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Data-Informed Decision Making and the Pursuit of Analytics Maturity in Higher Education

Karen L. Webber
Institute of Higher Education, University of Georgia, kwebber@uga.edu
&
Henry Zheng
The Ohio State University

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Karen L. Webber and Henry Y. Zheng

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Abstract
Data analytics is beginning to transform the culture, strategy, operations, and outcome assessment of college and university campuses in part due to the use of data, statistical analysis, and explanatory and predictive models to gain insight on complex issues across the business and learning domains of higher education. This chapter summarizes some important points discussed in previous chapters of this book and offers examples of analytics maturity models that could be considered for use in the higher education setting. To ensure proper and beneficial use of data analytics, senior institution leaders may wish to consider four key aspects of technology development: people, process, technology, and culture.

Introduction

The transformation in the use of data for informed decision making in higher education has begun. Facing growing competition for educational delivery, rising education costs, and shifting demographic trends, the competitive higher education environment today has encouraged a deeper understanding and use of data-informed decision support. Data analytics is beginning to transform the culture, strategy, operations, and outcome assessment of college and university campuses, in part due to the use of data, statistical analysis, and explanatory and predictive models to gain insight on complex issues across the business and learning domains of higher education. Analytics practices are informed by publications from higher education partners such as The American Council on Education (Gagliardi and Turk 2017) and Educause (Dahlstrom 2016; Educause 2019), institutional leaders have an opportunity to use enterprise-level analytics to drive digital transformation and redefine the student experience and success. To accomplish this, leaders must create and continue to support a data-informed culture that values data and appropriate analytics. While the discussions in this book have focused on data analytics in U.S. higher education, similar trends and activities are happening in higher education around the world. Although higher education in different parts of the world may face some unique issues, a large number of topics and challenges are similar. Indeed, considerations for the implementation of data analytics, incorporating the use of data amidst growing complexities in higher education organizations, and challenges with data security and privacy resonate comparably to higher education officials in every region of the world.

In the previous chapters of this book, we have seen principles of good practice, examples that have been implemented, and convincing arguments for the use of data analytics to inform admissions and enrollment management decisions, to promote student success via advising and course management systems, to connect and engage stakeholders, to maintain energy efficient buildings and physical plant practices, and to support the finance and business decisions of colleges and universities. Often, new processes and practices are slower to be implemented in education compared to the business sector. However, data analytics is now moving strongly into many higher education practices and the value received from data analytics is clear. We agree with Davenport (2006) who believes that organizational leaders who embrace the analytics culture and attempt experimentation are creating competitive advantage.

Data-Informed Decisions Are Better

Rather than from the perspective of *data-driven* decision making (DDDM), we framed the discussions in this book from the perspective of *data-informed* decision making (DIDM). Where DDDM lets the data "drive" the decision-making, removing human consideration of the context, DIDM recognizes that human judgement is a key element in complex, dynamic, and strategic decision-making. A number of factors may need to be taken into consideration, thus 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. Even when equipped with sufficient data and excellent analysis, higher education leaders need to draw on their professional experience, political acumen, ethical practice, and strategic considerations in making decisions. Data-informed decisions wisely consider knowledge learned from the data, but also factors in unique facets or features that are important in the formulation of a decision. We agree with Lane and Finsel (2014) who purport that data cannot be very useful unless they can be analyzed in a timely way and developed with contextualized meaning.

Technology to assist with data-informed decision making has advanced rapidly in the past half century. While desktop computers became common place in the 1970s, computing power to manage higher education institutions advanced significantly in the 1980s and 1990s. Locally-developed administrative computing systems were soon replaced with commercial Enterprise Resource Planning (ERP) systems such as Banner and PeopleSoft. These enterprise systems were helpful in linking up some institutional operations such as student records, billing, and budgeting, but they did not capture other important aspects of the institution including management of learning outcomes, teaching effectiveness, and research outcomes. However, more recent customer relations management (CRM) systems for additional operations such as admissions, learning management systems (LMS) for teaching and learning, assessment management systems for educational outcomes, and donor management systems are becoming more prevalent.

Without a doubt, a critical factor in one's success in integrating a strong and successful data analytics program is the use of an actionable, sustainable, but adaptable data governance program. Such a plan includes a system of decision rights and accountabilities for information-related processes, identifies roles and responsibilities for various stewards, promotes high data quality, and emphasizes

collaboration and frequent communication to ensure good decision making. Staff members in units such as Institutional Research are critical for their knowledge of data definitions and nuances of the specific context, and members in IT are valuable contributors for their technical skills in data security, enterprise-level management, and storage.

