John Carroll University First in the World Project
Linked Learning and Early Warning Approach for At-Risk Student Success (LLASS)
Grant # P116F150059
Year 4 Final Annual Report
(Oct 1 2018 – September 30, 2019)

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Summary of Activities

The First in the World (FITW) program is designed to support the development, replication, and dissemination of innovative solutions and evidence for what works in addressing persistent and widespread challenges in postsecondary education for students who are at risk for not persisting in and completing postsecondary programs, including, but not limited to, adult learners, working students, part-time students, students from low-income backgrounds, students of color, students with disabilities, and first-generation students (Office of Postsecondary Education).

Over the four-year period of this grant (2015-2019), the project has been directed toward identifying factors associated with student success and thriving, and proactively intervening with students who may be at-risk for having academic difficulty during their first year. The primary source of data comes from four self-report surveys that were administered early in the students' first year. The surveys included: the College Student Inventory (CSI), from which the *predicted academic difficulty* measure is derived, and is used to determine placement into the intervention; the Mid-Year Student Assessment (MYSA), the Thriving Quotient (TQ), and the Emotional Intelligence (EQ-*i*™). During the first year of the grant, twelve faculty and staff completed the EQ-i™ training and certification, which gave us the competencies to administer, interpret, and provide feedback on the emotional intelligence assessments. We expect that going forward, this group of EQ-i™ certified colleagues would contribute to enhancing the academic and career advising on campus.

Also during the first year of the grant, there was no data collection, because the project team effort was focused on planning for the aligned courses for the intervention. This involved working with academic departments, and student support teams to coordinate with New Student Orientation, working with the Registrar and department chairs to schedule classes for the intervention, recruiting for the project coordinator position, and in general preparing to intake participants into the study starting in year 2 of the project. Implementing this project was an institutional effort, which certainly disrupted a way of knowing and doing to accommodate the impositions of project. The cooperation of many colleagues and departments is virtually immeasurable, and greatly appreciated.

For the aligned-course intervention, faculty collaborated in interdisciplinary teams such as biology and English, to link courses together around a common theme. These *aligned-course learning communities* were developed for the intervention participants who, based upon their predicted academic difficulty score on the CSI, were co-enrolled into the courses in their first semester.

Faculty who taught the aligned courses participated in several workshops on *how learning works*, presented by leading experts in curriculum development. However, one of the challenges in developing these aligned courses was finding the time for the faculty course partners to collaborate, particularly when a course was taught by adjuncts. Still, most of the adjuncts expressed appreciation for the faculty development opportunities, which typically have not been available to them. Noteworthy is that a number of the adjuncts were long-term hires.

One of the greatest impacts the First in the World grant had on the John Carroll community was provided by faculty development opportunities for both full and part-time (adjunct) faculty. Prior to the implementation of the grant, very few resources had been devoted to the part-time faculty who teach a number of our first year students' courses. The ability to support

these faculty in improving their teaching and student learning is invaluable. Since the FITW grant, additional programs have been implemented to support part-time faculty. For example, there is now a part-time faculty member *Teaching Award* and a mechanism to apply for funding for travel to professional conference. More details about the faculty development workshops are presented later in this report.

It is important to note that during the early time of the grant, we received significant assistance and support from Allan Porowski of the abt Associates Technical Assistance team. In particular, Allan provided guidance and confirmation of our approach to, and understanding of regression discontinuity design. Allan was able to discuss and get into the nuances of the design, and set the project team on the right path with his enthusiastic support and guidance. He also developed an Excel file for our use, with the necessary functions and calculations to conduct the tests for baseline equivalence. Receiving this support was a critical turning point in our knowledge and confidence around regression discontinuity design, and the evidence standards we need to meet.

We also acknowledge Dr. Stacey Slijepcevic our Program Officer, who listened carefully to our technical support concerns, particularly that our project was one of a small few among *all* First in the World awardees that was using regression discontinuity design, which is an approved design approach. In many ways, a random controlled experiment would have been easier to implement, but not practical given the goal of this project.

Consequently, we needed support from someone who knew the regression discontinuity design method, not just general statistical assistance. Stacey made the initial effort to connect us with Mr. Porowski and his colleagues by facilitating that first meeting. We also want to complement her for organizing several webinars during the first two years of the grant, which gave all the grantees a way to convene and learn from each other. Unfortunately, in recent years of the grant, there has not been any convening of FITW awardees.

During this 4th year, the project did experience some transitions. We found it necessary to make changes in the external evaluation group, and were approved to do so in December 2018, at which time we welcomed The Rucks Group, LLC, a minority woman-owned firm in Dayton, OH. The evaluation is proceeding in positive manner and we have broader levels of support, particularly for data analyses, but even more important, we now have a clear and independent assessment of the project. The working relationship is very good. Typically, the project team and evaluators have regularly scheduled online conference calls, and we exchange much e-mail to discuss and review data analyses or other project activities. Also, during this year, Dr. Graciela Lacueva retired from the university. Dr. Lacueva was the initial Co-Project Director, and was largely responsible for coordinating with our academic department colleagues, and the Registrar's office to plan the enrollment and scheduling of the aligned courses for the intervention. The depth of her involvement and the cooperation of so many others in order to get the students into the aligned classes are also difficult to adequately describe, but greatly appreciated.

We requested, and were approved to have Dr. Chrystal Bruce become the new Co-Project Director. Dr. Bruce has been a member of the project team since inception of the project, having previously been responsible for faculty development activities. Additionally, Dr. Todd Bruce who previously served on the project's faculty development team moved into a new position in Institutional Research. However, Todd has continued to be very engaged with the process for the data visualization component of the project. Finally, this year, our long-time grant

accountant, Matt Verleny retired from the University. But we are pleased that Tammy Wisz has been assigned this responsibility. We are also pleased to report that none of these transitions has negatively impacted the project, or caused any delays or change in project goals or timelines.

In the course of this year 4 of the grant, several key milestones where achieved. Most importantly, we administered the final pre- and post-test surveys of the College Student Inventory (CSI) and Mid-Year Student Assessment (MYSA), therefore collecting the proposed three cohorts of first-year students' data (2016, 2017, 2018); and we also concluded the planned aligned course offerings for the intervention with established aligned course catalog. Now, the project team and external evaluators are able to focus more sharply on data analyses. Overall, from the three entering cohorts we have collected pre- and post-test data from approximately 1,800 first-year, first-time student participants.

Now that we have the cohort data from three successive entering classes, we are situated to begin more detailed data analyses in effort to identify important data relationships, interpret and disseminate the findings. Doing so entails the knowledge and skills the project team has developed during the process, and applying our understanding of the survey data to analyze and evaluate student success and thriving. Given the large amount of data on hand from multiple platforms, the project team continues to work diligently to assure the quality and integrity of these data.

The project team has given much thought on how to present the outcomes of this project internally to our John Carroll University (JCU) colleagues, as well as disseminating to a broader population. One lens through which to view the outcomes data is the Higher Learning Commission (HLC), the accreditation commission for our region in Ohio, who has emphasized student success as being integral to their strategic plan, as well as to accreditation standards and review. They endorse several programs and projects designed to test variables that affect student success, and to define key terms such as persistence, retention and completion (HLC, 2018). In that regard, this project is compatible with the concern and approach of the HLC. So, internally, JCU ought to consider ways that this project speaks to that compatibility. Another lens through which we view how the information could be disseminated is that of the standards and requirements of the *Institute of Education Science What Works Clearinghouse* (WWC). A target for the project is to meet What Works Clearinghouse (WWC) evidence standards for regression discontinuity design "with reservations." In a broader sense, this project provides a paradigm that other institutions might adopt and adapt for their specific institutional culture and climate.
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An essential aspect of this project, beyond the intervention *per se* is to develop a "low cost" predictive analytics capability. During the project's three-year engagement with GlyphEd, Inc. we have met at regularly scheduled times via Teams or WebEx to discuss data integration or software development issues with the data wrangler, Taylor Riggs. This frequent communication has resulted in a dynamic data visualization capability that integrates institutional data with all the cohort data including the four surveys (CSI/MYSA/TQ/EQ-i). We have concluded the steps of integrating the data into visualizations, and now, we are positioned to involve selected members of the John Carroll University student support team in training to use and apply the data visualization capability to enhance student success and thriving. We will be implementing the onsite training in February 2020.

Due to the voluminous amounts of data, and the timing of data collections during the grant, we found it necessary to request a one-year no-cost extension (NCE) during which we will focus on

rigorous data analyses. In July 2019, we were approved for the NCE, which extends the period of the grant to September 30, 2020.

So, as we turn our attention to analyzing and interpreting these data, the question that is prominent in our thinking is whether this effort to identify factors associated with student success and thriving will continue after the grant funding has ended? How might the university build on the investment we obtained through the First in the World grant (FITW), by adopting aspects of the intervention and the considerable data, to help plan, develop, or enhance student advising and support strategies? This is a conversation that needs to take place with JCU stakeholders. Hopefully, we will be able to advance this conversation during the NCE year.

It is important to point out that our project has already made an impact on other educational institutions. Recently, in response to the National Science Foundation solicitation #18-522, Morehouse College, a historically black college (HBCU) in Atlanta, GA adopted the John Carroll aligned learning approach for a “Broadening Participation Research” grant application supporting STEM students. If funded, Morehouse College will begin their project in Fall 2020.

In previous annual reports, we have summarized descriptive analyses, as well as how we have addressed the relevant What Works Clearinghouse (WWC) standards for regression discontinuity design, and baseline equivalence. Our plan during this NCE year is to conduct more rigorous analyses of the three cohorts of student data, develop scholarly journal articles and disseminate our findings through our JCU website and at national conferences. Also, we plan to submit the findings of this study to ERIC the Education Resources Information Center, and to the WWC for review.

Goal of the Study

This project aims to identify factors associated with student success and thriving among a population of first-year freshmen identified as being “at risk,” measured by a construct of predicted academic difficulty. We apply the concept of “aligned learning communities” and collaborative course development as our intervention that consists of a series of aligned foundational courses, linked by common themes and assignments. By offering the aligned courses, the goal is to mitigate effects of potential academic difficulty that an average incoming freshman may encounter.

Engagement in aligned foundational courses provides a mechanism for the organic development of cohort-based learning communities and a framework for success in our new core curriculum and linked courses. Participation in aligned courses is determined by student's responses to CSI indicators of predicted academic difficulty and targets numerous factors that are important for an average student to succeed. Identifying student academic difficulty allows for proactive interventions to ensure greater success. The catalog of aligned courses includes Biology, English, Oral Communication, Theology and Religious Studies, and Economics.

The hypothesis is that compared to freshmen enrolled in foundational courses under the standard or “business as usual” model, those freshmen enrolled in aligned learning communities will show positive effect on the outcome measures such as accumulated course credits, persistence, raw GPA, and adjusted GPA. The College Student Inventory (CSI) composite measure of predicted academic difficulty was used to determine placement into the intervention or comparison groups.

