The Value of Common Definitions in Student Success Research: Setting the Stage for Adoption and Scale

Abstract

As the fascination with innovation continues to catalyze change in contemporary post-secondary education, the field of innovation science is being to emerge, so that the relationships between and among the endeavors of *Invention, Innovation* and *Implementation* are better understood. This article explores the use of data analytics as an innovation trigger for supporting student success. Very few organizations have approached improving student success using an open strategy that involves data scientists and the many implementers of student success working across America's colleges campuses. In an effort to expand student success research, the Predictive Analytics Reporting (PAR) Framework created common data definitions and organizing principles to support collaborative student success research among like-minded universities. By starting with common data, the members of the PAR collaborative have the ability to share, compare and disseminate results, insights and strategies for student success. The approach is yielding interesting research on success factors within student segments and learning modalities. The ability to share the results paves the road to adoption at other institutions or within systems.

Introduction

Innovation refers to a new way of doing things: incremental, radical, and revolutionary changes in thinking, products, processes, or organizations. A distinction is typically made between *invention*, an idea made real, and *innovation*, the real-world application of an invention in practice. When an invention is applied to solve a problem or to do something completely differently than it has been done before, innovation occurs. *Disruptive innovation* is a term, theory and phenomenon defined and analyzed by Clayton M. Christensen beginning in 1995, based upon his work in the corporate arena (Christensen, Raynor & McDonald, 2015). A disruptive innovation is one that that creates a new market and value network and eventually disrupts an existing market and value network, displacing established market leading firms, products and alliances.

As demands for improving higher education have increased, American higher education has become increasingly drawn to the proposition of innovation, in general, and with disruptive innovation in particular. Examples of disruptive innovations include for-profit colleges, online learning, and competency based education, providing students with pathways that provide a variety of alternative approaches toward program completion as they work toward high value certificates and degrees. Learning analytics promises to be another disruptive innovation.

The challenge in higher education is that the *implementation* of a new idea in practice – that is, taking an invention, and putting it to work so that innovation occurs – depends upon implementers willing to navigate through the myriad changes to practice that ripple through institutions when a new idea is introduced to current practice. Some innovations simply have too much associated overhead, or may not be able to scale, or may be too hard for mere mortals to

use. Practitioners are much more willing to commit to an implementation when it solves a problem.

Finding common ground between innovators and implementers can be tremendously challenging. Everett Rogers sought to explain how, why, and at what rate new ideas and technology spread in his Diffusion of Innovations theory, first published in 1962. Rogers (2003) suggested that four variables influence the spread of a new idea: the innovation itself, communication channels, time, and a social system (see Figure 1). He suggested that this process depends heavily on the people involved in the adoption of an innovation, since an innovation must be widely adopted in order to self-sustain. He described categories of adopters as innovators, early adopters, early majority, late majority, and laggards. He further noted that diffusion manifests itself in different ways and is highly subject to the types of adopters and innovation-decision processes.

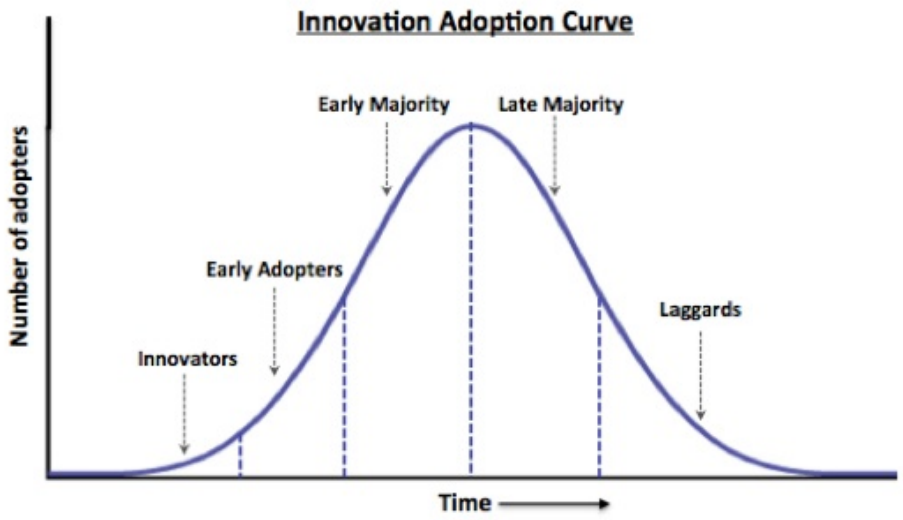

Figure 1: Roger's Diffusion of Innovation downloaded 10.17.16 http://bit.ly/2enXbUY