Institutional leaders who encourage integrated data, stewardship, and collaboration among relevant colleagues for data governance programs are providing leading examples of good practice with data analytics. With 2020 in sight, we see an increase in the use of data analytics for informed decision making across campus. Today's advanced educational technologies include learning management systems (LMS), early alert or early warning advising systems (EWS), dashboards, and other tools that provide information on student application and enrollment, the management of student performance, course retention, and degree progress. Big Data and other data analytics are also being used to monitor heating and cooling of campus buildings, to examine frequency and length of library and recreation facility use, and to identify the most time-efficient bus routes. Advanced analyses, both traditional inferential analyses based on previous or current data, as well as predictive modeling and machine learning techniques, enable analysts to discern patterns that can be combined with contextual judgement to inform decisions. While the focus of the 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. Separate volumes are needed to unpack the many ways in which Big Data, AI, and other advanced analytics are contributing to knowledge production across many academic disciplines.

Indeed, the quickened pace of technological developments such as artificial intelligence, machine learning, and block-chain, prompt higher education leaders to consider the development and application of data analytics capabilities as an urgent institutional priority. The changes in the higher education marketplace suggest that having strong analytical capabilities and leveraging them to inform decisions will help create more effective strategic and operational capabilities leading to organizational competitive advantages.

Privacy, Responsible, and Proper Use of Data

Along with improved analytics, new techniques and strategies abound for the presentation of data. Visual software packages have improved the ability to present data in colorful charts and graphs, infographics, dashboards. Interactive visuals can be quite helpful to guide the reader through the view and can also help ensure clarity through definitions or caveats that appear when the user scrolls over a data point. However, while data visuals can be of great assistance, adherence to principles of good graphic design (e.g., Cairo 2013, Tufte 2001) will lessen the likelihood of misinterpretation. Cognitive psychologists remind us of important principles related to how one ‘sees’ data and how the brain interprets that data into information. Color, spacing, scale, and the calculation of numeric data are among important factors to consider when designing graphs and charts. Today’s new infographics, while intuitively appealing, may offer challenges to read and understand fully. In designing good graphics, Tufte’s (2001) words still ring true: *above all else, show the data*.

As advances in technology call us to collect more data, senior leaders must be explicitly wary of collecting data for collection sake. The volume of data currently collected has already shown that many institutions have more data available than is being used for informed decision making. Senior leaders and other lead officials in the institution’s data governance program should consider strategies for the addition of data before it is collected. Issues of student and staff privacy as well as adherence to data collection and sharing policies (e.g., GDPR, FERPA, HIPPA) must be followed. Transparency, and security should be integral aspects of learning analytics technology rather than afterthoughts

(Reidenberg and Schaub 2018). It should go without saying that higher education officials and commercial learning vendors should establish appropriate safeguards to govern appropriate access and use of learning analytics data. Reidenberg and Schaub (2018) further suggest that legal safeguards for education privacy should reflect the reality of increased use of data in education by expanding privacy protections to clearly cover learning analytics. Related to transparency and ethics of data use, Mathies (2018) urges higher education officials to consider a data-sharing mandate that would allow institutional data to be more accessible to campus colleagues but done so within a data governance plan. In such a data bill of rights institution officials would be required to develop a plan that respects and protects individuals' data, requires programming language that limits coding failures, and includes a data ethics board to review and ensure good data practices.

There are a number of critical success factors that have been identified by various chapter authors (consistent with the points made by collaborative conversations and meetings across leaders from AIR, Educause, and NACUBO). A number of important points have been made and are agreed upon by leaders across the three organizations, including the value and need for a data-informed decision culture. These leaders believe that such a culture requires:

- senior leadership commitments;
- building a collaborative culture to drive analytics development;
- securing and sharing data resources that empower the analytics community; and
- focusing on key strategic priority areas to deploy analytical solutions.

It is critically important for HEI senior leaders to have a roadmap that will guide their data analytics journey. This roadmap can be effectively supported and by a data analytics maturity model and assessed by metrics often designed in a scorecard.

