Understanding and Developing a Data-Informed Culture

ADVISING SUCCESS NETWORK | EDUCAUSE

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Introduction

ADVISING SUCCESS NETWORK

Formed in 2018, the Advising Success Network (ASN) is a dynamic network of five organizations partnering to engage institutions in holistic advising redesign to advance success for Black, Latinx, Indigenous, Asian, and Pacific Islander students and students from low-income backgrounds. The network develops services and resources to guide institutions in implementing evidence-based advising practices to advance a more equitable student experience to achieve our vision of a higher education landscape that has eliminated race and income as predictors of student success. The ASN is coordinated by NASPA - Student Affairs Administrators in Higher Education and includes Achieving the Dream, the American Association of State Colleges and Universities, EDUCAUSE, NACADA: The Global Community for Academic Advising, and the National Resource Center for the First-Year Experience and Students in Transition.

ABOUT EDUCAUSE

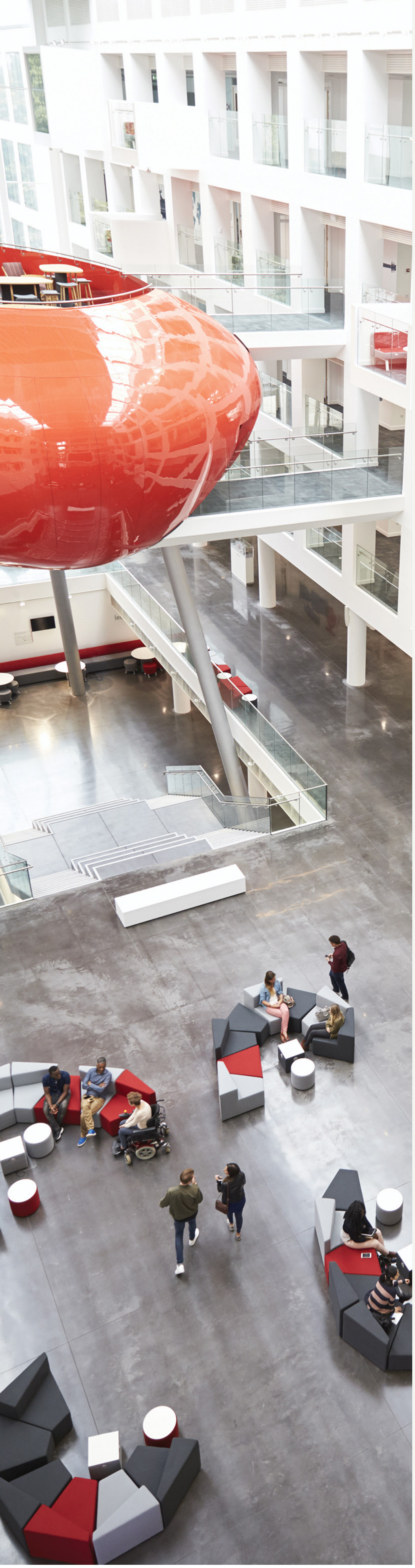
EDUCAUSE is a higher education technology association and the largest community of information technology (IT) leaders and professionals committed to advancing higher education. Technology, IT roles, IT responsibilities, and higher education are dynamically changing. Formed in 1998, EDUCAUSE supports those who lead, manage, and use information technology to anticipate and adapt to these changes, advancing strategic IT decision-making at every level within higher education. EDUCAUSE is a global nonprofit organization whose members include U.S. and international higher education institutions, corporations, not-for-profit organizations, and K–12 institutions. With a community of more than 100,000 people at member organizations around the world, EDUCAUSE encourages diversity in perspective, opinion, and representation.

USERS OF THIS GUIDEBOOK

This guidebook is designed for strategic use by stakeholders across the *institutional community*, particularly staff and faculty involved in advising, information technology, institutional research, and data analytics business areas. Principal groups who might benefit most from using this guidebook as an operational framework are listed below:

INSTITUTIONAL RESEARCH AND DATA ANALYSTS can use the information in this guidebook to:

- Integrate teams focused on redesigning and adopting technology-enabled advising.
- Establish effective data storage and retrieval systems and processes, in collaboration with IT.
- Advise on and track key performance indicators around using, managing, and sharing data.
- Collaborate with functional leaders in advising to formulate strategy and implement tactics with metrics to achieve greater adoption of data use, data management, and reporting.
- Increase cross-functional collaboration with offices that use data to inform decisions, such as advising.
- Increase cross-functional collaboration with offices that are responsible for enterprise-level technology infrastructure.
- Provide reports and data that advising leaders can use to communicate holistic advising redesign efforts campus-wide.
- Support continuous quality-improvement initiatives with information and reports that are easy to access, understand, and use.



ADVISING LEADERS & OTHER STUDENT AFFAIRS PROFESSIONALS can use the information in this guidebook to:

- Integrate teams involved in technology-enabled advising redesign.
- Recognize and advocate for the structures, culture, and systems required to support the integration and optimization of advising / student services technology products.
- Formulate student success strategy and implement tactics with metrics to achieve greater adoption of data use, data management, and reporting.
- Increase cross-functional collaboration in offices that work with data, such as institutional research, data analytics, and information technology.
- Differentiate among types of data that can be used to inform intervention or measure outcomes and contribute to continuous quality-improvement initiatives.

INFORMATION TECHNOLOGY LEADERS can use the information in this guidebook to:

- Integrate teams involved in technology-enabled advising redesign.
- Recognize and advocate for the systems, structures, processes, and culture required to support the integration and optimization of advising technology products.
- Develop strategic planning goals and key performance indicators around using, managing, and sharing data.
- Collaborate with advising functional leaders to put strategy and tactics into action and develop metrics to achieve greater adoption of data use, data management, and reporting.
- Increase cross-functional collaboration in offices that use data to inform decisions, such as advising.
- Implement data systems, structures, and processes to support strategy and student success goals.
- Integrate the technology-enabled advising data ecosystem into the overall institutional technology and data management strategy.

SENIOR LEADERSHIP can use the information in this guidebook to:

- Convey a clear vision and call to action for campus stakeholders related to cross-functional collaboration, data-informed decisions, and data culture.
- Develop strategic direction of institutional policies related to data-informed decisions and culture.
- More intentionally improve the data-informed decision-making processes and culture that are essential to successful technology-enabled advising transformation.

HOW TO USE THIS GUIDEBOOK

This guidebook was developed to help institutions build or improve data structures and governance related to advising and student success analytics and to identify ways to develop their data-informed decision making and culture. These investments in improving awareness around the strategies and practices used to collect, store, and share data are an important component in holistic advising redesign, as the quality of data-informed decisions is underpinned by the accuracy of the underlying information.

Cross-functional collaboration is a key factor in ensuring that the right people have access to the right data at the right time. The reflection questions, callout boxes, and activities in Section 6 are intended to encourage readers to answer critical questions individually or as part of a team to promote strategic use of data that can ultimately support high-quality advising practices at scale. Regardless of role, staff can use the content presented here to engage in important conversations with others across different departments. For institutions that already have strong working relationships in place across the advising, information technology, and data analytics business areas, reading this guidebook as a team and meeting regularly to discuss may result in the greatest benefits to the institution.

This asset is intended to act as part of a set of ASN resources related to data and advising technology. Additional resources can be found on the ASN website: https://www.advisingsuccessnetwork.org/

KEY TERMS AND LANGUAGE

Advising: Advising is a critical component of student success and a "bright star" in the integrated constellation of student supports at an institution. The advisor–advisee relationship supports students as they identify and attain their academic, career, and personal goals. ASN defines "advising" as encompassing more than the student interaction. It also includes the structure and operations of academic advising; the roles and responsibilities of primary-role and faculty advisors; and advising pedagogies, approaches, and models.

Holistic Advising Redesign: Holistic advising redesign can help institutions identify, implement, and/or refine equitable, high-quality, and effective institutional practices.

By addressing people, processes, and technologies in equal parts, institutions are able to offer students advising experiences that are sustained, strategic, integrated, proactive, and personalized. Successful redesign requires centering student voices and collaborating across advising, leadership, information technology, institutional research, and other student support offices.

Equity: A concept grounded in the principles of justice and "do no harm," equity calls for both the acknowledgement of and commitment to rectifying historical injustices toward minoritized populations. In higher education, pursuing equity begins with institutions acknowledging that Whiteness is the norm and foundational to how the institution of higher education was created. Institutions pursuing equity articulate both their commitment to and actions in identifying, dismantling, and rebuilding the structures, systems, and cultures that uphold oppression and challenge minoritized students' access to postsecondary opportunities and success.

Importantly, equity is not something institutions or practitioners *achieve*; rather, it is an ongoing process and commitment to ensure every individual has what they need to achieve their academic, career, and personal goals.

Student Success: From an institutional perspective, and for the purposes of this guidebook, student success is defined as enrolling, retaining, and graduating students, capped with securing post-college outcomes of employment or graduate school (at minimal cost and debt to the students and with maximum potential for earning). For students, student success is the outcome of a personal, rigorous, and enriching learning experience that culminates in the achievement of students' academic goals in a timely manner and fully prepares them to realize their career aspirations.

REFLECTION

As you begin to explore the *what, why, how, and who* behind the strategic use of data to align institutional vision, equity goals, and advising goals, take a moment to reflect on your institutional context and resources. Every campus differs in terms of mission, staffing, processes, and approach. As you read through this guidebook, focus on your starting point and what information may be most applicable to your situation. Set realistic goals based on your particular needs. And remember, even incremental change is progress.

Throughout the guidebook, you will encounter additional reflection questions at the end of each section for you and/or your cross-functional team to answer. Please use these questions to help you identify potential next steps and actionable items as you develop your capacity to use data to inform your advising and student analytics goals.

GOAL-SETTING QUESTIONS

1. What do you hope to learn from reading this guidebook?
2. What does your institution's data culture look like? What does "data informed" mean at your institution for different functional areas?
3. Do you have access to disaggregated student data that would enable you to identify and describe equity gaps in student outcomes? If not, what would your "utopian data world" look like? What information would you want to collect and share with decision makers?
4. Who are the advocates for adopting a stronger data-informed culture at your campus?
5. What's a small, interim goal related to data-informed culture you might set? What's a long-term goal related to data-informed decision-making you might set?

SECTION 1:

Data-Informed Culture

Traditionally, providing access to data involves specific "use cases" that clearly define the specific questions or intended outcomes along with the specific data needed to reach an answer or outcome. Today's decision-making begins more with the discovery and identification of interrelationships between data that have been previously underutilized. Innovation requires iterative cycles of trial and error as potential solutions are identified and analyzed, then revised, adopted, or discarded. Additionally, professionals working in nearly all areas of the institution are increasingly considered to be "knowledge workers"—defined by Peter Drucker in his book *The Landmarks of Tomorrow* (1959) as workers who apply theoretical and analytical knowledge. To a greater and greater extent, effective decision-making—regardless of how strategic or tactical the context—requires discovery and innovation, rather than formulas or recipes derived from the status quo (Drucker, 1959). A data-informed culture removes unproductive and unnecessary barriers to accessing institutional data, within reasonable risk tolerance, and invests in the training and tools that anticipate what may be necessary. Simply put, a data-informed culture creates the data infrastructure and broad data accessibility for people to be able to answer the questions critical to the success of their organizations as well as those they do not yet know to ask.

IN THIS SECTION

What Is a Data-Informed Culture?

A data-informed culture is one that bases decisions on data-derived facts, research, experience, and input from credible sources as opposed to assumptions and "gut feelings." In a data-informed culture, data are available, accessible, reliable, and entrusted to all members of the organization to inform their decisions and actions. Just as important, potential assumptions and biases in data are also explored to reveal and address systemic biases and equity gaps. Leadership plays a key role in creating this culture, as does thoughtful data governance, particularly when it comes to student success analytics. It can be helpful to think about data-informed culture in terms of both enabler and barrier attributes.

ENABLER ATTRIBUTES

Attributes and behaviors that enable an institution's ability to develop a data-informed culture include seeing data as an asset, democratized use of data, strategic investment in quality data infrastructure, widespread data governance practices, risk management, and consistency in relying on uniform sources of truth.

Institutional Data as an Asset and Not a Resource

The first and perhaps most important attribute of a data-informed culture is the shared understanding that the catalog of institutional data is an asset to be invested in and not a resource to be consumed. The institution recognizes that all data and information created, collected, consumed, and communicated by the institution's processes and functions are institutional data, regardless of the format (electronic, paper, staff knowledge, etc.). Like all assets, institutional data must be invested in to advance the institution's mission. Simultaneously, the institution must consciously and continuously invest in the data to increase their value and usefulness. Policies and standard operating procedure guide how the investment office stewards and invests endowment dollars for the good of the entire enterprise and then how those endowment dollars are made available and used by units to support activities, initiatives, and programs. Similarly, units responsible for institutional data (data stewards) must tend to the institution's data for the good of the entire enterprise and ensure that those using the data do so appropriately to inform decisions.