The advent of data analytics has brought opportunities for testing new methodological techniques – including business intelligence, predictive analytics and data mining – for measuring the impact of innovations on educational outcomes, and making sure to bridge the distance from innovation through implementation, on the way to adoption. The excitement comes from the promise of disrupting old, ineffective practices by replacing them with new innovative ones, guided by data analytics. The work is motivated by the promise of being able to generalize research results beyond a single experimental condition, a single pilot program, or a single

institution. The danger comes from NOT evaluating educational technology innovation using empirical evidence, generated using open frameworks and common data definitions.

The methods of the academy have traditionally forced the evaluation of innovation-in-practice to be measured using experimental and quasi-experimental methods that employ inferential statistics and small n studies under relatively tightly controlled conditions. The introduction of learning analytics introduces the ability to explore the effects of interventions on all participants in the messy situations they inhabit. This in itself is disruptive, as are the more global changes that use of learning analytics diffuse through higher education (Swan, 2016).

This paper explores the use of data analytics to guide student success initiatives in the context of a particular, cross-institutional collaborative project, the Predictive Analytics Reporting (PAR) Framework. What is perhaps most important about the project is that it created a social system to support the diffusion of innovation. Applying new approaches to supporting student success depends upon our collective ability to find common ways to articulate the shared benefits of using data to help students better navigate their educational experiences, and to obtain essential support at points and times of need. This paper explores the value and impact that using common data definitions and frameworks to organize information generally available at postsecondary institutions brings for sharing results. Those results may help with both generalizability of research and strategies for adoption that help bring data-driven innovation to all members of the college community.

In the sections that follow, the Predictive Analytics Reporting (PAR) framework is introduced and its creation and dissemination of common data definitions and a shared structure for inventorying and testing student success interventions are discussed. The paper then explores how common frameworks can inform the scaling of finding cross-institutionally with specific examples from PAR research and a general discussion of how PAR tools can be used. The paper concludes with some observations on what PAR can tell us about the adoption of a disruptive technology.

Improving Student Success

Nationally, colleges and universities struggle to improve student success; improvements have been especially challenging for realizing improvements with the lowest socioeconomic groups (Shapiro, Dundar, Yuan, Harrell, Wild & Ziskin, 2014). Demands for improvement have resulted in a stronger focus on exploring student outcomes, including college completion. The scrutiny of outcomes have contributed to both an expanding market for educational technology that addresses outcomes issues, and the internal institutional drive to innovate in the area of support for student success. These two trends set the stage for institutions to leverage academic and learning analytics (Norris & Baer, 2013). The educational technology marketplace responded by creating tools, products and services designed to serve the needs of individual institutions.

A different approach to improving innovation to optimize student success is to work through a community of practice. The Predictive Analytics Reporting (PAR) Framework was a project

originally funded by the Bill & Melinda Gates Foundation and guided by a management team from the WICHE Cooperative for Educational Technologies (WCET) (Ice et al., 2012). The PAR Framework later became a non-profit, multi-institutional collaborative that provided member institutions with tools and resources for identifying risks and improving student success. The assets of the not-for-profit PAR Framework were acquired by Hobsons in 2016, with the intention of continuing to support member-driven collaborations that help institutions and systems through the combined power of a collective dataset, analytic tools to improve member metrics, and research based approaches to identifying student success interventions.

Common Data Definitions

The goal of the six founding institutions who participated in the original PAR Framework discussions was to demonstrate that it was possible to use predictive analytics to find students at risk of dropping out of college. To do this work, the PAR Framework create a single, federated, cross-institutional data set to investigate factors affecting the retention and progression of undergraduate students. The creation of such a common data set clearly required the creation of common data definitions that were specific enough to ensure reliable findings but that could also be applied to most undergraduate programs. The original six participating institutions included public two and four year colleges, a university system, and a for-profit universities met to establish common ground for all members of the postsecondary community to engage in a common conversation. All the participating offered both fully on-ground and fully online classes. Participating programs ranged from traditional semester terms to eight and five week terms with start dates happening every week. Thus, the initial work of the collaborative was to find ways of defining such seemingly simple outcome variables as "retention" and "progression" relative to a common timeframe, something with which the Federal government continues to struggle. Table 1 shows categories of input variables defined.

