Option #1: Business Analytics Program

Scott Miner

Colorado State University – Global Campus

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For his *Portfolio Project* for *MIS542 – Business Analytics,* the student will evaluate the business analytics program at an institution in the education industry, Institution A. Following the trend in education to move more courses online, Institution A is amassing ever-increasing amounts of learning-related data. Institution A wants to extract value from these big data sets and optimize online learning opportunities (Ferguson, 2012). As the cornerstone of his analysis, the student uses Figure 11.1 and Table 11.1, as presented by Nelson (2018), which emphasize the importance of balancing effectiveness and efficiency in a business analytics program. *Effectiveness* refers to doing the right thing to create value, whereas *efficiency* refers to generating maximal productivity with the least possible expense. The student divides his analysis of the business analytics program into the five following stages: (a) *problem framing*, (b) *data sensemaking*, (c) *analytics model development*, (d) *results activation*, and (e) *analytics product management* (Nelson, 2018). Lastly, within each of these five sections, the student includes a plan of action to help Institution A improve its business analytics program.

**Problem Framing**

Often, analysts within the Institutional Research (IR) department at Institution A skip the *problem framing* step and jump right into the data collection phase, overly eager to solve a problem before adequately defining it. In the *problem framing* stage of Table 11.1, Nelson (2018) outlines several ways for organizations to increase the effectiveness of their analytics programs, one of which includes prioritizing the right problem to solve. To prioritize the problem, Institution A should follow the five processes of *problem framing* as outlined by Nelson: (a) *problem definition,* (b) *root cause investigation,* (c) *hypothesis generation,* (d) *question design,* and (e) *business case prioritization.* In essence, Institution A needs to define the problem, whom it affects, its impact, and what a successful solution looks like, all of which comprise the **problem statement.** In defining the problem, analysts at Institution A might state that the institutionis experiencing a shortfall in projected student retention rates*.* After all, Shapiro *et al.* (2016, as cited in Larrabee Sønderlund *et al*., 2019) describe that nearly 8 million (39%) of the 20.5 million US students enrolled in university courses will drop out before graduating. Likewise, the College Board Advocacy and Policy Center (2010, as cited in Jayaprakash *et al.,* 2014) asserts that the US ranks 12th globally in the percentage of 25- to 34-year-olds with an associate degree or higher. In effect, there is tremendous potential for Institution A to increase student retention rates.

Once we have defined a problem, we should subject it to *a root cause investigation* to determine why it exists. Strategies in this area outlined by Nelson (2018) include using affinity and fishbone diagrams to conceptualize problem causes by type, also known as **category brainstorming.** For instance, Frankola (2002, as cited in West *et al*., 2015) describes potential causes of student attrition, including difficulties with technology and social isolation. Likewise, Mazza and Dimitrova (2004) describe how students may become disoriented in online course hyperspaces and lose motivation. Lastly, Cambruzzi *et al.* (2015) describe how students may fail to see a course material’s importance and drop out accordingly. All these examples represent potential causes of the problem Institution A is facing.

Nelson (2018) presents the next step within *problem framing* as *hypothesis* *generation*, where we utilize **divergent thinking** to develop ideas about how we believe the world works. We work in teams in this step, employing sticky notes to generate hypotheses that allow us to translate our belief statements into SMART goals. For instance, in the case of Institution A, we might say that by implementing learning analytics (LA) for a student, Andrew, we will increase student retention rates, which we will know to be true when they have increased by 20%. Constructing hypotheses in this format allows for more easily measurable goals. We can find many successful implementations of LA systems in the literature. For instance, Arnold and Pistilli (2012) found that courses at Purdue University implementing an LA software called *Course Signals* (CS), which gauges student performance based on multiple dynamic indicators and feeds this information back to students, retained 10 to 25% more students than courses not using the software. Lastly, in this process area, Nelson suggests that organizations use a two-by-two matrix to evaluate the risk and impact of their hypotheses.

