Business Intelligence at the University

Jonathan Fowler, May 2018

Common in business vernacular as early as the late 1990s, *Business Intelligence* (BI) in its first iterations meant data, reporting, and visually-pleasing presentations. Consider it Analytics 1.0: data were still fragmented and siloed, BI tools were relegated to internal IT and actuarial-related departments, and the amount of time involved in producing relevant reports was not often cost-effective. By the 2000s, *Big Data* had become a household term and Analytics 2.0 had arrived. Traditional barriers to relevant BI methodologies had started to come down. Further advances in cloud computing and desktop analytical tools (among other developments) have ushered in Analytics 3.0, wherein virtually any type of firm in any industry, can participate in the data economy.

As the name might imply, *Business Intelligence* has mostly been applied in business circles. Higher education is a relatively emerging market in this field. Both domains often sit on a tremendous amount of internal data stores but are unable to effectively utilize it "to make predictions or trigger proactive responses."[1] We may draw parallels between business and higher education. Both need actionable information in order to maintain their marketplace position; in addition, the organizational structure of a large university may resemble that of a large company.[2] The goals of BI may differ in context, but the outcomes remain the same: tell us what happening, why it is happening, and what we can do about it.

[1] Jacqueline Bischel, "Analytics in Higher Education: Benefits, Barriers, Progress, and Recommendations," Louisville, CO: EDUCAUSE, 2012: 25.

[2] Mihaela Muntean, Gheorghe Sabau, Ana-Ramona Bologa, Traian Surcel, and Alexandra Florea, "Performance Dashboards for Universities," In Proceedings of the 2nd International Conference on Manufacturing Engineering, Quality and Production Systems, 2010: 207.

Assessing BI Maturity and Implementation

Different models have emerged in recent years to assess an organization's BI maturity. LaValle, et al., outline a three-stage model of analytics adoption that covers BI efforts from planning to full culture transformation.[3] That model is reproduced in Table 1.

TABLE 1. BI MATURITY MODEL (LAVALLE)

	Aspirational	Experienced	Transformed
Motive	Analytics justify actions	Analytics guide actions	Analytics prescribe actions
Functional Proficiency	• Financial management & budgeting • Operations & production • Sales & marketing	• All Aspirational functions • Strategy/business development • Customer service • Product/research development	• All Aspirational & Experienced functions • Risk management • Customer experience • Workforce planning • General management • Brand/market management
Business Challenges	• Competitive differentiation through innovation • Cost efficiency (primary) • Revenue growth (secondary)	• Competitive differentiation through innovation • Revenue growth (primary) • Cost efficiency (secondary)	• Competitive differentiation through innovation • Revenue growth (primary) • Cost efficiency (secondary)
Key Obstacles	• Lack of understanding how to leverage analytics for business value • Executive sponsorship • Culture does not encourage sharing information	• Lack of understanding how to leverage analytics for business value • Skills within line of business • Ownership of data is unclear or governance is ineffective	• Lack of understanding how to leverage analytics for business value • Management bandwidth due to competing priorities • Accessibility of the data
Data Management	• Limited ability to capture, aggregate, and analyze data • Limited ability to share information & insights	• Moderate ability to capture, aggregate, and analyze data • Limited ability to share information & insights	• Strong ability to capture, aggregate, and analyze data • Effective at sharing information & insights
Analytics in Action	• Rarely use rigorous approaches to make decisions • Limited use of insights to guide future strategies or day-to-day operations	• Some use of rigorous approaches to make decisions • Growing use of insights to guide future strategies or day-to-day operations	• Most use of rigorous approaches to make decisions • Almost all use insights to guide future strategies or day-to-day operations

While this model is suited for business, it serves as a cursory introduction to BI in the higher education sphere. A university, much like a business, seeks competitive advantage within the marketplace over its peers. Of course, these specific points take some tweaking to apply. For

[3] Steve LaValle, Eric Lesser, Rebecca Shockley, Michael S Hopkins, and Nina Kruschwitz, "Big data, analytics and the path from insights to value," *MIT Sloan Management Review*, 52, no. 2 (2011): 21-31.

example, in a Transformed BI environment, functional proficiency may include student engagement rather than business-centric customer service.