Democratized Use of Data

It is also important to recognize data as an enterprise asset to be used in a democratized manner, meaning that it belongs to the institution as a whole and is not "owned" by any functional unit or area. While data stewards have responsibility for setting guidelines for the responsible use of data produced by their unit, these data are ultimately generated to assist in meeting the strategic initiatives of the institution as a whole. To support this concept, institutions with a strong data-informed culture accept and proactively manage a certain level of risk that will always be associated with making data widely available. As with endowment funds, the adage "nothing ventured, nothing gained" is true for data. A thoughtful, established, and transparent definition and understanding of the appropriate amount of risk tolerance for widespread use must balance with the potential for the value returned. For example, privacy and security risks come with sharing data across units, along with the possibility that data could be mishandled or misused. To mitigate risks, some try to hide or limit access to data, and as a result there may be missed opportunities to use institutional or departmental data to inform decisions, reveal knowledge and equity gaps, and celebrate successes. Two main mechanisms help protect data: controlling access to the data and training staff to use the data properly.

A good illustration of data democratization is the way the Toyota Production System (Power, 2011) engages all its workers to improve its products. From the senior executive to the frontline assembly worker, everyone is not only enabled but actively engaged in using data to make product and process improvements. Further, everyone is enabled and expected to stop their own and all related processes when a quality issue is identified, so that the associated problems can be resolved before moving on. A data-informed culture embraces this same approach. From senior leadership to the data stewards and the data consumers, all share the responsibility for ensuring that the data are accurate, available, accessible, complete, and relatable—in other words, ensuring that the entire institution may have trust and confidence in its data so that democratized, data-informed action can take place. Prioritizing investments on which data need to be made available and accessible is a key component of data leadership.

Quality Data Infrastructure

The cornerstone of a data-informed culture is, of course, the data. However, to be the basis on which this culture is developed, data must be trustworthy, and a structure enabling appropriate monitoring and use must be established. Therefore, understanding the attributes that promote data quality are essential in supporting widespread data use and acceptance within an institution.

Accessible	*Accessible* refers to the assurance that, to the greatest extent possible, users are permitted to see and use any data necessary and that they have access to the infrastructure, tools, and training necessary to enable their efficient and effective access and application of institutional data. This refers to a user's ability to obtain and use data without meeting unnecessary barriers, silos, or technical constraints.
Accurate	*Accurate* refers to the assurance that institutional data are free from errors, comply with data definitions and standards, and match reality.
Available	*Available* refers to the assurance that necessary institutional data are captured and stored for potential use. Operational systems and processes generate enormous amounts of data, much of which will never be used or accessed for analytical or strategic purposes. However, implementation of data tools, repositories, and security measures are needed to translate available data into accessible data.
Complete	*Complete* refers to the assurance that, where possible, nothing is missing from the data, both from within the data (for example, a month of missing financial transactions) and entire data elements (for example, missing data about who attended certain events).
Transparent	*Transparent* refers to the assurance that the contents of the institutional data catalog and metadata describing the contents of the institutional data catalog—definitions, sensitivity/risk classification, access rules, identification of the data steward(s), and key stakeholders, retention, and archiving standards, etc.—are known to all, even if the data described have access restrictions. This transparency increases confidence and trust that the decisions being made by others are based on trustworthy data.
Uniform	*Uniform* refers to the assurance that data are using the same units and that the appropriate indexes and keys exist to enable a user to combine or cross-reference multiple data sets in meaningful ways, such as ensuring that academic units (e.g., colleges and departments) can easily be cross-referenced with their financial, operational, and organizational counterparts.

Risk Management & Governance Practices

An additional enabler attribute of a data-informed culture is risk management and mature governance practices. As stated earlier, steady investment in strengthening and regularly using data governance enables trust and confidence. Standards associated with data structure, storage, security, retention, and archiving should be clearly articulated and followed by all staff. Processes that create, capture, transform, and move data must align with the standards and remain predictable and stable over time. Issues with data (errors, discrepancies, not available or missing, etc.) are quickly identified and corrected, and appropriate preventive fixes are implemented to the underlying processes. In addition to immediately reacting to "bad data," a regular data audit practice is implemented to verify that the policies and standards in use are continuing to enable high-quality data and mitigate potential risks that can compound over time.

In practice this also means ensuring that everyone who uses data shares in the responsibility for maintaining THE quality and stewardship of the data and is empowered to identify and seek to address issues with the data and with the processes that govern their handling. While governance may designate certain roles as "data stewards" or "data managers" for specific data domains, everyone understands and accepts the accountability of ensuring that the data are accurate, reliable, and complete. All stakeholders and data users should be encouraged to collaboratively "call out" issues with data quality or the processes that create, capture, gather, and handle those data. In data-informed cultures, corrective actions are sometimes necessary if compliance issues arise. However, those corrective actions can be instructive and enabling—rather than punitive—such as offering clarification on policies and procedures, additional training and coaching, and improved communication to ensure data users comply with correct data governance and processes.

A Common and Consistent Source of Truth

To ensure that data are an asset that can be trusted, institutions with strong data-informed culture ensure that data are referred to with consistent terms and language and that all data originate at a common and consistent source of truth. Throughout the institution, the terms used to describe data elements are consistently used; their meanings are well documented, maintained, and understood; and the data themselves—wherever and whenever used—remain unchanged from their single, authoritative source of truth.

Additionally, without knowing what a particular data element represents, it is impossible to know whether the data are accurate, whether the processes handling data are effective and in control, or whether, perhaps, the wrong question was asked. Consider this: Without a clear definition of "student," each person posing or responding to the question "how many students do we have?" may apply their own interpretation, yielding significantly different outcomes. Should part-time students be included in this count? Does the question refer to a headcount of a full-time equivalency? What about non-degree-seeking students? Are full-time staff members who are taking a course for professional development counted toward the total? To clarify and make a point, through the governance and culture, the institution must come to a clear definition of "student," along with well-understood guidelines about when and how different interpretations of the concept or measure of a "student" can and should be used.

SEE SECTION 6, PAGE 56: ACTIVITY #2

Developing Definitions for Specific Data Elements

BARRIER ATTRIBUTES

Common attributes and behaviors that inhibit an institution's ability to develop a data-informed culture include hoarding or being possessive of institutional data (i.e., creating "silos"), data skepticism, low or no risk tolerance, and proliferation of alternative and/or unauthorized collections of data maintained outside the designated sources of truth.

Data Hoarding

Data hoarding is a common barrier. Users with control over the data—particularly people or units responsible for stewarding data—may be reluctant or unwilling to make data available to others in the institution without significant or severe controls, or they may have tendencies to hoard or be possessive of the data they steward. Drivers or rationalization of hoarding typically stem from the belief (either with merit or unfounded) that people outside the data stewards' area of control do not possess the expertise to appropriately access, understand, interpret, or publish data due to lack of training, understanding of internal or external compliance drivers, or concern over use of proprietary or confidential data. Symptoms of this hoarding include requiring significant justification cases, the need to extensively review and cleanse data before making them available, or requiring the stewarding unit to be present as the data are used. Hoarding or possessive units may say they (or their unit) are the "data owner" or that it is "their" data, be unwilling to provide access or share the data, require significant time to "prep" the data before access or sharing, and may make changes to the data without consideration of other users.

The antidote to data hoarding is to empower and enable democratized use of data through appropriate training, collaboration, and governance practices. Practices and policies that expand *appropriate* access while maintaining commensurate standards of excellence for transparent use are essential to building the kind of trusting environment in which a data-informed culture can emerge. While data hoarding is often driven by legitimate sources of concern about the misuse of data, the solution to those concerns is not to tighten control over the data in a way that prevents the data from being used proactively, safely, and within established guidelines by all who are willing to engage in needed data literacy training.

Data Skepticism

A second barrier to developing a data-informed culture occurs when decision makers are unfairly or overly skeptical about the veracity of certain data sources. While data can be inaccurate or include missing elements, questioning associated insights the data provide can sometimes be overly tempting for those who don't like what the data are saying or who simply do not want to change. Remaining vigilant against "bad" or "garbage" data is necessary, but being overly mistrusting or critical of data insights, especially without being able to articulate specific concerns, can often inhibit the development of data-informed practices.

While questions and curiosity about data accuracy should be encouraged and a regular part of a data-informed culture, skepticism that is misguided, overly aggressive, or motivated by ulterior values should be discouraged. Those who help transform data to insights should have proper and appropriate training and background in understanding both the strengths and limitations of the data so that the conclusions they draw are sound. Developing insights in a collaborative way can help guard against producing incorrect intelligence so that those involved in the decision-making process can have confidence that the data they are provided with are accurate and actionable.

Risk Tolerance

Another barrier attribute that prevents data-informed culture is the practice of restricting access to data at institutions with low or no tolerance for data-related risks. This often is characterized by the organization's taking steps to eliminate all potential risks, regardless of their impact or likelihood. Organizations will make data decisions based on the worst-case scenario happening at the worst possible time under the worst possible conditions. The low- or no-risk tolerance perspective does not accept that the use of any asset, including institutional data, always includes some level of acceptable risk. Institutions that are not data-informed rely heavily, if not exclusively, on access restrictions as the primary mechanism for data-related risk mitigation. Restricting access to a small group of users creates data or information silos that inhibit discovery that can occur from cross-functional data access and analysis.

Proliferation of "Alternate Sources of Truth"—Shadow Systems

The final barrier presented here is the existence and proliferation of multiple sources of truth for institutional data. Distrust and restricting access to data increase the institution's data-related risk by leading to the development of stand-alone repositories of data that are not accessible or relatable to the rest of the institutional data and separate access policies, standards, or agreements imposed by the department. Users who aren't permitted access but need the data will find ways to get those data, ranging from gathering the data themselves to getting them from those who do have access. In doing so, the data begin to show up in repositories throughout the institution, invisible to those charged with stewarding those data and outside any institutional controls. These "shadow databases" may also hurt decision-making, as they may be outdated or incomplete.

Inevitably, the different sources of data will begin to result in contradictory answers and reports that do not match, undermining confidence in all the data sources, creating disagreement and contention between users and units, and confusing the institution as a whole. This can be as seemingly trivial as different academic departments maintaining mailing lists for their graduates separate from the institution's academic or alumni records, resulting in misunderstanding and miscommunication with external constituents. It can also be as obviously and significantly harmful as presenting conflicting information when responding to official or regulatory reporting requirements.

Developing a Data-Informed Culture

As an institution begins to embrace one enabling attribute of a data-informed culture, it naturally leads toward the adoption of other enabling attributes and, in turn, moves the entire institution toward a more data-informed culture. Early wins that start in one area, such as standardizing data definitions, can kickstart culture change. In the same way, however, barrier attributes can create and magnify other barriers, inhibiting progress. As such, becoming a data-informed culture is more a journey than a destination. Progress and adoption are rarely linear, comprehensive, or permanent. The journey must be driven top-down and bottom-up, with the institution's most senior leadership working in partnership with a disparate coalition of the willing to consistently, firmly, visibly, and actively promote enabling attributes while eliminating barrier attributes. Because it is generally the individual users or units that directly capture, create, and consume institutional data in their most granular state, if they are hesitant or unwilling, the journey slows to a crawl or stops completely.

Successful transformation requires a balance of persistence and patience, with a healthy dose of candor. This transformation is not usually driven by changes in organizational charts, policies and procedures, unit or departmental standards, or executive orders but more frequently by senior leaders acting as change agents alongside mid-level leaders and frontline staff. It is imperative that change agents driving data-informed culture understand that these shifts take time and, necessarily, must include some level of discomfort for the organization. In her book *Danger in the Comfort Zone* (1991), Judith Bardwick writes that organizational culture changes only when there is significant discomfort. Organizations and people will almost always seek an environment that tries to eliminate risk and maximize comfort and familiarity. It is only when the organization and its people become significantly uncomfortable (Bardwick uses "fear" and "pain"—natural consequences of failing to adapt and innovate in needful ways) that they will move out of their comfort zone and accept significant change. Even then, unless some level of "healthy discontent" continues to exist, the organization will revert to its original state, negating any short-term transformation.