Maturity Models for Data Analytics

Following similar upward growth, expansion, and sophistication in the related processes in the business sector, and despite an overall low level of data analytics (Gartner 2018), leaders in the higher education community are becoming more aware of the need to be focused on the use of data for informed decision making and how that translates into good business practices for the institution. Furthermore, Petty (2019) predicts that by 2022, 90% of corporate strategies will explicitly mention information as a critical asset and analytics as a critical competency.

Senior administrative leaders who are focused on the impact of technology can identify goals to increase the maturity of their institution's analytic structures and capabilities. In general, a *maturity model* is a technique used to a business process or aspects of an organization, with the goal of moving toward a more organized and systematic way of doing business (Proença and Borbinha 2016). A maturity model typically includes includes tiered or hierarchical levels that describe how well the behaviors, practices and processes of an organization reliably and sustainably produce required outcomes related to information technology. It is a tool that is used to develop, assess and refine one's IT focus, to know where the institution currently sits in relation to the institution's mission and goals, and to help determine where it wants to go in the future. A maturity model can be used as a benchmark for comparison with other institutions and to understanding of IT practices. Institution leaders can also seek to obtain an IT *maturity assessment* to identify gaps between the current state and future goals. As such, it can include an indication of the institution's strengths, weaknesses, opportunities, and threats. An IT maturity assessment can help establish a path to make improvements over time to create an improved, stronger, and/or more efficient IT landscape.

Maturity models originated in the business sector, but they are relevant and can be used for a variety of practices within higher education. Of interest here in this chapter are maturity models that relate to data and analytics in higher education. In addition to the innovations at Northeastern University described by Glasgal and Nestor in Chapter 5, a number of maturity models are available for specific aspects such as data governance, for example, The IBM Data Governance Council Maturity Model (Russom 2008; IBM Data Governance Council 2007). Further, a number of other leading companies partner with higher education organizations to customize strategies to help the organization improve organizational performance.

In addition to data governance maturity models, a number of broader maturity models for the implementation and use of analytics are available. Where data governance maturity examines change in data governance as an enabler of the analytics culture, analytics is the broader use of data within the context of organizational processes used to derive insights for decision making. Both involve technical capabilities, leadership, skills, strategies, and policies, and despite overlap in concepts, we see maturity models for data governance distinctively different from analytics maturity models.

Now refined over a number of years, Davenport's *Five Stages of Analytics Maturity* (Davenport 2018; Davenport, Harris and Morison 2010) and the subsequent *DELTA model* from Davenport, Harris and Morrison (2010) are well known and described here briefly.

Davenport's Five Stages of Analytics Maturity

Most organizations, including higher education institutions, grow in their understanding and complexity of organizational data. According to Davenport (2018), organizations mature their analytic capabilities as they develop their organizational structures and processes related to data. Davenport purports that his Maturity Model (Davenport and Harris 2007), and further refined (with Harris and Morison in 2010) helps organizational leaders measure growth in analytic capabilities. Shown in Figure 12.1 the five stages are:

Stage 1: Analytically Impaired. Organization leaders rely primarily on gut feel to make decisions and have no formal plans for becoming more analytical.

Stage 2: Localized Analytics. Analytics or reporting at the institution exists within silos. There is no means or structure for collaborating across organizational units or functions in the use of analytics. This often leads to "multiple versions of the truth".

Stage 3: ***Analytical Aspirations***. The organization sees the value of analytics, and intend to improve their capabilities for generating and using them. Thus far, however, it has made little progress in doing so.

Stage 4: ***Analytical Companies***. Companies in this category are good at multiple aspects of analytics. They are highly data-oriented, have analytical tools and make wide use of analytics with some coordination across the organization.

Stage 5: ***Analytical Competitors***. These companies use analytics strategically and pervasively across the entire enterprise. They view their analytical capabilities as a competitive weapon, and they already seen some competitive advantage result from analytics