We can look to other models specifically designed for higher education. The National Association of Student Personnel Administrators conducted a survey of higher education institutions and their experiences with BI. In 2017 those results were published and a simple three-stage model of BI adoption emerged.[4] That model is represented in Figure 1.

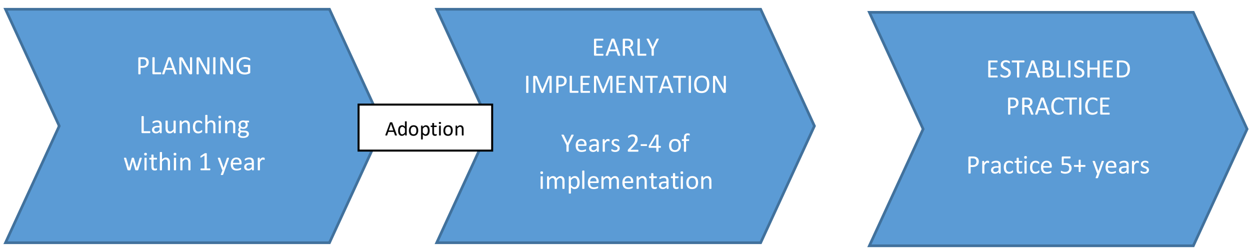

Figure 1. NASPA Maturity Model.

Within the NASPA model, universities were identified within a stage based on their time and experience in the BI implementation process. Note that the Planning stage begins only when an institution has a 12-month (or less) window for implementation. While the groundwork for a BI initiative may be laid well over a year before launch, an institution is only considered in the Planning stage when go-live is within 12 months. Adoption, a stage not included in the model but added here, spans the gap between Planning and Early Implementation. As Business Intelligence is a very fluid process, the Adoption stage is neither fully apart from Planning nor entirely into Early Implementation.

Planning is a critical success factor in BI implementations, for reasons we will outline in more detail later in this paper. For now, let us address the importance of assessing current BI maturity. That is possible to some degree with the LaValle model (Table 1), but as it is specific to business, a precise application is not possible. Jisc, a digital advocacy nonprofit in the UK, has established a two-part model specific to higher

[4] Michelle Burke, Amelia Parnell, Alexis Wesaw, and Kevin Kruger, "Predictive Analysis of Student Data: A Focus on Engagement and Behavior," 2017.

education institutions. Part I is a maturity index borrowed from the Oficina de Cooperacion Universitaria that an institution may use to quantify its current situation.[5] This index is reproduced in Table 2.

TABLE 2. JISC PART I – MATURITY INDEX

		LEVELS									
			ABSENT		INITIAL		EXPANDED		CONSOLIDATED		INSTITUTIONALIZED
	I2* TEAM		ABSENT		LOCAL		GLOBAL VIRTUAL		GLOBAL FULL-TIME		COMPETENCY CENTER
	SCOPE		UNKNOWN		SPECIALIZED		MULTIPLE		GENERALIZED		FULL
	SBU+ ROLE		UNAWARE		AWARE		PARTICIPANTS		SUPPORTING		DATA STEWARDS
	DATA PRODUCTS		UNKNOWN		LIMITED		EXPANDED		MAJORITY		COMPLETE
DIMENSIONS	USER COVERAGE	1	UNKNOWN	2	LIMITED	3	EXPANDED	4	MAJORITY	5	UNIVERSAL
	USER ENGAGEMENT		UNAWARE		AWARE		CUSTOMERS		DRIVERS		CO-OWNERS
	DATA MANAGEMENT		UNAWARE		AWARE		MANAGED		SUPPORTED		ENFORCED
	BUSINESS VALUE		SCARCE		OPTIONAL		INTERESTING		NECESSARY		CRITICAL
	STRATEGIC SUPPORT		FREE FLOATING		LOCALLY EMBEDDED		PROJECT FOOTING		SUSTAINABLE SERVICE		INTERDEPENDENT WITH STRATEGY

* Institutional Intelligence
+ Source Business Units

Much more relevant and precise than the previous maturity model, this index allows a quantifiable assessment of all dimensions that are impacted by, or will impact, BI implementation. A composite score may be calculated from the average of all dimension scores. This index allows stakeholders to identify specific areas of competency and risk, rather than try and decipher a composite score that covers the entire effort and may be misleading.