What Are Linked or Aligned Courses?

Kellogg (1999) states that linked or aligned courses put together a cohort of students with two common courses. One course is typically content-based (science, math) and the other is an application course (writing, speech). The faculty of each course may teach independently or together and coordinate syllabi and assignments so that the classes compliment each other. The Linked Courses Model provides a shared experience for students that focus on a content-based course that is actively supported by a skills course.

Study Characteristics

Intervention Condition – Students were block registered into a pair of aligned foundational courses that were linked by common themes and assignments, thus forming a cohort-based, interdisciplinary learning community. These courses were developed during a series of faculty workshops conducted prior to implementing the intervention.

An example of this alignment is the Biology and Oral Communication pair, where the common assignments includes each student demonstrating skills with a series of presentation styles, such as informative, or persuasive. A goal of this set of aligned courses is to prepare students in natural science courses to more effectively communicate to diverse audiences, and in diverse settings.

Comparison Condition – Students in the comparison group consisted of those freshmen not identified as having “predicted academic difficulty,” as indicated by results CSI. This group of students was block registered in a “business as usual manner” for similar pairs of stand-alone foundational courses as those taken by the students in the intervention group. Courses taken by students in the comparison group were not aligned. Faculty teaching these courses to the comparison group did not collaborate to develop common themes or assignments. In effect, the comparison group was not enrolled into any “learning communities.”

Setting – A four-year private Liberal Arts institution in Northeast, Ohio, with an undergraduate population of approximately 3,000.

Participants – All enrolling first-time, first-year freshmen other than Arrupe Service Scholars, Borremeo students, or Honors Program students at John Carroll University.

Study Design and Analysis

Sample formation - Participants in the intervention and control groups were determined using a forcing variable, “Predicted Academic Difficulty,” which is a composite index in the College Student Inventory (CSI) that uses a Stanine scale of 1-9, with 5 as the mean, and standard deviation = 2. To assure that we meet WWC requirements for balance on each side of the cut-score, we used the raw scores, rather than the Stanine score for Predicted Academic Difficulty. Higher scores on Predicted Academic Difficulty indicate greater risk of difficulty.

The major scales of the CSI include: receptivity to academic assistance, academic confidence, attitude toward educators, career closure, receptivity to career counseling, desire to finish, desire to transfer, family emotional support, receptivity to financial guidance, opinion tolerance, receptivity to social enrichment, self-reliance, study habits, sociability, math and science confidence, verbal and writing confidence. Used as an "early warning system," the CSI can accurately identify at-risk students for intervention.

A student is considered "average" or "near the mean" if the Stanine score is 4,5, or 6. After careful consideration, the researchers chose "4" as the cut-score because our study also is informed by the literature on the "murky middle," which suggests that 45% of total dropouts nationwide finish a year of college and with a grade-point average between 2.0 and 3.0 (Venit – The "Murky-Middle Project," 2014). The CSI's independent scales have an average homogeneity coefficient (coefficient alpha and Spearman-Brown split-half reliability) of .81. The CSI compares favorably to several well-respected personality inventories. Jackson's Personality Research Form (PRF Form E, 16 items per scale, N=84) obtained an average homogeneity coefficient of .72. The Meyers-Briggs Type I indicator, used by many college counseling centers, has an average coefficient alpha reliability of .81, while the California Psychological Inventory (CPI), respected by psychologists, has an average coefficient alpha reliability of .72 (USA Group Noel-Levitz, 1993). With this solid homogeneity as a base, the CSI's stability (test-retest reliability) is also quite good (Noel-Levitz, 1993).

TABLE 1 – Distribution of Raw Scores of Predicted Academic Difficulty

LOWER RANGE OF RAW SCORES	STANINE SCORE	UPPER RANGE OF RAW SCORES
-52.957	1	-44.544
-44.509	2	-38.791
-38.653	3	-32.259
-32.138	4	-24.467
-24.404	5	-16.112
-15.985	6	-8.928
-8.451	7	-2.906
-2.594	8	1.488
4.059	9	4.625

WWC Standard 1 - Integrity of Forcing Variable Predicted Academic Difficulty

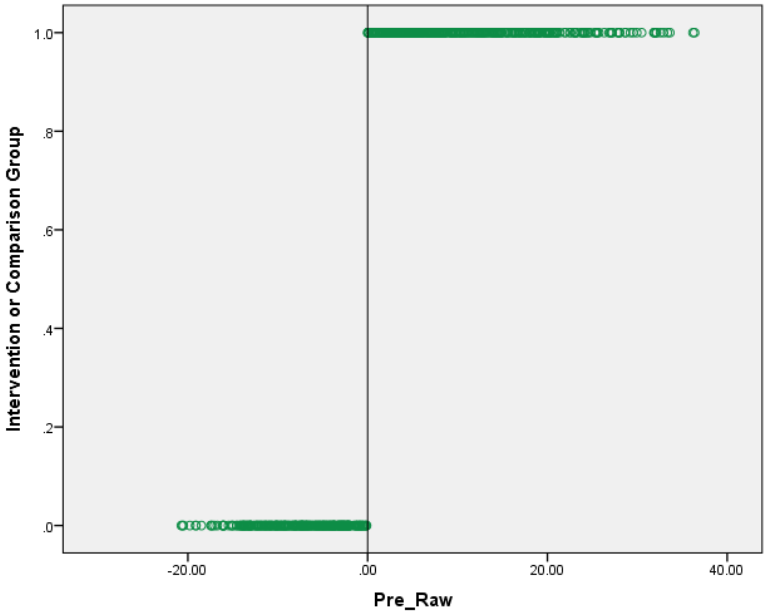
Institutional Integrity – There was no systematic manipulation of the CSI "forcing variable," which is, as discussed above, a standardized measure. No scores were changed from their true values to influence treatment assignments, and the researchers, prior to administration of the CSI survey determined the "cut value." Moreover, scorers had no opportunity or incentive to manipulate CSI scores. Stated differently, manipulation not could occur since the scoring and treatment assignment processes were independent. This approach meets WWC standard 1.0 criterion "A" for RDD designs.

Statistical Integrity - We have acquired the R+ software, which has the McCrary test. This concept is that if students know about the treatment they may manipulate the design by intentionally moving to the treatment group. We expect the running variable, or the forcing variable, predicted academic difficulty (PAD) to be discontinuous at the cut off with surprisingly many individuals just barely qualifying for treatment (e.g., with low PAD), and surprisingly few failing to qualify (e.g., too many with low PAD in treatment).

Graphical Integrity – meeting this requirement satisfies WWC standard 1.0, criterion "C" for RDD designs.

We began our analyses by plotting the probability of receiving treatment (0= comparison group; 1=treatment group) as a function of Predicted Academic Difficulty raw scores (PAD). Figure 1 shows a discontinuity at the cut-point, indicating there is a treatment contrast to test (Bloom 2009). Given there is a discontinuity (as shown in the top graph of Figure 1, where the horizontal line breaks at the cut-point) the next step is to examine the relationship between outcomes and PAD (see Figure 2).

Figure 1 – Probability of Receiving Treatment



[redacted]

Figure 2 - Fall Semester GPA And Predicted Academic Difficulty at Full Bandwidth (1-9)

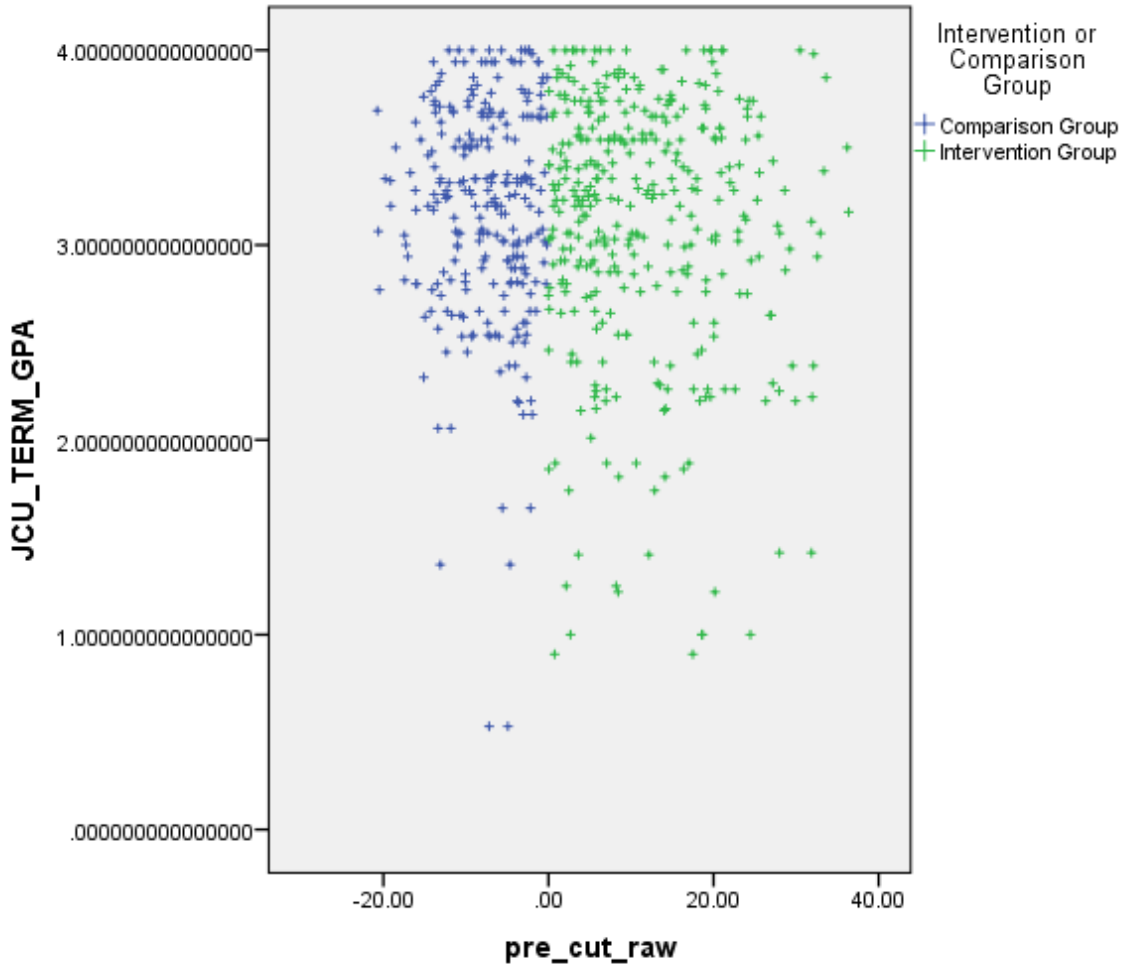


Figure 2 indicates a decently clear and steady downward sloping regression line between JCU-Term-GPA and the forcing variable. To see this relationship more clearly, consider selecting a bin width (e.g., 3 points, or a fraction of a Stanine); that will reduce noise in the data.

