Data Collection to Lower Withdrawal Rate in Higher Education

Shayla K. Heavner

DDDM Plan

Johns Hopkins University

Spring 2018

Retention in the eLearning environment in higher education is a systematic problem. In this data-based decision making plan, we attempt to develop a data-protocol for a public university in combination with a DDDM model to guide our actions to attempt to identify the cause and formulate ideas on how to lower the withdrawal rate, particularly in online mathematics courses.

The Issue

Technology is the preferred medium of the time. Everyone is incorporating its seemingly endless features into their daily activities, and education is no different. As such, eLearning has become increasingly popular. In a recent study, the Babson Survey Research Group (2018) found, "31.6% of all students now take at least one distance education course" (p.3). *See Figure 1.* This popularity allows for universities to extend their reach and their enrollment to students of all ages all over the world. However, this too means distance education faces many of the same issues traditional schools battle. Our focus: retention.

> **Distance Education**
>
> "Online and blended learning are changing the way instruction is provided in this country. More than six million students or approximately one-third of the higher education population enrolled in fully online college courses in 2010"
>
> -Picciano, A. *The Evolution of Big Data and Learning Analytics in American Higher Education* (2012, p.9-10).

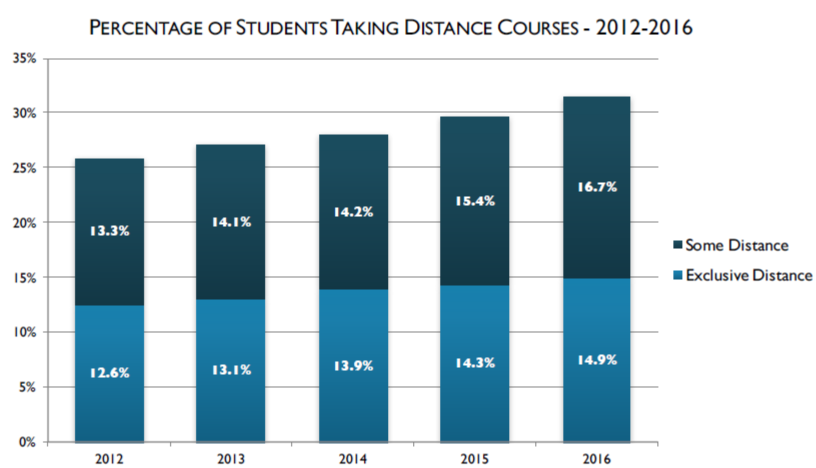

Figure 1: Percentage of Students taking Distance Education Courses 2012-2016.
Source: Grade Increase Retrieved from https://onlinelearningconsortium.org/read/grade-increase-tracking-distance-education-united-states/

Student retention is not a new concern nor is it unique to eLearning. The accompanying data shows much higher withdrawal rates than we would like at a 4-year public institution (*See Figure 2).* As such, it is a systemic issue that needs to be addressed. Keith Tyler-Smith (2006) states, "The problem of dropout rates in eLearning programmes has been argued over at length without any consistent conclusions about the degree of the problem, or a clear understanding of what factors contribute to learners dropping out, withdrawing or not completing eLearning courses". I argue that the reason for this inconsistency is a lack of data and specifically a data protocol that could provide more insight especially for students at a particular institution. Until we have a proper system to collect the needed data, we will continue to guess at the cause of the problem. The intent of this plan is to create the basis of a data protocol for Indiana University's online mathematics programs, the data collected will then drive our decision making process to adopt new policies in order to lower the withdrawal rate.

> The Problem
>
> "Student attrition/retention has been a significant issue in higher education for decades. The issue is not unique and all of higher education need[s] to pay attention"
>
> - Picciano, A. *The Evolution of Big Data and Learning Analytics in American Higher Education* (2012, p.15)

Tinto (1975) states, "Despite the very extensive literature on dropout from higher education, much remains unknown about the nature of the dropout process" (p.89)[1]. I posit that we can learn more about our students and their reasoning for withdrawal through adoption of a data protocol.

To truly understand the issue, a plethora of data must be collected and analyzed. Picciano (2012) states, "Student attrition is not a simple phenomenon and involves a host of variables" (p.15). It would be impossible to comprehend, measure and analyze these "variables" by hand, thus we must consider the

[1] Though dated, Tinto's work remains as a top resource in the field of drop-outs in higher education

use of technology to aid our quest. Further, once we examine said data, we will be able to allow it to guide us in our decision making process to create programs and interventions that specifically tackle this