Table 1. *Common input variables explicitly defined by PAR researchers*

Student demographics	Course information	Course catalog	Lookup tables	Student financials	Student academic progress
Gender	Course location	Subject	Credentials offered	FAFSA on file	Current major / CIP
Race	Subject	course number	Course enrollment periods	FAFSA file date	Earned credential / CIP
Prior credits	Course number	Subject (long)	Student types	Pell received /awarded	
Zip code	Section	Course title	Instructor status	Pell date	
High school information	Start/end date	Course description	delivery modes		

Transfer GPA	Initial grade/final grade	Credit range	Grade codes
Student type	Delivery mode		Institution characteristics
	Instructor status		
	Course credit		

Common definitions are a key feature of the PAR dataset. Through the original grant work, a group of researchers identified and then openly published a set of common data definitions (https://community.datacookbook.com/public/institutions/par). Because all of the data that was and is provided by PAR member institutions utilizes these common definitions, cross-institutional "apples to apples" analyses on the combined data set can be performed to better understand the factors that impact student success generally as well as locally.

The success of these original PAR researchers was due in a large part to their willingness to collaborate and share data and analytic approaches in a safe, supportive environment, a benefit that continues today. PAR member institutions comprise a range of the many diverse options for postsecondary education, including traditional, open admission community colleges; 4-year, traditional, selective admission, public institutions; and nontraditional, open admission, primarily online institutions, both for-profit and nonprofit.

Since all of the data provided by PAR member institutions meet the parameters of the common definitions, PAR researchers were able to do both aggregated and cross-institutional comparisons and analyses on the combined data. Having relatively comprehensive, detailed data for all credential seeking students (as opposed to a sample from each institution) creates a more accurate understanding of the student and institutional level factors that impact risk and success. It also makes it possible to more effectively control for confounding variables that might be contributing to observed differences between student groups.

The PAR Framework data modeling yielded positive, negative and variable predictors for being retained after 12 months. The positive predictors included high school GPA (when available), dual enrollment (HS/college), prior college credits, community college GPA, successful course completion, completed developmental education courses, and credit ratio, a progression measure consisting of the number of credits successfully completed divided by the number of credits attempted. The negative predictors included withdrawals and a low number of credits attempted. Finally, the predictors that varied from positive to negative depending on institution included: Pell grant eligibility (low income), enrollment in developmental education courses, age, fully online status, and race.

Student Success Matrix

Building on these findings, the data scientists worked with educational practitioners (implementers) to move the innovative findings from theoretical information to system that supported acting on analytic evidence from the dataset. The education theorists played a critical role of tying the data science innovations to what was known about student success. Researchers within the PAR community began to explore whether the PAR dataset could be extrapolated to create an updated model for retention and progression. In reviewing seminal retention studies including Tinto (1987), Bean & Metzner (1985), and Falcone (2011), the researchers developed an updated PAR model of retention as shown in Figure 3 below.

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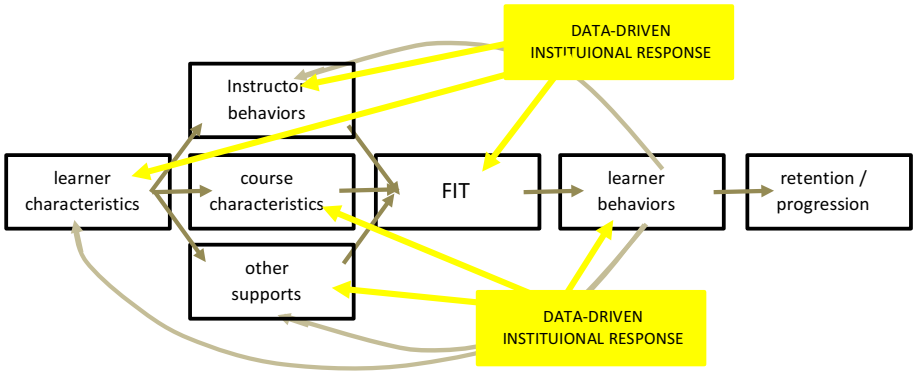

Figure 3. PAR model of factors affecting student retention and progression

Based on these initial findings and the research literature, the PAR model (Daston, Swan & James, 2015) shown in Figure 3 begins with "learner characteristics," the relatively consistent attributes students bring to the learning experience. It views these characteristics as being filtered through "instructor behaviors" in the courses they take, the characteristics of those courses themselves ("course characteristics'), and "other supports," supports not aimed at specific parts of the model, most importantly financial aid, to influence learners' feelings of "fit" or academic and psycho-social integration which in turn affects how the learners behave in their courses and programs ("learner behaviors"), including their decisions to continue their studies ("retention/progression"). The model also shows that learner behaviors feedback to impact the factors contributing to these and suggests where data-driven interventions might address these specific categories of what the model views as predictors of retention and progression.

