Practical Assessment, Research, and Evaluation

Volume 27 Article 21

2022

Building Intrapersonal Competencies in the First-Year Experience: Utilizing Random Forest, Cluster Analysis, and Linear Regression to Identify Students' Strengths and Opportunities for Institutional Improvement

Marilee Bresciani Ludvik
San Diego State University

Shiming Zhang
The University of Texas Health Science Center at Houston

Sandra Kahn
San Diego State University

Nina Potter
San Diego State University

Lisa Richardson-Gates
San Diego State University

See next page for additional authors

Practical Assessment, Research & Evaluation

A peer-reviewed electronic journal.

Volume 27 Number 21, August 2022 ISSN 1531-7714

Building Intrapersonal Competencies in the First-Year Experience: Utilizing Random Forest, Cluster Analysis, and Linear Regression to Identify Students' Strengths and Opportunities for Institutional Improvement

Marilee Bresciani Ludvik, *San Diego State University*
Shiming Zhang, *The University of Texas Health Science Center at Houston*
Sandra Kahn, *San Diego State University*
Nina Potter, *San Diego State University*
Lisa Richardson-Gates, *San Diego State University*
Stephen Schellenberg, *San Diego State University*
Robyn Saiki, *San Diego State University*
Nasima Subedi, *University of Texas Arlington*
Rebecca Harmata
Rey Monzon, *San Diego State University*
Randy Timm, *San Diego State University*
Jeanne Stronach, *San Diego State University*
Anna Jost

In seeking to close equity gaps within a first-year student seminar course, course designers leveraged emerging research on intrapersonal competency cultivation, known to significantly predict student success across diverse students (NAS, 2018). After re-designing the course to intentionally cultivate specific intrapersonal competencies, researchers set out to explore how well the course closed historical institutional equity gaps as measured by end-of-term GPA. Over four years of data collection and course refinement, traditional regression analysis were useful for informing course improvements that resulted in the closing of some equity gaps. However, students were still being placed on academic probation and certain identities of students were over-represented in academic probation numbers. As such, the team utilized random forest, cluster analysis, and then regression analysis that allowed them to focus improvement efforts on a cluster of students that would have otherwise remained unidentified through traditional analysis measures.

Background

There is an increasing awareness that intrapersonal competencies play a vital role in postsecondary student success, particularly for underrepresented students. The National Academies of Sciences (2017, 2018) has repeatedly compiled evidence to show that when educators spend time cultivating students' intrapersonal competencies, such as metacognitive awareness, psychological well-being, sense of belonging, prosocial behaviors, and other such employer-desired skill sets, then students will be more likely to persist toward degree attainment. However, these same scholars (NAS, 2017, 2018) also stress that context and culture influence students' abilities to cultivate these competencies.

Berryman et al. (2013) shared key messages from an analysis of narratives discussing cultural responsiveness. Their findings revealed that culturally responsive inquiry linked to previous research, while researchers "critically interrogated their own ways of knowing, resisting traditional ways of doing research, reframing researcher bias as unique subjectivities and valuing the participants and one's invitation to do research". This work embodied these key narratives of cultural responsiveness in several ways. First, this work is linked to previous research on intrapersonal competencies. We disaggregated our data and involved a large research team driven to become more inclusive and more culturally responsive in our own research. We sought to honor the kinds of histories and ethnicities that this institution serves, and the intersectionality between the ethnicities and the intrapersonal competencies. Berryman et. al also suggested that one of the implications of their research was "using culturally responsive methods to undertake collaborative participatory inquiry", to improve students experience, which was an outcome of this study, (2013).

Furthermore, Trainor and Bal (2014) created a 15-item rubric to help evaluate the cultural responsiveness of research. All the measures of the rubric are scored out of 3 and Trainer and Bal (2014) further score one of the items of the rubric "analysis and interpretation" according to the students' competencies or the lack of those in relationship to their living conditions, demographic characteristics, physical, socio cultural, and historical context. Other factors that affect a student's competency while in college are "organizational structure and power distribution", (Trainor and Bal, 2014). Recognizing the importance of intrapersonal competencies for student success and the research behind it, the researchers of this study has tried to analyze how intrapersonal competencies are determinant of the success of the diverse student population at their HSI.