Establishing Baseline Equivalence For Binary Variables

<u>Demographic Measure Using Pell Eligibility</u>

$$g = M_1\text{-}M_2/S_{pooled}$$

Using Hedge's *g* calculation for binary variables, we determined the mean (proportion) of Pell eligible students in the intervention (0.21, SD= .410, n=151) and comparison group (.28, SD= .449, n=116) at the bandwidth (3-4). The result is a relative effect size *g* = -0.23, with correlation coefficient *r*=-0.081, suggesting there is a small or trivial difference in Pell eligibility among students in the treatment and comparison groups. We also tested this measure using the full bandwidth (1-9) intervention (0.25, SD= .433, n=358) and comparison group (0.20, SD= .400, n=262). For this bandwidth, *g*=0.17. Both these results meet the WWC standard for acceptable effect size ≤*0.25.* Some statistical adjustment is still necessary such as regression covariate adjustments in ordinary least squares models, analysis of variance, or nonlinear regression analyses such as probit or logistic regression.

Establishing Baseline Equivalence for Continuous Variables

Academic Measure using ACT Verbal scores – Since some students took both SAT and ACT standardized tests prior to college admission; we first assessed our data to identify which of the test students took. Additionally, if students took either test more than once, we used the highest score in our assessment. Then, using SAT conversion table, we transformed all SAT scores to ACT equivalent scores. Baseline equivalence for this academic measure was determined using a model-based linear regression for individual assignment:

$$Basevar = B_0 + B_1 (X_i - X_c) + B_2 Z_i + e_i$$

Where:

Basevar = the baseline covariate (ACT verbal score).
X = "pre-cut" = the pretest centered on the cut-point
Z = the treatment indicator (dichotomous)
e= the error term

TABLE 2 - Distribution of participants by cohort and treatment condition

	Gold (intervention)	Blue (control)	Total
Cohort 1	352	252	604
Cohort 2	353	209	562
Cohort 3	401	236	637
Total	1106	697	1803

TABLE 3 - Distribution of participants by cohort and race/ethnicity

	Cohort 1		**Cohort 2**		**Cohort 3**		**All cohorts**		
	Blue	Gold	Blue	Gold	Blue	Gold	Blue	Gold	Total
White/ Caucasian	89.9 %	79.8 %	96.1 %	85.4 %	92.8 %	85.5 %	92.7 %	83.7 %	87.2 %
Black/African American	2.4%	7.6%	1.0%	5.2%	3.4%	4.2%	2.3%	5.6%	4.3%
Hispanic or Latino	1.2%	5.6%	1.4%	3.4%	2.1%	6.5%	1.6%	5.2%	3.8%
Asian or Pacific Islander	3.6%	2.3%	1.0%	4.3%	1.7%	2.5%	2.2%	3.0%	2.7%
Multiethnic or other	2.8%	4.7%	0.5%	1.7%	0.0%	1.2%	1.2%	2.5%	2.0%

Study Data Cohort 1 (2016-2017)

Wave 1: Pre-intervention Data – Baseline Sample – In preparation for Fall 2016 semester, all entering freshmen that completed the College Student Inventory (N=719) and attended New Student Orientation. High Need Students – Among the students in our baseline sample, 21.1% (N=152) are Pell eligible. Of our initial baseline sample, 11.4% (N=82) were first generation students.

Pre-intervention Data – Analytic Sample – Those students eligible for the study and for whom we have complete data (N=604) were enrolled in the standard foundational courses. The analytic sample excludes Arrupe Service Scholars, Honors students, and Borrameo scholars who are enrolled in specifically designated foundational courses, as well as some students for whom the intervention courses could not be scheduled (N=115). High Need Students – Of the students in the intervention group, 25.9% were Pell eligible (N=91); and among those students in the initial comparison group, 20.6% were Pell eligible (N=56). First-generation College Students – In the intervention group, 14.5% (N= 51) were first-generation, while 10.3% (N=26) of the comparison group are first-generation college students. Among the intervention group – 20.0% (N=70) were non-white compared to 11.6% (N=29) in the comparison group (Chi-square=7.579, P=.006). In wave 1, the intervention group had more males (59.7%) than the comparison group (45.6%) (Chi-square=11.621, P=.001)

Predicted Academic Difficulty:

Intervention. As per the study design, students in the intervention group has a significantly higher PAD (M=5.03 SD=1.16 n=352) vs. the students in the non-intervention group (M=2.27 SD=.78 n=252, p=.000)

Gender. For the overall sample, Men (M=4.13, SD=1.78, n=325) demonstrated significantly higher predicted academic difficulty scores, as compared with women (M=3.65, SD=1.62, n=279; p=.001).

Ethnicity. Non-White students (M=4.36, SD=1.70, n=99) on average scored significantly higher on PAD, compared to White/Caucasian students (M=3.82, SD=1.70, n=502; p=.004).

Pell. Pell eligible students had higher scores (M=4.16 SD=1.16 n=143) compared to the non Pell eligible students (M=3.83 SD=1.74 n=461, p=.044).

First Generation. Students who were the first in their families to attend college did not have a significantly higher PAD (M=4.22 SD=1.62 n=77) compared to those who were not first generation (M=3.86 SD=1.73 n=527, p=.087).

Overall, the distribution of the sample is shown in table below:

Cohort 1 - Ethnicity self-reported					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Asian or Pacific Islander	22	3.7	3.7	3.7
	Black/African American	32	5.1	5.2	9.0
	Hispanic or Latino	24	3.8	3.9	12.9
	Multiethnic or other	24	4.0	4.1	16.9
	White/Caucasian	502	81.1	83.1	100.0
	Total	604	97.6	100.0	
Missing	Missing	4	.6		
	Prefer not to respond	11	1.7		
	Total	15	2.4		
Total		619	100.0		

Study Data Cohort 2 (2017-2018)

Wave 2: Pre-intervention Data – Baseline Sample – In preparation for Fall 2017 semester, all entering freshmen that completed the College Student Inventory (N=748) and attended New Student Orientation. High Need Students – Among the students in our baseline sample, 19.1% (N=143) are Pell eligible. Of our initial baseline sample, 17.1% (N=128) were first generation students.

Pre-intervention Data – Analytic Sample – Those students eligible for the study and for whom we have complete data (N=563) were enrolled in the standard foundational courses. The analytic sample excludes Arrupe Service Scholars, Honors students, and Borrameo scholars who are enrolled in specifically designated foundational courses, as well as some students for whom the intervention courses could not be scheduled (N=185). High Need Students – Of the students in the intervention group, 21.5% were Pell eligible (N=76); and among those students in the initial comparison group, 17.76% were Pell eligible (N=37 (no significant difference). First-generation College Students – In the intervention group, 16.9% (N= 60) were first-generation, while 15.3% (N=32) of the comparison group are first-generation college students (no significant difference). Among the intervention group – 15.3% (N=54) were non-white compared to 4.8% (N=10) in the comparison group (Chi-square=14.297, P=.000). In wave 2, the intervention group and the comparison group had similar distribution of males and females (55.9 vs. 54.1, respectively.)

Predicted Academic Difficulty:

Intervention. As per the study design, students in the intervention group has a significantly higher PAD (M=5.03 SD=1.16 n=352) vs. the students in the non-intervention group (M=2.27 SD=.78 n=252, p=.000)

Gender. For the overall sample, Men (M=4.20, SD=1.73, n=311) demonstrated similar predicted academic difficulty scores, as compared with women (M=4.02, SD=1.77, n=252; p=.208).

Ethnicity. Non-White students (M=4.88, SD=1.90, n=64) on average scored significantly higher on PAD, compared to White/Caucasian students (M=4.02, SD=1.71, n=499; p=.000).

Pell. Pell eligible students had higher scores (M=4.42 SD=1.90 n=113) compared to the non Pell eligible students (M=4.04 SD=1.69 n=452, p=.038).

First Generation. Students who were the first in their families to attend college did not have a significantly higher PAD (M=4.15 SD=1.75 n=92) compared to those who were not first generation (M=4.11 SD=1.75 n=471, p=.843).

Cohort 2 - Gender

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Male	311	54.8	55.0	55.0
	Female	252	44.8	45.0	100.0
	Total	560	99.6	100.0	
Missing	System	3	.4		
Total		563	100.0		

Cohort 2 - Ethnicity self-reported

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Asian or Pacific Islander	17	3.0	3.1	3.1
	Black/African American	20	3.6	3.6	6.7
	Hispanic or Latino	15	2.7	2.7	9.4
	Multiethnic or other	7	1.2	1.3	10.6
	White/Caucasian	495	88.1	89.4	100.0
	Total	554	98.6	100.0	
Missing	Prefer not to respond	6	1.1		
	System	3	.4		
	Total	8	1.4		
Total		563	100.0		

Cohort 2 - First gen to attend college?					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	yes	91	16.2	17.6	17.6
	no	426	75.8	82.4	100.0
	Total	517	92.0	100.0	
Missing	Missing	43	7.7		
	System	3	.4		
	Total	45	8.0		
Total		563	100.0		

Cohort 2 Factors Associated with Students Thriving

The focus here is on Cohort 2 students who as of fall 2019 are in their junior year. The following analyses concentrate on Thriving Quotient (TQ) data collected during the second semester of their freshman year (the spring of 2018). Comparative data show that there was consistency between Cohort 1 to Cohort 2, which suggests value in continuing to develop programs to address findings.

What Drives Intent to Graduate? The TQ data shows that there are significant differences between Intervention Group and Non-intervention Group drivers of intent to graduate. For example, students in the Gold (intervention) group were significantly less likely to feel they know how to apply their strengths to achieve academic success (t = 3.96, p<.001). This was the most substantial difference between the groups. Additionally, among students in Blue (non-intervention) group, ability to apply strengths is a significant predictor of intent to graduate, consistent from Cohort 1.

The analytical method we used to examine intent to graduate was stepwise multiple regression. The amount of variance in the dependent variable by each significant predictor is represented by R^2. Reported as cumulative, final predictor notes total variance explained by the model. For example, t = predictive strength must be > +/- 2.0; F = predictive strength of the model; p = probability that the test statistic is not due to chance. Indicators of significant probability are p < .05; p < .01, or p < .001.

As shown in TABLE 4, when considering all students in cohort 2, the data show that intent to re-enroll net year is predicted by the perceptions of goodness of fit coupled with confidence in reaching educational goals, and making a difference in other's lives. The extent to which students find it hard to make friends further adds to the explanation of ratings for intent to re-enroll, bringing variance explained to 57%. Scores were at the midpoint of the scale. Moreover, good fit given goals is the most significant predictor of re-enrolment. Predictive analyses of goodness of fit follow.