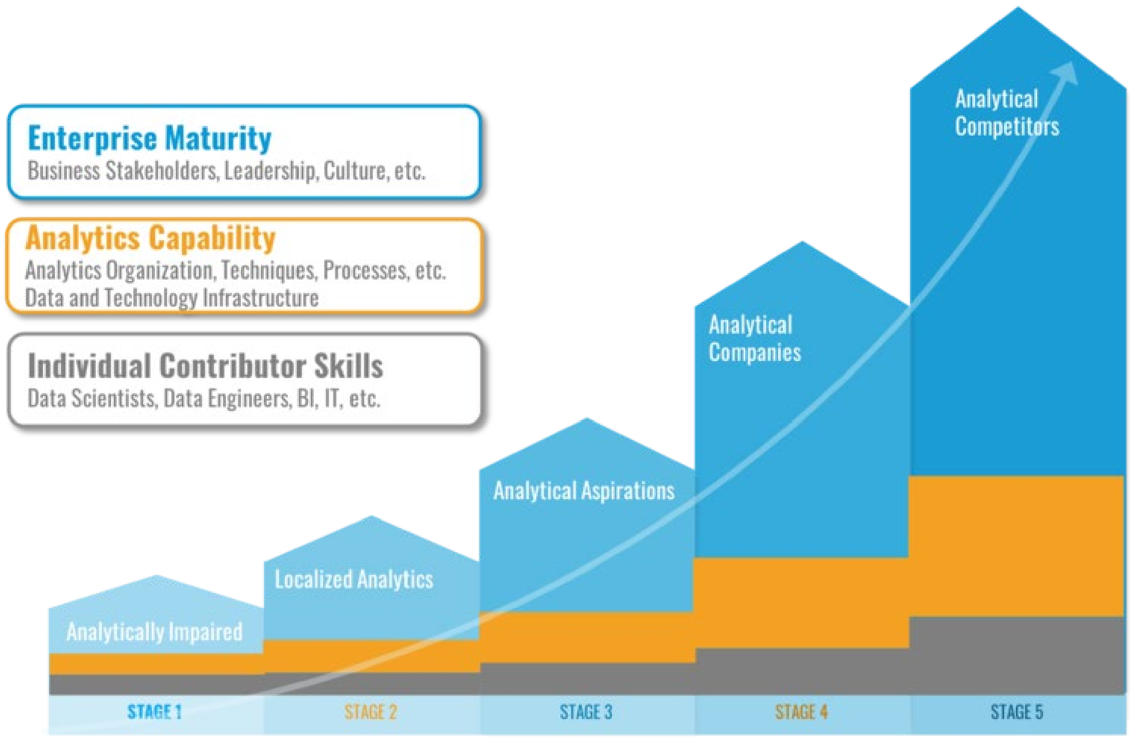

Figure 12.1 Five Stages of Analytic Maturity.
Davenport and Harris, 2007, Used with permission from Davenport, 2019.

According to Davenport (2018), an institution may have specific analytic strengths or weaknesses that identify them across different levels of the model. For example, an organization may achieve a Stage 4 in analytics leadership maturity, but achieve only a Stage 3 in its management and use of data. This assessment enables targeted investment to mature analytics weaknesses based on the DELTA Model (Davenport 2018). Furthermore, proceeding through an exercise to gauge the institution's current status of analytics maturity is not a one-time exercise. It should be repeated to measure progress and to ensure that institutional practices and policies related to data and analytics are continuing in the desired direction.

The DELTA Maturity Model

Following earlier versions of an analytics maturity model including Figure 12.1 (Davenport and Harris 2007; Davenport, Harris, and Morison 2010), Davenport developed the DELTA Plus Model to enhance the Five Stages of Analytics Maturity (2018). Davenport and colleague purport that in order to create meaningful analytics, data must be organized, unique, integrated, accessible, and of high quality (Davenport 2018, 3). Further, Davenport believes that analyses are influenced by the structure, cleanliness, and uniqueness of the data. Unsurprisingly, Davenport believes that organizations need to integrate their data across organizational silos and, where possible, combine and harmonize transactional systems across different business units. The five essential elements are:

D for accessible, high quality ***data***

E for an ***enterprise*** orientation to managing analytics

L for analytical ***leadership***

T for strategic ***targets***

A for ***analysts***.

Recently, Davenport (2018) added two additional elements to the DELTA model. Spurred by the continued growth of Big Data, and coupled with the introduction of new analytics techniques like machine learning, two additional elements (the Plus factors) that should also be considered are:

T for ***technology***, and

A for ***analytics techniques***.

Davenport and colleagues clearly advocate for an enterprise approach. The occurs by setting an analytics strategy and building a road map for strategy implementation. Integrating data and managing a unified data and analytics platform are essential components of an analytics road map, as is cultivating a culture of analytics across the organization. Senior leaders must embrace and support this approach and analytic efforts must be aligned with specific, strategic targets that reach to meet institutional goals.