In a process similar to that involved in the creation of the data definitions, PAR researchers classified interventions by the predictors identified in the research as affecting student success. The review of the literature used to substantiate the new framework also revealed that, previously, student interventions were often classified by administrative functions. The ability to identify predictors offers an opportunity to apply a community of practice process to the

collection of actionable student interventions. The multi-member educational community once again agreed to an open research process that resulted in a common framework. The framework was based on the updated model of retention, predictors from the dataset, and the recognition of a student lifecycle during which particular interventions might be more or less effective at different times. The student lifecycle periods, see Table 2, that were identified included: "connection," the period from when a student first contacts the institution, through admissions and initial advising until they first take classes; "entry," the first year or so of classes when students get most of their general education courses taken and, if they have not already, decide on a major; "progress," the major period of progression towards degree; and "completion," when students finish up the requirements of their degree and make plans for employment or further studies.

Table 2. *Predictor categories by stage in academic career instantiated in the Student Success Matrix*

	CONNECTION	ENTRY	PROGRESS	COMPLETION
LEARNER CHARACTERISTICS				
LEARNER BEHAVIORS				
FIT (Academic & Psycho-Social Integration)				
OTHER SUPPORT				
COURSE/PROGRAM CHARACTERISTICS				
INSTRUCTOR BEHAVIORS				

Table 2 shows how the combination of predictors addressed and stage in the students' academic lifecycle resulted in the creation of the Student Success Matrix (SSM^X). The SSM^X provides an efficient structure for inventorying, organizing and conceptualizing supports aimed at improving student outcomes. An exploratory research process was used to test whether interventions would fit into these categories. In 2012, the 16 then-members of PAR were asked to submit on a spreadsheet the interventions that were used at their institution. The collection yielded over 1,000 interventions, all of which fit into the intervention categories. The PAR team has since refined and automated the intake process and interventions are now collected online. Using the SSM^X, member institutions have contributed descriptions of supports currently in use on their campuses including programs, services, actions, interventions and policies. The common structure in SSM^X for categorizing interventions makes it possible to link them to participating students, and through the PAR data set explore their efficacy. By providing common predictors to classify interventions across institutions, particularly effective approaches can be identified and shared among PAR institutions, paving the way for better understanding, measuring, and scaling the highest impact tools for improving student outcomes.

Looking for Scale within the Dataset

The combination of a commonly defined dataset and a common framework to measure interventions provides powerful information for institutions to identify potential challenges or opportunities to improve student outcomes. Since the dataset and common framework is shared by all PAR Framework members, the opportunity to have a broader discussion with other community members who experience similar challenges can start immediately. The ability to measure across this continuum of universities allows data scientists and researchers to identify whether challenges are unique or shared by members. The notion of achieving scale across the industry is tantalizing and can be equated to finding generalizability in research. The dataset allows PAR data scientists and community researchers an opportunity to explore important research questions. To date, analyses have been completed on whether there is generalizability of positive predictors of success across multiple institutions' transfer students, what the PAR Framework dataset tells us about post-traditional students, and whether taking online classes is detrimental to retention and progression.

Are the predictors of successful transfer students the same at multiple institutions?

One of the analyses performed by PAR Framework researchers involved identifying similar predictors of transfer student success across institutions. One institution, University of Maryland University College (UMUC), conducted a research study that found both positive and negative predictors for transfer students. In order to replicate the study, an institution or system needed to report data on transfer students. The University of Hawaii system dataset included students who transferred from community colleges to four-year universities. The PAR Framework data scientist looked at eighteen variables at both institutions to address the research questions. Since the variables were comparable because of shared common data definitions, the research could proceed.

There were three variables that predicted a student's grade point average at the bachelor's level that were shared at both institutions including:

- Did the student complete his or her math requirement?
- Did the student earn an associate's degree?
- Did the student repeat a course?

Completion of a math course at a community college was positively associated with earning a GPA over 2.0, as was earning an associate's degree before transferring and having a higher GPA at the Community College. Repeating a course in community college was negatively associated with first term GPA at a four-year university. The dataset was able to reveal that each institution had unique predictors as well.