While research that informs student success initiatives is important, analytical methods are needed to ascertain whether such student success efforts, such as intrapersonal competency cultivation, are being developed and within which students. In addition, given limited institutional resources, it is important to note whether such student intrapersonal competency cultivation is contributing toward student success measures, such as end-of-term GPA (EOT GPA). Intrapersonal competency measures may serve as critical equity indicators given their potential to reveal disparities when disaggregated by various demographics (Bresciani Ludvik, 2018a; Bresciani Ludvik et al., 2021). To better understand intrapersonal competency measures and their relationship to EOT GPA to inform course improvement decisions, scholars have stressed the importance of implementing a variety of analytical methods (NAS, 2018).

This study sought to explore whether course designers could learn more personalized and nuanced opportunities for supporting specific students' intrapersonal competency development in a 1-unit course and close historic institutional equity/achievement gaps as measured by end-of-term GPA. Through the leveraging of random forest, cluster analysis, and linear regression, the inter-disciplinary team wondered whether this type of analysis would provide course designers with more information than traditional linear regression. And they wondered whether such information could inform specific curriculum improvements that could close equity/achievement gaps as measured by intrapersonal competency scores as well as EOT GPA, particularly if disaggregated sample sizes are small.

Traditionally, multivariate linear regression methods are used by educators for evaluating and exploring relationships between students' performance on multiple measures across identities and their intersections as well as across different educational experiences and interventions (Wells et al., 2015). However, statistical significance in specific learning competency cultivation measures and their correlations with institutional performance indicators may be difficult to identify for identity groups of small sample sizes (Wells & Stage, 2014). Related studies leveraging traditional linear regression address improvements in academic resilience (Akos & Kretchmar, 2017; Goyer et al., 2021), social support (Altermatt, 2019; D'Amico Guthrie & Fruiht,2020; Katrevich & Aruguete, 2017), perceived institutional commitment (Brecht & Burnett, 2019; Hepworth et al., 2018), metacognitive learning strategies (Chevalier et al.,2017; Trinidad, 2019), belonging (Goyer et al., 2021, Hepworth et al., 2018), and other psychosocial factors (D'Amico Guthrie & Fruiht,2020; Heller & Cassady, 2017; Sass et al., 2018).

Each of these cited works relied on regression to predict student outcomes, with the exception of one (Sass et al., 2018), which used structural equation modeling.

Lingjun, et al (2018) posited the benefit of using tree-based machine learning algorithms over traditional regression models for higher education institution leaders to use as a solution when regression assumptions are often violated in big data applications. While our data sample is not "big data," we wondered whether using a random forest approach might be useful to identify potential missed variables of importance. Bowers (2010) illustrated the benefit of using cluster analysis on PK-12 data to increase the accuracy of predictions of students who would not persist. Yu et al., (2018) suggested that "among many machine learning methods, bagging is popularly utilized to decrease the variance whereas boosting is widely used to weaken the bias in the process of building a predictive model" (p.3). Therefore, we chose to utilize random forest and cluster analysis to differentiate students into groups to identify course design effectiveness and its influence on specific institutional performance indicators (Singh, Sharma, & Sharma, 2012).

With a desire to leverage the NAS research and apply it in a quasi-experimental manner using random forest, cluster analysis, and regression analysis, a team of scholars and practitioners re-designed a 1-unit, credit/no-credit seminar course for first-year, first-time students intended to promote the development of metacognitive awareness, aspects of psychological well-being, sense of belonging, and self-compassion as a proxy for prosocial behavior. The seminar course involved a flipped classroom design with pre-recorded mini-lectures focusing on the importance of growing these specific skill sets; students watched these videos prior to their in-class seminar sessions. The seminar sessions focused on interactive in-class assignments that applied these skills as well as invitations to reflect on the application of these skills in other contexts (Bresciani Ludvik, 2019).

Several formative assessments were utilized to assess students' ability to apply the skills in class; for example, reflective journal prompts were used to evaluate the degree to which students could reflect upon the out-of-class applications of the curriculum. A key source of data – the one that was used in this particular study - included a set of inventories selected to measure intrapersonal competency skill development and, in particular, how each skill correlated with or predicted desired institutional performance indicators, such EPT GPA that often reveal equity gaps when disaggregated by identities. Table 1 describes the intrapersonal competency inventories used in this analysis, the student success behavioral aspects of each intrapersonal competency they measure, their subscales, the inventory citation, and the reliability for our sample population for the end-semester deployment.