Avoiding Bias in Data-Informed Environments

The use of data to inform decision-making also carries a very real risk of perpetuating bias. Bias is defined as viewing a person, thing, or group more favorably than another. Data are often considered ideal tools for avoiding or mitigating biases because many believe that using quantitative analysis removes all subjectivity from the decision-making process. In reality, the unconsciously held biases that people working on data collection, analysis, and management may hold can sometimes be unintentionally reproduced within the data. Data analysis may reflect the following:

- The biases of the people who collected the data
- The biases of the people who performed the analysis
- The biases of the people who applied the results
- The biases of machine learning, algorithms, and artificial intelligence (which are invariably created by humans)
- The structures, processes, and policies of the time when the data were collected

IMPLICIT BIAS

People are inundated with stimuli and data every day, and the human brain creates mental shortcuts that unconsciously categorize, make associations, and speed the processing of this information. The ways in which this information is stored and quickly accessed by the brain often subconsciously affect thoughts and decisions. As a further result, people form implicit biases based on the recollection of the unfiltered information that remains stored in the brain (New Jersey School Boards Association, 2020). Implicit biases are based on stereotypes, experiences, and associations that people unknowingly hold. They are expressed automatically, without conscious awareness. Many institutions' decision-making processes and data governance structures fail to include steps to intentionally review or audit the data for implicit biases. A recent study conducted by Mark Chin, David Quinn, and Tasminda Dhaliwal (2020) found the following:

1. The implicit biases of instructors vary significantly by the person's race. Racially minoritized instructors were found to have lower levels of pro-White/anti-Black bias than White teachers, with Black teachers having the lowest levels of anti-Black bias when researched.
2. Instructors with lower anti-Black bias were more drawn to working in places with larger populations of Black students.
3. Areas with stronger pro-White/anti-Black bias among teachers show larger gaps between test scores and suspension rates for Black and White students, even after controlling for factors like differences in socioeconomic status that might influence test scores or discipline. These results may provide a potential explanation for why Black students who have Black instructors have better outcomes.

IMPLICIT BIASES IN DATA AND ANALYTICS

Analytics often uses historical data to visualize patterns in human behavior or decisions. In one example, predictive policing models were used to more effectively allocate limited public safety resources (Karppi, 2018; Ekowo & Palmer, 2016). However, upon deeper examination of the data, researchers discovered that these predictive models were replicating patterns from decades of racially driven over-policing and overreporting of crimes in communities of color. As a result, use of the predictive models was further exacerbating issues of racial inequity in the criminal justice system (Karppi, 2018; Ekowo & Palmer, 2016).

Implicit biases may also affect the decisions that staff make regarding what data they choose to collect and analyze, or with whom they choose to share their data, or the ways in which they place limits on access and opportunities. In another scenario, a university president created an initiative to collect data on newly admitted students for the express purpose of improving student retention but instead used the resulting analysis to find students who could be targeted to withdraw from the institution before the census date (Ekowo & Palmer, 2016). This was a clear example of confirmation bias: using new evidence to support a preexisting opinion or decision that marginalized students instead of providing them with additional support. The promise and perils of artificial intelligence (AI) algorithms is another area of student support applications and tools that make "recommendations based on how students with similar data profiles performed in the past," which could be used to streamline success or widen gaps in outcomes if their limitations and biases are not well understood or addressed (Zeide, 2019).

It is crucial for institutions working toward greater integration of a data-informed culture to also consider issues of human bias and biased information systems deeply, with the goal that such issues be widely understood and proactively mitigated.

REFLECTION

1. At your institution, what barrier attributes or behaviors do you observe that might inhibit the institution's ability to adopt a data-informed culture?
2. Would you describe your institution as one that invests in its data? If so, what steps does your institution take to invest in its data?
3. What measures does your institution take to ensure data quality, including that the data are:
   - accessible
   - accurate
   - available
   - complete
   - transparent
   - uniform
4. At your institution, how do you define data elements around student success and advising? For example, do you know the definitional difference between a full-time and part-time student? Do you know how a first-generation student is defined at your institution?
5. What steps might your institution take to build awareness around implicit biases and assumptions that may show up in data and analytics?

SECTION 2:

Leadership and Data-Informed Culture

The demand for insight-filled data in higher education is intense, and associated needs and desires of the institution must be considered in the establishment of a strong data-informed culture. There are many stakeholders—senior leadership, mid-level leaders, frontline staff, accreditors, and state and federal agencies, to name a few—that require data for operational decision-making and for reporting. It is important to understand how each role supports the process of creating and maintaining a data-informed culture, including the ways they each use and apply student success analytics. Exploration of campus data needs should include both the *current and potential future requirements* of the organization, as well as proactive application of data governance to ensure appropriate data access and transparency. Ultimately, all members of the higher education professional community require some level of data literacy and would benefit greatly from becoming more educated about issues related to data ethics and privacy, as well as the different data roles that stakeholders play in promoting a culture of data.

IN THIS SECTION

Organizational Structure and Data-Informed Culture

In a data-informed culture, people incorporate data alongside experience, research, and input from other sources to make decisions for the organization. When leaders use a data-informed approach, they showcase their value for seeing the big picture during the decision-making process. Furthermore, widespread use of data ensures that all members of the organization, from the most senior leaders to the frontline worker, are empowered to make better decisions, from the very tactical to the very strategic.

SENIOR LEADERSHIP

Advocacy and support of the processes and policies associated with a data-informed culture by senior leadership are necessary to enable mid-level leaders and frontline workers to act effectively. At a college or university, senior leadership refers to the president or chancellor, as well as their direct reports and cabinet members. The direct reports typically include the provost or chief academic officer and all vice presidents (including enrollment management, student affairs, finance, administration, marketing, campus operations, advancement, human resources, information technology, etc.). Senior leaders are responsible for the health and well-being of the institution. These leaders set and guide all aspects of institutional culture for the organization, which "consists of shared beliefs and values established by leaders and then communicated and reinforced through various methods, ultimately shaping employee perceptions, behaviors, and understanding" (SHRM, 2020). Senior leaders are instrumental in establishing and reinforcing a culture of data. Relative to student success analytics, they also have a great deal of influence on the ways the institution funds and handles student and academic data, both strategically and operationally.

The understanding by senior leadership that data are an *institutional asset* is a key component to establishing a stronger data-informed culture. Reinforcing this concept of stewardship and dissuading individual units from the idea that data can be "owned" or secured within a data silo is one of the most important steps senior leadership can take toward enabling data-forward practices. The collection, management, and governance of data, therefore, should be invested in and receive appropriate attention, as with other institutional assets. Institutional leaders committed to data-informed practice should eliminate "bottleneck(s) at the gateway to the data" and encourage, embrace, and reward accessibility, equity, and widespread use of these data (Marr, 2017).

Senior leaders must create and enforce a "culture of empowerment, trust, transparency, and inquiry" to create or expand a data-informed culture (Mircoff, 2018). Empowering and trusting staff can help to reduce some of the silos that often occur on a campus and can encourage cross-functional engagement that can more proactively identify and collaboratively solve problems. It is important for senior leaders to talk often about what data and information are needed to make data-informed choices, not just in the abstract but in ways that tie data to the strategy of the institution. Senior leaders' transparency about their data use and decision-making processes emphasizes the democratization of the equitable access, use, and shared responsibility for data. Senior leaders should champion and model the importance of data accessibility and transparency through meaningful data governance. This top-down element of building a data-informed culture helps reiterate or formalize the sustainability of a culture of data at the institution and should integrate seamlessly with bottom-up efforts to support the same outcomes.

Data democratization occurs when data become more widely available (both vertically and laterally) and accessible to end users throughout the institution, not just leaders or key staff. This distributed access to data is an important component to transforming organizations and "unlocking the value embedded within" (Kholkar, 2019). When leaders and teams throughout the institution can access high-quality data, they can translate their contextualized perspective into actionable tasks and meaningful results. In fact, when data-informed actions promote greater collaboration and flexibility across the organization, the result often promotes improvement throughout the institution (Grajek & Reinitz, 2019). In return, the institution begins to see a variety of benefits and more effective resource distribution. Improving the speed and effectiveness of a campus initiative also allows for additional time and resources to create new initiatives (Yardy, 2019).

To facilitate broader use of data and to break down data silos, leaders can model and practice the behavior that they seek at an organizational level, such as implementing cross-functional projects or initiative collaboration. Improving student outcomes—such as increasing retention rates— provides a prime example where a cross-functional team can have a greater effect than individuals acting within the constraints of their own departments. Usually, many factors affect student retention, including academic affairs, advising, financial aid, institutional research, IT, etc. As such, assembling a collaborative team with department or unit representatives from across the institution can often more holistically and effectively address retention issues, encourage data sharing among departments, and promote practices and organizational changes that better support the institution's goals.

Senior leaders play a key role in setting the example for faculty and staff to follow, in both embracing data as an institutional asset and valuing democratized access to the data. Being a change agent sometimes means having to communicate tough issues or ask tough questions. Senior leaders need to be willing to engage others and bring out the "question behind the question." They can help address challenging situations by asking candid questions that get at the underlying issues (Miller, 2004). Senior leadership should be intentional in both how and whom they ask for data. They should seek clarification on the data source(s), the assumptions, the limitations, the biases, and the parameters that exist in the data. By engaging more assertively in data-oriented communication, senior leaders build confidence in institutional data, drive attributes of increasing data quality, and encourage other staff to adopt the enabler attributes of a data-informed culture. For example, in an enrollment update to the cabinet, it is important that senior leaders are provided with data-rich, nuanced details about the information being shared—such as whether the report uses live or census information, or whether it includes all majors of each student or only their first or primary major. Lack of awareness about such details could easily lead to misinformed conclusions or inappropriate actions, ultimately undermining the value of engaging in a data-informed process in the first place. Senior leaders should also seek expanded training and professional development to further hone their data-informed skills if they are finding it difficult to keep up with the latest approaches to data-informed practice.

As a note on the importance of equity, senior leaders should take an equity-minded stance by encouraging more regular use and application of information-rich data, improving the framing of questions being asked of the data and the standards they expect the data to meet. Data stakeholders must be made aware of potential gaps in access to data, biases that impact data collection, and underlying assumptions present in data analysis to identify policies that may appear neutral but may actually contribute to reproducing outcomes that perpetuate systemic biases and/or systemic racism. For example, when asking questions, leaders can use data to call attention to patterns of inequity in student experiences and outcomes and champion initiatives intended to ensure that the institution takes responsibility for the success of its students—all with an emphasis on protecting the interests of Black, Latinx, Indigenous, Asian, and Pacific Islander students, as well as students from low-income backgrounds. Senior leaders must partner with solution providers and campus stakeholders to disaggregate data more regularly to detect differences in experience, needs, and outcomes for students from different backgrounds.

MID-LEVEL LEADERS

Mid-level leaders and managers often act as a bridge between senior leadership and their frontline staff, who may directly and more frequently interact with and advocate on behalf of students. Mid-level leaders are typically responsible for oversight of day-to-day operations and serve as directors of functional units or departments (such as advising, IT, institutional research, etc.). These mid-level officers play a crucial role in the success of any institution and play an important part in the establishment and reinforcement of the kind of data-informed culture that promotes accessibility, use, and transparency of meaningful data. Mid-level leaders in IT or institutional research (IR) may provide support in data analysis, visualization, and storytelling. They often have the data skills necessary to help advising managers and frontline staff identify and pull data that add evidence, establish trends, and provide context to issues for which the advising staff might only have anecdotal support. As advocates for data-supported student success initiatives, advising directors are also among those responsible for change management, or the processes by which organizational change is introduced and implemented, which is required when maturing an organization's culture and practices around data use and literacy.

Mid-level advising leaders often find themselves caught between the needs of advising staff (who advocate on behalf of their students) and the expectations of senior leaders. As mentioned, while senior leadership is responsible for setting the organization's culture, directors and managers play a key role in establishing, enforcing, and reinforcing the values that senior leadership have set. Mid-level leaders are responsible for implementing policies and processes that align with and enact the culture set by leadership. These policies and procedures should embrace the mission and activities of the department and should have the thread of data-informed culture woven throughout, including a focus on data creation and data use as an integral part of daily activities. Mid-level leaders can be thought of as the "knowledge crew, conceptualizing and really justifying ideas from upper management, and also leading implementation throughout the entire organization" (Diaz, Rowshankish, & Saleh, 2018). Mid-level leaders often face the dilemma of not just managing their staff but also managing information and communication up to senior leadership, as well as lateral communication to their counterparts in other departments. Managing this web of communication is crucial to the success of an institution and often requires separate and unique skill sets for success, which can make establishing widespread data-informed practices challenging.

Mid-level leaders must also "manage-up," a practice that keeps senior leadership informed of their units' activities and challenges in a way that shapes the outcomes units can achieve. Senior leaders often have responsibility and oversight of units and areas with which they have less experience. They are also sometimes removed from daily functions. In these cases, senior leaders need to rely on their mid-level leaders to fill those knowledge gaps and guide the strategic management of departments. If a culture of data has not been visible or encouraged, mid-level leaders have the opportunity to share the ways in which a stronger data-informed culture could improve the work the functional area is doing.