[5] Oficina de Cooperacion Universitaria, "Maturity Model for Institutional Intelligence v1.0," 2013.

For implementation, Jisc offers a model that allows an institution to map out where it stands along the road to BI adoption.[6] That model utilizes an overall stage or score for implementation efforts and is reproduced in Table 3.

TABLE 3. JISC PART II – IMPLEMENTATION MODEL

Stage 1	Data are fragmented and distrusted, scattered among traditional, often locally held data sources; manual reports available to departmental, faculty, and institutional management.
Stage 2	Information is increasingly coherent, held in centrally managed systems with clear local responsibility for data entry and data quality. Most reporting is still manual.
Stage 3	A Business Intelligence (BI) project is started, and a vendor and system are selected.
Stage 4	An initial BI system is put in place which allows managers at each level to access data when they need to.
Stage 5	The BI system and its links to data sources are increasingly automated; reporting becomes more sophisticated and spreads to a wider user population.
Stage 6	Systems are used for evidence-based decision-making and for predictions, models, and assessment of future options.

Given these various models, we believe it is wise to integrate them into a blended taxonomy for BI implementation. The Jisc Part I Index stands apart from this; however, the Part II model specific to implementation fits well with the others. An integrated taxonomy is shown in Figure 2.

[6] Vincent Koon Ong, "Business Intelligence and Big Data Analytics for Higher Education: Cases from UK Higher Education Institutions," *Information Engineering Express* 2, no. 1 (2016): 65-75.