Following IRB exemption approval, these inventories were deployed as a single Qualtrics-based survey at the beginning and end of the semester via personalized in-class email to each first-year, first-time student enrolled at the HSI inviting them to voluntarily participate in the quasi-experimental study.

Sampling

This HSI institution had previously disaggregated institutional performance data (cum GPA, term-to-term persistence, and academic probation rates) which revealed achievement gaps in various identity groups and their intersections. To increase the size of each identity group known by this institution to have historically experienced an equity gap, the current study sample included the end-of-semester inventory dataset (hereafter "post-assessment") from participants who enrolled in the standard seminar course delivered in variations designed to better serve individual students in their first-semester experience, regardless of identity (e.g., commuting students who were a part of a Commuter Life Learning community, an adapted version of the seminar course embedded into a Residence Life Learning Community, students who were co-enrolled in a leadership development course, and various other STEM-related Learning Communities). The complete post-assessment dataset includes 785 diverse first-year, first-time students characterized by 61 demographic or academic achievement independent variables. Post-assessment data was specifically selected to focus on students' intrapersonal skills at the end of the semester, after the different intended experiences of the intervention took place, and potentially ascertain course effectiveness across these various groups and its relationship to end-of-term (EOT) cumulative GPA. While we had hoped

Table 1. Inventories Used in This Analysis

Intrapersonal Competency	What the Inventory Measures	Subscales	Inventory Citation	Reliability Data (Cronbach Alpha)
Sense of Belonging	Measures the extent the student reports a sense of belonging among peers, faculty, classroom, and overall affective state. Includes twenty-six items and four subscales.	Perceived Peer Support, Perceived Faculty Support, Perceived Classroom Comfort, Perceived Isolation	Hoffman, M., Richmond, J., Morrow, J., and Salomone, K. (2003). Investigating 'Sense of Belonging' in first-year college students. *Journal of College Student Retention*, 4 (3), 227-256.	0.85
Metacognitive Awareness in Placement as a proxy for Conscientiousness and Academic Self-Efficacy	Assesses awareness, planning and control of thought processes, and self-regulated learning skills. Includes fifty-two items classified by eight types of cognitive knowledge.	Declarative Knowledge, Procedural Knowledge, Conditional Knowledge, Planning, Information Management Strategies (not used), Comprehension Monitoring, Debugging Strategies, Evaluation	Schraw, G., & Dennison, R.S. (1994). Assessing metacognitive awareness. *Contemporary Educational Psychology, 19,* 460-475.	0.88
Psychological Well-Being as a proxy for Planning, Emotional Regulation, and Positive Future Self	Measures dynamic aspects of well-being in six dimensions: self-acceptance, quality ties to others, autonomy in thought and action, management of complex environments, pursuit of meaningful goals, and a sense of purpose. Includes 42 items.	Autonomy, Environmental Mastery, Personal Growth, Positive Relations with Others, Purpose in Life, Self-Acceptance	Ryff, C., & Keyes, C. (1995). The structure of psychological well-being revisited. *Journal of Personality and Social Psychology*, 69, 719–727.	0.93
Self-Compassion as a proxy for prosocial goals and values	Measures kindness and understanding, rather than harsh self-criticism, toward oneself in instances of pain and failure. Self-compassion is significantly correlated with positive mental health and life satisfaction. Includes twelve items grouped into six subscales.	Self-Kindness, Self-Judgment, Common Humanity, Isolation, Mindfulness, Over-identification	Raes, F., Pommier, E., Neff, K. D., & Van Gucht, D. (2011). Construction and factorial validation of a short form of the Self-Compassion Scale. *Clinical Psychology & Psychotherapy*, 18, 250-255.	0.85

