Bichsel 2012, 6). Analytics programs can offer institutions a way to be responsive to the increasingly challenging demands of organizational performance and strategic development they now face. Educause's definition of analytics is in alignment with the data-informed decision-making concept. It recognizes the need for data to be statistically analyzed, explained, and used to support complex decision situations.

DIDM is also important to organizational decision making in higher education because many strategic, operational, and management decisions that leaders face are dynamic, complex, and more nuanced than most algorithms can predict well. The organization's unique and nuanced issues make it difficult to suggest a perfect decision. According to a McKinsey survey of US companies (Marr 2018), only 18% of business leaders believe they can gather and use data insights effectively. Concerns include the need for proper analysis, how data is communicated to decision-makers, and who, in turn, take action from the insights. This finding is similar to what we discussed earlier in this chapter about higher education leaders' perception. In a recent survey of provosts and chief academic officers among US colleges, Jaschik and Lederman (2019) reported that only 16% of private university provosts and 19% public university provosts believe that their universities use data very effectively to inform campus decision making.

Enabling Conditions for Data-Informed Decision Making in Higher Education Institutions

DIDM in higher education does not happen overnight, nor, in most cases, smoothly. It requires a strong push from top down and a reciprocal enthusiastic support and participation from bottom up. Data analytics is part of a university's decision fabric that requires strategic planning from an institutional perspective and the allocation of resources that reflect its growing importance in support of the institution's mission and vision for the future. To be successful in instituting a data-informed decision culture, there are three main conditions that enable DIDM to

[2] For a brief definition and discussion on IoT, see: https://www.forbes.com/sites/jacobmorgan/2014/05/13/simple-explanation-internet-things-that-anyone-can-understand/#5318c8971d09.

be accepted and practiced in the higher education environment. They are the people, the technology, and the process and culture.

People: Leadership and the Analytics Community

University leaders have a very important role to play in data-informed decision making. Their commitment, support, and willingness to use data in supporting their decision making are critical factors in ensuring the successful development of a data-informed decision culture. In its Leadership Agenda series, leaders of *Achieving the Dream* (ATD), a non-profit organization advocating for college access and success, urges institutional leaders to set the tone of commitment to data. ATD believes that committed leadership is central to establishing a culture of continuous improvement that is grounded in inquiry and evidence. Presidents, department heads, and other institutional leaders should model behaviors that support a culture of evidence and inquiry throughout the institutions. ATD further believes that institutional leaders should regularly review and explore student outcome data with diverse stakeholders in ways that spur thoughtful problem solving for student success. (Achieving the Dream 2012).

Institutional leaders can provide support to data analytics development efforts by relating analytics programs with the University's strategy and vision. In hiring new leaders, institutional officials may find it helpful to ask new leaders about their interest, vision, and experience in using data to support organizational growth and performance assessment. Trustees should hold senior leaders accountable for delivering accurate, reliable and comprehensive data for strategy conversations. University leaders can demonstrate their support for DIDM by investing in data talents and analytical capabilities.

In 2016, leaders of Lehigh University conducted an organization-wide risk assessment and identified data analytics as a critical gap in their organizational capabilities. Lehigh University leaders immediately took action to appoint the chief information officer and the chief institutional research officer to assemble a planning team made up of senior administrative leaders and data stewards to develop a strategic analytics plan. The plan addressed some of the most critical areas of building a DIDM analytics culture, including the data management infrastructure, data governance, data reporting and collaboration, and the sharing of analytical insights. Most importantly, Lehigh University's leadership put resources behind these initiatives and enabled the hiring of key personnel and the acquisition of new data management and reporting tools. Actions included moving the business intelligence staff to co-locate with the institutional research and analytics staff, setting up a centralized data repository, establishing a Tableau server for generating data reports and data visualization, and hiring a data architect and a data governance manager. With positive outcomes, leadership support provided the momentum and resources that Lehigh University needed to embrace data-informed decision making.

Another important base of support for developing a data-informed decision culture is the existence of a critical mass of campus data analytics users and developers who are actively collaborating and sharing their knowledge and skills. Díaz, Rowshankish, and Saleh (2018) believe that analytical talents and users have different roles to play and the same individual can play different roles depending on the circumstances. These roles include:

- Business leaders - lead analytics transformation across organization;
- Data engineers - collect, structure, and analyze data;
- Data architects - ensure data quality and consistency of present and future data flows;
- Workflow integrators – build interactive decision-support tools and implement solutions;
- Visualization analysts - visualize data and build reports and dashboards;

- Data scientists - develop statistical models and advanced algorithms to solve problems;
- Analytics translators – ensure analytics solve critical business problems; and
- Delivery managers - deliver data and analytics-driven insights and interface with end users.