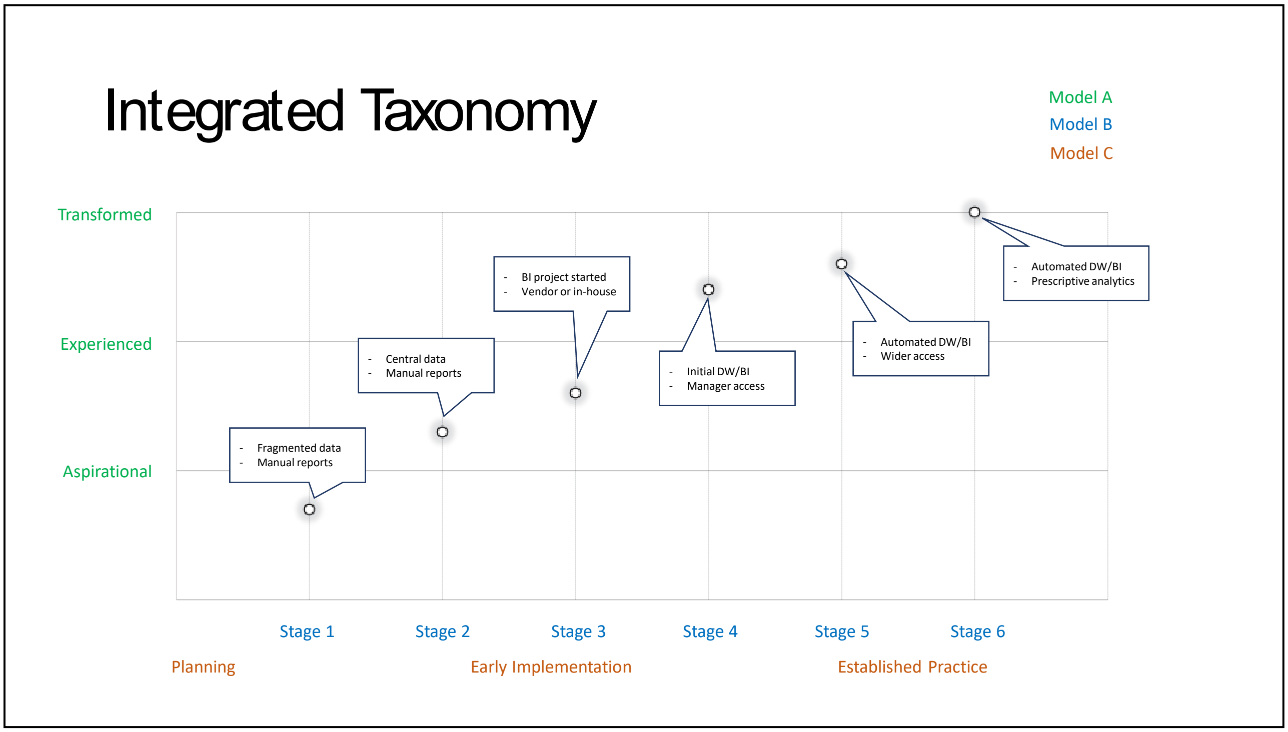

Figure 2. Integrated Taxonomy Model.

In this integration, we blend the three relevant models on an X-Y plane in order to show how each of them relate to the other. Models A (LaValle) and C (NASPA) are continuous in nature; Model B (Jisc Part II) is ordinal. The former two serve as spectra on the X and Y axis against which to plot the six ordinal stages. Using this chart, an institution may find its point at any step along the way in BI implementation and accurately identify where it stands.

Planning and Early Implementation

Any planning effort begins with goals in mind. Perhaps the most obvious for institutions of higher learning are enrollment, retention, and graduation—i.e., get them in, keep them in, and graduate them. Parallels can be drawn between higher education and business domains here. Figure 3 aligns the 3 main goals of higher education BI with similar functions within business.

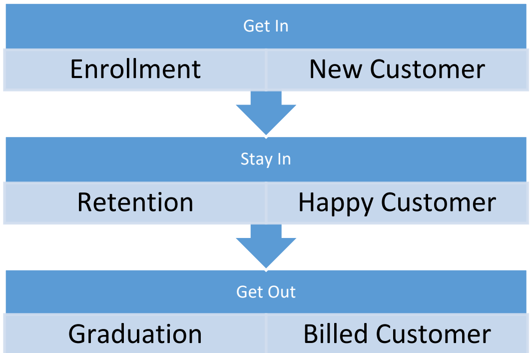

Figure 3. Higher education (left) goals aligned with business goals (right).

Of course, other goals may be identified within an institution, but they fall within one or more of these three main objectives. Ultimately, the institution seeks to reduce *cost* and *time* to a degree.[7]

Taking a more detailed look at how institutions set BI objectives, we can identify four goals[8] that acknowledge different functional areas of a university:

1. Short-term decisions and long-term plans
2. Relevant educational opportunities for students
3. Attraction and retention of students
4. Compliance

Each of these four may be mapped to one or more of the three primary objectives in Figure 3. Like the maturity models, we can begin to identify an integrated taxonomy of BI objectives. However, as objectives and directives are always institution-specific, this paper will refrain from delving further into detail. It is critical that institutions do their due diligence in identifying why a BI initiative exists and what goals *specific to the institution and its students* are important.

Such a conversation requires a cross-sectional effort. This is a common thread throughout all of the existing literature to date. From the earliest stages of planning, a multidisciplinary team

[7] Donald Norris, Linda Baer, Joan Leonard, Louis Pugliese, and Paul Lefrere, "Action Analytics: Measuring and Improving Performance That Matters in Higher Education," *Educause Review* 43, no. 1, (2008): 42-67.
[8] Muntean, et al., "Performance Dashboards for Universities."

from all impacted areas of the institution allows the efforts to guide, and be guided by, institution-wide strategic initiatives and goals. Depending on the maturity level at this particular phase, coming at BI implementation this way can "help unify the institution by focusing on key strategic initiatives and centralizing data. In addition, integrating data from multiple sources makes it more consistent and increases accessibility, visibility, and usefulness."[9] This then becomes not only a matter of functional proficiency but also one of culture. Norris, et al., emphasize such focus: "Advancing performance measurement and improvement in a college or university requires changing from a culture of reporting to a culture of high-agility, evidenced-based (sic) decision-making and action."[10]

In practice, a cross-divisional planning group breaks down siloed units that may have existed in a previous reporting culture, and transforms how an institution approaches data governance and problem-solving. This group may "either specifically assigned to the predictive analytics effort or part of existing retention, advising, or enrollment management committees."[11] Such a structure ensures that the group is not too far entrenched in a particular way of thinking native to one specific department or unit. BI implementations often require taking a step back from current methods and assessing more than just what is getting reported—institutions must think of questions that need answering and how data is to be governed, rather than just what insights can be gained from existing data.