Davenport (2018) also reminds us that while technology was stable for several decades in analytics, it is changing rapidly today. With the advent of big data, AI, cloud and open source options, creating an effective technology strategy for analytics is a critical prerequisite for success (Davenport 2018).

Gauging Analytics Maturity

While it is important to begin a campus-wide strategy for data analytics, it is helpful for institutional leaders to understand their progress in analytics implementation. To that end, Educause developed maturity and deployment indices to measure and benchmark analytics practices. Gauging the institution's current level of analytics development, identifying areas of strength and challenge, and developing strategies for progress can help officials engage in analytical strategic planning.

Following refinements in the original 2012 version, Educause offers (through their Core Data Service, CDS) a current maturity analytics maturity index that measures 32 factors contributing to analytics maturity. The dimensions examine multiple areas of progress such as culture, process, expertise, investment, and governance and are organized into six dimensions:

1. *Decision-making culture,* including senior leadership commitment and the use and cultural acceptance of analytics
2. *Policies,* including data collection, access, and use policies
3. *Data efficacy,* relating to quality, standardization, and "rightness" of data and reports and the availability of tools and software for analytics
4. *Investment/resources,* consisting of funding, an investment-versus-expense mentality, and the appropriateness of analytics staffing
5. *Technical infrastructure,* consisting of analytics tools and the capacity to store, manage, and analyze data

6. *IR involvement,* capturing interaction between the IT and the IR (institutional research) organizations[3]

Each dimension is scored on a scale of 1 (absent/ad hoc) to 5 (optimized), and the mean of those scores represents the overall institutional maturity score. This score provides a way for an institution where it sits currently and to assess if or to what extent, and in what areas, the institution is moving forward related to analytics. For more information on Educause's maturity index, refer to Educause's Benchmarking Service at: https://www.educause.edu/about/discover-membership/educause-benchmarking-resources.

Strategies for Success

Managing today's complex higher education institutions requires a thorough understanding of issues related to data management and use. It also requires support for campus faculty and staff who are leaders in data analytics, insistence on interpreting data within the institutional context, and regular interactions with external stakeholders to explain the value as well as the limitations of data analytics in higher education. Strategies must be in place to ensure adequate infrastructure, governance, security and compliance, process for operations, and ways in which to articulate and promote the value that comes from the analytics. As the role of the chief data officer takes hold, gaining authority and influence on par with other executives, organization leaders will likely move away from merely using data as a resource to analytics as reporting and decision-making support tools. Data and strategic data analytics will likely become the centerpiece of enterprise strategy, focus and investment (Hippold 2018; Petty 2019).

In many ways, data and analytics have the potential to help higher education students and institutions succeed. Institution leaders who have been on the forefront of these changes have seen benefits, and in some cases strategies that haven't quite hit the mark. As mentioned by Klein et al. in

Chapter 10, more than 1,400 papers were presented at the Learning Analytics and Knowledge conference from 2012 to 2018, and the inertia for research and strategies on learning analytics in higher education is now under way. Along with increased use of course management systems, early warning systems, and other aspects of learning analytics, researchers and senior institution leaders must consider how the tools and techniques are contributing to institutional business practices and student learning. For example, the volumes of data available on students can be used to identify learning environments and student acquisition of skills (Kinnebrew and Biswas 2012). Analysis of learning can occur through traditional human judgement of data results, but newer automated techniques are also being used including sequence mining (Kinnebrew and Biswas 2012) or classification (Sao Pedro, Gobert and Baker 2012), collectively called educational data mining (EDM, Baker and Siemens 2014). These forms of assessment can be similar to traditional psychometric approaches or advanced evidence-centered models of complex student skill (Baker and Corbett 2014). While the advantages of educational data mining can be seen, particularly the possibility of customized analysis of student ability early in a course or academic program, we see value in additional analysis and study of EDM assessment methods and their routine validation of results across multiple populations and for agreement with human judgements.

Institutional Impact

According to Gartner (2018), organizational leaders can follow four steps to move their institution's capabilities to have greater organizational impact:

1. *Develop holistic data and analytics strategies with a clear vision*. Coordination and collaboration among data and analytics, IT, and business leaders can enable continuous and dynamic attention to strategies for data analytics;

2. *Create a flexible organizational structure, exploit analytics resources, and implement ongoing analytics training*;
3. *Implement a data governance program; and*
4. *Create integrated analytics platforms that can support a broad range of uses.*

These steps require a deep and long-term commitment. As the institution moves to a more mature position in data analytics, tasks move from stand-alone disconnected activities, to ones that are connected and designed by leaders who are striving for comprehensive solutions and processes.