Clearly, as organizations face the challenge of Big Data, they need analytical talents to help clean the data, organize it, store it, along with training people to analyze and build models using data. High performing organizations tend to support data sharing and encourage collaboration among different types of users. A data community is a mutually-supportive environment where data users with analytical needs and appropriate security clearance can connect to all available data resources across different organization vectors to detect patterns or connections that a single data silo will not help. Mathies (2019) proposes that institutions develop a data-sharing mandate and Arellano (2017) recommends that a data user community be designed as a combination of people across the enterprise whereas common data and analytical tools are shared. This networked approach helps share information and analytic results across interested groups and those with more skills being seeing as a source of trusted analytics for the whole network. This combination of central governance and distributed data access and contribution can help everyone get needed information without slowing down the business by depending on the central IT team (Arellano 2017).

Technology

Another critically important enabling condition for DIDM is the availability and access to up-to-date and user-oriented data management and reporting tools, including but not limited to the following core components:

- Ability to integrate data from many different sources, including but are not limited to enterprise resource planning systems (i.e., PeopleSoft, Banner etc.), third party software systems, and cloud-based platforms, both internal and external sources;
- A strong data governance system that helps standardize and systematically document data definitions, data dictionaries, data specifications, and data lineages;
- Availability of effective data reporting, data analysis and data visualization tools; and
- Ability to harness the power of structured, semi-structured, and unstructured data resources through data architecture designs such as a data lake.

An enterprise-wide data management and sharing infrastructure typically comes in the form of an enterprise data warehouse (EDW). Traditionally, an EDW is installed on site at the institution in a database server and managed by the IT department. Technological advances in the last several years have allowed organizations to move EDW operations to the cloud. For Big Data storage, the concept of a *data lake* is now becoming more popular. A data lake is a data management methodology enabled by a massive data repository based on low cost technologies that improves the capture, refinement, archival, and exploration of raw data within an enterprise. This repository may contain unstructured, semi-structured, and structured data where most part of these data may have unrecognized value for the organization (Khine and Wang 2017). Data lakes are often built by tapping into the vast storage space made available by cloud-based computing platforms such as Amazon's or Microsoft's cloud solutions.

The availability of more data and from many more sources not only poses a challenge for storage and access, but also for the documentation and standardization of data elements. No matter it is in an EDW environment or a cloud-based data lake environment, a data governance structure with strong enforceability is a must. As a collection of practices and processes that help to ensure the formal management of data assets within an organization (Knight 2017), data governance is an organizational process that involves other activities such as data stewardship, data quality control, and data security. Together, these activities help an institution gain better control over its data assets, including methods, technologies, and behaviors around the proper management of data. For more detail, Glasgal and Nestor systematically introduce the concept of data governance and share how the system was implemented at Northeastern University in Chapter 6 of this volume.

Another technological must for DIDM is the wide adaption of data reporting and visualization tools in sharing data insights with constituent groups especially with the senior leadership. Gone are the days when data reports come in with tens of statistical tables and many pages. With data visualization tools such as Tableau (tableau.com) and PowerBI (powerbi.microsoft.com), data are now shown in different graphical formats, fitting the types of data used in the reporting. For example, to report historical trends in college enrollment, instead of using a table with columns and rows, data visualization tools now make the trend displayed in a line or bar graph, with many different filters to drill down to different colleges and departments and by different types of students. When done well following principles of good graphic design, a data visualization page can replace a large number of traditional tables. Described in Chapter 4, clear and concise communication is essential and visualized data reports can deliver the data insights quickly and provide an interactive element that can be more useful than static tables. With newer data reporting tools, key data reports such as management dashboards, fact-books, student profiles, and productivity reports can now be made visually attractive and easy to understand. For DIDM, data insights delivered in easy to understand, easy to access, and flexible packages are the key to acceptance and utilization. Figure 1 is an example of Lehigh University's Enrollment Report in a visually pleasing and highly intuitive format. As shown in Figure 1, the visualization module enables a user to interactively query the data by many layers of data filters: semester, level of students, class of students, race/ethnicity, cohorts, on-campus vs. off-campus, and FTE vs. headcounts. This report replaces many detailed data tables in a traditional paper-based or PDF-generated reports[3].

[3] Lehigh University's interactive data visualization tool can be accessed at https://oirsa.lehigh.edu/enrollment.