First institution type, degree or certificate program, and degree expectations	Cumulative postsecondary withdrawal rate among those who had not earned any degree or certificate and were not enrolled at any institution as of spring 2009						Attainment status at any institution as of spring 2009		
	Spring 2004	2004–05	2005–06	2006–07	2007–08	2008–09	No degree or certificate, not enrolled	No degree or certificate, enrolled	Attained any degree or certificate
All first-time postsecondary students, 2003–04									
Total	8.1	15.6	22.6	27.4	32.7	35.5	35.5	15.0	49.5
Type of first institution									
4-year	3.4	7.1	12.3	16.5	21.5	23.6	23.6	12.2	64.2
Public	3.2	6.4	11.1	14.8	20.1	22.2	22.2	12.9	64.8
Private nonprofit	2.5	5.1	9.4	13.5	17.1	19.0	19.0	11.1	69.9
For-profit	9.1 !	22.4	35.1	44.0	52.1	54.8	54.8	11.3	33.9
2-year	12.4	21.3	30.8	36.6	42.7	46.4	46.4	18.5	35.1
Public	12.9	20.0	29.7	35.7	42.1	46.0	46.0	19.6	34.4
Private nonprofit	10.1 !	29.9	29.8	36.5	41.2	43.4	43.4	10.4 !	46.2
For-profit	7.9 !	33.3	43.1	46.3	49.5	50.9	50.9	9.6	39.5
Less-than-2-year[1]	8.5	27.9	30.6	32.1	34.3	35.5	35.5	8.8	55.6
Public	14.5	22.2	23.6	25.9	26.1	26.3	26.3	4.5 !	69.2
For-profit	7.1	28.8	31.8	32.9	35.5	37.0	37.0	9.6	53.3
Degree or certificate program, 2003–04									
No degree or certificate	16.8	23.5	32.5	38.9	45.2	48.7	48.7	20.6	30.7
Certificate	8.8	27.2	29.5	31.3	34.3	35.6	35.6	9.3	55.1
Associate's degree	11.3	20.0	30.3	36.4	42.7	46.4	46.4	18.4	35.1
Bachelor's degree	2.7	5.8	10.4	14.2	19.0	21.0	21.0	11.8	67.3
Highest degree ever expected to complete, 2003–04									
No degree or certificate	43.8	49.3	59.0	60.8	63.4	64.6	64.6	9.8 !	25.6
Certificate	13.6	32.0	35.6	38.2	41.7	43.2	43.2	5.9	51.0
Associate's degree	17.5	29.4	39.8	44.9	48.4	50.5	50.5	11.4	38.1
Bachelor's degree	9.9	18.7	26.0	31.6	37.9	40.6	40.6	16.5	42.9
Advanced degree or certificate	4.5	9.4	16.0	20.5	25.7	28.8	28.8	15.5	55.7

Figure 2. Higher Education Withdrawal Rates
Source: U.S. Department of Education, National Center for Education Statistics. *Six-Year Attainment, Persistence, Transfer, Retention, and Withdrawal Rates of Students who Began Postsecondary Education in 2003-04* (NCES 2011-152)

problem. Picciano (2012) goes on to say, "Student performance, especially related to attrition and retention, has emerged as a primary focus of learning analytics applications" (p.17). Thus, I suggest we approach this topic using a data driven decision making

Withdrawal

"Barely more than one-half of all four-year college students in the United States earn their bachelor's degrees within six years from their initial institution."

-Tinto, V. *Completing College: Rethinking Institutional Action.* (2012, p.2) model, specifically creating a data protocol in conjunction with an analytic program to guide our commitment to change.

Having discussed and witnessed a high drop-out rate in online mathematics courses at Indiana University, I propose the creation and adoption of a data-based decision making model and a data protocol to attack this systemic issue. While some data will be easy to transform as it is already being collected (achievement data), it will be necessary to also gather other types of data such as perception, which will help us connect individual reasons for withdrawal, as well as demographic. Tinto (1975) writes, "[to build a theoretical model] one must include not only background characteristics of individuals (such as those measured by social status, high school experience, community of residence, etc., and individual attributes such as sex, ability, race and ethnicity) but also expectational and motivational attributes of individuals (such as those measured by career and educational expectations and levels of motivation for academic achievement." (p.93). The collection and analyzation of this data will allow the online mathematics department at Indiana University to make informed decisions based on our findings. Our goal is to first identify the types of data that need to be collected and generate ideas on how best to do so. Once this data protocol is in effect, we will focus on using a data-based decision making model to determine how to lower the withdrawal rate in online mathematics courses at our institution.

The Plan

In order to solve the systemic problem of student withdrawal from online mathematics courses, we will follow a data-based decision making model. We have chosen Phillip Streifer's (2002) model (*Figure 3*) as he states, "90 percent or better is spent on data gathering and analysis due to the complexity of the process." While our overall goal is to generate solutions to the problem, it is imperative we first develop a data protocol to ensure we collect and analyze accurate data to drive our decision making process.