"Managing-out," or laterally across departments, typically occurs when mid-level leaders seek other managers and directors to rally around an issue or initiative by establishing a collaborative, cross-functional team. Bringing other managers together to grow greater support for data accessibility helps break up departmental silos and foster data sharing, a critical attribute of developing a data-informed culture. This team can then advocate with senior leaders to encourage and stimulate further conversation on the need and applications for better data-informed decision-making.

FRONTLINE STAFF

The frontline staff (those who serve students directly, such as advisors and other student support staff) play an important role in upholding a truly sustainable data-informed culture. They collect or use data daily and are responsible for making the institution work. With this daily involvement in running the business, they are often the first to observe shifting trends and potential roadblocks as they arise. It is important that frontline staff have access to and a strong understanding of the use and applications of the data used in their department and across other functional units. Depending on their role, they may also benefit from a basic understanding of the structure and flow of data across the institution, how to extract insight and take actionable steps, and whom to turn to if they have questions about the source, accuracy, or completeness of the data they use.

It is important for frontline staff to share in the vision established by senior leadership and implemented by managers. These staff members should be able to work with data analysts to ensure that the collected data will effectively answer the questions and/or issues the senior leaders and institution would like to address. They are the subject-matter experts and should be relied upon to help contextualize and tell the data story. The frontline staff also bring to life the organization's data culture. For example, in an organization lacking clear data governance and widespread data democratization, frontline staff may not have access to the information they need to successfully perform their job. At an institution with a stronger data-informed culture, the frontline staff are more likely to have confidence in the data and either have direct access or know whom to ask for specific information that informs their day-to-day work and decisions.

Institutional Data Roles

Many roles exist in relation to data within an institution. It is important to understand how these roles differ, how each role relates to or interacts with the data, and how each role adds value within the data ecosystem. Among these are the data analyst, data scientist, data steward, data custodian, and data concierge, as well as recipients of the data, including data stakeholders and consumers.

DATA ANALYSTS AND SCIENTISTS

For data to be useful, they must be transformed into usable information, intelligence, and insight. These roles are analytical in purpose, taking operational data and storing, organizing, transforming, and reporting on them in a way that leadership can use for actionable results. Therefore, data analysts and data scientists play an important role in establishing and maintaining data culture by creating a bridge between the creation of data through operational and other activities and the use and analysis of data by leadership. These positions can be powerful tools for breaking down data silos when access and use of data across the organization are permitted and promoted.

Data analyst	A data analyst retrieves and gathers data, organizes them, and then applies them to reach a meaningful conclusion. Data analysts can bring many valuable insights to an institution that may influence decision-making. Data analysts can be involved in any part of the analysis process, making them invaluable to the team (Slyter, 2019).
Data scientist	A data scientist holds a more technical role than the data analyst and typically has graduate-level training in statistics, mathematics, computer science, or social science, with experience engaging in applied research. A data scientist works toward incorporating new ways of organizing data that data analysts will use. Data scientists gather and analyze large sets of structured and unstructured data. They analyze, process, and model sets of data and interpret the results to create actionable plans for institutions. One might find that a data scientist's work often involves making sense of messy, unstructured data, from sources such as smart devices, social media feeds, and emails that don't neatly fit into a database (Masters in Data Science, 2020).

DISCUSSION QUESTION

Who are the data analysts and data scientists at your campus?

DISCUSSION QUESTION

Who are the data trustees, data stewards, data custodians, and data concierge at your campus?

DATA STEWARDS, CUSTODIANS, AND CONCIERGES

A challenging tension exists between data democratization (making all data available and accessible to staff across the institution) and the need for those using the data to have some data expertise or basic literacy regarding the origin and significance of the available data. As an institution's data culture grows, services and training for all data users will ensure a shared expertise and understanding of the data. Unfortunately for most institutions today, data expertise is not yet widespread throughout the institution, and there are some barrier attributes such as restrictions on access to the data. Thus, the need for the data trustee, steward, custodian, and concierge roles (each defined in the table) persists as institutions develop their data governance and data democratization. Certainly, these roles are operational: they combine a service component (responding to requests from colleagues for data) with expertise to expand and encourage the use of data across the institution. Institutions with more developed data culture also explicitly identify data concierges and stewards as cultural agents of change who train, educate, and empower those they serve. As people with data caretaking responsibilities more intentionally think of "their" data as an institutional asset and engage in more opportunities to make the data accessible and transparent, the institution will improve and evolve its data culture. While some initial resistance to data sharing may result from distrust and fear, these issues can be resolved by intentionally developing transparency around shared data definitions, increasing awareness of available data, and engaging in regular data audits as new data elements are added.

Data trustee	Data trustees are senior leaders responsible for funding, governance, and institutional strategy surrounding implementation and use of data systems. They typically are divisional leads and signatories on contracts for systems/software, and they oversee the broad-level work undertaken by data stewards and their teams.
Data steward	Data stewards are responsible for the security, quality, integrity, and availability of specific domains (subject areas) of data. For example, the registrar might be the data steward for course data and student academic records. Typically, data stewards report directly to senior leadership (data trustees) from units that are the most directly responsible for the creation or collection of data corresponding to that particular subject area.
Data custodian	Data custodians are most often responsible for the safe custody, transport, and storage of the data and the implementation of rules that govern data sharing and access within the organization's business units, including compliance with privacy and security requirements. The data custodians often handle the details of transporting and storing data, rather than focusing on issues pertaining to the data that are going into the system and why, and are often members of the institution's IT department. As with a custodian of a building, data custodians often have widespread access to all sources of data. However, having a key to every room should not be confused with being "in charge of" or owning those spaces, which is the purview of the stewards and trustees.
Data concierge	Data concierges are the primary contacts for researchers seeking the creation of—or access to—specific data sets that address research goals and questions or to help obtain an understanding of the data needs of the institution. The data concierge may also be responsible for providing an explanation of the resources available for the data, background information on how the data were obtained, noted limitations of the data, and how the data relate to other data. The data concierge offers valuable links between data and metadata that are not captured within primary and data integration resources (Fenstermacher, 2021).

DATA STAKEHOLDERS, CONSUMERS, AND SUPERHEROES

Roles often not categorized are the data stakeholder, data consumer, and data superhero (each defined in the table) . It is important that those in these roles—who often include a wide body of people or classes of people—are informed, where possible, of changes, clarifications, and nuances in the data. In higher education, *an important and often overlooked example of a data stakeholder and data consumer is the student.* While the students are often affected by policies, procedures, and organizational culture, they are rarely included in the decision-making process. Therefore, it is vital to realize the effect these data have on them as individuals and as a group.

Data stakeholder	A data stakeholder is any person—inside or outside the organization—who has an interest in the data and who is directly affected by the data. Data stakeholders may include institutional researchers, data managers, data architects, advisors, advising leaders, and staff at any level of leadership or management.
Data consumer	A data consumer is any person—inside or outside the organization—who uses the institutional data. ("Use" may be defined as viewing, communicating, creating, modifying, storing, or deleting/destroying data.)
Data superheroes	Data superheroes can be defined as people throughout the institution who are adept at, comfortable with, and recognized as good at working with data. These are the staff who, regardless of their specific job, title, or role, are the ones colleagues seek out with questions about the data. Ideally, an institution's "data stewards" would be the "superheroes," but in practice this could also include colleagues to whom the data steward will turn.

DISCUSSION QUESTION

Who are the data stakeholders, data consumers, and data superheroes at your campus?

Central to any data governance structure is the identification of roles and responsibilities around data use and management. Unsurprisingly, advising units and IT will have different responsibilities within this framework. The primary responsibility of advising units is to understand the data's content and apply it to practice (Sherman, 2015). Advisors or faculty working in frontline positions in these offices know the raw data—often because they are the ones entering them into the systems. The primary responsibilities for IT groups are the storage, retrieval, and protection of data (Olavsrud, 2020; Sherman, 2015). This means that IT professionals will be engaged in work such as the following (Olavsrud, 2020; Sherman, 2015).

Data architecture	The overall structure used for data and the systems connected to those data
Data modeling	The analysis of data to support the design and construction of data processes and systems
Data integration	The ability to extract, move, and associate data from multiple systems
Data warehousing	Managing the storage and use of data for reporting and analysis

Leadership and Institutional Politics

The history, organizational structure, and politics of an organization can just as easily inhibit a data-informed culture as they can promote it. To move toward using data as important and accessible assets, it is important for leaders to understand the blind spots in their structure as well as organizational strengths. Institutional leaders provide an organization with direction, encourage equity and innovation, and promote data-informed culture.

It is important to identify institutional politics that will affect and influence the establishment of a data-informed culture so those politics can be proactively and successfully navigated. Institutional politics can stem from formal or informal power and can function at either an individual or organizational level. Institutional politics can have a profound effect on the success or failure of establishing or expanding a culture of data. Senior leadership and mid-level leaders should be appropriately engaged and aware of stakeholders and others who have strong influence within the institution. There may be de facto leaders across campus who are not in explicitly named leadership positions. They may be longtime staff who possess certain skill sets that put them in high demand, or they may have cross-campus information or other forms of influence. These leaders can have a great effect on an organization and its culture, as well. Managers and leaders should listen to and validate legitimate criticisms raised by devil's advocates, as openness to hearing these concerns may reveal potential gaps in the data or ways in which the data are collected, managed, and shared. Proactively addressing these challenges as they arise can help to further the adoption and implementation of a strong data-informed culture, as the most vocal critics witness their concerns being taken seriously and addressed, which can turn those people into strong allies and advocates who support additional changes.

Mid-level managers can institute departmental procedures that encompass and promote accessibility, transparency, and equity-minded practices such as the disaggregation of data. Data custodians, data concierges, and data stewards may also play data management roles by sharing and promoting appropriate, effective, and ethical uses of the institution's data. It is important that these data managers are empowered by leadership to address quality and access issues. However, it is equally important that data stewards avoid developing gatekeeper mindsets, as that can result in perpetuating barrier attributes such as restricting access to critical data for some users.

Data literacy is a critical professional skill for mid-level managers to have across the institution to support a strong data-informed culture, and there are several components of data literacy basics (Reinitz, 2019). For example, faculty and staff must develop a fundamental understanding of the importance of data use. At a campus with a data-informed culture, people with access to data also typically receive the additional information and training to understand the data nuances and can thus make better-informed decisions. Accountability for providing and monitoring this training lies with senior leadership and can be used as a key method to reinforce the importance of an institution's data assets among all faculty and staff.

Wrapping Things Up—Important to Remember

1. Pay attention to the leadership structure, including awareness of the relational structures and the decision makers at the institution.
2. Remember the importance of how institutional roles relate to or interact with the data.
3. Leaders and managers must take a proactive stance on promoting data equity by using a transparent and accessible approach to use of the data.
4. Identify the influencers within the organization and learn to cultivate relationships with them.
5. Acknowledge all data stakeholders and data consumers and how they add value within the data ecosystem.

REFLECTION

1. Who are the stakeholders and influencers at your campus who can help your department and institution move toward achieving a data-informed culture?
2. Who are the leaders and managers with the influence and decision-making power to drive changes to data culture and student analytics?
3. How can senior leaders promote equity best practices and the use of disaggregated data to improve student success analytics at your institution?
4. What steps can you take to ensure that the perspectives of data stakeholders and data consumers (including students) are considered in student success analytics and advising initiatives on your campus?
5. What professional development or capacity-building opportunities might you or your colleagues need to foster better data use and data sharing practices?

SECTION 3:

Data Governance and Data Access

In the simplest of terms, data governance refers to an organizational framework for determining rights and responsibility for and with data (Alhassan, Sammon, & Daly, 2016). Units across the institution with a vested interest in the use of data in a higher education institution include, for example, institutional research, the business office, IT offices, and academic and functional units like advising. However, each area of the organization has responsibility in the collection, management, and use of institutional data. This ranges from frontline staff who have variable levels of access to student data, data literacy, or comfort with technology to senior leadership who provide strategic guidance around the use and value of data. A well-executed data governance program can serve as an organizing framework to guide the management, use, access, and security of an institution's data assets.

While units have responsibility over the data within their area, they also have a responsibility to participate in institution-wide data governance. For example, student affairs staff often have job responsibilities that include reporting, interaction with analytics and technology systems, and data collection and sharing. Other offices may have responsibilities that include providing the institution with standards for appropriate data use and definitions, as well as ensuring data quality and completeness. Though the perspectives on what data should be made available and shared may differ from unit to unit, data governance can serve as an organizing framework to ensure that the department and institution are maximizing the value and use of data and their ability to inform decisions within the organization.

IN THIS SECTION

What Is Data Governance?