Another technological advancement in data analytics is the collection and analysis of social media and human interaction data. This new approach is best captured in the "connected campus" idea proposed by a number of companies such as Salesforce, Oracle, and Microsoft. Many higher education institutions are data rich and information poor. Institutions collect student data using enterprise resource management (ERP) systems like Banner or PeopleSoft but the data are mostly locked behind security layers and not utilized for analytical processing. Officials track high school students who visit institutional web sites, come for campus tours, and submit applications, but in most cases these data are not connected to predict and support their future success once they arrive on campus. Records are kept for students who participated in various campus activities but the data are scattered and not utilized to personalize and enhance students' learning experience. Academic advisors meet with student regularly but are not equipped with the right data to individualize their interactions. Degrees are granted to graduates but have limited knowledge about their career success and continuing engagement with their alma mater.

While these data issues may not have been major barriers to student success in the past, institution officials' ability to improve retention, graduation and lifelong engagement of students depends on improving our "connectedness." The connected campus idea is based on the "customer relations management" (CRM) platform (e.g., Salesforce.com) that acts as a communication tool for different campus departments to track their interactions with different stakeholder groups. A CRM stores data from all sources and organizes it in a way that facilitates personalized communications. For example, an academic advisor armed with a CRM will be able to interact with the student more effectively if he or she can access the student's academic records, student life, and career development opportunity data in one place. In Chapter 9, O'Brien explains how college officials can change their level of engagement with students by connecting the disparate data points to understand the full life cycle of student engagement from the time of initial interest in the institution throughout the students' interaction with the institution before and after graduation.

Process and Culture

Leadership support, a community of analytics talents, and a strong technology infrastructure are the strong foundation for developing DIDM. To truly make DIDM a success, universities also must change their business processes and intentionally build an analytics culture. This cultural transformation starts with the articulation of the basic principle of treating data as an institutional asset and not a resource owned or monopolized by a department or unit. In a survey of higher education leaders, Educause (2012) found that most agreed that the data silo is a particular common problem in higher education. For analytics program to become a success, it is generally agreed that organizational policies must be changed to encourage the sharing, standardization, and federation of data resources, balancing the needs for security with needs for access. For DIDM to take root, the followings are key considerations:

- Senior leadership needs to show commitment to using data to inform decisions by asking for and utilizing data analytics insights;
- DIDM requires the breaking down of the organizational silos to facilitate data sharing and collaboration –no individual unit or department 'owns' the data, but rather it is part of the University's data resources and needs to be shared based on appropriate security and data governance rules;
- IT, IR, and operational management should work in close collaboration to explore data and analyze data findings to discover actionable insights; Organizational leaders must be

willing to take the actionable insights to pilot test new organizational change or operational improvement ideas; and

- Given the large number of challenges facing higher education institutions, DIDM efforts will add greater value if such efforts can focus on institutional priorities (such as student success).

Data silos are often a barrier to greater level of transparency in performance assessment and institutional planning. Gagliardi and Turk (2017) point out that the democratization of data analytics might reveal some inconvenient truths about the performance of colleges and universities. However, greater level of data transparency is needed as the higher education sector becomes more competitive and stakeholders demand greater accountability. Instead of letting organizational silos become barriers to make needed changes, colleges and university leaders should empower change by providing critical operational and performance data to key stakeholders so that they can use the shared data resources to make informed decisions. For example, at a private college in the Northeast US, a college-wide interactive dashboard project got stuck in the implementation phase when the deans and department chairs demand that their data be kept from other deans and chairs. To meet the needs of the deans and chairs, the complexity of the data classification schema and access privilege rules increased almost exponentially, making the data programmers job a nightmare. Even when the programmers are able to create data visualizations for the reports with multiple layers of administrative access rules, the resulting data reports lost all the connectivity and relative comparisons that a visualization tool is designed to deliver. To truly embrace DIDM, college leaders must break down the data silos and show some courage in enabling data transparency.

Another important aspect of cultural transformation in data analytics is the willingness to give data insights a chance to inform decision making. Leaders must have both the patience and the willingness to let data provide clues, to take some risk, and allow program experimentation. To have an innovation mindset is critically important because Big Data, artificial intelligence (AI), and machine learning (ML) will likely create disruptive changes. For example, one college's admissions office staff produced a well-designed and detailed glossy brochure to attract more applicants to help achieve its goal of expanding its enrollment for five consecutive years. Admissions officials sought to send the brochure to every applicant who visited their web site and requested additional information. Given the high cost of printing, the Vice President for Admissions decided to divide the prospects into two groups, with Group A prospects receiving the glossy paper brochure and prospects in Group B receiving a PDF version of the brochure through email with enhanced web-based contents. With the goal to find out if an electronic brochure is equally effective in encouraging application, this experiment definitely came with risk; if the electronic brochure was not well received, the college would have missed its enrollment target. College officials proceeded with the experiment, affirmed that it was a risk worth taking because they believed that Generation Z students (the primary demographic group who are interested in this college) are more receptive to electronic materials. More importantly, they wanted to use data and results from this quasi-experiment to inform future admissions strategies.