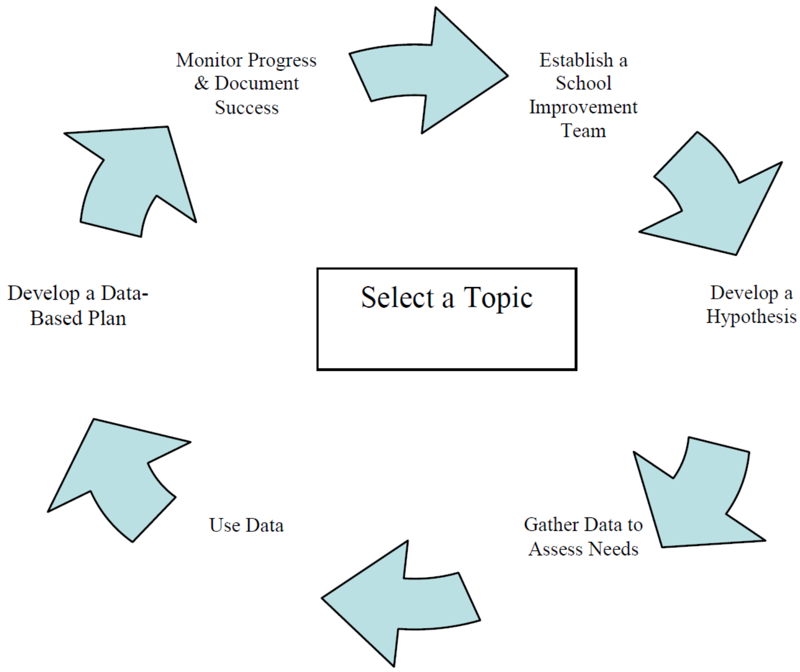

Figure 3: Data Driven Decision Making Model
Source: *olms.cte.jhu.edu/olms2/data/resource/.../DDDMOverview%20-%20Castellani.pdf*

Castellani and Matzusaki discuss this model pointing out, "[Streifer stresses] the importance of bringing all of the data into one database or spreadsheet to effectively analyze the data" (p.13). This is key as in a moment we will discuss how our institution already has a plethora of data available, our challenge will be to aggregate this into a single system. In addition, Castellani and Matzusaki comment. "DDDM is a [cyclical] ongoing process and therefore, the leader can go to any of the components as needed at anytime and one can also go in any order that is suitable to his or her needs" (p.13). This is also of importance to our plan because at times we must simultaneously collect data, develop hypotheses and possible solutions while also consistently monitoring progress and changes.

Establishing a Team

Our first step will be to establish a team that will be responsible for aiding in data collection, analyzation as well as developing and implementing possible solutions. Due to this wide array of duties, our team must consist of members from multiple departments. We begin with those on the front line: the educators. It is key that all mathematics faculty who currently instruct or are scheduled to instruct an online course participate. However, to keep our team small so that all ideas can be heard and discussed, only a few representatives will participate in all steps. In order to have a complete and diverse team, teaching assistants, course aides and other supplementary personnel should also be included. This is important because TA's often have different student interactions that will provide a valuable point of view to solving our issue. Student advisors will also be included. Holds are placed on registration which require students to discuss their enrollment plans with an advisor. As such, advisors are familiar with common issues, complaints, and possess insight on how and why students may enroll and subsequently drop courses. In addition, because of the registration holds already developed, they have the ability to collect needed data in their student meetings. Additional personnel will include: representatives from the IT department, school leadership, the student body and the board. Each of these groups have unique knowledge and are stakeholders in solving our systemic issue. Valerie von Frank (2011) presents the following traits as integral in selecting a school improvement team (p. 4-5):

The Team

- SME's – current educators for online mathematics courses
- Student Advisors
- IT department
- School Leadership
- Student representation
- Board representation

- Respect for and influence among colleagues
- Knowledge and leadership capacity
- Unique or specialized perspective
- Content-area expertise
- Specialized Training
- Sense of the school's history traditions and context
- Relationships with key members of staff
- Aspiration to become administrator
- Ability to balance the team makeup

We believe the team as described above represents most, if not all, of these criteria. It is important that as we build the team, we work to ensure each of the above traits are represented on our team. Each team member/group has vital duties in implementing our plan. They have been chosen due to their already developed expertise and thus we do not expect additional training will be necessary. However, when we begin developing a data protocol and analyzation, it will be necessary for the IT representatives to work closely with and obtain some training from our sister school which will be expanded upon shortly. Below is a table that includes each team member and their role in our DBDM plan.

Step in Plan	Team Member	Description
Establish Team	**Team Leader (Mathematics Instructor)**	**After pitching plan to mathematics department leadership, we will assign a team leader to begin developing the essential personnel to carry out plan.**
Develop Hypothesis	**Online Mathematics Instructors Student Advisors**	**These two key groups will help to identify possible reasons for our systemic issue. This includes, *why* we think withdrawal rates are so high and *how* we can fix them. In this process, identifying how to collect the needed types of data will be a main focus in our first cycle of the process.**
Gather Data	**Mathematics Instructors Student Advisors IT Department**	**In this step, we must work together to aggregate data that is already being collected as well as gathering additional information. Our IT department will act as the leaders in this step, working with instructors to unify their course data into one system and with advisors to set up a perception survey.**
Use Data	**IT Department**	**For this step our IT department will work with our sister school to utilize their already created learning analytic application to analyze the data and identify trends.**
Develop a Plan	**Entire Team**	**Using the results from the previous steps, the team will work together to develop possible solutions based on the data collected and trends from analyzation.**
Monitor Progress	**Team Leader School Leadership**	**Our team leader will work in conjunction with school leadership to determine if our interventions, data collection and hypothesis garnered successful results. They will make determinations of resources that can be expended to help the process, and any changes or additions to the team for the next cycle.**

Training

It is not a reasonable assumption to believe that our team, while all experienced personnel, will have the knowledge needed to interpret the data collected. While our IT team will need additional training in the development of a learning analytics application and how to data mine and analyze the data, the remainder of the team will also need some training on how to effectively interpret the data. All team members already participate in a FERPA course, relating to student privacy. It is recommended they also cover an additional section directed specifically to data ethics to ensure the information we collect is used in an ethical and responsible manner. Focus on what Barquin and Northouse (2003) deem the "three part relation" (p.7) will help us to understand the amount of trust instilled in the team and our responsibility to uphold said trust. In addition, the team will need to understand the process of turning data into knowledge and an understanding of data analytics for our plan to be successful and produce meaningful results. Our team must also be aware of how to use a data protocol. The IT department will be aggregating information from various sources and attempting to make sense of it. Understanding this process is key for our interpretation of their results.