Data governance is processes, policies, and methods used to manage institutional data. A solid data governance foundation is an essential part of this process, ensuring that data conform to standards, are of high quality, and are available when needed. Comprehensive data governance also helps foster transparency, collaboration, and communication across the institution. Data governance connects multiple business units with information technology across the institution and provides organization around the roles and processes enabling data management and use, in addition to ensuring legal compliance and alignment with strategic priorities (Weber, Otto, & Österle, 2009). The first step in understanding the need for data governance is the recognition that data are an organizational asset (Alhassan, Sammon, & Daly, 2016). As an asset, data have demonstrable value to guide decision-making, organizational strategy, and performance; therefore, managing and monitoring data allows organizations to benefit from the data's value (Weber, Otto, & Österle, 2009). Institutions gather large amounts of data throughout the student life cycle (from recruitment and admissions to learning analytics and student engagement) and use a variety of technology tools to collect, use, and store information. This means there are many data assets available that need to be managed by a governance process.

Many frameworks exist for data governance, but all are focused on maximizing an organization's data as a strategic asset. This includes focusing on those practices that impact institutional data, including processes around the collection, retention, and storage of data; enabling data security and access measures; maintaining legal and compliance protocols; and ensuring proper understanding and use of data assets. In addition, just as colleges and universities come in different sizes with varying priorities, the organizational structures used for data governance are diverse and varied. Instead of focusing on creating the perfect data governance structure, institutions should determine the number of people and offices to collaboratively develop and maintain a structure that best fits the organization's needs (Sherman, 2015). Effective data governance requires that organizations look closely at mission, goals, and strategies, as well as people's roles and knowledge base. While there are many models of data governance, some common components create a conceptual framework for building effective data governance, given as follows (Sherman, 2015):

1. Collaboration between business units and information technology
2. Intentional communication
3. Definition of roles and responsibilities
4. Iteration and change management

COLLABORATION BETWEEN ADVISING AND INFORMATION TECHNOLOGY

Data governance must be based on a strong, collaborative relationship between information technology and business units—such as advising departments—at all institutions, regardless of size or structure. Because so many of the resources needed to enable data governance leverage the very systems that collect, store, and secure data, the information technology office is always a critical partner in any data governance effort. However, such collaboration is not always easy to achieve due to differing priorities, perspectives, and who has the power to make decisions (Sherman, 2015). For example, after seeing her advising team struggle with supporting students on academic probation, an advising director learns of a technology platform that uses data from a learning management system to identify students struggling in their classes. Eager to improve outcomes, she wants to purchase the tool right away, but the chief information officer (CIO) delays the project after learning the platform pulls data from the university's student records, too. In this situation, it would be easy for the advising director to feel frustration with the CIO for restricting access to a needed resource. Conversely, the CIO and IT staff may feel frustrated that the advising department was committing to purchasing and implementing an external technology solution that required access to the university's systems and data without consulting IT in a more intentional and collaborative process. Instead of viewing the other as obstructionist or unsupportive, advising and IT groups must see each other as partners with different values and priorities, understanding that each brings different expertise to the table (Sherman, 2015). One of the ways to accomplish this is to commit to intentional communication and to align priorities to best serve the institution's mission through data governance.

INTENTIONAL COMMUNICATION

Strong cross-functional partnerships require open and intentional communication between all relevant stakeholders. First, all parties should be transparent about their priorities and expectations because strategic alignment is essential to maximize data use (Sherman, 2015; Weber, Otto, & Österle, 2009). In addition to discussing goals, communication around expectations, scope of work, and means of monitoring progress and providing feedback should be included in the initiation of projects or development of new relationships. This means that any successful data governance framework will include a regular cadence of meetings that bring all stakeholders together or plans for keeping critical partners engaged or informed about specific data projects. To ensure that all potential stakeholders have an opportunity to participate, consider implementing an "opt in" approach to inviting participation.

- Develop and maintain a catalog of people and departmental areas that may have a stake in the data.
- Avoid using overly technical language or jargon that may isolate those from a different business unit.
- Check that the identified communication channels used to share information are reaching the right stakeholders with the right frequency.
- Ask questions to confirm that the data or data project stays aligned with the goals and purpose and can be properly used to answer specific institutional or research questions.

Because data are *institutional* assets, never assume that it is obvious which people and units have a stake in any particular set of data. In fact, data are almost always depended upon to support and facilitate the work of a broad cross-section of the institution's functions. For example, the same student data and success metrics that inform advisors of progress on their interventions could also provide admissions data points to include in messaging for prospective students around institution demographics, provide input to budget officials for projected enrollment and tuition income, and be used later by alumni affairs to develop targeted programming and outreach efforts. As such, it is important to provide an opportunity for this broad cross-section to weigh in on considerations and work being done to govern and make available all institutional data. By providing this broad cross-section opportunity, the cross-functional team will discover ways in which, and to whom, the institutional data matter that were likely never previously realized or considered. Also, it is often the insight of these unanticipated stakeholders that will most significantly enhance the value of the institutional data asset.

DEFINITION OF ROLES AND RESPONSIBILITIES

Confusion around responsibility for data elements and conflict around decision-making can sow distrust and be a barrier to developing a data-informed culture. The use of a RACI (Responsible, Accountable, Consult, Inform) matrix or chart can be a useful tool in developing data governance structures and ensuring that the right stakeholders are involved at critical decision points. This resource also offers the opportunity to establish and agree upon a shared understanding of the roles and responsibilities that each person or department plays.

Examples	Stakeholder 1	Stakeholder 2	Stakeholder 3	Stakeholder 4	Stakeholder 5
Decision 1	R	A	I	C	A
Decision 2	A	C	R	I	I
Decision 3	I	I	A	R	C

For each decision point, one of four responsibilities is allocated to the various stakeholders. These are:

- **Responsible:** They are responsible for the data element and carry out the work surrounding others' use of the data. They are the data stewards or the ones who provide the source of truth for the data element's contents.
- **Accountable:** They are accountable for the outcome of the work being done on the particular data element. Note that this stakeholder role is generally held by the most senior role and may involve facilitating or supervising the work.
- **Consult:** Although they are not responsible for the particular data element, they rely on the data represented to inform and support decisions and actions required of their function at the institution. Moving ahead without their advice or consent would be problematic.
- **Inform:** They do not have a significant enough stake to feel the need to be consulted, but they do have an interest in the outcome of the work being planned and may want to hear updates on the progress of the work. Unlike the Consult role, their advice and consent about the work are not required for its success.
- **None:** Although not part of the RACI acronym, it is important for transparency to know with certainty that everyone was given a chance to opt in and that some people have specifically elected to opt out.

Finally, as a facilitator of these engagements, ensure that all participants have an opportunity to provide input that is given appropriate consideration and weight in the process. All decisions about the data should be based on an equitable consensus of the stakeholders. For more information, consider reviewing Speaking the Same Language: Building a Data Governance Program for Institutional Impact (EDUCAUSE, 2013).

SEE SECTION 6, PAGE 57: ACTIVITY #3

Organizing for Action

ITERATION AND CHANGE MANAGEMENT

Data governance is best viewed as a living community of practice rather than a collection of black and white rules and regulations that live on a website or in a policy manual. Even after properly considering each of the factors listed above, a data governance structure will be unsuccessful if it stagnates or sits on a shelf. In fact, institutions often invest considerable time in "defining" data governance (e.g., defining roles, defining responsibilities, and defining data policies) but fail to fully implement and monitor the use of those roles and policies through an active community of governance practice (Alhassan, Sammon, & Daly, 2016). Remember that data governance can improve access to data and maximize their value as an asset only if they are put to use; in other words, "use it or lose it" (Sherman, 2015). The implementation of data governance inherently requires the ability to manage the needed changes to roles, process, and policies, as well as the attitudes and behaviors of the people involved (Olavsrud, 2020; Sherman, 2015). One recommended strategy for facilitating change management is to establish feedback cycles, also called "iterative loops," where participants create, implement, reflect, and modify their work and then meet cyclically to discuss progress and next steps (Olavsrud, 2020; Sherman, 2015). This process helps keep the data governance structure alive, relevant, and effective.

Why Is Data Governance Important?

Data are defined as organizational assets, and data governance is a tool that can maximize the effect of those assets on institutional goals. With the implementation of new and more robust systems and repositories, organizations are generating more and more data as part of normal daily operations. As such, colleges and universities collect data throughout the student life cycle, and much of those data go unused (Howells, 2021). A 2017 NASPA study showed that few institutions were using student data effectively, with only 31% of respondents indicating that they systematically collect, integrate, and use data from their student information systems (Parnell et al., 2018). As discussed in the first section of this Guidebook, barrier attributes such as data hoarding and skepticism, low risk tolerance, and proliferation of alternate sources of truth (shadow systems) inhibit communication, data sharing, and proper training on available data sources. This impedes institutions from effectively using their institutional data to achieve strategic goals related to advising and student success. Implementing data governance and clearer roles and responsibilities is another way institutions can better account for their data assets and develop frameworks that provide accessibility and transparency into the breadth of data available. From a strategic perspective, data governance is an important institutional strategy.

Effective implementation of data governance can also manage the moral and ethical implications to data use and can offer a method to reduce the risk involved with using and sharing data. In higher education, risks involved in data include actual physical risks, risks associated with analysis and integration, and risks resulting from improper retention and storage (Waterman & Bruening, 2014; Slade & Prinsloo, 2013).

HOW IS ACCESS TO THE DATA DETERMINED?

Data governance encapsulates many areas of data management, but none highlights the difficulties of bureaucracy more acutely than the question of who can and should have access to certain data, reports, or dashboards. Although a lot of emphasis is placed on the importance of data privacy and security, the definition of data governance itself, which, again, views data as valued assets for institutional goals, means that an essential function of a data governance framework is to "democratize data." With proper training for everyone who uses data as part of their role, the democratizing process makes data accessible to everyone who needs them. For information to provide the maximum return as an asset, it must be used effectively *and* often. Critical to this process is identifying the assumptions that often drive institutions to develop barrier attributes:

- **Assumption #1:** Data are for decision makers, and decision makers are only those in senior leadership positions.
- **Assumption #2:** Providing more access to data threatens data security and privacy.
- **Assumption #3:** Frontline staff do not have the necessary technical skills or data literacy to use this information.

By preventing these assumptions from influencing structure and processes, the data governance model becomes a tool for expanding the effective and widespread use of data in decision-making and addressing potential barrier attributes.

Assumption #1: Data are for decision makers, and decision makers are only those in senior leadership positions.

Teams in institutional research, decision support, or business intelligence units often have intentional connections to provide information to senior leadership like enrollment managers, deans, provosts, and presidents. Why? Because senior leaders make decisions. However, overly restrictive access to data leads to many unintended and counterproductive consequences, such as lack of diverse perspectives, implementation of shadow systems, and mistrust in data that people are accustomed to seeing or working with.

Frontline staff and managers can use data regularly and intentionally to improve their decision-making. For example, academic advisors make decisions every day that influence the recommendations they make for students, such as what classes to take, what interventions will support a student's progress, and what major options align with a student's career goals. By equating decision-making with positions of authority, institutions perpetuate data hoarding by limiting the ability of frontline staff to use data to support informed decision-making. Students should also be empowered with access to their own data to encourage them to develop greater involvement and ownership of their educational decisions. Including more diverse perspectives and voices in data governance (especially those of frontline staff and students experiencing poverty, first-generation students, and racially minoritized students) can offer insights into how greater access to and use of data in decision-making can empower more departments and communities within the institution.

Assumption #2: Providing more access to data threatens data security and privacy.

Ensuring compliance with data privacy laws (e.g., Family Educational Rights and Privacy Act [FERPA], General Data Protection Regulation [GDPR], Health Insurance Portability and Accountability Act [HIPAA], etc.) is an important part of data governance. It is reasonable to be concerned that providing more access to larger numbers of people will cause more opportunities to compromise data or permit unauthorized access to protected data, but these legal requirements often result in lower risk tolerance to institutional data sharing, leading to implementation of severe access restrictions. However, providing greater access to data is not necessarily about making all data sources available to all users at any time but rather is about ensuring that the right data are accessible and available at the right time to those who need them. Different data, pulled from the same common and consistent source of truth, can be made available to faculty, advisors, and others in support of the same goals. For example, a university examines its retention data and recognizes that its new students within the highest percentile of test scores are not persisting to the second fall term. The provost shares this information with academic deans, and the message is passed along to academic advising. But what data are shared and with whom? Although senior leadership may need only aggregate enrollment reports to inform their decisions, advisors might benefit most from viewing more complete, disaggregated data sets that show who uses tutoring services for strategic and targeted outreach, and faculty and departmental chairs may be interested in seeing which courses students commonly struggle in during their first year. A data governance structure can provide the right combination of checks and balances so the institution can offer access to specific data sets and reports tailored to different business units while complying with essential privacy and ethical guidelines.