In the next phase, *question design,* Nelson (2018) recommends formulating the problem into a question and generating potential study designs based on this question. For instance, to determine if an association exists between student demographics and retention rates, we could use simple regression models in our study design. Milliron *et al.* (2014) implemented another study design, randomized control trials, finding that at-risk students who received a phone or email intervention were 3.21 to 7.62% more likely to remain enrolled than students in the control group. Nelson recommends having a control group when possible. Furthermore, Larrabee Sønderlund *et al.* (2019) recommend experimental research methods over correlational designs. All these recommendations provide ways for Institution A to improve its analytics program. In the last phase of problem framing, *Business Case Prioritization,* Nelson suggests using a project prioritization matrix to assess the importance of solving a problem. In this step, we create the **business case**,whichis a justification for the proposed project according to its expected benefits and describes what the project does and how it impacts the organization’s strategic business objectives (Nelson, 2018).

**Data Sensemaking**

Nelson (2018) divides the *data sensemaking* best practice area into four processes: (a) *data identification and prioritization*, (b) *data collection and preparation*, (c) *data profiling and characterization*, and (d) *visual exploration*. Institution A’s biggest challenge in this area relates to efficiency and utilizing the most appropriate technology to eliminate waste and avoid redundancy. Institution A can access its data warehouse via web-based tools but could benefit from updated technology, as it relies primarily on Excel to publish reports. As an example of updated technology, three institutional case studies conducted by Milliron *et al.* (2014) utilized Civitas Learning’s Illume software, a predictive analytics platform that displays student progression dynamics filtered by chosen segments, and its Inspire application, an action analytics application that uses design thinking to leverage insight analytics in easy to consume formats for administrators. In effect, implementing updated software at Institution A would benefit all areas of the *data sensemaking* best practice area. Nelson also suggests implementing an analytics **sandbox** environment to aid computationally complex data transformations. Lastly,when seeking to understand relationships between multiple variables, Institution A should classify these variables into **explanatory** (e.g., predictor) and **response** (e.g., outcome) variables. For instance, the Student Probability Model (SPM) implemented at the Open University UK (OU) predicts whether students will reach specific milestones based on explanatory factors, including the total number of student failures and credits (Herodotou *et al.,* 2019).

**Analytics Model Development**

Nelson (2018) divides the *analytics model development* best practice area into four processes: (a) *making comparisons,* (b) *measuring associations,* (c) *making predictions,* and(d) *detecting patterns*. Nelson describes *making comparisons* as one of the most common activities in analytics. Milliron *et al.* (2014) exemplify this concept by studying the effects of LA interventions on course completion rates, comparing the results of those who did not receive interventions (the control group) to those who did (the test group). Their results show that those who received interventions completed their courses at a 3% higher rate than the control.

Unfortunately, the analysts at Institution A often fail to generate hypotheses before performing statistical tests. To increase an analytics program’s effectiveness, Nelson (2018) suggests that organizations test the validity of their hypotheses. To do this, analysts must create both null and alternative hypotheses and then check whether the data obtained provide evidence against the null hypothesis. Fritz (2011) demonstrates this concept within the *measuring associations* process area by hypothesizing that students more active in the course management system (CMS) at the University of Baltimore in Maryland would receive higher grades. Results indicated a positive correlation between grades and online activity; students who earned a D or F used the CMS 39% less than students receiving a C grade or higher (Fritz, 2011).

*Making predictions* refers to developing advanced analytical models to predict the value of one variable given another. Institution A may wish to predict at-risk students or letter grades. Similarly, the SPM implemented at OU exemplifies this concept, using logistic regression to predict whether students will reach specific course milestones, a categorical outcome variable (Herodotou *et al.,* 2019). Finally, *pattern detection* is nearly synonymous with machine learning, assigning labels to objects. Lykourentzou *et al*. (2009) used machine learning techniques to classify students likely to drop out of e-learning courses, achieving a 75 to 85% overall student classification rate. Institution A may wish to use any of the above concepts to improve the efficiency and effectiveness of its business analytics program.