Developing a Hypothesis

We have already determined that the high withdrawal rates is a systemic issue, in addition we know that in order to attack this problem, more data is needed. Thus, this step will help guide us in developing the questions to be asked when collecting data. As we are in search of *why* withdrawal rates are high in addition to *how* we can fix them, some questions to present to the team include:

Is the withdrawal rate in your courses (if applicable) higher than desired?

Have you discussed withdrawal with students? If so, what information did you collect?

Would additional data help decide why students are withdrawing?

What types of data would you find useful to guide new protocols or course design to attack this problem?

WHAT DO YOU THINK ARE THE TOP 3 REASONS STUDENTS WITHDRAW FROM A COURSE?

SHARE ANY IDEAS FOR ATTACKING THIS ISSUE.

Castellani and Matzusaki state, “Streifer stresses the importance of creating a concept map to fully understand the problem” (p.13). As such, in our initial meeting we will work to create a mind map combining our team’s responses to the above questions to gain a collective idea of our perceived cause of the issue, the data that will help to confirm or expose differing causes to student withdrawal, and some general ideas for possible solutions. One important note is that solutions take time, money and development. While we want the data to drive our decision making process, it would be wise to begin some preliminary budgeting and development of solutions. This allows us to easily augment later in response to our data findings, rather than delaying intervention.

Gather Data

This will be our primary focus at this time. Our team will ultimately analyze the data, develop and implement possible solutions and monitor changes to repeat the process. However, we must first decide on and implement a data protocol to gather the needed information. The next sections will describe in detail the type of data that needs to be collected and some ideas on how to collect the needed data. The following figure taken from Tinto (2012) displays the complexity and number of variables present when making a withdrawal decision.

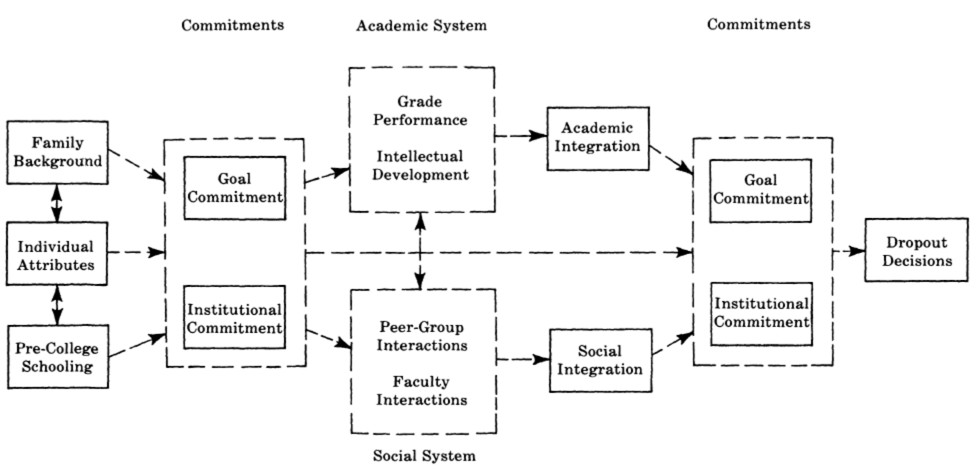

Figure 1
A conceptual Schema for Dropout from College

96

Achievement Data

This type of data may not seem immediately useful to solve the systemic issue of withdrawal in online mathematics courses. However, I will argue based on research and data systems already in use, that achievement data can be a vital aid to our plan. Tinto (1975) states, “failure to distinguish academic failure from voluntary withdrawal, has very frequently led to seemingly contradictory findings” (p.90). Thus, collecting and analyzing achievement data can help un-blur this line and categorize these two types of withdrawal, allowing us to find solutions for each. This will be the easiest data to collect. Our institution already uses a Learning Management System that collects much of this information. Picciano (2012) writes, “it is important that instructional transactions are collected as they occur. This would be possible in the case of a course management/learning management system” (p.13). Our challenge, as previously mentioned will be to aggregate this already existing data into a single spreadsheet or application. Picciano (2012) goes on to state, “a robust fifteen-week online course could generate thousands of transactions per student. Real-time recording and analysis of these transactions can be used to feed a learning analytics application” (p.13). This represents a plethora of data that can be analyzed for our cause. However, real-time analysis and development of a learning analytics application is both costly and time consuming. Picciano (2012) cites Michael Cottam, a school dean who has undergone this type of data mining, “[We] crunched data from tens of thousands of students [and] the statistics we encountered are anything but simple” (p.16). His “PACE” program has the ability to “predict after the first week of a course, with 70% accuracy, whether any given student will complete the course successfully” (p.17). This type of data protocol is ideal for our circumstances, it would enable us to identify students at risk of withdrawal for academic reasons and provide early intervention. Lastly, Picciano (2012) explains, “[Learning Analytics] systems are fairly sophisticated and [take] a long time to develop, test, and implement. Educators who are considering developing a learning analytics application would be wise to consult with others who have already started using this technology" (p.17). I hope to assuage fears with the following silver lining. First, developing such an application will have far greater use at our institution in addition to attacking the problem of withdrawal. The multifaceted benefits should help to justify the cost. In addition, following Picciano's advise, our sister school, Purdue, already has developed a learning analytics application. Having our IT department work closely to learn and train from this system should help to streamline the process lowering both cost and time. Thus, for achievement data, we need not collect only aggregate. If we are able to develop an application similar to Cottam's, that is predictive in nature, this along with additional interventions and changes can greatly reduce the number of student course withdrawal.