Assumption #3: Frontline staff do not have the necessary technical skills or data literacy to use data and analytics.

Unfortunately, some leaders believe there may be more misuse of data by frontline staff because of lack of technical skills or data literacy. The reality is data stakeholders at all levels can struggle to prepare, use, and read institutional data, reports, and data visualization tools. The number one strategy for mitigating such concerns is to provide widely available and regularly occurring training for all professionals who need to use data as part of their role. As data and analytics become more widespread in higher education, there is a growing interest in pursuing professional development for related technical competencies. Rather than restricting data and limiting their use, stewards of data systems should look for opportunities to expand access to data by providing proper training about ethics and governance, as well as dynamic and effective uses of data. Developing and maintaining a data dictionary can help ensure that all data users operate under a shared understanding of the data's meaning, sources, appropriate uses, and relationships to other data points and is an important attribute of data quality.

The table below provides some examples of common risks of data use and how the implementation of a data governance framework can mitigate them (Waterman & Bruening, 2014; Slade & Prinsloo, 2013).

Type of Risk	Risk Category	Scenario in Higher Education	Effect of Data Governance
Data are manually entered into systems incorrectly.	Data Quality	Advisor fails to enter data on students who are active-duty military, leaving the data set on veterans incomplete.	Create a data dictionary of shared terminology.
Stored data are damaged or corrupted.	Data Retention and Storage	IT is unable to fulfill a request to create a dashboard of student engagement data because the institution uses an old server that is not adequate for storing metadata.	Members from advising and IT units have an open and honest conversation about what data they have and the best way to store them for retrieval. These units might team up to make the case to leadership to invest in more effective data storage tools.
Merging data from two systems results in data errors.	Data Quality	A dashboard created for advising shows incorrect major information for students after merging with data from the course management system.	Communication between advising, academic affairs, and IT units before data integration identifies potential issues and strategies to avoid misalignment.
User does not understand the data's context during analysis.	Analysis Risk	After requesting a report to help register students for orientation, an advising director is frustrated because the report is missing key information.	Advising stakeholders are involved in defining, monitoring, and measuring the success of data projects from the outset of the work.
Confidential information is shared in error.	Data Retention and Storage	Data provided for a records request unintentionally include personally identifiable information on students.	Governance structure implements and monitors policies and processes to protect data privacy and security.

By identifying and taking steps to reduce the risk in using data, institutions build confidence in the institutional data and develop a common and consistent source of truth that data users trust. Taking intentional steps to protect data accuracy and ensure security helps users feel more comfortable using data to support key decisions. If more people in the community are encouraged to use data within proper limits, the institution can better maximize data as assets. Finally, democratizing access to institutional data mitigates the risk that a shadow system develops or that there is a lingering lack of clarity on appropriate or official data sources.

Data governance also creates mechanisms to ensure accuracy and relevance in how data are interpreted and applied. Advising, institutional research, and IT units that collaborate and clearly identify roles and responsibilities support higher levels of data literacy by promoting understanding of the data themselves, the context of the questions asked of the data, the methodology used to analyze data, and the intent of data collection and use. These understandings together help reduce the bias that can further systemic racism.

Data governance can also serve as a protective measure against unchecked assumptions and biases by facilitating inclusive, proactive conversations using such questions as these:

- Which source(s) of data should be used?
- How can and should data be disaggregated?
- Who will do data analysis, and what biases might they bring to their interpretations?
- Who will use the results of data analysis?
- How will the data be reviewed before use?

Wrapping Things Up—Important to Remember

It is important to understand the process used at the institution to determine who has "ownership" over specific data and which stakeholders are involved in deciding how the data can be used and accessed. These are fundamental to establish data culture within an institution. Data governance can help provide clarification and guidance. Although the actual organizational structure an institution uses for data governance will vary based on the institution's size, type, and mission, the concepts of successful data governance remain the same:

1. Data governance is a structural framework used to govern data within an organization and address issues such as data structure, storage, use, training, and protection.
2. Data are assets that can support an institution's successful pursuit of its mission, so it is in the organization's best interest to set up a system to maximize the use of data at all levels. That system is data governance.
3. The touchstones of successful data governance are collaboration between IT and business units such as advising; open and honest communication; clearly defined responsibilities; and a proactive cycle of change management.
4. Creating a data governance structure reduces the risks inherent to the collection, interpretation, and use of data, risks which often result in the development of barrier attributes to data access and use. Data, statistics, and analytics are not free from biases that cause harm, so institutions have a responsibility to establish data governance structures to reduce the negative impact of bias.
5. Data governance is successful when it is an established system of roles and processes that an organization uses repeatedly in an iterative cycle regardless of the size or scope of the data project.

Frontline Staff	Mid-Level Leaders
• Where can you find the data you need to report on and analyze student success outcomes? • What is the process for finding out more about the data available to you? (How do you know if the data are complete? How do you know the source of the data?) • What resources do you have access to that provide transparency and clarity on the terms and definitions in the data? • What data might be useful to you (that you do not already have) in making more informed decisions about advising and student success?	• What is the process for determining how data are captured, stored, and shared with advising staff, academic affairs support staff, and/or faculty within your institution? • What is the process for deciding which data stakeholders and data consumers have access to student success analytics data? • How does your institution ensure data privacy, security, and FERPA compliance? • What steps or training does your institution offer to mitigate bias in the access and application of student success analytics data?

REFLECTION

1. How would you describe the relationship and communication between IT, institutional research, and advising at the institution? What processes or strategies are needed to establish or foster stronger communication between different departments and business units?
2. Which staff members and/or departments/offices should be involved in making decisions about the collection, sharing, and use of advising and other student analytics data?
3. What tools, training, or resources would help your advising staff better access, understand, and use institutional data?
4. What kinds of questions and decisions might a governing body for advising-related data need to make at your institution?
5. Which stakeholders and decision makers will be involved in planning and implementing iterative strategies for mitigating risks related to biases in data use and interpretation?

SECTION 4:

Architecture and Integrations: What's the Big Deal?

Once an institution has committed to developing a data-informed culture and begins to adopt enabler attributes and engage in a holistic advising redesign, the institution may determine that a different technology or software solution is needed to achieve its outcomes or scale its initiative. Many institutions may not have the necessary architecture and integrations in place to fully support a student success analytics program. Therefore, it is critical to investigate which technology and data structures at the institution are in place—and what needs to be modified—before purchasing advanced advising technology tools. It is natural that there may be tension between an ideal architecture and working with what is available. This section provides an overview of the basics of data architecture and analytics to advising support staff and faculty working with key IT colleagues and/or institutional data solutions and repositories. By achieving a high-level understanding of the technological resources supporting institutional data access and use, advising staff are enabled to assess current practices and advocate for more intentional data strategies that meet the institution's student analytics needs.

IN THIS SECTION

What Are Data Architecture and Integrations?

To understand and recommend improvements in the quality and availability of student achievement data, it is necessary to have a basic understanding of the technological resources enabling data availability and analytics. Data architecture is the overarching strategy an institution uses to govern how data are collected, stored, accessed, and managed across multiple systems and applications. A critical part of data architecture is how well different systems are integrated—that is, how data will be exchanged between tools to support advising use cases, answer critical questions, and generate actionable reports. Institutions that develop a robust data architecture strategy and data ecosystem have more tools to track key performance indicators (KPIs) and movement toward institutional goals. When built well, the data architecture will allow for system growth and integration with future data systems or applications that will enable innovation for years to come. For example, the learning management system generates data (login frequency, time spent using the system, content accessed, grades, etc.) that are then made accessible to other systems through a process specific to that application. The way these data are generated, stored, and accessed is part of the institution's data architecture.

Integrations are one component of a data architecture. Departments across the institution gather many sources of information, and it is often challenging to determine how to combine, use, and apply the data from disparate systems together in a meaningful way. For example, a student's name, gender identity, or other demographic information may be collected on applications, in enrollment documentation, in housing records, or in student health information, to name a few potential sources. This is where integrations become important. Data integration is the process by which data coming from different sources are combined. The integration process typically includes initial input of data, followed by data cleaning and transformation to result in usable analytics and reporting tools. To bring the information together into a useful dashboard, source data must be collected and organized in a common place.

WHAT MAKES A SUCCESSFUL DATA STRATEGY?

A variety of solutions will provide data storage, with the choice among them based on the purpose, intended use, and level of access to the data that will be needed. All of these factors must be considered to determine the best way to organize the data and optimize loading and access. In the context of advising and student success analytics, organizing different types of data together might sometimes make most sense (for example, within a student's profile, pulling together data about courses, career interests, extracurriculars, etc.), and other times organizing similar types of data would be most beneficial (for example, aggregated data in a report that lists all chemistry majors or all transfer students). Two common data storage strategies are a data lake and a data warehouse.

Most institutions rely on data warehouses that store business event data from disparate sources to support analytics and reports. These systems started out as centralized relational databases, or data repositories where the data elements are related to one another and these relationships are mapped or modeled for greater ease of use, and they still exist largely to serve day-to-day business intelligence reports and queries. Because modeling of data within a data warehouse can be both time and labor intensive, data lakes—repositories of raw, unmodified, and often modeled data—have become more useful options to help manage the volume and storage of data. Data warehouses, data lakes, and other options (e.g., data marts) are not mutually exclusive, and it is common to find multiple storage options within the same system. Today many organizations initially store data in a data lake environment. In some cases, those data can be queried directly, and in others the data need to be transformed and loaded into a separate data warehouse. Some important distinctions exist, and it is important to understand the capabilities and limitations of each option based on the needs of the institution before determining an appropriate path forward. For example, if the institution is prioritizing self-service analytics that are broadly accessible to users across the institution, a data warehouse with an integrated business intelligence reporting tool may be the preferred option. If the institution is looking to store larger volumes of data and has the necessary business intelligence (BI) and programming expertise to access and manipulate this data, a data lake might be more beneficial and cost effective.

Data Lake	A data lake is an effective way to organize raw enterprise data in a central location. The benefit of a data lake approach is that raw data can be collected using whatever process is best suited for that source.
Data Warehouse	A data warehouse is a central repository of information that can be consulted to make more informed decisions. The data warehouse allows the delivery of cleaned, user-friendly data to many users across the organization. A data warehouse is particularly helpful in analyzing data coming from different sources and is a great tool to ensure consistency, share insights across departments, and reduce the risk of error in reporting.

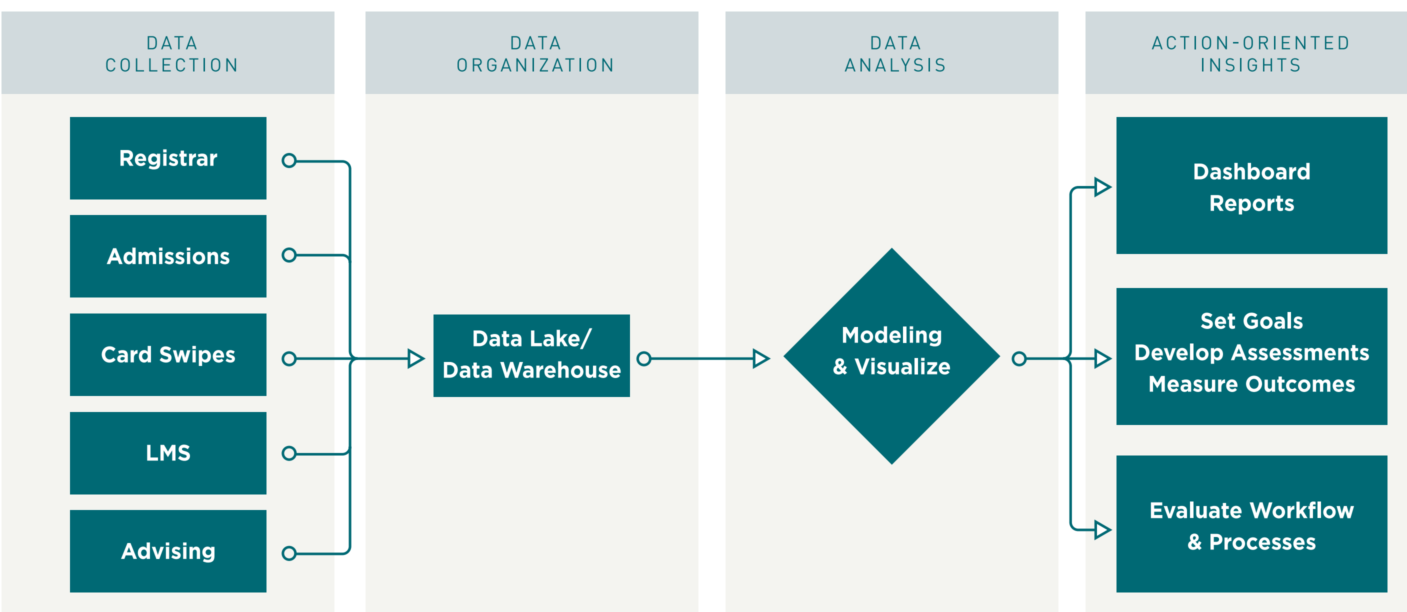
Another example that illustrates different strategies for organizing data is how most of us use email. Email systems have inboxes and the ability to create folders for categorized messages. Email inboxes are designed to be flexible, with no restrictions on structure. In other words, email inboxes can receive and process any type of message or information from different servers with different types of files attached. Once the messages are processed into an inbox, the user can choose how to further structure and organize the content of their inbox to make it more usable. Users who have a set way they need to access the same type of message or messages with a specific subject line or sender might create a specific folder for this type of content, similar to the setup of a data warehouse. For users who might not know what types of data or questions they need, keeping the data pooled in a more accessible way might be preferred, so they can search using different types of filters, which is more akin to the setup of a data lake.