**Results Activation**

Nelson (2018) suggests creating visualizations and assessing improvement opportunities to improve efficiency and effectiveness within the *results activation* area. Institution A could benefit from both recommendations. Nelson divides this stage into three process areas: (a) *solution evaluation*, (b) *operationalization*, and (c) *presentation and storytelling*. In the *solution evaluation* phase, we validate our model, evaluate our results, and assess our model’s impact. The area under the receiver operating characteristic (ROC) curve is a useful visualization to convey model robustness. Milliron *et al.* (2014) used this visualization to explain how their study’s predictive model provided a 141% improvement in accurately identifying students at risk for intervention compared to randomly selecting students for outreach.

During the *operationalization* phase, we determine the most appropriate strategy for deployment. Herodotou *et al.* (2019) provide several recommendations for an organization’s successful adoption of LA initiatives, including providing evidence of LA’s effectiveness, encouraging communication across stakeholders, setting a shared LA vision, considering ways to mitigate teacher resistance to change, and using LA to complement, not replace, the teaching practice. Likewise, Larrabee Sønderlund et al. (2019) recommend breaking all outcomes down by relevant population characteristics, recording student and faculty experiences, and standardizing the assessment of LA intervention programs. Institution A will operationalize analytics results more effectively and efficiently by following these guidelines. Lastly, for Institution A to master storytelling, Nelson suggests using visualizations to bring a story to life and using a story blueprint to understand what we want to convey with our data. From this point on, we tell our data stories, intending to create a sense of urgency and a clear pathway to action (Nelson, 2018).

**Analytics Project Management**

Finally, to improve Institution A’s effectiveness within the *analytics project management* area, Nelson (2018) suggests right-sizing the analytics process depending on expected value and, to increase efficiency, suggests capturing knowledge for future use. Nelson divides this best practice area into five processes: (a) *value management,* (b) *analytics lifecycle execution,* (c) *quality processes,* (d) *stakeholder engagement and feedback¸* and (e) *capability and talent development.* Within the *value management* process, analytic product managers want to maintain alignment with organizational strategy, lead the product management culture, define the quality of analytics products, and promote value. Nelson emphasizes the importance of maintaining a highly transparent process regarding how we handle analytic requests, rather than adhering to strict prioritization guidelines, to engender trust between analytics teams and customers. Institution A can, indeed, benefit from this recommendation. The institution currently uses a dashboard to track project progress, but it is only visible to IR team members and not customers.

Within the *analytics lifecycle execution* area, product managers are responsible for the analytics processes that produce value. **Product lifecycle management** encompasses six vital steps: (a) *opportunity identification*, (b) *design*, (c) *testing*, (d) *launch*, (e) *assessment*, and (f) *retirement*. Institution A currently utilizes a single “decider” who triages product requests. Nelson (2018) advises against this approach and recommends using an analytics product prioritization matrix to promote team collaboration. Essentially, we want to **right-size** theanalytics product requirements appropriately. In the *design* phase, we want to *prototype* a minimum viable product (MVP) that adequately addresses the customers’ needs before *testing*. After *launching* a solution, we should *assess* product performance. Likewise, Larrabee Sønderlund *et al.* (2019) suggest developing standardized assessments of LA intervention programs and recording student and faculty experiences. Lastly, while neglected in Institution A’s current business analytics program, *retirement* planning is essential because analytics products have expected lifespans (Nelson, 2018).

Product managers should document all analytics product procedures during the *quality* *processes* stage to capture knowledge for future use. Within the *stakeholder engagement and feedback* stage*,* we want to engage stakeholders early and often. Likewise, Herodotou *et al.* (2019) recommend that organizations allocate resources for communication across stakeholders. Furthermore, analytics done well leads to change, and Herodotou *et al.* also recommend we consider ways to mitigate teachers’ resistance to change when implementing LA initiatives. Lastly, in the *capability and talent development* process, we want to create a supportive learning culture. If we understand the organization’s strategic goals and our team members’ competencies, we can use this framework to integrate personalized professional development plans for each team member (Nelson, 2018). Institution A can benefit from all the above recommendations.