The analysis also included determining whether predictors were the same at the two institutions for retention. Retention was defined as whether the students were still enrolled between six and twelve months after they first enrolled. Only four variables were found to be positive predictors at both institutions. The variables in common that predicted student success included the number of credits attempted during the first term at the four-year institution, the grade point average of the first term at the four-year institution, the number of credits taken and successfully completed

(credit ratio), and whether the course was online or face-to-face. Each institution also found unique positive predictors among its students.

The ability to apply results from one research study based on a local sample to a larger, national population has traditionally been compromised by limited generalizability. The PAR Framework's common data definitions provided the means for validating the results of research conducted at one institution with results from another institution.

Getting to know post-traditional students.

The PAR data science team explored the dataset and reviewed the literature to better understand post-traditional students. (Watt & Wagner, 2016) What it is clear, nationwide, is that this student segment is growing. Current data gathering practices, whether in federal requirements, state assessments, or most recruitment surveys, continue to rely on the first-time, full-time cohort. Assessment of post-traditional students leads to many related concerns for today's higher education ecosystem.

For example, students who vary from the traditional path are not eligible for many federal financial aid programs, or they find that the aid they do receive is not flexible enough to work around their enrollment plans. Such antiquated practices do a disservice to institutions that focus on recruiting, educating, and graduating post-traditional students. Similarly, if more "traditional" institutions were required to report on post-traditional student outcomes, they might alter their student success practices to be more inclusive. The common dataset at PAR offers member institutions an opportunity to investigate whether post-traditional students are similar throughout the membership. Identification of whether the data on this student segment are similar or unique to an institution, is another example of how open and common data definitions support scalable research.

A little online learning is a good thing.

Authors James, Swan and Daston (2016) provide a review of a large dataset compiled within the Predictive Analytics Reporting (PAR) Framework by comparing students taking only on-ground courses, students taking only online courses, and students taking a mixture of both at five primarily on-ground community colleges, five primarily on-ground four-year universities, and four primarily online institutions. Their work suggests that online courses can provide both flexibility and access while improving student completion.

The results suggest that taking online courses is not necessarily harmful to students' chances of being retained. While the PAR Framework dataset represents a microcosm of institutions across American universities, it does include a more representative sample of institutions serving nontraditional students. It is clear from other work, including recent reports from the Integrated Post-Secondary Education Data System (IPEDS), that these students are taking more accessible course modalities like online and blended courses. Their research also reveals essentially no difference in retention between delivery modes for students enrolled in primarily on-ground four-year universities participating in the PAR Framework. At participating primarily online institutions, students taking both online and on-ground courses had slightly better odds of being retained than students taking exclusively on-ground or exclusively online courses. The same was

true of students at primarily on-ground PAR community colleges. Only at these latter institutions, did taking online courses negatively impact success, and then only when only online courses were taken.

Examples of Student Success Interventions using the Common PAR Framework

Building on the common approach to identify trends and to investigate research questions within the PAR data set, the SSMx is used to categorize interventions. When the SSMx and analyses involving the PAR datasets are combined, the results can help to identify particularly important interventions. The information can then be shared among PAR institutions, paving the way for better understanding, measuring, and scaling the highest impact tools for improving student outcomes. This approach differs from the comparison institutions might do when exploring other reported data. Other sources of data are not easily connected to ongoing student success interventions. There is scant evidence showing that institutions catalog their interventions at all. SSMx helps an institution commence the laborious process of inventorying student interventions. Institutions can then assess whether any given intervention improves student outcomes.

The benefit grounding student success efforts in analytics is the opportunity to test whether a particular intervention or set of interventions improves student outcomes. Using the SSMx, institutions can enter interventions, link them to participating students and then measure whether a change in outcomes occurred. When an institution joins PAR, it can compare its data to other peers' benchmarks and immediately discuss with those peers interventions they may be using to address challenges. Members of PAR also include statewide systems which can benchmark their progress within the state. By choosing a system that is built on a common set of definitions and a research-based framework, institutions can measure progress both internally and externally. In addition to the progress being measured, PAR membership also creates community-driven discussions around interventions which are invaluable.

The process of collecting interventions also allows institutions and communities of institutions to look for gaps or redundancy in services. Academics report regularly on different interventions launched and progress made but few institutions report intra-institutional collection and comparison and even fewer report interventions that are compared against peer institutions. By recording the institution's interventions, student success staff have a comprehensive view across all units responsible for interventions.