TABLE 4 – Cohort 2 Predicting Intent to Re-enroll (All groups Gold/Blue)

As we can see in TABLE 5 below, for the Gold (intervention) group, intent to re-enroll next year is predicted by perceptions of, good fit and the extent to which students agree that it is important to become aware of the perspectives of individuals from different backgrounds.

Thinking about learning outside of class adds to the explanation of intent to re-enroll, as does the extent to which students spend time making a difference in the lives of others, bringing total variance explained to 70% For the intervention group, this suggests there is an opportunity to increase potential for re-enrollment with service engagement in diverse settings inclusive of reflection tied to other learning

TABLE 5 – Cohort 2 Predicting Intent to Re-enroll (Gold Intervention group)

TABLE 6 below indicates that for the Blue, control group, again intent to re-enroll is predicted by perceptions of good fit (R^2 =.68), coupled with perceptions of difficulty in making friends, and the extent to which non-intervention students perceive themselves as having a positive outlook. Being proud of the university chosen is additionally explanatory and predictive of intent to re-enroll, however it is rated at 3.0 on a 6-point scale suggesting opportunity for improvement.

TABLE 6 - Cohort 2 Predicting Intent to Re-enroll (Blue Control group)

So, what is the bottom line on intent to re-enroll? Intent to re-enroll is primarily predicted by students' perceptions that the university is a good fit for them. A focus on making a difference in others' lives is integral to re-enrollment intent. Re-enrollment for students considered "at risk" is further predicted by their awareness of the importance of varied perspectives. Moreover, if they are not guided to reflect on learning outside the classroom, their re-enrollment likelihood erodes*;* hence recommendation for experiential service learning opportunities.

For more typical students (control) a focus on pride in the university and opportunities to make friends leads to re-enrollment. Connecting students with new "friends" within the Jesuit higher education network, particularly those at the margins, can substantially impact re-enrollment intent. This type of work is in place at multiple American Jesuit universities (Creighton, Regis, Georgetown, Fordham) and currently in place in some JCU programs (e.g., marketing). So, what drives perceptions of Good Fit?

Predicting perceptions of good fit. "*Given my current goals, this institution is a good fit for me"* This variable is most significant predictor of intent to re-enroll as well as intent to graduate for *all* students, regardless of predicted academic difficulty. Therefore we identify significant predictors of perceptions of "good fit". First, we compute the effect for All students TABLE 7). Next we compute the effect for the Gold intervention group (TABLE 8), and Blue control group (TABLE

9). Overall, this measure is rated 4.9 on 1-6 point scale. However, for the Gold group (intervention) is was 4.8, and for the Blue group (control) was 5.1.

As we see in TABLE 7 overall, pride in the university is the most significant predictor of students' perceptions of good fit. As expected, students who would have chosen a different university do not necessarily see JCU as a good fit. The extent to which students agree that what they are learning is improving them as a person, further adds to ratings for "good fit" as does a sense of belonging

TABLE 7 – Cohort 2 Predicting Good Fit (All students)

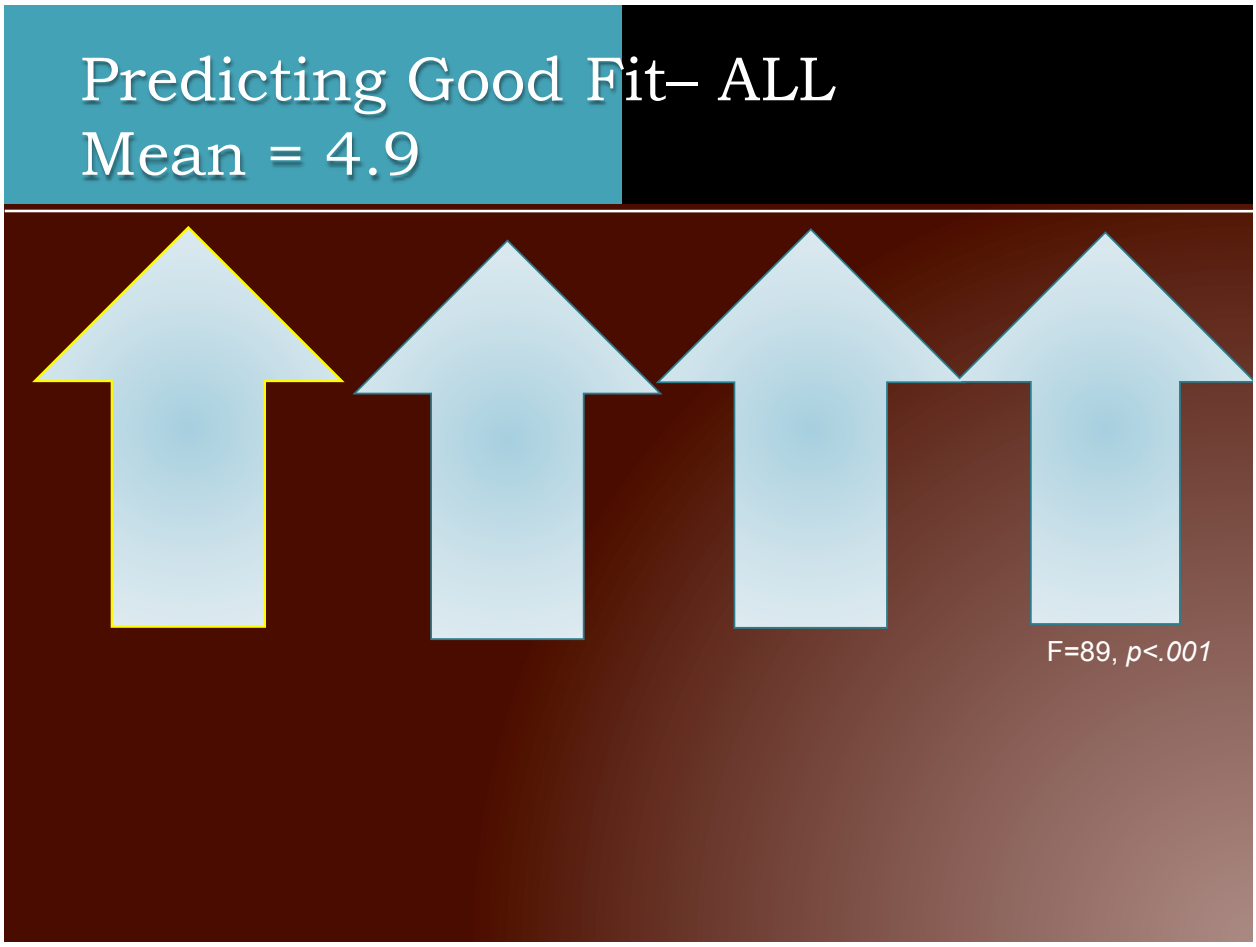
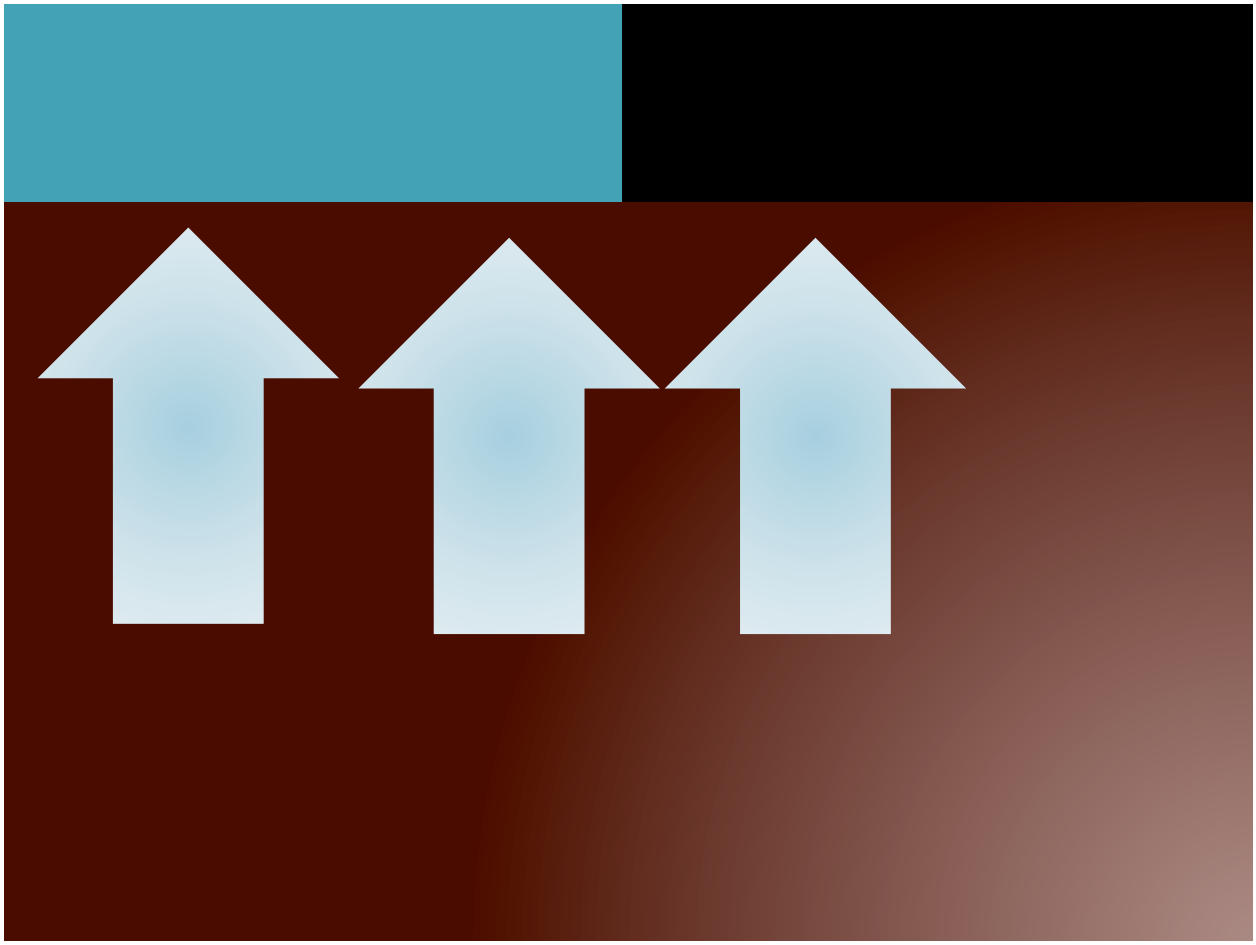