Perception Data

I would argue that perception data will be the most insightful as well as the most difficult to quantify and obtain. Asking students directly, "why did you withdraw?" will provide a wealth of information and help us to directly classify the problem. This is where our student advisors will play a prominent role. Our idea is to require students to complete a short survey in order to withdraw from a course. Tinto (1975) states, "Much remains unknown about the nature of the dropout processes, in large measure, the failure of past research to delineate more clearly the multiple characteristics" (p.90). Perception data will allow us to determine what characteristics are driving students to drop a course by obtaining their thoughts directly. In addition to guiding our goals regarding withdrawal, gathering this perception data will go a long way to understanding our students, and their thoughts can also lead to improved programs.

Demographic Data

In my personal experience, I have witnessed students withdraw from courses based on personal factors such as change in income or distance. One student was struggling in the course and reached out for help but withdrew before this could be set up. Collecting data regarding these factors can be very insightful for our institution and help us for instance in improving our online resources for students not physically near a campus. Tinto (1975) writes of the importance of this data (see sidebar), but Tyler-Smith (2006) speaks directly toward student retention in an online environment stating, "[Berge and Huang (2004)] cluster the range of variables into three primary groups;(1) Personal variables such as age, ethnicity, gender, income, previous academic experience and personal attributes". We will take a look at the addition attributes below when we discuss the collection of data. Overall, it is clear that researchers agree demographic data is vital to determining the cause of withdrawal. Moreso, much of this needed data is already collected by the university. Like achievement data, our goal will be to simply aggregate and analyze.

The Data

"[to build a theoretical model] one must include not only background characteristic of individuals (such as those measured by social status, high school experience, community of residence, etc., and individual attributes such as sex, ability race and ethnicity)."

-Tinto, V. Dropout from Higher Education: A Theoretical Synthesis of Recent Research. (1975, p.93)

Program Data

Individual instructors utilize differing techniques throughout the mathematics department. Collecting program data can help to identify trends within our sample of students who have withdrawn. For instance, if courses who utilize a teaching assistant or hold online office hours have lower withdrawal rates, this can help guide us in deciding the types of resources and instructional methods that are most beneficial to our students. It is important that our instructors do not feel penalized or targeted for their techniques, but understand that we are trying to solve a systemic issue and improve quality for our students.

Data Collection

We see that the amount of information that we seek to collect is immense. Our process will consist of aggregating data already collected, as well as the creation of new data. First let us look at the data we already are collecting. This consists of achievement and demographic data. Through our learning management system, Canvas, information such as student scores, time spent on the course website, and participation in course are available. Our IT department will take charge of moving this data into one unified source. Gill, Borden and Hallgren (2014) state, "developing standardized procedures for the collection and storage of student achievement and behavioral data that are integrates with the existing work of teachers and staff rather than imposing an additional burden-improves data quality and data security" (p.3). Thus, we will work to create a program that extracts the data instructors are already entering into the Canvas platform. Currently, in order to access this data, one must click through each course individually. By aggregating in one place we will be better able to investigate withdrawals as an institution without submitting instructors to additional protocols. We will look for trends in the amount of time spent on a course, and low initial participation or scores in a course with respect to withdrawal. The demographic data on students should also be added to the application. This includes factors such as age, ethnicity, gender and location. Of particular interest is whether students who do not reside near a campus have a higher rate of withdrawal. This can lead us to develop more online resources to ensure our long-distance students are receiving the course assistance to succeed. Often changes in demographic data are not collected in the traditional system. Certainly not in a real-time scenario. Students may wait until the following semester to update their demographic data. Thus, when collecting perception data, we will also seek to gain additional demographic information. Perception data is not currently being collected. A digital survey is in use for end of course evaluations that allows the student to bypass by selecting, “I have withdrawn from the course”. In addition, completion of this survey is entirely voluntary although instructors often provide incentives such as additional course points for participation. We suggest a mandatory survey is created to be completed in order to successfully withdraw from a course. Our student advisors will take point for this step. It may also be necessary to bring in an expert in survey creation to ensure we collect meaningful data in a concise format. We will follow Collie and Rine’s (2009) survey design outline to obtain optimal results. Beginning with “why are you withdrawing from this course?”, it is my opinion that we use a multiple-choice format to easily quantify this data. Providing an “other” option in which additional input is required can help us to avoid the confirming the evidence trap. While we are aware of some of the main reasons students drop a course, in order to collect meaningful data, it is key that we avoid forcing students to put themselves into one of our preconceived “boxes”. Collie and Rine also suggest placing demographic type questions at the end of the survey. We will do this in order to collect changes in income or location, for example, as it occurs to determine if these factors play a significant role in withdrawal. The utilization of a Likert scale will be beneficial for the majority of questions. This type of question can be quickly answered by students, is easily quantified and allows us to interpret how students perceive some of our proposed possible solutions. We will look for overall trends in the survey, but pay close attention to reasons for withdrawal and resources that may deter withdrawal. I also suggest the implementation of a survey for our mathematics faculty. This will help us to collect program data. In order to successfully link our information, the survey wording should mirror the student perception survey. For instance, we can ask students to rate on the Likert scale from “strongly agree” to “strongly disagree”, *I would be less likely to withdraw if: there was more instructor interaction.*