HOW IT WORKS

When designing data infrastructure, there are several important DOs and DON'Ts to keep in mind:

DO think of questions that your data will be used to answer. What are some of the most important questions that your stakeholders will want to answer? Are your questions anchored in your equity goals?	**DON'T** feel you have to imagine an exhaustive list of queries before you even collect the first row of data.
DO take the time to ensure you have a clear way to tie data records to key dimensions such as course and student identifiers, term codes, organization, school units, etc.	**DON'T** be afraid to reassess and refine processes or infrastructure along the way. This is part of the learning process as you and the team gain experience with the organizational and technology-related factors.
DO try to build basic dashboards using one or two sources to learn about gaps or about processes that need to be in place. The lessons learned from the first mini-exercise in collecting and organizing your data for queries will be very valuable for the team, and it's best to practice on a small scale first.	**DON'T** worry about needing a reason to store all your data. One of the advantages of a data lake architecture is that you can collect and store both structured and unstructured data over time. Data storage allows you to lower the bar for bringing in data even if you don't have a planned need for them today, knowing that they might be useful tomorrow.

A common misconception is that data lakes are too costly to maintain and institutions should thus wait to collect and manage data until there is a specific need to do so. In reality, inexpensive options are available that would enable the creation and maintenance of a data lake at an accessible cost. Although thinking about collecting and storing data when there is not an immediately clear need for them may seem counterintuitive, collection of a history of data may prove vital to future analytic needs. When deciding on the best data storage option, an institution will need to engage not only the IT staff but users in the business units, such as advising, to understand the access, reporting, and analytics needs of these users. In addition, well-organized and documented data governance processes and policies can help inform and manage data access and literacy to make adoption of these data repositories more successful.



Working with Technology Solution Providers

Student data enter the institution through many sources (e.g., admissions, registrar, advising), and as a result the information required for student analytics and student-centered decision-making may also reside in multiple places. When considering software solutions and data systems to consolidate this information for ease of access, it is necessary to consider how the data will be integrated, or transferred or exchanged, from the source system. Commercial technology solutions and products vary in their support for integrations, and selection criteria should include considerations regarding ease of integration. This factor could make a huge difference in the speed of implementation of the new technology solution, the impact it has on the staff in data management roles, and the rollout and overall user experience. Related terminology can be beneficial when including or conferring with colleagues who are familiar with integrations. They can help evaluate the validity and feasibility of integration claims from prospective solution providers.

Institutions typically use requests for information (RFIs) and requests for proposals (RFPs) to solicit specific information from prospective technology solution providers. Creation of an RFI or RFP is typically managed within an institution's IT or procurement department but requires significant input from the units that will be employing the application or software (the end users) to understand and address the business needs and functional requirements (what the solution is intended to do), as well as to evaluate the fit of the potential solution with the institution's goals and resources. The goal of these documents is both to share mission-critical information about the institution and its intended outcomes and to pose "probing questions for the vendor" to determine whether it might be a good fit (Ada Center, 2020, p. 44). Examples of information about the institution might include company background and mission, current data systems, and technology products in use. Clearly stating the institution's needs can range from high-level functional statements to including specific product capabilities such as integration requirements and data access needs. Depending on the project and intended outcomes, including information about potential constraints such as timeline and budget may also be helpful. RFPs and RFIs also include requests for the vendor to provide technical specifications, data flows, or schema (a visualization of the organization of data within the tool or system) to ensure that the tool can be integrated with existing technical resources.

EXAMPLE SECTIONS TO INCLUDE IN YOUR RFP:

Company Overview (Background, culture, history, vision; Existing related technology resources/applications)

Executive Summary (Project context)

Scope of Work

Goals (Expectation for intended outcomes)

Schedule

RFP Points of Contact

Pricing Proposal

Institutional Needs (Product requirements and capabilities; Data access needs; Integration requirements)

Questions for Vendor

The scope of work may vary greatly depending on what is discovered through initial conversations with potential software solution providers regarding the ways their tools support data standards with product certifications. Involving staff from IT in the procurement process is vital, as they can properly evaluate a potential technology solution provider's answers to these questions and understand how they might integrate with the current "tech stack" (the technology and data systems in use). The selection and implementation processes will likely go more smoothly if the provider is asked specific questions upfront and is required to describe in detail how it might support the institution's specific data architecture and integration needs.

During the RFP process, thinking about integrations for your specific needs is important. Here are some examples of critical, probing questions to ask potential technology solution providers:

- How can external data be imported into your product?
- How can internal data from your product be exported?
- Which data standards and schema do you support?
- Which product certifications (e.g., IMS Caliper) do you have?
- What implementation services and resources do you provide for integrating your product with our architecture?
- Which of your clients have successfully integrated your product with their local data architecture?
- What controls do your product integrations provide to ensure equitable student outcomes?
- What plans do you have for adding additional integration support for your product?

To continue to explore your institution's readiness to procure a new advising technology, refer to *Success Factors for Advising Technology Implementation* published by EDUCAUSE in 2021 or *Advising Technology Procurement & Planning* playbook published by The Ada Center in 2020.

Wrapping Things Up—Important to Remember

1. Data architecture is not one-size-fits-all.
2. It's better to start small and remain open to iterations when devising an analytics architecture.
3. You don't need to have a complete plan before you begin.
4. The best way to start is to think about what questions you want to ask of your data.
5. Many important architecture improvements will have longer-term indirect benefits and will require clear strategic alignment for leadership support.

REFLECTION

1. How does your institution approach data architecture and integrations related to student success analytics data and advising decisions?
2. How are data about students' goals, plans, activities, and achievements documented and used in advising the student?
3. How are data currently assembled, shared, and presented to students, faculty, and other frontline staff who work directly with students? Who at your institution should be involved in making decisions about the content and format presented in often-used reports and dashboards?
4. What is the process for—and who is involved in—identifying and updating key terms and definitions in the institution's data dictionary related to student outcomes?
5. What processes are in place (or should be in place) to conduct data audits and ensure that errors and corrections are documented?

SECTION 5:

The Power of Leading Indicators

Although colleges and universities have always collected masses of data about their students, much of those data were not readily available or accessible to use in ways that could inform decision-making. As the digitization of student information has become more common and institutions migrated physical data (paper degree plans and student records, for example) into digital formats, the quality of information and the speed and accuracy with which reports are generated have vastly improved. The legacy computer systems and unit-developed spreadsheets and other business-unit-specific mechanisms used to record and use data were developed independently of one another at most institutions and lacked the ability to "talk" with one another or share actionable information across multiple data streams. Most frontline staff had little authority to make requests for data, severely limiting their ability to improve processes, create new policies, or promote a data-informed culture.

Today, college employees have more data and information at their fingertips than at any time in the history of the academy. Enterprise resource planning systems, self-service dashboards, business intelligence systems, and a variety of analytics platforms are more common than not at colleges and universities. Depending on permissions settings, staff at all levels of the institution have access to better data and more sophisticated analytics. These shifts have expanded the roles and responsibilities that institutional research and IT departments play regarding the management and governance of data.

But the irony lies in the unevenness of the application of these data and systems, as well as the expertise needed to transform data into usable insights to improve student success outcomes. Some institutions have had tremendous success improving student achievement measures; others have seen mixed results or little improvement at all. A further irony is that some of the institutions with the most sophisticated analytics systems available are not necessarily the best at using them to produce successful outcomes.

Given these and other factors, figuring out how to use data to improve student success outcomes can seem intimidating and overwhelming. However, like many matters in our work, employing simple and straightforward approaches is often the most useful strategy for starting the work.

IN THIS SECTION

Centering the Student

Student success is both obvious and elusive. By addressing people, processes, and technologies as part of holistic advising redesign, institutions can offer students sustained, strategic, integrated, proactive, and personalized advising experiences. Successful advising redesign requires centering the needs and experience of the student, and this depends on collaboration between senior leadership, information technology, institutional research, advising, and other student support offices. Few institutions have fully developed student success data systems, and seemingly small improvements can lead to changes that have a large effect on the student experience.

You've probably already thought about measures of student success and understand some of the limitations with any measure. Everyone wants students to grow, be happy, and find contentment in their lives. But questions arise:

- How are your institution's student success and advising practices reviewed and improved over time to address the shifting needs of students?
- Is your scope and thinking inclusive of student perspectives and voices?
- What are the limits of your student success program? How do you know if your programs are working?

Answering such questions will help your institution come to a better understanding of its focus. While developing your cross-functional team, you'll encounter issues and challenges that expand your concept of student success or more explicitly define it for your institution. Those areas that lie beyond the cross-functional team are important to identify and can lead to future collaborations but shouldn't be a barrier to improving in the areas you are focused on. More and more institutions are beginning to grapple with defining the domain of student success, and connecting with other institutions can expand your network and develop your institutional practices (Pelletier, 2019). To continue to explore and more deeply understand how to better center students' identities and experiences along their advising journey, refer to the guidebook *Knowing Our Students: Understanding & Designing for Success*, published by Achieving the Dream in 2021.

Lagging vs. Leading Indicators

To understand how data can be transformed into usable indicators of student success, it is important to understand the different types of indicators that are used in analytical reporting. Indicators are data elements that contribute toward the causes of an outcome or are correlated with an outcome that the institution wishes to measure and/or influence. Indicators can be viewed as either lagging or leading. Generally defined, lagging indicators measure an event that has occurred, whereas leading indicators can be used to provide insight into future actions and outcomes.

Lagging Indicators	Lagging indicators are after-the-fact data elements that describe whether the interventions were successful. It is harder to course-correct quickly relying only on lagging indicators, as they describe what has already taken place.	• Four-year and six-year graduation rates • Student completion data (IPEDS, etc.) • Retention rate (fall-to-fall persistence) • Fall-to-spring persistence
Leading Indicators	Leading indicators in student success work are best described as those measures that are as close to "real time" as is realistically possible given the specific outcome the institution seeks to achieve.	• Registration status • Attendance and participation in classes • Assignment completion rate, individual assignment grades • Student meets/does not meet with advisor • Predictive modeling of student success

Lagging indicators are most often found in official records for the institution. For the sake of simplicity, consider the student experience throughout their academic career in terms of *input, throughput,* and *output*:

- Input measures from official record sources typically describe the students who enroll at an institution. They include ACT/SAT scores, high school grade point average, high school class rank, race/ethnicity, average age, gender, geographic origin, and so on.
- Throughput measures encompass the student's experience while enrolled and might include first-year persistence rates from fall to spring, first-year retention rates from fall to fall, average number of hours completed by semester, credit completion ratios, and retention rates for student classifications other than first-time, full-time first-year students (e.g., continuing first-year students, sophomore, junior, senior, and transfer).
- Output measures might include four-year graduation rate, six-year graduation rate, and percentage of students employed within six months of graduation.

The best illustration of lagging indicators is found in official records, including institutional "fact books," Integrated Postsecondary Education Data System (IPEDS), and many state-level education reports. Lagging indicators are typically "scrubbed" or cleaned data, meaning they have been reviewed and validated, typically by college officials who are responsible for collecting, analyzing, and disseminating institutional data. Importantly, these data are always retrospective; although trend data are especially important in student success, their use is limited beyond understanding and describing the institution.

Many indicators we think of as leading are collected and used too late to function as leading indicators. For example, final class grades are a poor leading indicator for student achievement in a course, since they leave no time for intervention if a student is having trouble. Quiz or assignment grades, participation rates, and attendance are better leading indicators because these provide insight into a student's overall performance and allow for assistance and interventions to be employed before a student has received a poor final grade. It is useful to note that while lagging indicators help in a review of outcomes and trends, they can also be used to develop models and make predictions based on historical data. For example, input measures such as standardized test scores or student demographics are commonly used in predictive models of student retention or persistence through the first year of college enrollment.