This step back from current methods allows a fair assessment without taking existing practices for granted. In some cases, the structures governing the data can be just as high a barrier to functional proficiency as gaps in the data itself. For example, Georgia State University found this to be the case when planning for a BI implementation:

> The problem-solving approach of using high-quality data revealed the interconnectedness of academic policy, financial aid, billing, and student choices (among other factors) in setting up barriers to student success. The decision to pull together the typically isolated functions of registrar, advising, admissions, financial aid, and student accounts into a single unit provided the organizational wherewithal to address

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[9] Bischel, "Analytics in Higher Education: Benefits, Barriers, Progress, and Recommendations," 25.
[10] Norris, et al., "Action Analytics: Measuring and Improving Performance That Matters in Higher Education," 47.
[11] Burke, et al., "Predictive Analysis of Student Data: A Focus on Engagement and Behavior," 14.

those tangled issues. […] When analysis of student pathways revealed multi-faceted financial and academic problems that blocked student advancement […], and further investigation revealed that the units responsible for different aspects of the problem could not be coordinated to solve the problem, this lack of coordination became the barrier that needed to be addressed.[12]

Data Warehousing

The cross-divisional spirit evident in the planning team is also critical in designing the data warehouse that underpins any BI effort. The "typically isolated functions"[13] of institutional units often keep their data in equally isolated data stores; a cross-divisional BI effort seeks to remove those barriers and bring these disparate stores of data into one unified source of truth.

Figure 4 illustrates this process and how it fits into the purposes of a data warehouse, ultimately being accessed through a user portal.

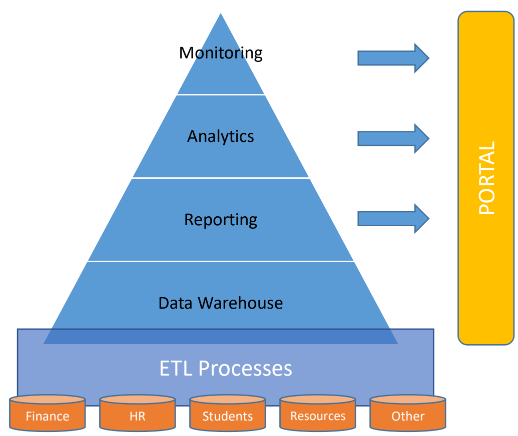

Figure 4. Data Warehouse and Portal.[14]

[12] Martin Kurzweil, and Derek Wu, "*Building a Pathway to Student Success at Georgia State University,*" 2015: 13.
[13] Ibid.
[14] Muntean, et al., "Performance Dashboards for Universities."

Data to be brought into this unified warehouse may include the following:

1. Pre-Enrollment: demographics, high school GPA, test scores, legacy
2. Academic: attendance, grades, portal activity, registration, LMS
3. Motivation & Self-Efficacy: comfort with academics, financial issues, social network
4. Support Services: advising, career services, counseling, disability support, financial aid, health, library, tutoring
5. Student Engagement: athletics, student government, organizations, residency, wi-fi usage, leadership roles, dining[15]

These data points are under the administration of different departments across the institution and often in different ERP systems and schemas. The ETL (extract-transform-load) process is an important step in normalizing the data into a common framework and allowing relationships to be established between data points. In Analytics 3.0, the data points themselves are less important than the *relationships* between the points, which may identify trends and phenomena that traditional aggregate reporting of Analytics 2.0 cannot. Bringing the data from disparate sources to a common store allows for such examination, as well as dashboard-type views of in-domain and cross-domain metrics.