Mirroring this concept in the instructor survey would be, *I provide regular opportunities for student-teacher interaction.* This allows us to asses if an activity like online office hours would be a possible solution to lower withdrawals.

Use Data

Our IT department will play a large role in the aggregation and analyzation of data collected. We will follow Gill, Borden, and Hallgren's (2014) framework. It is imperative that the data we collect and ultimately use is accurate. The framework provides, "Assembling high-quality data requires strong data infrastructure" (p.3). This includes the concepts previously discussed including the "linking" of information, "creating low-burden data collection mechanisms" and in addition "certifying and monitoring those who collect data". As mentioned before our entire team will undergo additional data privacy training and our IT department will have exclusive access to all data and specialized training in the collection and analyzation of data. During the next phases, all data will be removed of all identifying factors and restricted to the team. The IT department will link the various data types into one system and it will be structured in such a way that it does not create additional data-entry tasks for our instructors. The combination of these factors will help to ensure we receive high-quality data. Next, Gill, Borden and Hallgren (2014) state, "producing relevant and diagnostic data analysis requires strong analytic capacity" (p.3). The framework suggests "creating in-house technical assistance", "training to staff at all levels" and "improving the accessibility of data" (p.4). Our institution already houses a robust IT help department, in addition, having a representative on the team will allow just-in-time assistance to team members reviewing and accessing the data. As this plan involves a large amount of work, it may be necessary to hire new IT personnel or devote a specific employee to manage this project exclusively. We

The Framework

- High-Quality data through infrastructure
- Relevant data through analytic capacity
- Create culture of Data Driven Decision Making

have previously discussed that all team members will attend data training, we will follow Gill, Borden, and Hallgren's suggestion of "[training should] include implementation of data driven decision making practices, how to access and analyze data, using data to change instructional practices, and data management and security" (p.4). Lastly, Gill, Borden and Hallgren suggest, "promoting effective use of relevant and diagnostic data to inform instructional and operational decisions requires a strong organizational culture of DDDM" (p.4). We hope that this plan is a first step in obtaining this goal. In addition, we will hold multiple "data conferences" throughout implementation of the plan. As stated, it is important that all online mathematics instructors participate in the process. Thus, we suggest having 1-2 meetings per semester with all instructors currently teaching an online mathematics course or scheduled to teach in the subsequent semesters. This will allow them to begin analyzing the data specific to their courses and sharing possible solutions with their peers. The plan team members will then relay this information back to the team. We previously mentioned that multiple parts of the plan may happen simultaneously. This is because securing resources, personnel and infrastructure to enact change is costly and time consuming. These data conferences can help instructors begin to test out possible solutions and changes in the data which can lead to insightful information.

Develop a Data-Based Plan

How will we use the data collected and analyzed to address the systemic issue of withdrawal? It will be vital that our team is diverse. It is our goal that through the inclusion of students, teaching assistants,

> *"Although analyses can be conducted with statistical programs and electronic data tools, another process cannot be overemphasized, digging through the data, finding patterns, diagramming observations, and collaborating about what is seen, It is a powerful process. Working in a team, individuals can discover new ideas and views by collaborating with their teammates-discoveries they would have never made on their own"*
>
> =-Learning Point Associates (2004, p.13)

and other stakeholders we are able to consider multiple views. At this step in our plan, the IT department will have already collected, aggregated and done some initial analyzation through the use of a learning analytics application and data mining, our team will be vital to final analysis as well as the development and implementation of solutions.

The diverse backgrounds, unique points of view, and creative solutions of our team will be essential to our process. We wish to develop an inclusive environment where all ideas are heard and discussed. The group should begin looking at the overall withdrawal rate over the last few semesters and attempt to hypothesize why possible changes have occurred. Then, using the perception data, they should discuss and diagram the top reasons students have stated their reasoning for withdrawal and begin determining possible solutions. Incorporating program data, specifically with students who have stated their withdrawal was due to academic struggles, they should reflect on the courses this occurred in and what teaching techniques were or weren't being used. While only looking at students who have withdrawn is a large task, the team should also use the achievement data to consider success. Were there courses with very little withdrawals and what teaching methods or circumstances could be the cause of this.