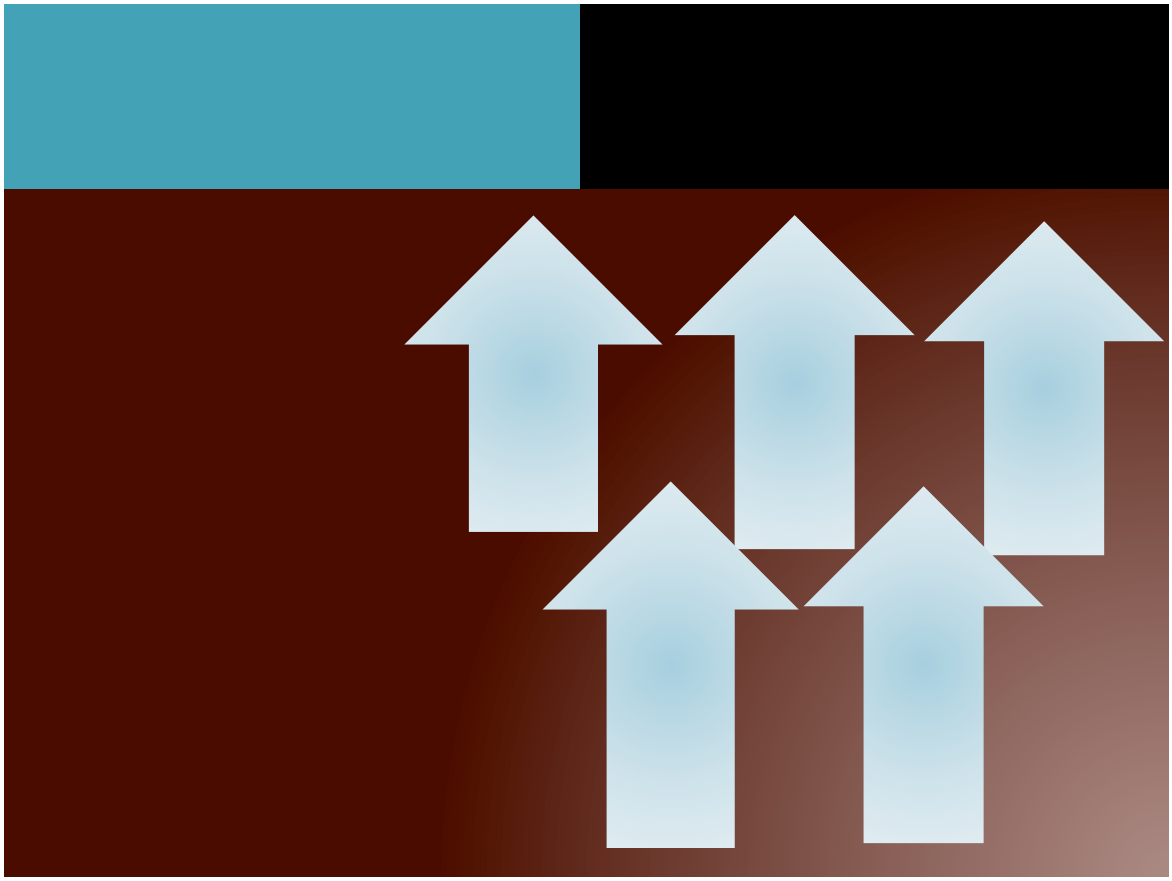
TABLE 8 below shows that for the intervention (Gold) group, pride in the university is the most significant predictor of students' perceptions of good fit. The extent to which students agree that what they are learning is improving them as a person, further adds to ratings for "good fit" As expected, at-risk students who would have chosen a different university, do not necessarily see JCU as a good fit.

TABLE 8 – Cohort 2 Predicting Good Fit (Gold Intervention Group)



As with the intervention group, for the control (Blue) group, pride in the university is the most significant predictor of students' perceptions of good fit. Notably, the extent to which students agree that Spiritual / Religious Beliefs add meaning to my life (rated at 4.5 on 6 pt. scale) also predicts fit. Disagreement has the potential to erode perceptions of fit (TABLE 9).

TABLE 9 – Cohort 2 Predicting Good Fit (Blue Control Group)



When considering all Cohort 2 respondents (Juniors in fall '19), we found that overall, pride in the university is the most significant predictor of students' perceptions of good fit. The extent to which students agree that what they are learning is improving them as a person, further adds to ratings for "good fit" as does a sense of belonging. Among the Control (Blue) group it is notable that the extent to which control group students agree that Spiritual / Religious Beliefs add meaning to my life also predicts fit. Disagreement has the potential to erode perceptions of fit.

Cohort 2 - Self-perceptions About Thriving

As shown in TABLE 10 below, Cohort 2 Gold (intervention) group (now Juniors) rate their *self-perceptions significantly higher* *than Blue (control) group on the following:*

- Intelligence cannot be changed
- Would have chosen different university
- More likely to engage in community service
- More likely to join ethnic organizations (although low)

TABLE 10 – Cohort 2 Comparisons of Self-perceptions (Control vs. Intervention)

Item	Blue	Gold	T statistic	< p-value
Apply learning to life	**4.81**	4.51	2.10	.05
Work on uninteresting assignments until done well	**5.04**	4.64	2.7	.01
Apply my strengths	**5.15**	4.68	3.96	.001
Good at juggling demands	**4.78**	4.31	3.22	.01
People say I'm a hard worker	**5.28**	4.76	4.16	.001
Spiritual or religious beliefs provide sense of strength when life is difficult	**4.66**	4.25	2.05	.05
Academic determination	**5.07**	4.68	4.21	.001
Physical health	**4.77**	4.41	2.25	.05
Intelligence cannot be changed	2.60	**3.23**	2.84	.01
Would have chosen different university	2.44	**2.97**	2.46	.05
More likely to engage in community service	3.04	**3.88**	3.00	.01
More likely to join ethnic organizations	1.36	**1.94**	3.51	.01

Study Data Cohort 3 (2018-2019)

Wave 3: Pre-intervention Data – Baseline Sample – In preparation for Fall 2018 semester, all entering freshmen that completed the College Student Inventory (N=861) and attended New Student Orientation. High Need Students – Among the students in our baseline sample, 20.9% (N=181) are Pell eligible. Of our initial baseline sample, 9.6% (N=83) were first generation students.

Pre-intervention Data – Analytic Sample – Those students eligible for the study and for whom we have complete data (N=635) were enrolled in the standard foundational courses. The analytic sample excludes Arrupe Service Scholars, Honors students, and Borrameo scholars who are enrolled in specifically designated foundational courses, as well as some students for whom the intervention courses could not be scheduled (N=226). High Need Students – Of the students in the intervention group, 26.6% were Pell eligible (N=106); and among those students in the initial comparison group, 16.5% were Pell eligible (N=39, chi-square=8.581 P=.003). First-generation College Students. In the intervention group, 17.2% (N= 51) were first-generation, while 14.6% (N=23) of the comparison group are first-generation college students (no significant difference). Among the intervention group – 15.8% (N=63) were non-white compared to 8.9% (N=21) in the comparison group (Chi-square=6.043, P=.014. In wave 3, the intervention group had more males (63.7%) than the comparison group (53.4%) (Chi-square=7.898, P=.019)

Predicted Academic Difficulty:

Intervention. As per the study design, students in the intervention group has a significantly higher PAD (M=4.91 SD=1.04 n=399 vs. the students in the non-intervention group (M=2.46 SD=.698 n=236, p=.000)

Gender. For the overall study sample, Men (M=4.16, SD=1.53, n=380) demonstrated higher predicted academic difficulty scores, as compared with women (M=3.77, SD=1.44, n=254; p=.001).

Ethnicity. Non-White students (M=4.42, SD=1.52, n=84) on average scored significantly higher on PAD, compared to White/Caucasian students (M=3.94, SD=1.49, n=550; p=.006).

Pell. Pell eligible students had higher scores (M=4.27 SD=1.43 n=145) compared to the non Pell eligible students (M=3.92 SD=1.52 n=489, p=.013).

First Generation. Students who were the first in their families to attend college did not have a significantly higher PAD (M=4.15 SD=1.39 n=74) compared to those who were not first generation (M=4.03 SD=1.55 n=381, p=.843).

Cohort 3 - Ethnicity self-reported

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Asian or Pacific Islander	14	2.2	2.2	2.2
	Black/African American	25	3.9	3.9	6.1

	Hispanic or Latino	31	4.9	4.9	11.0
	Multiethnic or other	4	.8	.8	11.8
	White/Caucasian	560	88.1	88.2	100.0
	Total	635	99.8	100.0	
Missing	Prefer not to respond	1	.2		
Total		635	100.0		

Cohort 3 - First gen to attend college?					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	yes	74	11.6	16.3	16.3
	no	381	59.9	83.7	100.0
	Total	455	71.5	100.0	
Missing	Missing	180	28.5		
Total		635	100.0		

Cohort 3 - Pell Eligible					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	490	77.2	77.2	77.2
	Yes	145	22.8	22.8	100.0
	Total	635	100.0	100.0	

Cohort 3 - Gender					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Male	380	59.7	59.9	59.9
	Female	254	39.9	40.1	100.0
	Total	634	99.7	100.0	
Missing	Missing	1	.3		
Total		635	100.0		

All Cohorts Combined - Ethnicity self-reported

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Asian or Pacific Islander	58	2.6	2.8	2.8
	Black/African American	91	4.1	4.5	7.3
	Hispanic or Latino	76	3.5	3.7	11.0
	Multiethnic or other	46	2.1	2.3	13.3
	White/Caucasian	1768	80.4	86.7	100.0
	Total	2039	92.7	100.0	
Missing	Missing	136	6.2		
	Prefer not to respond	22	1.0		
	System	2	.1		
	Total	160	7.3		
Total		2199	100.0		

All Cohorts Combined - First gen to attend college?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	yes	284	12.9	23.4	23.4
	no	931	42.3	76.6	100.0
	Total	1215	55.3	100.0	
Missing	Missing	982	44.7		
	System	2	.1		
	Total	984	44.7		
Total		2199	100.0		

All Cohorts Combined - Pell recipients

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	491	22.3	77.2	77.2
	Yes	145	6.6	22.8	100.0
	Total	636	28.9	100.0	
Missing	Missing	1561	71.0		
	System	2	.1		
	Total	1563	71.1		
Total		2199	100.0		

All Cohorts Combined - Gender

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Male	768	34.9	55.6	55.6
	Female	614	27.9	44.4	100.0
	Total	1382	62.8	100.0	
Missing	Missing	815	37.1		
	System	2	.1		
	Total	817	37.2		
Total		2199	100.0		

All Cohorts Combined - Assessing The Students' Emotional Intelligence (EQ-i™)

To analyze these data, a series of t-test were run to determine if there is any significant differences between the means of various measures on the emotional intelligence instrument (EQ-*i*™) between the intervention and control groups. Outcomes from these t-tests allow us to develop hypotheses for further testing assumptions about these two groups. In Table 11 below, for each attribute of the EQ-I, .00=control group; whereas 1.00=intervention group.