Another key aspect of building a data-informed decision environment is the collaboration between the information technology (IT) and the analytics communities. IT is a critical partner that contributes to the strong and dynamic analytical environment of the campus. When asked, "What is your data strategy?" DalleMule and Davenport (2017) argue that a data strategy framework should distinguishes between data defense and data offense – each with different objectives, activities, and architecture. A defense data strategy focuses on ensuring data integrity, data security, data access, and data documentation. An offense data strategy centers on generating insights from data to support business process, generate business value, and achieve organization objectives. In other words, defense is what IT is good at providing and offense is what business users and analysts are good at developing. Defense and offense need to work well together to become effective in implementing organizational data strategies. All higher education institutions need both offense and defense data strategies to be successful in DIDM.

The Imperatives for DIDM in Higher Education

The Expectation Imperatives of DIDM

Many individuals hold high expectations for higher education. Stakeholders such as student and parents expect costs to be controlled, time to degree to be reasonably short, graduation rates to be high, and for students to secure employment after graduation. Business leaders expect universities to equip students with employable skills who can contribute to problem solutions. Government leaders expect universities to operate efficiently and contribute to regional and local economic development. With these expectations, universities are under scrutiny to prove their value. Many aspects of the university's operations will need to be supported by strong analytics programs. These include:

Student success and outcomes. For all higher education institutions (HEIs), student success and outcomes should be the most important mission. The success of Georgia State University in improving student success using analytical insights (see Chapter 8 of this book) is a great example of how DIDM can add value and truly make a great difference. Student success should be a core element of university strategy at the most senior level of the organization. Marketing and communications should highlight student success as a central piece of the institution's strategic mission. A sustainable plan should include data models and results showing return on investment at an institutional level. As the process scales, retention improvement will help improve revenue stream and improve instructional quality. Leadership should consistently communicate a vision of student success—this can in turn effectively align resources to support defined goals.

New academic program and curriculum innovation. Analytical tools such as learning analytics, customer relations management (CRM), machine learning, and artificial intelligence will create opportunities for new designs of academic programs and through mass customization. New developments such as stackable credentials, learning badges, and experiential transcripts are more connected with student learning needs and with demands of the job market. Davenport et al. (2001) point out that armed with Big Data analytics, more organizations will be able to better understand customers' needs and will, subsequently, create new products that those needs. Higher education can and should use Big Data analytics to support program innovations and changes that meet the changing needs of the students and employers.

Meeting the needs of the community and industry. In discussing a university's relation with external communities Gavazzi and Gee (2018) use spousal relationships as a metaphor to argue that universities must cultivate relationship to have harmonious and prosperous interactions with its communities. To address the value propositions to its community and industry partners, university officials should work proactively to create and sustain programs that are mutually beneficial. In today's digital age and global competitions, universities cannot be an ivory tower isolated from its surroundings. University missions and programs are connected to the communities and the industry in large part as students acquire employable skills and knowledge that meet community and industry needs. DIDM will help by informing universities leaders and faculty members about labor market trends, assessing students' learning experience and leadership capabilities, and measuring the effectiveness of different pedagogical approaches.

Operational efficiency and effectiveness. One of the biggest opportunities for higher education sector in leveraging data analytics for decision making is the ability to improve operational efficiency and effectiveness. Big Data technologies, cloud-based solutions, machine learning and artificial intelligence will make some of the older technologies and costly solutions obsolete (See Chapter 11 of this book for Wayt et al.'s discussion and examples on how analytics support financial and business operations in higher education). For example, enterprise resource planning systems, including human resources, finance, research administration, and student information, will no longer need to be installed and operated on premise and budgeted as an expensive capital expenditure, saving a lot of resources and personnel cost. Instead, universities that migrated to new cloud-based solutions will be in better position to allocate budget IT spending as operating expenses which is easier to budget on an annual basis and minimizing cost surges for major upgrades. Data analytics can also help achieve operational efficiency and effectiveness by bringing data transparency and disciplines to performance assessment. As resources management and outcome measures become more accessible through dashboards and scorecards, the conversation on how to achieve better results and improve collaboration will lead to newer opportunities for shared services and reduction of redundancy.