The Future Forward

Collaborations among campus personnel as well as collaborations across relevant professional organizations is also important. Similar or joint meetings and published materials can offer a strong and consistent message to members across groups who may have similar interests. The 2019 *AIR/Educause/NACUBO Joint Statement on Data Analytics* is an important message that describes the value of data analytics to higher education organizations. The joint statement includes six principles of action to promote the meaningful use of analytics in higher education. The statement and the working committee from these three key associations have taken advantage of their collective knowledge and insights derived from data to suggest an action plan that can help ensure implementation of strong data analytic strategies on campus.

The joint statement reminds us that the use and implementation of data analytics is complex and will require input from many individuals. However, the impact of data analytics across campus will be high, and when accomplished jointly with colleagues across organizations, the outcome can yield even greater benefits that are carried out efficiently. In their suggestions for how to build organizational capacity for analytics, Norris and Baer (2013) offer a framework that considers how to optimize student success through analytics (see p. 23). Except for perhaps a too heavy emphasis on data mining, the framework offers relevant suggestions for eliminating impediments for retention and student success, utilizing analyses to respond to at-risk students, and creating personalized learning analytics. In a similar vein, but focused on building capacity in Institutional Research, Webber (2018) posited four important factors that, collectively, can build capacity in IR. Shown in Figure 12.2, knowledge of needed skills and analytic techniques is paramount, as is previous research on relevant issues that are related to the analytic task(s) at hand. As mentioned in a number of the previous chapters, clear and accurate communication of the analytics results, via printed report, visualization, or face-to-face discussion is critical. Framing results within the context is vital, and working with partners across campus greatly contributes to the success of data analytics tasks. Perhaps the model applies to the ways in which higher education leaders can build and strengthen data analytics in higher education.

Figure 12.2 Factors in Building Capacity

Adapted from Webber, 2018.

This figure is a reminder that data governance and analytics are components of a larger strategic approach. As discussed by Marsh and Thiriani in Chapter 5, leaders strive for program alignment to ensure student and organizational success. To that end university leaders and trustees seek to leverage data resources and strategic analytics to fully understand the decision contexts and to objectively evaluate the trade-offs, cost-benefits, and long-term impacts of major organizational decisions. These goals require a high-level view.

Many leaders in higher education in the US and in other countries acknowledge the benefits of building an integrated data environment that empowers informed decision making. For example, MIT's Center for Information Systems Research's Advisory Board acknowledges that data strategy is a central, integrated concept that works within the larger business strategy (http://cisr.mit.edu/reports/create-a-data-strategy/intro.php). Collaborative efforts between institutions in the University System of Georgia and data scientists at the UGA Carl Vinson Institute of Governance are using predictive and other data analytics along with innovative visualizations to examine student admissions, pathways through their degree program, and other measures of success (Nolan, Byars, and Jones 2018). Efforts at this USG institution is offering new insights into student success that will likely contribute to institutional success as well.

Describing the framework developed at Stonybrook University, Hosch (forthcoming 2020) purports that a data strategy is an intentional plan to capture, integrate, and use data to advance the institution's mission and goals. While the maturity of each element in the data strategy may vary across institutions, data assets ideally encompass data across an institution and therefore require enterprise-level thinking and planning. Hosch (forthcoming 2020) reminds readers that data strategy should be informed by institutional priorities, goals, and return on investment. All strategies need to be forward-looking, should consider how the institution can accomplish its goals and mission, and must be documented, shared with others, and used to guide practice. We believe that these strategies can be accomplished most effectively when institutional leaders, faculty, and staff have the relevant skills and knowledge needed, ensure that the specific context is considered, can communicate effectively, and work collaboratively with relevant colleagues.

Concluding Remarks

As leaders consider options to support or boost their institution's analytic capabilities, the following are some questions to consider. The questions may serve as a useful checklist along four key aspects of technology development: *people, process, technology, and culture*.