The EQ-i™ is a self-report measure of emotionally and socially intelligent behavior that provides an estimate of emotional-social intelligence. The *EQ-i*™ is the first measure of its kind to be published by a psychological test publisher, the first such measure to be peer-reviewed in the *Buros Mental Measurement Yearbook*, and the most widely used measure of emotional-social intelligence since it was first published in 1996. The *EQ-i*™ is suitable for individuals 17 years of age and older. The original version of the *EQ-i*™ comprises 133 items in the form of short sentences and employs a 5-point response scale with a textual response format ranging from "very seldom or not true of me" (1) to "very often true of me or true of me" (5). The individual's responses render a total EQ score as well as scores on the following 15 scales in addition to the validity indicators, which is described in detail below:

- Self-Regard
- Emotional Self-Awareness
- Assertiveness / Emotional Self-Expression
- Independence
- Empathy
- Social Responsibility
- Interpersonal Relationship
- Stress Tolerance
- Impulse Control
- Reality Testing
- Flexibility
- Problem Solving
- Self-Actualization
- Optimism
- Happiness / Well-Being

Raw scores on the EQ-i™ are automatically tabulated and converted into standard scores based on a mean of 100 and standard deviations of 15. This scoring system resembles that which is used by cognitive intelligence tests that generate an IQ (or Intelligence Quotient). An average EQ score ranges from 90-100, with a perfect score measuring 160.

Emotional intelligence is the ability to identify and manage your own emotions and identify the emotions of others. It is generally said to include 3 skills:

1. Emotional awareness – the ability to identify your own emotions and those of others
2. Emotional harnessing – the ability to harness emotions and apply them to tasks, like thinking and problem solving
3. Emotional management – the ability to manage emotions, including the ability to regulate your own emotions, and the ability to cheer up or calm down another person

The emotional intelligence test asks a series of questions to find out how you react in various situations. These include:

- Stressful or frustrating situations
- Failures or discouraging situations
- Leadership positions and methods for achieving success
- Methods for managing the emotions of others of various ages
- Methods for assessing various personality traits in others
- Dealing with diversity and cultural sensitivities

Table 11, below shows the emotional intelligence means and standard deviations for control group (.00) and intervention group (1.00) for 22 attributes of emotional intelligence. These results are from pooling the data of the three cohorts. In general, the means for both groups are slightly above the "standard mean" of 100 for emotional intelligence. On the surface, it appears that the intervention group scores lower on each attribute. However, it is necessary to review independent samples to determine whether these differences are meaningful (see Table 12).

TABLE 11 – Means and Standard Deviations Emotional Intelligence Attributes

	FITW_cohort_FINAL	N	Mean	Std. Deviation	Std. Error Mean
TOTAL EQ	.00	589	106.96	13.350	.550
	1.00	918	104.07	13.137	.434
SELF PERCEPTION	.00	589	108.11	12.607	.519
	1.00	918	104.94	13.273	.438
SELF REGARD	.00	589	106.99	14.041	.579
	1.00	918	104.57	13.986	.462
SELF ACUTALIZATION	.00	589	108.69	11.700	.482
	1.00	918	105.19	12.888	.425
EMOTIONAL SELF-AWARENESS	.00	589	104.29	14.507	.598
	1.00	918	102.49	14.161	.467

SELF EXPRESSION	.00	589	103.49	13.928	.574
	1.00	918	101.92	12.839	.424
EMOTIONAL EXPRESSION	.00	589	101.59	15.343	.632
	1.00	918	99.98	14.144	.467
ASSERTIVENESS	.00	589	104.77	13.972	.576
	1.00	918	103.89	13.812	.456
INDEPENDENCE	.00	589	102.20	13.946	.575
	1.00	918	101.22	13.849	.457
INTERPERSONAL	.00	589	106.96	13.701	.565
	1.00	918	105.43	13.114	.433
INTERPERSONAL RELATIONSHIPS	.00	589	105.49	13.359	.550
	1.00	918	104.91	12.544	.414
EMPATHY	.00	589	105.00	14.573	.600
	1.00	918	102.95	14.538	.480
SOCIAL RESPONSIBILITY	.00	589	107.43	12.938	.533
	1.00	918	106.33	12.671	.418
DECISION MAKING	.00	589	105.99	14.062	.579
	1.00	918	102.07	14.116	.466
PROBLEM SOLVING	.00	589	102.74	14.015	.577
	1.00	918	99.92	14.168	.468
REALITY TESTING	.00	589	105.53	16.426	.677
	1.00	918	102.97	15.738	.519
IMPULSE CONTROL	.00	589	105.68	16.712	.689
	1.00	918	102.57	14.576	.481
STRESS MANAGEMENT	.00	589	104.20	13.999	.577
	1.00	918	102.30	13.853	.457
FLEXIBILITY	.00	589	103.10	14.140	.583
	1.00	918	102.56	13.920	.459
STRESS TOLERANCE	.00	589	101.47	14.657	.604
	1.00	918	99.13	14.867	.491
OPTIMISM	.00	589	105.24	13.265	.547
	1.00	918	103.74	12.701	.419
HAPPINESS	.00	589	107.68	12.587	.519
	1.00	918	105.77	12.678	.418

Independent Samples Test **-** For two-tailed tests, the alternative hypothesis is $\mu = x$, and the null hypothesis is $\mu \neq x$; where $x = 0$. In TABLE 12 below, we see significant difference in means between intervention and control groups for 17 of the EQ-I attributes; and five EQ-I attributes that were found to be non-significant.

To interpret these results, first, we consider Levene's test to determine whether the intervention and control groups have similar variability in the means for EQ-I attributes If Levene's test Sig has a value > .05, it means that the variability in these two conditions is about the same. Therefore select the value from top row, "Equal variances assumed," since the scores in one condition do not vary too much more than the scores in your second condition.

Conversely, if the Sig value is < .05, select the value from the second row, "Equal variances not assumed." After this, we look at the column labeled, "Sig (2-tailed) to determine whether the similarities or differences in mean values are significant. In TABLE 12 below, significant differences (Sig. 2-tailed) are indicated in GREEN, while non-significant differences are indicated in RED.

TABLE 12 – Independent Samples Test of Significance for EQ-I Attributes

		Levene's Test for Equality of Variances		t-test for Equality of Means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
									Lower	Upper
Total EQ	Equal variances assumed	.240	.624	4.142	1505	.000	2.891	.698	1.522	4.260
	Equal variances not assumed			4.127	1238.968	.000	2.891	.700	1.517	4.265
Self Perception	Equal variances assumed	.530	.467	4.606	1505	.000	3.165	.687	1.817	4.513
	Equal variances not assumed			4.658	1300.077	.000	3.165	.680	1.832	4.498
Self Regard	Equal variances assumed	.223	.636	3.277	1505	.001	2.423	.739	.973	3.874

	Equal variances not assumed			3.274	1250.092	.001	2.423	.740	.971	3.875
Self Actualization	Equal variances assumed	4.995	.026	5.333	1505	.000	3.502	.657	2.214	4.790
	Equal variances not assumed			5.447	1339.446	.000	3.502	.643	2.241	4.763
Emotional self-awareness	Equal variances assumed	1.256	.263	2.388	1505	.017	1.803	.755	.322	3.283
	Equal variances not assumed			2.376	1231.582	.018	1.803	.759	.314	3.291
Self-expression	Equal variances assumed	4.158	.042	2.251	1505	.025	1.577	.701	.203	2.952
	Equal variances not assumed			2.211	1179.172	.027	1.577	.713	.178	2.977
Emotional Expression	Equal variances assumed	5.119	.024	2.084	1505	.037	1.609	.772	.095	3.124
	Equal variances not assumed			2.048	1179.242	.041	1.609	.786	.067	3.151
Assertiveness	Equal variances assumed	.008	.927	1.205	1505	.229	.882	.732	-.554	2.319
	Equal variances not assumed			1.202	1243.148	.230	.882	.734	-.558	2.323

Independence	Equal variances assumed	.012	.913	1.327	1505	.185	.973	.733	-.465	2.411
	Equal variances not assumed			1.325	1247.327	.185	.973	.734	-.467	2.414
Interpersonal	Equal variances assumed	.591	.442	2.165	1505	.031	1.526	.705	.144	2.908
	Equal variances not assumed			2.145	1213.579	.032	1.526	.711	.130	2.921
Interpersonal Relationships	Equal variances assumed	4.063	.044	.855	1505	.393	.581	.679	-.752	1.914
	Equal variances not assumed			.844	1196.044	.399	.581	.689	-.770	1.932
Empathy	Equal variances assumed	.075	.784	2.665	1505	.008	2.047	.768	.540	3.554
	Equal variances not assumed			2.664	1251.513	.008	2.047	.769	.539	3.555
Social Responsibility	Equal variances assumed	.000	.989	1.634	1505	.103	1.102	.674	-.221	2.425
	Equal variances not assumed			1.626	1234.617	.104	1.102	.678	-.228	2.431
Decision Making	Equal variances assumed	.052	.820	5.269	1505	.000	3.921	.744	2.461	5.380

	Equal variances not assumed			5.273	1257.142	.000	3.921	.743	2.462	5.379
Problem Solving	Equal variances assumed	.138	.711	3.780	1505	.000	2.815	.745	1.354	4.276
	Equal variances not assumed			3.789	1263.580	.000	2.815	.743	1.358	4.273
Reality Testing	Equal variances assumed	.033	.855	3.025	1505	.003	2.557	.845	.899	4.215
	Equal variances not assumed			2.997	1214.501	.003	2.557	.853	.883	4.231
Impulse Control	Equal variances assumed	.425	.515	3.806	1505	.000	3.104	.815	1.504	4.703
	Equal variances not assumed			3.695	1129.503	.000	3.104	.840	1.456	4.752
Stress Management	Equal variances assumed	.018	.892	2.587	1505	.010	1.900	.734	.460	3.340
	Equal variances not assumed			2.581	1244.086	.010	1.900	.736	.456	3.344
Flexibility	Equal variances assumed	.553	.457	.732	1505	.464	.541	.739	-.909	1.992
	Equal variances not assumed			.730	1239.327	.466	.541	.742	-.914	1.997

Stress Tolerance	Equal variances assumed	.023	.880	3.001	1505	.003	2.342	.781	.811	3.873
	Equal variances not assumed			3.010	1266.647	.003	2.342	.778	.816	3.869
Optimism	Equal variances assumed	.835	.361	2.204	1505	.028	1.504	.682	.165	2.842
	Equal variances not assumed			2.183	1213.822	.029	1.504	.689	.152	2.855
Happiness	Equal variances assumed	.039	.843	2.862	1505	.004	1.910	.667	.601	3.219
	Equal variances not assumed			2.866	1260.245	.004	1.910	.666	.603	3.217

Establishing Functional Form and Bandwidth For Regression Models

Using the procedure outlined by Trochim (2002), we compute generalized linear regression models to assess the treatment effect for the full bandwidth of the data (Stanine 1-9). The dependent variable will be JCU cumulative GPA or the ratio of credits earned/credits attempted, and the independent variable is pre-cut, which was constructed using raw score (raw score - 32.138) to set forcing variable to zero by subtracting the lower interval value of the raw scores from the full scale. The data file is split into intervention and comparison group data, for which separate regression models were run for each group to determine whether there are different slopes. For each group regression model, we add the coefficients for the constant + precut. Then, we take the differences in the slopes to determine the treatment effect. We also test a simple linear model (Bloom, 2009).

$$\mathcal{Y}_{\mathrm{i}} = \propto + \mathcal{B}_{\mathbf{0}} \cdot \boldsymbol{PAD} + \boldsymbol{n}_{\mathrm{i}}$$

Where:

Y_i = JCU-TERM-GPA
B_0 = is slope of PAD scores
PAD = raw Predicted Academic Difficulty score
n_i – error term.