Multiple institutions within the PAR community have expressed surprise at the number of student interventions offered across their campuses. The collection process often led them to review interventions in a more systematic way. These institutions report asking questions such as:

- Do we have data to support the effectiveness of the intervention?
- If the intervention has been practiced over multiple years, has the impact on the intended population been determined and did it change over the years?
- Do we know the cost of the intervention?
- Are we aligning interventions to our greatest student retention challenges?

This introspective reviewing process is important. As a member of a community of institutions, it leads to the sharing of insights, interventions, and retention challenges.

The community sharing then leads to collaboration. Within the PAR community, members have identified similar challenges and agreed to try similar interventions and report the findings from researching the effects of the interventions. The PAR Framework tools, such as Obstacle Course Explorer, allow institutions to identify courses where course completion could be improved. Obstacle courses are those courses where the data show that if students do not complete the course with a C or better grade that the course serves as a barrier to retention and progression. The SSMx tool can help align an intervention to obstacle course improvements. The combination of data and targeted interventions can then be shared with other members to determine if colleagues are using similar interventions.

The PAR data team explored obstacle courses that had particularly high fail rates. Several universities recognized that their beginning accounting courses were all part of the dataset and that these courses were particularly concerning as they had both high enrollment and high fail rates, and were often damaging to progression because they were prerequisites for other courses. After a review of research on improving accounting course outcomes and a discussion with faculty, administrators, and student services support staff, the institutions decided to intervene by adding peer mentoring or embedded tutoring to certain accounting sections. Each institution ran their own tests, but continued to share with each other the results including how to improve the intervention if it was iterated. Although a cross institutional study was discussed, it was not created. While iterative scale was not realized, cross-institutional practices were shared and disseminated.

As referenced earlier, PAR members include several state systems. The state systems have promoted an evidenced-based culture and are leveraging the SSMx to review interventions that would specifically improve statewide student outcomes. The University System of Maryland (USM) adopted the PAR Framework as part of a system-wide effort to optimize investments aimed at improving student success. All USM institutions will adopt the PAR Framework Student Success Matrix (SSMx) in order to inventory, categorize, and explore the returns on investment for student success programs deployed at each institution. The intervention measurement focus of this initiative targets innovative student supports and interventions used by institutions with their students. The effort to categorize interventions and improve outcomes is part of an active commitment to improve graduation rates to 55 percent for students entering four-year institutions. The USM will look for opportunities to impact academic outcomes and identify interventions across the academic life cycle where academic advisors have the potential to identify struggling students at optimal points and in times of need. The collaborative nature of identifying statewide student success interventions speeds up the dissemination of what practices work.

The early examples of the SSMx set the stage for intervention measurement. If the measurement indicates that an intervention is successful, the stage is set for that intervention to be adopted by other institutions facing similar challenges. Since members of the PAR Framework have access to their data, they can measure the impact of the intervention to see if a successful intervention is scalable across institutions. The alignment of common data definitions with a common framework for intervention measurement sets the stage for adoption of effective interventions that can be scaled across a community.

Conclusions

Adopting better student success strategies is dependent on having good data and educational technology to support better decision making. The PAR Framework relies on a community approach to the development of common data definitions and an organizing framework that identifies and categorizes student success interventions. The innovation surrounding the PAR Framework is not only the data science, even though many in the field would equate educational analytics to a powerful innovation (Dunbar, Dingell & Pratt-Resina, 2014). The power lies in the combination of an innovation within a community that is capable of implementing and diffusing the innovation. The common data definitions and framework clearly set the stage for scaling of successful strategies. The development of open tools for student success research promotes innovation amongst a community of educational practitioners (implementers). The community based approach connects high priority issues of student success to the development of innovations within the analytics tools.

Predictive analytics experts have the power to evaluate data on specific variables to yield answers related to improving student success. Research across the learning analytics community strongly suggests that institutions can now avail themselves of better student success information including information about students across multiple groups, such as veterans, transfers, and even stop-outs. It would be beneficial to the higher education community to understand where there are commonalities across the student ecosystem, where small changes lead to big differences, and where niche programs may be best. We may even learn that our populations perform better overall when we consider post-traditional student needs. With evidence comes the ability to focus solutions, and dollars, where they will make a difference.

The PAR Framework tools can be used to internally analyze predictors of student success and the effectiveness of student success interventions, as well as support external collaboration with others. External collaboration assists with the dissemination of best practices in a way that internal analyses can't (Stiglitz & Greenwald, 2013). Achieving a balance of innovation and implementation that both promotes internal introspection and external collaboration offers the community a better way to innovate in the important area of student success.

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