To that end, common dashboarding methods may be employed to present appropriate audiences with the necessary information relevant to their domain. Across the institution, common dashboards must be (1) easy to understand, (2) relevant, (3) strategic, (4) quantitative, and (5) current. These dashboards most often include (a) graphical key performance indicators, (b) high-level dimension summaries, and (b) low-level detail.[16]

Cultural Considerations

Conventional wisdom in academic institutions, much like business, may present roadblocks to a top-down examination of current practices and cross-divisional planning. Departments may be protective of their practices and data, faculty may be resistant to change, administration may lack buy-in, and their may be fear of treating the institution too much like a business. Within planning groups, there may be

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[15] Burke, et al., “Predictive Analysis of Student Data: A Focus on Engagement and Behavior,” 17.
[16] Afshin Karimi and Edward Sullivan, “Student Success Dashboard at California State University, Fullerton,” Paper presented at C-IDEA, University of Oklahoma, 2013.

mismatched expectations from stakeholders. Rushing to judgement and overlooking true indicators, or favoring bolt-on solutions to existing practices, may emerge in planning.[17]

At the heart of these potential pitfalls is culture. It may be tempting for institutions to align a BI initiative in the wake of an academic reorganization, strategic plan, or other large-scale benchmark. Such a move puts the analytics effort in a subservient role to objectives and goals that have already been determined without any analytics insight. Rather, "institutions should not wait for a cultural shift to be fully in place before beginning an analytics program."[18] If anything, the analytics effort should run parallel or precede change, and culture will follow. A significant number of polled universities "highlighted the interplay between institutional culture and analytics, suggesting that initiating an analytics program before a philosophy of data-driven decision making is ensconced may help establish that culture."[19]

Guiding Principles

Bischel (2012) identifies eight guiding principles in any BI implementation. It is tempting to start by corralling all the data across the institution and then asking questions around it, allowing the available data and governance to drive the analytics effort and ultimately the culture. Rather, data should be seen as part of the solution to the problem. The primary product is a culture of data-driven decision-making—not a robust data warehouse or a bevy of attractive dashboards.

Map out strategy and planning

We have covered the planning process earlier in this white paper. This underpins the entire analytics effort—having a quantifiable measure of existing BI maturity, and where the institution wishes to go with the initiative in the short and long term, is critical.

Look for an early win

The BI effort involves a tremendous amount of work on the back end to get the data warehouse established. When the front end does start to take shape, it won't be fully baked overnight. BI is an iterative process that often involves generating more questions than answers. Look for early wins that answer burning questions—these efforts can (a) quickly legitimize the effort in the eyes of stakeholders and (b) lead to more in-depth questions and insights into the data.

[17] Bischel, "Analytics in Higher Education: Benefits, Barriers, Progress, and Recommendations."
[18] Ibid., 12.
[19] Ibid.

Invest in people over tools

BI tools have evolved to the point now at which the average desktop user can create meaningful visualizations and insights. These tools range from expensive enterprise deployments to open-source packages. While it may be tempting to invest in attractive BI packages and then hire analysts to run them, such a practice identifies the BI effort with a specific software package that may not even be the best for the job. Just as we start with a planning group to determine what data is necessary and how to get it, we focus on having the right people for the effort, who will determine what tools are necessary to get the job done.

Don’t wait for perfection

In looking for an early win, the processes and outcomes do not have to be perfect. In fact, the process itself may yield valuable insight into how the institution’s existing governance and internal structures affect the analytics effort. Early implementation will include multiple stakeholders still determining exactly what they want. It will not be neatly packaged.

Partnerships and communication are key

Implementation begins with planning, and planning begins with the cross-functional team. This is a common thread throughout the process. Break down the data silo walls and establish open, frequent, and meaningful lines of communication.

Plan for infrastructure that supports analytics across the institution

Does the institution handle its own IT infrastructure or is it managed? Are the servers on-premise or cloud? What is the health of the campus network? Do department chairs and deans have the requisite access to see basic data warehouse functions? These questions are a sample of considerations an analytics team must make when rolling out a BI implementation.

Plan the support function

Especially if BI has not been part of the IT offerings to date, the institution must consider how it will be supported. Who is responsible for ETL and the health of the warehouse infrastructure? Who are the

Subject Matter Experts (SME's) for the different departmental data coming into the warehouse? Who are the assigned support personnel for end-user analytics tools?