Simple Linear Model - Alternative Discontinuity Analysis. In addition to computing separate regression models, as outlined above, we test an alternative approach by computing a simple linear regression model with a constant slope and an intercept shift at the cut-point, as

suggested by Bloom (2009).

$$Y_i = \alpha + B_0 \cdot T_i + B_1 \cdot PAD + n_i$$

Where:

Y_i = the outcome.
B_0 = the shift in the intercept at cut-point (.034), which is the difference between treatment and comparison groups at the cut-point.
T_i = one for treatment group members and zero for comparison group members.
B_1 = estimated slope of GPA/PAD relationship (.103).
PAD = raw scores for Predicted Academic Difficulty.

Table 13 shows the results of a regression discontinuity model that tested the effect of the Predicted Academic Difficulty scores on cumulative GPA at the end of year 1 for the pooled student participant data from the three first-year cohorts. As shown, the effect size is .103 with a significance level of .045. This indicates that for those students in the intervention groups, in their first year, there was an increase in cumulative GPA (0.103), as compared to the control group. Although this is an encouraging result, showing a very small positive effect of the intervention, our target effect size to meet WWC standard is 0.25. At this time, we continue to investigate what constitutes the appropriate model specification. Methodologists suggest testing a variety of functional forms including linear models, linear models with a treatment interaction, quadratic models, and quadratic models with treatment interactions, as well as employing nonparametric estimation techniques such as local linear regression to make sure the functional form that is specified is as close as possible to the correct functional form. Much of the current literature discusses how to choose among these various specifications (e.g., van der Klaauw, 2008; Cook, 2008).

TABLE 13 - RDD for DV = Cumulative GPA end of Year 1

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.520[a]	.271	.269	.55745
a. Predictors: (Constant), IV - Treatment X PDA – re-centered, IV Treatment group, IV FV - PAD – re-centered				

In the model summary above, we see that 27% of the variance (R^2 = .271) in cumulative GPA is explained by the covariates in the model. From the ANOVA model shown below, we can determine that the independent variables reliably predict Year 1 cumulative GPA (Sig = .000).

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	200.992	3	66.997	215.596	.000[b]
	Residual	541.955	1744	.311		
	Total	742.948	1747			
a. Dependent Variable: DV GPA - Cumulative Year 1						
b. Predictors: (Constant), IV - Treatment X PDA – re-centered, IV Treatment group, IV FV - PAD – re-centered						

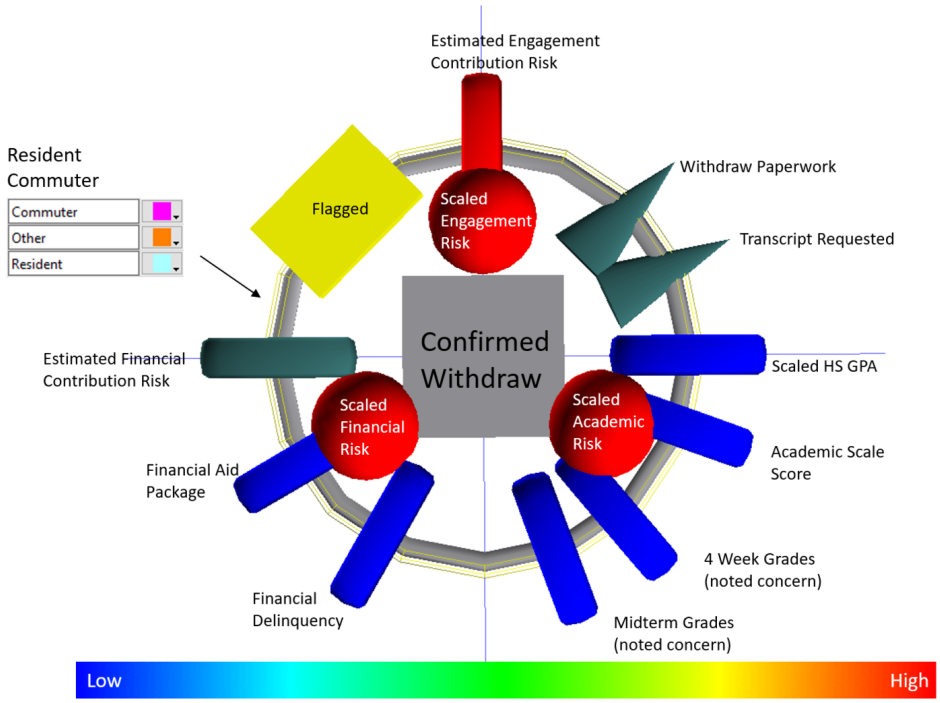
As previously discussed, in the coefficients model below, we see the impact of the intervention on cumulative year 1 GPA. What the data show is that when holding all other variables constant, for every unit increase in GPA, there was a .103 points increase for those in the intervention group, as compared to those in the control group (*Sig* <.05).

Coefficients[a]						
Model		Unstandardized Coefficients		Standardized	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	3.002	.042		70.714	.000
	IV Treatment group	.103	.052	.077	2.004	.045
	IV FV - PAD – re-centered	-.031	.003	-1.138	-9.243	.000
	IV - Treatment X PDA – re-centered	.019	.003	.589	5.601	.000
a. Dependent Variable: DV GPA - Cumulative Year 1						

Analytics And Data Visualization (GlyphEd)

We have now concluded the product development stage for the data visualization capability, and tested the software under various conditions including creating customized visualizations for specific functions such as financial aid; and integrating all data for the three cohorts of student participants. During the NCE period, we will roll out the product during on-site training at John Carroll University for up to eight (8) student support staff members. This will include hands-on training, as well as online technical support.

Figure 3 – Example of Glyph show multiple data points for student record.



Everything you see on the Glyph above is mapped to different variables in the JCU dataset. We are able to customize the appearance of a Glyph, from the shapes or colors, to the size of the individual objects, as well as transparency, rotation, and even animation. When we map our data to a Glyph, we can see n-dimensions of information at one time, such as whether a student is Pell eligible, is male/female, their CSI. MYSA, TQ, or EQ-I survey data. All these data are all floating in one place. Like placing a grey square in the middle to indicate a student is a confirmed withdrawal, or color coding a Glyph red to show its negative impact or even making it scale larger with the severity of the problem. In its actual use, the Glyphs appear in a three-dimensional space that can be manipulated, and also overlaid in a geo-spatial map if we need to look at data relative to cities or state locations.

Faculty Development Activities During the Grant

During the Spring 2016 semester, a series of three workshops were conducted with the goal of identifying appropriate cross-discipline partners, for which aligned courses would be developed. During the initial session, the project goals were presented, and faculty collaborators discussed the essential learning outcomes for their respective foundational courses. Subsequently, subject matter experts paired across disciplines to begin discussions of ways to develop alignments. The outcome of the workshops was a catalog of aligned courses that will be offered each fall semester during the grant. To facilitate development of aligned courses, brief presentations were given on the following topics:

- Using Linked Courses in the General Education Curriculum.
- Linking the Classroom and Community Through Service Learning.
- Syllabus Development, Learning Outcomes, and Aligned Partner Work.
    - (More information is available on our project website: http://sites.jcu.edu/fitw/home-page/resources/

Five workshops were offered for faculty participants in the JCU FITW program in the 2016-2017 Academic Year. Two primary initiatives provided the focus for the 2016-2017 faculty development activities: 1) improved teaching and learning through group study of *How Learning Works: Seven Research-Based Principles for Smart Learning* by Susan A. Ambrose, Michele di Pietro, Michael W. Bridges, Marie K. Norman, and Marsha C. Lovett and 2) facilitating the use of clickers in the classroom.

Faculty Development Workshop Dates

- Friday, September 23, 2016 – Check in meeting
- Friday, October 21, 2016 – Using Clickers
- Friday, November 18, 2016 – Initial workshop on *How Learning Works: Seven Research-Based Principles for Smart Learning*
- Friday, February 24, 2017 – Dr. Marie Kendall Brown, Second workshop on *How Learning Works: Seven Research-Based Principles for Smart Learning*
- Friday, May 12, 2017 – Orientation of new faculty

All FITW faculty were provided with copies of the book *How Learning Works: Seven Research-Based Principles for Smart Learning*, and two separate workshops were conducted on topics from the book. In the first workshop, FITW faculty divided into small groups to answer discussions questions regarding learning principles of particular interest to them in the first half of the book. A large group discussion at the end of the workshop provided faculty the opportunity to share what they had learned and what strategies they were considering

implementing in their courses. In the second workshop, Dr. Marie Kendall Brown, Associate Director for Teaching, Learning & Innovation at the Delphi Center for Teaching and Learning at the University of Louisville, conducted an interactive workshop where faculty participated in activities using the strategies presented in the Ambrose book. Dr. Brown asked faculty to submit a plan to use one of the strategies.

Three workshops and one faculty orientation were offered for faculty participants in the JCU FITW program in the 2017-2018 Academic Year. The primary initiatives of the 2017-2018 faculty development activities were that of student success and retention.

The first workshop focused on encouraging student retention and persistence via metacognition. We again utilized the principles in the book *How Learning Works: Seven Research-Based Principles for Smart Learning* by Susan A. Ambrose, Michele di Pietro, Michael W. Bridges, Marie K. Norman, and Marsha C. Lovett. The second workshop addressed identification and outreach to at-risk students. The third workshop also focused on student success and retention, math core course and informatics and directed research in STEM. Faculty Development Workshop Dates

- October 20, 2017 – Dr. Sarah De Swart of Case Western Reserve University. Metacognition and Student Success.
- April 27, 2018 – Dr. Loralyn Taylor of Ohio University: Building student success: Identification and Outreach to At-Risk Students.
- August 11, 2018 Faculty orientation for new FITW instructors
- September 12, 2018 – Dr. Malcom D'Souza and Wesley College Team: Student Success and Retention.