People

- **Leadership support and commitment**: Do senior leaders have a vision and plan for how data analytics will help transform the campus decision environment? If there is a plan, does it support the incremental progression to higher level of analytics maturity?
- **Analytics talents development**: Does the institution have a professional development and career progression plan to help move data analytics staff from the more traditional data cleanup and reporting roles to the more skilled data researcher or data scientist roles with the right statistical and analytical knowledge and experience? Is there a formal or informal community or network for like-minded analytics talents to share knowledge and work collaboratively?
- **Acceptance of analytical insights by operational leaders**: Do operational level leaders (directors and managers alike) understand and take advantage of the benefits of analytical insights as they manage their organizations? Even the best research is worthless if the research findings are ignored and not being utilized to effect changes.

Process

- **Breaking down silos**: Do institution leaders make intentional efforts and policies to break down the data silos among different functional areas to improve data transparency and access for integrative analytics development? Analytics is more powerful if data assets are connected to paint a more robust picture of the relationships.

- **Data governance**: Does the institution have a robust enterprise-wide data governance program that effectively address the data quality, data curation, data documentation, and data access issues that key to the enablement of analytics development?

Technology

- **Data quality and integration capabilities**: Does the institution have a cohesive strategy to curate, manage, organize, and transform data as a strategy asset of the organization? A centralized or federated data warehouse or data lake is not the necessary condition for supporting and growing advanced analytics capabilities. However, having a robust data management infrastructure with the right access control will empower and accelerate analytics development.
- **BI platform and visualization tools**: Does the institution invest in business intelligence (BI) and data visualization and reporting tools that empower the analytics community? Analytics development is at its optimal state when BI and reporting tools are not monopolized by a few with access or specialized skills. Wide access to the tools and ease of use will liberate the creative energy among many data professionals as well as business users with an interest in analytics.
- **Ensure data security and ethical use**: Does the institution have a strong data security and data governance program to help ensure compliance with data security, privacy and ethical use of data assets? Be vigilant that data are well protected so that the information does not get into the hands of those who intend to misuse it. Staff should be trained on implicit bias of model algorithms and the limitations of data. This is especially important for predictive analytics that

directly impact the student populations. New America, an advocacy group, has a series of papers on how predictive analytics should be used ethically and their guidelines[1] are available on line.

Analytics Culture

- **Use of data insights for decisions**: Does the institution make intentional efforts to use data to support strategic and operational decision making? his may include the use of performance scorecards for senior leaders' annual reviews, budget allocation decisions, and board conversations.
- **Achieve value through focus**: Does the institution's predictive analytics efforts oriented towards your strategic and operational priorities? Analytics development efforts need to align with organizational priorities to generate the value and support among university stakeholders.
- **Translation of analytical insights**: Do the data analytics professionals know how to translate analytics insights to understandable knowledge? Even the most profound analytics findings must be translated and understood to be actionable and effective. Professional development is needed to help data science professionals to tell stories about data and data discoveries.
- **Communications and acceptance**: Do institution leaders communicate with the campus community about the need and urgency for use of analytics? Higher education is generally more accustomed to incremental changes and predictive analytics and its findings may point to rapid changes that might conflict with some of the business practices that have been in place for many years. Without clear articulation and communication of how predictive analytics may benefit the

[1] New America - Predictive Analytics in Higher Education – "Five Guiding Practices for Ethical Use." Available at https://www.newamerica.org/education-policy/reports/predictive-analytics-in-higher-education/

campus, even the most brilliant analytic insights may not yield desired outcomes if they are not accepted.

Ideally, the data analytics strategy incorporated in an institution's larger strategy will produce excellent results. However, having the skills, knowledge, people, tools, and processes to develop and implement that strategy require extensive resources. One great challenge is finding the resources needed, especially for institutions with limited budgets and staffing. No easy answers exist. Perhaps institutional resources can be set aside for this important need; or perhaps local, state, or federal level resources can be acquired. Once the large strategy is developed and documented, perhaps small successes can be promoted as a way to build positive community buy-in and work to complete a larger plan over time. The challenge will rest with each institution's leader to chart the best path forward. However that is accomplished, we believe that data analytics in higher education will only grow in importance for higher education. We look toward a bright future and believe that the discussions in this book have contributed to the discussion on data analytics in higher education. Due to space limitations, this volume includes case examples that represent only a portion of good programs and practices that exist. We hope the discussions offered provide insights into a better understanding of data analytics and necessary components of analytics strategies that have been developed and should be considered by those in institutions that may not have reached this step. Indeed, an optimal data analytics plan will require organizational, cultural, and strategic changes, but a beneficial and effective plan is possible and we hope that this volume leaves the reader with new insights and an excitement for the future of data analytics in higher education.

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