After further analyzation and discussion of the data, the team must create a data based decision making plan to reduce the withdrawal rate in the coming semesters. The plan should be based on the data collected and the analysis of the team. It should include specific measurable solutions as well as ideas for additional data needed. Our main strategy for developing solutions will be to develop methods based on the data as to how we can provide better support to students and changes in administrative procedures. For instance, we know that two common reasons for withdrawal are (1) low initial performance causes students to withdrawal to avoid a low grade, and (2) students intentionally enroll in more courses than they intend to take deciding later which to keep. Based on the perception and achievement data the team should reflect on possible interventions for students with low initial performance, early detection techniques and grading scales to help them succeed rather than withdrawal and re-enroll a different semester. Administrative changes can include not allowing students to enroll in more than a maximum number of hours to deter the practice of extra-enrollment. As many of the solutions will directly affect the instructors, their representative will be responsible for communicating solutions with the entire faculty, providing resources for help in changes in course design, hiring of course assistants and relaying the expectations of these changes.

Monitor Success and Repeat Process

We will need to monitor the progress of our solutions and determine which solution enacted a positive result, what changes should be made to the survey(s), additional data to be collected, changes in the method of collection, and changes in the team including administrators, experts or others that can allow us to continue to improve. To create a baseline, we suggest that some courses do not undergo any changes. For instance, one section of College Algebra can adapt a possible solution, such as including office hours, while another makes no changes. This will allow us to measure if our solutions are effective. As students only have the option to withdraw in a specific time frame, we will have to wait until the next semester to determine if any growth was made. We suggest weekly monitoring of withdrawals, and a team meeting that coincides with the last day to withdraw to discuss the results. Based on the findings the team will decide if we should implement solutions to all courses, as well as any changes that should be made in the process for our next cycle.

Data Analysis

As we do not yet have the data needed to provide analysis, we will instead focus here on the data protocol, data points we are looking for and knowledge management. Much of the data we are looking to collect has already been described, however here we add that in the process of data mining, our team will seek to answer the following questions.

WHAT ARE THE TOP REASONS STUDENTS STATE THEY WITHDRAW FROM A COURSE?

WHAT FACTORS INFLUENCE THEIR DECISION TO WITHDRAW?

WHAT ACHIEVEMENT DATA TRENDS CAN HELP US PREDICT WITHDRAWAL?

WHAT PROGRAM TRENDS CONTRIBUTE TO RETENTION?

The data protocol will follow the steps of aggregating the collected data from various means into a single program to make sense of it, identify trends, and point us towards possible solutions. Data mining will involve multiple methods of interpretation. Anomaly detection will be used with the hope of developing a predictive model of withdrawal due to academic reasons. We will look at the trend of successful students next to those who withdraw to attempt to determine a cause such as low initial scores, participation, and time spent in course as an indicator. This will be further analyzed by the team and possible solutions generated such as early intervention. Cluster detection and classification will also be used. Cluster detection will allow us to see what factors are common amongst students who withdraw, and classification will help us to clarify the data based on differences or similarities across all types of data. It is important that the team understands these different approaches in order to analyze and understand the results. While technology will play an important role in our plan, we must not ignore the importance of our team's perspective in further analyzing the data. Technology can show us the patterns, but only our team can turn this into something explicit through their knowledge, experience and insight.

> **Technology**
>
> "It is a mistake to equate knowledge management with a technology tool. Knowledge sharing must rely on human intelligence, energy, and the will to cooperate and use knowledge in collaborative endeavors. Technology can help, but the active nature of knowledge means that human intervention is a constant requirement for KM programs to be successful."
>
> -McInerney, C. Knowledge Management and the Dynamic Nature of Knowledge (2002, 53(12), p.1013)

Knowledge management and sharing will be handled as follows:

1. Collection of Data
2. Data-Mining for Trends
3. Turn data into knowledge by analyzation by team members, connecting their personal experiences and insight into data trends.
4. Share with stakeholders.

We have discussed many of these steps previously, what we wish to add in this section is the importance of sharing our findings with stakeholders. Our data will give us information, but in order to turn this into actionable knowledge, the diverse nature of our team is essential. From there, we must share and encourage continued sharing of this knowledge within the institution. This can include training events for instructors on our findings, solutions, and how to implement and track these changes. We must also share with students, so they are aware of the new policies and resources that will be provided to them. In addition, we want to continue to add to what we have collected. Regular professional development and discussion amongst instructors and team members is important for continued growth.

Leadership Issues

Our stakeholders for whom we are responsible to are primarily the students. In addition, the faculty and staff as well as the board who decide how and where to distribute resources. It will take understanding and collaboration from all involved to truly succeed.

Communication will be handled in a way that is clear for all involved. In our primary meetings with the team, our plan must be both verbally and visually represented, so we all have a precise understanding of the process and our responsibilities. The IT department will need to produce spreadsheets, graphs and statistics in various forms to the team. This will allow the team to analyze from many different perspectives and viewpoints, looking at the data from different sides. Once our data has been turned into knowledge and solutions proposed, we must communicate our needs to the board. This should be a well-developed presentation describing the resources needed and the results expected. Finally, we must communicate our goal, findings and solutions that will be available to students. They must fully grasp any new withdrawal policies and be made aware of, and encouraged to use, any new instructional techniques or resources. This should be in individual course syllabi, e-mailed notices and instructor encouragement to take advantage of these new opportunities to succeed.