The first workshop continued our focus from prior workshops on the book *How Learning Works: Seven Research-Based Principles for Smart Learning*. Dr. De Swart focused on Chapters 6 and 7, "why do student development and course climate matter for student learning?" And "how do students become self-directed learners?" Group discussion facilitated sharing and information exchange around what new strategies for enhancing student engagement that instructors might consider implementing in their courses.

In the second workshop, Dr. Loralyn Taylor, Director of Analytics for University Student Success Initiatives at Ohio University, presented practical information on student success and engaged participants in peer activities to help them think about strategies and measures to address these issues.

Finally, Dr. D'Souza, Dean of interdisciplinary/Collaborative Sponsored Research at Wesley College and his team (Mrs. Christine McDermott, Director of Student Success & Retention, Mrs. Danielle Archambault, Coordinator of Tutoring Services, Dr. Derald Wentzien, Professor of Mathematics & Data Science, Prof. Paul Olsen, Associate Professor of Mathematics, Dr. Stephanie Stotts, Associate Professor of Environmental Science) shared what strategies and successful interventions they have used at their university, including curriculum revision and undergraduate research efforts.

Three sets of 24 Q2 clickers with traditional clicker functionality (multiple choice, yes/no, true/false) and three sets 50 Q6 clickers with added functionality (including numeric response and multiple mark capability) were purchased from Qwizdom in late spring of 2017. Two different types of clickers were purchased, because the added functionality of the Q6 devices is necessary in courses where mathematical questions are asked. Prior to purchasing the

clickers, a faculty development session had been held to gauge interest and introduce faculty to the technical aspects of using clickers in their classes. Qwizdom was chosen as the supplier because they do not charge an annual fee for software access as some of their competitors do as well as the fact that their clickers included the functionality necessary for the courses with mathematical content such as the STEM courses and Economics. A core group of faculty have used the clickers and served as a resource for other faculty who have expressed interested.

A team of JCU faculty and staff who are engaged in retention and persistence efforts across campus will be trained as users of the GlyphEd data visualization software in February 2019 when the GlyphEd team comes to JCU to hold workshops. Participants are

- Sherri Crahen, Associate Vice President for Student Affairs and Dean of Students
- Stacey Love, Assistant Vice President for Enrollment Outreach and Student Success
- Laura J. Atkins, Assistant Dean of the Boler College of Business and Director of the Undergraduate Programs
- Carlo DeMarchi, Assistant Dean Academic Advising, College of Arts and Sciences
- Lisa Ramsey, Associate Director, Student Engagement.

Evaluator's Recommendations[1]

The evidence and information provided in this report clearly show that students, instructors, and the institution have benefited from JCU's investment in the LLASS project. Below we provide recommendations regarding what aspects of the LLASS project JCU should consider maintaining as well as other suggestions for JCU to consider as they continue to examine strategies for effectively identifying and supporting at-risk students at JCU. It should be noted that we have limited our recommendations to efforts and actions that strike a balance between impact and feasibility and tried to avoid suggestions that would likely require large systemic or structural changes at the university.

Elements of the aligned course intervention that should be retained or modified

The pre-registration process. The preregistration process for freshman students also seemed to be an overall positive aspect of the project that should be kept. The decreased stress on the part of students, instructors, and administrators suggests that this might be worth continuing in the future.

Grouping students into paired courses. The observable student bonding and mutual support that emerged from grouping students into paired courses suggests that some effort should still be made to design this into the freshman curriculum. Based on input from instructors and administrators, however, we recommend that JCU use a process for pairing courses and instructors that is driven by, or at least includes more input from, course instructors. The top-down approach for the LLASS project resulted in some teacher pairings that did not function well for reason including pedagogical differences, disparities in instructors' willingness to modify their course designs, and challenges in finding alignment between some courses. Teachers mentioned that they would like to have more say about whom they are paired with and expressed a preference for keeping the same pairing from year to year. This continuity would allow the relationships between teacher pairings to grow and it would enable them to continually

[1] Note – the full evaluation report is available online at jcu.edu/fitw

improve their aligned courses. This continuity would give instructors more opportunity to bond and work together to develop ideas and improve the alignment between the courses.

Some instructors experienced challenges with the emergence of negative dynamics such as groupthink and ostracization in their classes. If JCU maintains the practice of grouping students into paired courses, we recommend providing instructors with opportunities to learn more about how to prevent or how to identify address negative dynamics that can undermine learning.

Grouping at-risk students together

Some instructors found that the grouping of at-risk students together was helpful. They explained that in classes, which are typically comprised of students with a range of strengths and challenges, at-risk students' needs are often overlooked or – if addressed – can impede the progress of a course. Knowing that their course was comprised of at-risk students enabled them to consider and adapt their teaching practices for the benefit of the entire class. These instructors indicated that they would prefer to know more specific information about the specific challenges faced by their students. We agree that grouping at-risk students and providing instructors with more information about their students' challenges is something that JCU should consider maintaining. We do, however, realize that some instructors might adjust their teaching approach in a way that fails to appropriately challenge students who are at-risk due to low expectations. If JCU decides to continue grouping at-risk students in paired courses, careful decisions should be made regarding what information should be shared with instructors and some effort should be made to ensure that instructors are using this information in a way that improves rather than undermines learning.

Developing a feasible method to accurately assess variables that are most predictive for who are at-risk

What emerged from this project is that an intervention directed to at-risk students can have a positive impact on academic performance. The challenge becomes how best to identify at-risk students. For the purposes of this project, the JCU team utilized the CSI which has been well-validated and produces a report that includes tailored recommendations in terms of the areas in which a given student might need guidance. This can certainly be a valuable tool that JCU should consider maintaining, particularly for gathering information about incoming freshmen.

While the CSI is valuable in terms of collecting predictive information regarding attitudes etc. has limitations. Many of the variables or problems measured by the CSI such issues related to career interests, social connectedness, desire to finish college, and financial stresses do not emerge until the student has been enrolled for some time and might not become problematic. In addition, some of the more difficult problems that students might face after being enrolled can be very serious and lead to negative outcomes that are even worse than struggling academically. Mental health issues can arise after the student has enrolled. Other issues, of course are less serious but should be assessed accurately to ensure that the right intervention is used. Financial stress is a very common problem among students but simply identifying that the student is suffering from financial stress is not enough. It is also important to then determine if the student is experiencing real financial hardships or if they are – in fact – just not aware of the services and aid that are available to them.

It is recommended that the JCU teamwork towards the development of a customized assessment tool that targets the key variables and issues associated with academic difficulty or a lack of thriving for students at JCU. This tool can – and should – include adapted elements

from the CSI, the Thriving Quotient (TQ) and Emotional Quotient Inventory (EQ-I) that are determined to be important predictors for students at JCU as previously described.

Such a tool could be feasibly administered on a regular and periodic basis so that problems can be detected as they emerge. More importantly, the tool could be designed to identify problems more specifically to ensure the right guidance is provided. For example, the CSI and similar tools include questions to identify if students are experiencing financial pressures but are not designed to determine whether students understand the financial assistance that is available to them at a particular institution. In addition, a customized tool could be revised if additional issues are identified that need to be measured.

Developing a tool that is targeted and sensitive to the issues faced by JCU students would provide more useful information to those who provide student guidance by providing them with only the information that is most relevant and minimizing the potentially overwhelming complexity and confusion that can result from a tool measures too many variables. Consequently, it would enable advisors or faculty member to more easily provided clear and effective guidance for a particular student. The limited number of variables measured would also enhance the utility of the GlyphEd tool that has been developed to provide a way to visually assess and identify problems for a specific student or patterns that might be emerging within specific groups of students.

This kind of effort can be initially time-consuming and expensive. But once the tool is developed it will belong to JCU and can be updated and revised as needed. We recommend that the project team seek out funding in their efforts to develop this tool. One example to consider is the National Science Foundation's Improving Undergraduate STEM Education Program (IUSE) grant.

Identifying or developing an assessment method or tool for obtaining actionable data on factors that predict student success at JCU – in conjunction with the CSI - will be a critical component in JCU's efforts to identify at-risk students and provide guidance that is targeted and most effective.

Identify ways to facilitate student bonding outside of courses

One of the primary desired outcomes of the aligned course intervention was to facilitate the development of social groups that would support each other academically, and presumably also in terms of social support. Given the logistical complexities grouping students in classes, we suggest finding additional approaches for promoting student bonding. For example, freshmen could be placed into groups of 8 to 10 students who would be expected to meet periodically over the course if their freshman year. The meetings could be facilitated by an upperclassman who would ensure that each session provided opportunities to share concerns, suggest ideas, provide information, and promote mutual support. This kind of effort would also be an effective way to continually gather information regarding the factors that are hindering or supporting student success and thriving to better ensure that JCU's resources are aligned with students' needs.

Provide more information about services to both students and instructors

Based on discussions with administrators, it appears that instructors will sometimes make incorrect referrals for their students. From the student survey, most students reported that they believe JCU provides adequate support services, but some students reported not knowing how to access the services or that the services did not meet their specific needs. We recommend that JCU engage in some efforts to determine if and why services are being underutilized and

what can be done to address any gaps including a lack of knowledge about where students should go for specific services. It appears that some students in communication department might be looking into the issue as part of their capstone project to see if JCU is using the right means to communicate with students about its services. This certainly seems like an option worth exploring.

Communicating the results across JCU

A few instructors in the focus groups mentioned the importance of communicating what has been learned through this project and what JCU plans to do moving forward. We recommend that the team put together a plan to communicate the benefits of the program and describe in as much detail as possible plans for moving forward in JCU's efforts to identify at-risk students and to ensure that all students receive the guidance they need to not only succeed academically and graduate but also thrive at JCE and develop as adults. It is recommended that developing a core presentation to deliver a consistent message across JCU but also tailored modules to be delivered to specific departments or groups particularly with regards to next steps and any follow-up discussion about the implications of those next steps for that department or group.

Conclusion

Limitations of the study. Beyond the empirical findings of the study, we wonder about the process, and what, if anything might be done differently? In hindsight perhaps it would have been effective if the teaching partners could visit each other's class to discuss the assignments allowing the students to observe and participate in those lectures. Also, if assignments, or projects were more closely aligned in the syllabi using some assessment rubric for the linked courses, there may have been a clearer observation of the effects of the intervention.

Future directions for this research. From the perspective of population demographics, in many ways, the John Carroll University student population is homogenous. Not only in the typical distributions of gender, race, or ethnicity, but also in terms of general characteristics of the nature and quality of students that attend JCU. Every institution has its own culture and climate that also play roles in retention and persistence efforts. So, we wonder about the differential effects of the predicted academic difficulty intervention model in more heterogeneous student populations. We also wonder about how efficacious this intervention model might be in more targeted at-risk populations, such as among underrepresented students in STEM disciplines.