What are your institution's top 10 most predictive classes? Some courses have a very high prediction value due to several factors (the students' reading ability, time organization, etc.). Advisors may be proactive and suggest additional support if students didn't do well in a predictor course. Consider how these courses can be used as lagging or leading indicators at your institution:

- Lagging indicator—if you are looking at courses that are associated with high student attrition
- Leading indicator—if you use that knowledge to help predict a student's success based on that course

For example, an institution might find that academic performance in introductory organic chemistry is associated with further completion of pre-medical major requirements; those students who pass this course are more likely to complete that major. While the grade received in this course is a lagging indicator, this course can also be used to identify students in need of academic advising and assistance with tutoring or support options.

Moving from Lagging Indicators to the Zone of Opportunity

The use of data to gauge and shape the utility of student success initiatives in higher education is often paradoxical. Two of the most used metrics to gauge institutional performance are retention and completion rates. However, both rates reflect performance and outcomes that are months, if not years, in the past. The irony in the paradox is that modern student success professionals need actionable, real-time, predictive data and indicators to affect outcomes.

Consider, for example, the hypothetical situation in which an institution carefully develops a collaborative initiative to increase graduation rates. The program is implemented. Four years later, campus leaders examine "lagging" institutional data, such as the four-year graduation rate, to determine the effectiveness of the completion initiative. In this extreme illustration, if the program is not performing as anticipated, what are the next steps? Make modifications and assess the cohort's six-year graduation rate? Scrap the program and start over?

Although measuring the four- or six-year graduation rates in the above is a radical example, many institutions routinely focus on indicators like annual retention rates. Here, the common approach is to determine the percentage of first-time, full-time students who started in the previous fall and returned for the subsequent fall semester. Although first-year student retention is an official measure duly recorded in places like IPEDS and the institution's fact book, such data remain nonetheless a historical measure, a lagging indicator, with limited use to advisors and student success leaders working in the here and now.

There are many ways to analyze and categorize an indicator; for example, it can be purely functional (financial aid versus registrar/student versus bursars, etc.), it can be based on student-initiated events versus faculty- or staff-initiated indicators, or it can be chronological or based on a student's progression through an institution. No matter how it is initially categorized, keep in mind the adage: *"You change what you measure."* In this case, once a high-level goal is created, the team can start brainstorming the contributing or component factors that can lead to the desired outcome. Any goals developed should be "SMART" goals (Doran, 1981); in other words, they should encompass a set of criteria to make them achievable:

- **Specific:** Focus on a specific area for change or improvement.
- **Measurable:** Progress toward the goal can be captured in specific metrics.
- **Achievable:** Goals must be achievable given the time and resources available.
- **Realistic:** While aspirational goal-setting is useful for creating a common vision, in practice, goal results should be those that can be realistically attained based on a designated course of action.
- **Time-related:** Activities to achieve goals should be accompanied by time-boxing or scheduling of results.

Using the example above, while increasing the graduation rate is an important goal, it lacks specificity in terms of the actions associated with the goal and is difficult and unrealistic to achieve in a short time frame. A more useful goal might be to implement activities that would support student success, such as tutoring of students who meet certain admission or performance criteria. With this goal, the institution is able to be specific in identifying groups of students in potential academic jeopardy; measurable in monitoring students' progress through course activities; achievable in that a defined group of students with specific progress milestones are being measured; realistic in that tutoring is shown to be a proven remedy to assist in students' academic success; and time-related in that the institution can implement these activities in a finite and well-understood period of the academic year.

Wrapping Things Up—Important to Remember

1. Is the organization clear on the goals of the initiative?
2. What data are needed to support both decision-making and showing improvement?
3. Have all the indicators been reviewed for equity, implicit bias, and correctness of use?
4. Does the institution have plans for how each analytics deliverable will be used?
5. Is there a feedback mechanism to review how accurate or useful these indicators are, or is an assessment planned?

REFLECTION

1. What student success outcome metrics does your institution collect? How would you classify these—are they lagging or leading indicators?
2. What kinds of questions are you asking of the data, and are these questions centering equity and the student experience?
3. What, if any, changes might you introduce into your institution's metrics strategy?
4. What gaps exist between available data and necessary information that could drive change for your advising program and institution? What data could be included in advising reports that could point frontline staff and mid-level leaders toward specific actionable steps?
5. What are the current interventions for advising and student success? When are students experiencing barriers to persistence in their journey?

SECTION 6:

Activities and Future Directions

The final section of this guidebook includes activities that are an essential aspect of moving learning to action. Each activity provided in this section is offered to help guidebook users organize their thinking and work toward enacting a more data-informed culture.

Guidebook readers are invited to complete these separately or as part of a cross-functional team (preferably including representatives from IT, advising, and IR). The greatest benefits will come from sharing the outcomes of these activities with colleagues and engaging in further discussion and collaborative planning. These activities are intended to help catalyze a community of practice at the institution, which will be essential to recognize data points and processes that are useful/actionable, identify who has (and who lacks) access to the data elements they need, and take steps toward developing a more sustainable culture of data-informed excellence.

IN THIS SECTION

ACTIVITY #1:

Developing Definitions for Specific Data Elements

The discourse around student success includes many common terms and concepts aimed at measuring or comparing efforts or progress in this area. While these terms can have generally applicable and acceptable definitions across institutions to enable benchmarking, they can also be adapted or specified to meet the mission, strategy, and academic goals of a particular institution. For example, depending on the institution and advising program, "first-generation college student" might mean that neither primary caretaker completed college, neither primary caretaker went to college, or only one primary caretaker went to college.

IN THIS ACTIVITY, REVIEW THE FOLLOWING DATA ELEMENTS AND ANSWER THE FOLLOWING QUESTIONS:

1. Do you know how your institution officially defines each element?
2. Do you know who controls and certifies that definition?
3. Are you aware of how that governing process works, and do you feel you have access to contributing toward established, accurate definitions? (If not, consider collaborating with colleagues to discover or establish answers to the questions posed in this paragraph.)
   - Academic period
   - Academic year versus budget/fiscal year versus calendar year
   - Contact hour(s) versus credit hour
   - Course
   - Headcount enrollment versus full-time equivalency enrollment
   - First-generation student
   - Full-time student versus part-time student
   - Persistence/persistence rate versus retention/retention rate
   - Students of color/underrepresented students
   - Racially minoritized students
4. When disaggregating data for racially minoritized and other underrepresented students, what terms do you use to describe different student populations? What steps do you take to encourage widespread use of language and terms that are specific and that avoid deficit-based language choices?
   - African American/Black
   - Asian/Asian American
   - Hispanic/Latinx/Latino/Latina
   - Indigenous peoples/American Indian/ Alaskan Native
   - Low-income/socioeconomically marginalized

NOTES

ACTIVITY #2:

Planning for Action

AT THE END OF THE INTRODUCTION AND EACH OF THE FIRST FIVE SECTIONS ARE FIVE QUESTIONS THAT ARE CRITICAL TO MOVING YOUR LEARNING TO ACTION. REVISIT YOUR ANSWERS TO EACH SET OF QUESTIONS AND THEN RESPOND TO THE FOLLOWING PROMPTS:

1. What overarching themes do you notice in your own answers? Do you sound optimistic or pessimistic about the work needed to develop a data-informed culture?
2. What are the largest organizational gaps or barriers to moving forward with your goals? How can you start tomorrow to work to close those gaps or collaboratively overcome those barriers?
3. How can you work within a community of practice to develop a clear plan for the transformative work you want to do, with both realistic deadlines and built-in accountability loops?
4. What partners can you reach out to for help clarifying your thinking and developing further goals?
5. Finally, create an action plan outlining steps and considerations for establishing a data governance structure in support of a student success analytics system. Then put that plan into place and iterate toward a sustainable culture of excellence in practice.

NOTES

ACTIVITY #3:

Organizing for Action

RACI matrices are commonly used tools in information technology and can be an instrumental tool for cross-functional communication. IT projects typically involve members of departments or teams that may or may not work together regularly. Providing clarity on roles and responsibilities is critical for project or process success. Consider the following example of selecting and implementing a new advising technology software and how this might look with your institution's stakeholders and tasks filled in instead. Inviting expertise from multiple areas would help institutions identify the problem the new software could address, gather ideas on requirements for success from key stakeholders, and design an implementation plan. That expertise might come from advising and student affairs, project management staff, IT's technical support, and other key stakeholders participating as part of a steering committee or project team. The following RACI matrix provides an example of how roles and responsibilities might be allocated at major project decision points:

Tasks/Roles	Advising Lead	Advising SMEs/ Academic Advisors	IR SMEs/Data Analyst	IT SMEs	Project Sponsor	Steering Committee	Project Manager	Implementation Team
PHASE 1: PROBLEM DEFINITION								
Identify problem and submit project proposal	A/R	C	C	C			C	
Assemble project steering committee	I				A		R	
Gather requirements for success	C	C	C	C	C	C	A	
Research potential vendors and products	C	C	C	C	A	I	R	
PHASE 2: RESEARCH AND SELECTION								
Request information or proposal from vendors (RFI/RFP)							A/R	
Review RFIs/RFPs and select viable vendors					C	R	A	
Schedule vendor demonstrations	I	I	I	I	I	C	A/R	
Final evaluation and selection	C	C	C	C	A/R	R	C	
PHASE 3: IMPLEMENTATION OF NEW ADVISING TECHNOLOGY								
Assemble project implementation team				C		C	A/R	
Determine project implementation schedule	I	I	I	I			A	C
User process documentation and role definition	C	C	C	C	C		R	A
Key user training		C					C	A
Define key performance indicators	A	C	R	C	C		C	
Develop regular monitoring and reporting process	A/R	C	R	C	C			

Using the RACI matrix, the major decision points involved with moving the implementation of advising software from problem definition to daily operations are defined, as are the stakeholders from all areas of the institution who need to be involved to move the project forward.

Conclusion

REVISITING YOUR GOAL-SETTING

Several guiding questions were included at the start of this guidebook to help direct your goal-setting relative to use of the material and to establish next steps or an action plan for student success analytics. Take a moment to look back and reflect on your response to each goal-setting question to self-assess overall knowledge gained, new insights, action items, and questions remaining.

GOAL-SETTING QUESTIONS

1. What did you learn from reading this guidebook?
2. What does your institution's data culture look like?
3. How, if at all, might you revise your original "utopian data world" description from the question at the end of this guidebook's introduction?
4. Do you have the information you need (or know where to find it) to create an action plan outlining key decision makers, data stakeholders, and influencers who should be involved in developing or expanding on a student success or advising initiative?

THINGS TO KEEP IN MIND

1. **Be patiently persistent.** If you let the pressure off, the opponent gains an advantage; the opponent here is status quo. A change initiative needs to be "their" (the culture of the institution's) idea. If leadership doesn't feel the discomfort, change won't happen.
2. **Involve everyone who wants to be involved.** If you aren't the one leading the call to action, then get involved. You are a stakeholder.
3. **Candor, persistence, patience—all are necessary as a change agent.** If the data aren't working for you, ask why. Seek first to understand. Be bold and keep asking "why" until there are no more answers.
4. **There isn't one right answer or process that fits all.** The way that each institution proceeds is the right answer for that organization.

Student success and advising analytics includes a variety of stakeholders, decision makers, data consumers, processes, and systems. In reviewing this guidebook, and completing the activities, readers will have gained foundational knowledge about establishing and enriching a data-informed institutional culture, advancing data literacy and data governance structures, and processes that support high-quality decision-making around advising and student success initiatives.

Contributors

Nichole Arbino
Communities Program Manager
EDUCAUSE

Lilly Lavner
Portfolio Manager, Advising Success Network
EDUCAUSE

Kathe Pelletier
Director, Teaching and Learning Program
EDUCAUSE

Shama Akhtar
Director, Institutional Effectiveness
Goucher College

Mitchell Colver
Vice President for Community Practice
Civitas Learning

Linette Decarie
Assistant Vice President, Analytical Services & Institutional Research
Boston University

Linda Feng
Principal Software Architect
Unicon

Augie Freda
Campus Data Steward, retired
University of Notre Dame

Jeff Grann
Credential Solutions Lead
Credential Engine

Chris Hutt
Assistant Director
NACADA

Melissa Irvin
Assistant Dean, Academic Outreach and Support
University of South Florida

Andy Miller
Principal Educational Consultant
Anthology

Rick Sluder
Vice Provost for Student Success & Dean of University College
Middle Tennessee State University

Kal Srinivas
Director, Student Retention and Success
Syracuse University

John Tong
Application Analyst Principal
University of Georgia

Leah Chuchran-Davis
Vice President of Learner Experience Design
iDesign

Nikki Follis
Lead Learning Architect
iDesign

Whitney Kilgore
Co-Founder and Chief Academic Officer
iDesign

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