Strategic agility and differentiation. More so than in the past, the next 10-20 years in higher education will test the ability of university leaders to strategically steer their institution. The challenges facing higher education and the rapid changes in the digital revolution and connectivity may bring disruptive innovations at a speed that is faster than anticipated. Senior leaders in higher education must identify the strategic challenges facing their institutions. Questions may include what strengths or unique capabilities differentiate one institution from another, what new programs are needed in order to stay competitive, can one recruit the right number of students based on the desired student profiles given the significant demographic shifts to come, and can one grow the institution's revenue base without relying heavily on tuition increases. University leaders and trustees must grapple with these and many other questions in their decision-making process. Marsh and Thariani provide critical insights to address these questions in Chapter 5.

Data governance, security and ethical considerations. Another imperative for DIDM is the safeguarding and ethical use of our data resources. It is important that data be used to generate analytical insights to inform decisions. It is equally important that this is done is a manner that protect the privacy and rights of our students and employees. Chapter 6 addresses important points related to data use and governance and Chapter 4 shares important insights on responsible and secure use of data. Prinsloo and Slade (2015) remind us that the traditional paternalistic HEI culture, along with the more recent enthusiasm for possible enhanced student success through analytics, have influenced attitudes and policies on data collection but have not adequately addressed issues of privacy. Strong data governance and a thorough plan for safe collection and storage of data are critical keys.

Cloud-based solutions and the proliferation of third-party applications will continue to create challenges for data management. Most of the policy and process questions need to be addressed through a data-governance body to ensure legal and regulatory compliance and to reduce organization risk exposure. Similarly, as more data resources are being used to create predictive models and algorithms that impact students' lives and outcomes, greater attention and care need to be taken to ensure that the privacy rights of the study subjects are being safeguarded. In Chapter 4, Webber and Morn also address some of the human factors and subjective judgement needed in the use of data. Many decisions require careful calibration of the political, financial, and social factors.

DIDM is a cultural change and not a one-time project. For DIDM to work well, university leaders and the user community need to embrace it as a platform and a culture, not a project that needs to be completed. DIDM is not just about the data tools or the newer technologies, it is more importantly about the data-awareness and analytical insight acceptance and utilization mindset. Educause (2012) recommends that higher education leaders ask the right strategic and operational decision questions and seek to use data evidence to answer these questions and find the right solutions; invest in data talents and data insight translators and foster a vibrant data user community on campus; do not let perfection be the enemy of data uses, make the best out of available data information resources; encourage closer collaboration between the IT and the analytics communities; and invest in analytical tools and technologies that will facilitate the integrated view of data insights across the campus.

Conclusion

Advances in technology including storage for large volumes of data are challenging the ways in which decisions are made in higher education. Nearly if not all stakeholders desire more data, assuming that it will make better decisions. Unlike data-driven methods that rely heavily on pre-determined algorithms, we believe that data-informed decision making will facilitate goal completion and help achieve greater effectiveness for higher education institutions. DIDM involves both top down commitment and bottom up support, strategic planning and resources that acknowledge the institution's mission and vision for the future, and lots of hard work. A strong foundation for DIDM rests on leaders who support and facilitate organizational programs and procedures that develop and build a community of analytics talents. University leaders have a critical role to play in data-informed decision making; their commitment, support, and willingness to use data to support decision making is among the most critical factors that will ensure the successful implementation of a data-informed decision culture.

Although the volume and variety of data continue to increase at a faster speed, institutional leaders as well as external stakeholders must consider the practical and ethical uses of data in higher education as they strive to stay ahead of the data tsunami. While vendor products abound, users or potential users should ask hard questions about the "what" can practically be learned from the data as well as the accuracy of the statistical models or algorithms being used. Users must guard against predictive analyses that include subtle biases or produce other unintended consequences (Ekowo and Palmer 2017; O'Neil 2016). An institution's strong data governance plan is incredibly important. Officials may wish to review Mathies' (2019) proposed *Data Bill of Rights* that requires a plan to protect individual data as well as a practices that promote data definitions, rules of use, transparency, and shared governance.

Many aspects of the university's operation will benefit from a strong analytics program. Building partnerships with the local community and businesses, ensuring strong data governance and privacy policies are key drivers to the further advancement of data analytics in higher education that will facilitate student and institutional success. Analytic strategies of data will not be minimized, only further emphasized as we move forward in the future. The proceeding chapters will provide additional detail on a number of related topics.

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