**Conclusion**

In conclusion, this paper evaluated the business analytics program at Institution A, using the effectiveness and efficiency criteria as the basis for this analysis. The student divided the analysis into the five process areas outlined by Nelson (2018): (a) *problem framing*, (b) *data sensemaking*, (c) *analytics model development*, (d) *results activation*, and (e) *analytics product management.* Lastly, the student provided recommendations for Institution A within each best practice area. By implementing these suggestions, Institution A can vastly improve its business analytics program, moving from analytics infancy to maturity.

References

Arnold, K. E., & Pistilli, M. D. (2012). Course signals at Purdue: Using learning analytics to increase student success. *Proceedings of the 2nd International Conference on Learning Analytics and Knowledge - LAK ’12*, 267. <https://doi.org/10.1145/2330601.2330666>

Cambruzzi, W. L., Rigo, S., & Barbosa, J. L. V. (2015). Dropout Prediction and Reduction in Distance Education Courses with the Learning Analytics Multitrail Approach. *J. Univers. Comput. Sci.*

Ferguson, R. (2012). Learning analytics: Drivers, developments, and challenges. *International Journal of Technology Enhanced Learning*, 4(5/6), 304. <https://doi.org/10.1504/IJTEL.2012.051816>

Fritz, J. (2011). Classroom walls that talk: Using online course activity data of successful students to raise self-awareness of underperforming peers. *The Internet and Higher Education*, *14*(2), 89–97. <https://doi.org/10.1016/j.iheduc.2010.07.007>

Herodotou, C., Rienties, B., Verdin, B., & Boroowa, A. (2019). Predictive Learning Analytics “At Scale”: Guidelines to Successful Implementation in Higher Education. *Journal of Learning Analytics,* 6(1). https://doi.org/10.18608/jla.2019.61.5

Jayaprakash, S. M., Moody, E. W., Lauría, E. J. M., Regan, J. R., & Baron, J. D. (2014). *Early Alert of Academically At-Risk Students: An Open Source Analytics Initiative. Journal of Learning Analytics,* 1(1), 6–47.

Krumm, A. E., Waddington, R. J., Teasley, S. D., & Lonn, S. (2014). A learning management system-based early warning system for academic advising in undergraduate engineering. In *Learning analytics* (pp. 103–119). Springer.

Larrabee Sønderlund, A., Hughes, E., & Smith, J. (2019). The efficacy of learning analytics interventions in higher education: A systematic review. *British Journal of Educational Technology*, 50(5), 2594–2618. <https://doi.org/10.1111/bjet.12720>

Lykourentzou, I., Giannoukos, I., Nikolopoulos, V., Mpardis, G., & Loumos, V. (2009). Dropout prediction in e-learning courses through the combination of machine learning techniques. *Computers & Education*, *53*(3), 950–965. <https://doi.org/10.1016/j.compedu.2009.05.010>

Mazza, R., & Dimitrova, V. (2004). Visualising Student Tracking Data to Support Instructors in Web-Based Distance Education. *13th International World Wide Web Conference (WWW 2004) - Educational Track. 2004 May 17-22*, 154–161.

Nelson, G. S. (2018). *The analytics lifecycle toolkit: A practical guide for an effective analytics capability*. Wiley-Blackwell.

West, D., Heath, D., & Huijser, H. (2015). Let’s Talk Learning Analytics: A Framework for Implementation in Relation to Student Retention. *Online Learning*, 20(2). <https://doi.org/10.24059/olj.v20i2.792>

Zilvinskis, J., & Wills, III, J. (2019). Learning Analytics in Higher Education: A Reflection. *InSight: A Journal of Scholarly Teaching*, 14, 43–54. <https://doi.org/10.46504/14201903zi>