Benchmark to provide context

The JISC maturity index in Table 2 is a handy way of assessing maturity both before and throughout an implementation. This assessment can be administered in a number of ways; for example, scores can be gleaned from both the internal IT staff and departmental stakeholders to judge whether a gap exists between what is being offered and what is being used.

In Practice: Georgia State University

A prime example of how the sort of culture shift we have described in this paper can make a tremendous impact can be found at Georgia State University (GSU). From 2003 to 2014, graduation rates increased from 32 percent to 54 percent, and yet no single initiative or program can be cited as the driving force behind this improvement. Rather, it is found in the "accumulated impact of a dozen or more relatively modest programs" and "a particular approach to problem-solving."[20] The university had already treated its data as a university asset, and from that trove of information came a number of insights that ultimately yielded early wins and a stronger culture of problem-solving through data.

One of the first interventions targeted freshmen and sophomores, as the data showed falling off track in those years usually meant failure to graduate. GSU introduced a cohort model for freshmen, called Freshman Learning Communities (FLCs), which grouped students into blocks of 25 and had those blocks go through classes together. Those classes were offered on a block schedule. These FLCs offered advising and grouped students by major field of study. Ninety-five percent of freshmen participated in FLCs, maintaining a GPA of 2.96 and retention rate of 85 percent (vs. 2.73 GPA and 81 percent retention for those not participating). Similarly, students in classes with high drop/fail/withdraw rates (DFW) were enrolled in a peer tutoring program known as Supplemental Instruction. Students who participated in at least three of these sessions maintained an average GPA of 2.91 and retention rate of 91 percent (vs. 2.41 GPA and 84 percent retention). A more detailed analysis of the high-DFW classes showed that lower-level math classes were a particularly high barrier; as a result, targeted supplemental instruction known as MILE was implemented. As a result of MILE, the failure rate in the identified math courses dropped from 43 percent to 19 percent.

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[20] Kurzweil and Wu, "*Building a Pathway to Student Success at Georgia State University,*" 3.

An early win under the cross-functional culture that these analytics efforts ushered in was the Keep HOPE Alive initiative. In Georgia, a student must maintain a 3.0 GPA in order to keep their HOPE Scholarship. Falling below that threshold eliminates the scholarship. This was a barrier to retention. Analysis found that many students dropped just below the threshold (e.g. 2.95) and were well within range of getting it back with the proper aid—however, only nine percent of these students who lost the scholarship ever regained it. GSU targeted students with at least a 2.75 GPA with a $1,000 scholarship, financial counseling, and academic advising. As a result, 58% of the students who lost the scholarship were able to regain it, and the $1,000 expenditure per student became a revenue producer in regained scholarship funds to the university.

Similarly, students unable to pay all of their tuition were barred from enrollment per Georgia state law; in many cases, they were less than $1000 short of the full amount. The university believed it would benefit from offering small grants along with academic and financial counseling to get these students back in school, and using a $40,000 gift from a former university president, GSU did exactly that. The program has grown to $2 million and *generates net revenue*. Sixty-one percent of seniors receiving this grant graduate within two semesters of award.

As the culture and analytics capabilities evolved, GSU was able to leverage predictive ability to target incoming freshmen who were known to be at risk. Different predictive models were utilized to identify critical success factors for incoming freshmen. These factors were implemented into the Summer Success Academy, which enrolls the most academically at-risk 10 percent of incoming freshmen for 7 credit hours, academic advising, and financial literacy classes. Predictive modeling also contributed to the Graduation and Progression System, which utilized 10 years of academic data and identified longitudinal factors predicting graduation. This turned the academic advising process from a reactive process to a much more proactive one, and can identify key performance indicators that may not otherwise be considered.

Conclusion

Though Business Intelligence has been borne from the business domain, it is applicable—and critically so—to higher education. Institutions have the data stores already in place and an organizational structure similar to a large corporation. While objectives are different, they can mirror business goals. This paper has outlined both business and higher education BI maturity models, identified similarities in student goals and customer goals, and detailed specific academic initiatives at Georgia State University that are products of a data-driven solution environment. More importantly, we have explained how a BI initiative must be a part of the organizational culture; not waiting on change to happen, but leading that change.

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