There are many possible traps that we must take special care to avoid. I believe we are most at risk to fall into status quo, confirming the evidence and anchoring traps. Hammond, Keeney and Raiffa (1998) describe anchoring as, “giving disproportionate weight to the first information you receive” (p.1). This is a concern because of the nature of the withdrawal process. Withdrawals happen in the first 6-weeks or so of each semester, thus, we only have three opportunities to collect data per year and we wish to begin implementing solutions quickly. To avoid this trap, I propose that we begin aggregating and data-mining older information that has already been collected. While this will not include the new surveys, perception and changes in demographic information, it will allow us to get a deeper picture than simply acting on one semesters worth of data. Another benefit of our plan is that it is cyclical. Thus, for each semester we can repeat the process adding new data and making changes to solution paths. The status quo trap is described by Hammond, Keeney and Raiffa (1998) as, “favoring alternative that perpetuate the existing situation” (p.1). It is scary and costly to make changes. It is imperative that we remember we are doing this in order to better our institution and service our students. One example may be, “well, we already offer online tutoring. It is not our fault students don’t choose to utilize the program and instead withdraw”. This type of attitude is not progressive for anyone involved. Instead, finding ways to expand the program and inform students of its benefits would be productive. Professors can reach out to students individually and encourage them to reach out to our online tutors before withdrawing. We always want to move forward, and not become stuck in our ways. Lastly, confirming the evidence is defined by Hammond, Keeney and Raiffa (1998) as, “seeking information that supports your existing point of view” (p.1). This is difficult because it is our knowledge and experience that leads us to make assumptions regarding withdrawal. We must allow the data to guide us and be careful in survey construction and interpretation to avoid this pitfall. Having a diverse team with differing positions will also help to ensure we are giving all data a fair chance.

Finally, our leadership must be excited to embark on this new journey. Our team must be devoted to improving the institution, student experience and success. Fullan (2002) states, “Leading in a culture of change does not mean placing changed individuals into unchanged environments. Rather, change leaders work on changing the context, helping create new settings conducive to learning and sharing that learning” (p.3). This perfectly represents the nature of our plan. We must change the context of withdrawals and create new policies, programs, and data collection methods that will guide us to an improved setting that will allow our students to flourish. The data we collect and analyze, and the knowledge we transform, all must continuously be used to improve our courses and encourage student retention. Sharing our findings will also allow for professional development and the creation of a DDDM culture that will inspire our community to continuously work with data to improve all aspects of our institution. ■

References

Allen, I.E, Seaman, J.E., & Seaman, J. (2018). Grade increase: tracking distance education in the United States. Babson Survey Research Group.

Barquin, R. & Northouse, C. (2003). Data collection and analysis: Balancing individual rights and societal benefits. Paper presented at the Panel on Access to Research Data: Assessing Risks and Opportunities Workshop, Washington, D.C.

Collie, S. L. & Rine, P. J. (May 26, 2009). Survey design: Getting the results you need. Retrieved from University of Virginia, Office of Process Simplification website: http://www.virginia.edu/processsimplification/resources/survey_design.pdf

Fullan, M. (2002, March). The role of leadership in the promotion of knowledge management in schools. Paper presented at the Knowledge Management in Education and Learning: Organization for Economic Cooperation and Development (OECD) Conference, Oxford, United Kingdom. doi:10.1080/135406002100000530

Gill, B., Borden, B. C., & Hallgren, K. (2014). A conceptual framework for data-driven decision making. Princeton, NJ: Mathematica Policy Research.

Guide to using data in school improvement efforts: Compilation of knowledge from data retreats and data use at Learning Point Associates (Contract No. ED-01-CO-0011). (2004). Naperville, IL: Learning Point Associates.

Hammond, J. S., Keeney, R. L., & Raiffa, H. (1998). The hidden traps in decision making. Harvard Business Review, September–October 1998, 47–58.

Matzusaki, W., & Castellani, J. Models and tools for creating, collecting, codifying, and sharing information. Retrieved from olms.cte.jhu.edu/olms2/data/resource/.../DDDMOverview%20-%20Castellani.pdf

McInerney, C. (2002). Knowledge management and the dynamic nature of knowledge. Journal of the American Society for Information Science and Technology, 53(12), 1009–1018. doi:10.1002/asi.10109

Picciano, A. G. (2012). The evolution of big data and learning analytics in American higher education. Journal of Asynchronous Learning Networks, 16(3), 9-20.

Streifer, P.A. (2002). Using data to make better educational decisions. Lanham, MD: Scarecrow Press, Inc.

Tinto, V. (1975). Dropout from higher education: A theoretical synthesis of recent research. Review of educational research, 45(1), 89-125.

Tinto, V. (2012). Completing college: rethinking institutional action. Retrieved from https://ebookcentral.proquest.com

Tyler-Smith, K. (2006, June 1). Early attrition among first time eLearners: a review of factors that contribute to drop-out, withdrawal and non-completion rates of adult learners undertaking eLearning programmes. Retrieved from http://jolt.merlot.org/vol2no2/tyler-smith.htm.

U.S. Department of Education, National Center for Education Statistics. (2011). Six-year attainment, persistence, transfer, retention, and withdrawal rates of students who began postsecondary education in 2003-04. (NCES 2011-152). Retrieved from http://nces.ed.gov/pubsearch/pubsinfo.asp?pubid=2011152 .

Von Frank, V. (2011). Leadership teams set the course for school improvement. The Learning Principle, 7(1), 4-5.