Intrapersonal Competency	What the Inventory Measures	Subscales	Inventory Citation	Reliability Data (Cronbach Alpha)
Perceived Stress	Measures the degree to which situations in one's life are appraised as stressful. Items are designed to tap how unpredictable, uncontrollable, and overloaded respondents find their lives. Includes 10 items.		Cohen, S., Kamarck, T., & Mermelstein, R. (1994). Perceived Stress Scale.	0.76
Leadership Development	Measures student self-reported perceptions of mastery of learning outcomes for undergraduate leadership development course. Includes 14 items.		Timm, R., & Gates, L. (2018). Measure of Self-Assessed Learning. Department of Administration, Rehabilitation, and Postsecondary Education, San Diego State University.	0.90

to compare the effectiveness of the course with non-course participants, all participants who completed the survey also completed a variation of the course, while the learning community that was also associated with the course varied. In other words, the course itself remained the one constant within the varied out-of-class experiences provided by each learning community. As such, we sought to identify students for whom the course was working well and determine whether the cultivation of intended intrapersonal competencies was closing existing equity gaps as measured by EOT cumulative GPA.

Methods

Previous Analysis

In analyzing the effectiveness of this course previously (fall 2017 and 2018), the interdisciplinary team discovered, through t-tests and linear regression analysis, which identities needed something different than the institution was previously providing to improve end-of-term GPA (EOT GPA). The analysis findings, along with other formative assessments and open-ended survey results, provided useful information for course designers and learning communities to adjust their learning experience design. However, in fall 2019, the significant differences in intrapersonal competency cultivation by identity group lost its significance. While the interdisciplinary team was grateful for such apparent closing of equity gaps as measured by intrapersonal competencies gains and their relationship with EOT GPA, there remained a question about whether this course was truly successful as students who had participated in the course were still earning EOT GPA that placed them on probation. However, this group of students was not aligning with previously identified institutional equity gaps. As such, we needed another way of analyzing the data to inform decisions for improvement. We needed to find out whether there was some other identifiable variable that might help us become more proactive in supporting student success.

Analysis Flow

The analysis flow for this study is presented in Figure 1. A supervised random forest for regression algorithm was initially applied to EOT GPA to identify the proximity matrix and determine the relative importance of the large number of independent variables. A subsequent clustering analysis based on the partitioning around medoids (PAM) algorithm was then used to group students into pre-determined sets of two and three clusters. Within each cluster group, we then explored the strength of the relationships of the important variables identified by the supervised random forest and EOT GPA using regression analysis. All statistical analysis was performed in R V.3.6.1 (RStudio, 2021).

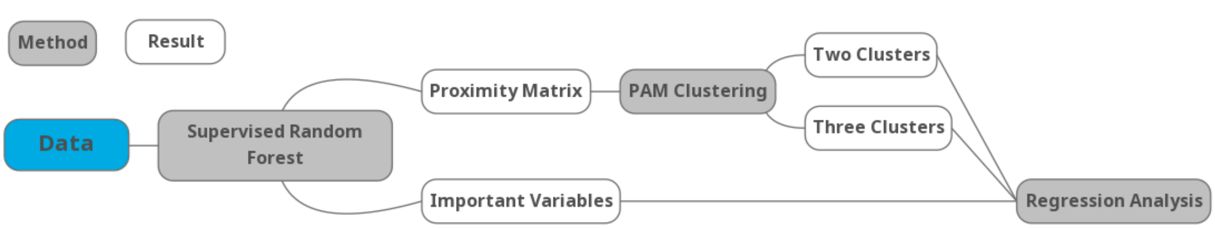
Study Design

The initial step involved conducting a random forest analysis to identify which factors were important for predicting EOT GPA outcomes. Random forest is a flexible machine learning method that generates a series of decision trees through a bagging algorithm, and together these trees create a forest of classifiers that supports a particular classification (Breiman, 2001). The approach has been widely used for classification and regression tasks in many disciplines (e.g., medical science, biology, psychology, and education); for example, O. Santos et al. (2019) used a Random forest approach to predict student attrition for certain courses with an accuracy of 70%. As a methodology, the random forest algorithm allows for analysis without the need for transformations of non-linear variables, which is typically necessary with more commonly applied methodologies such as multiple linear regression. Importantly, random forest also generates a standard ranking of the overall relative importance of independent variables (Petkovic et al., 2016), whereas multiple linear regression does not inherently produce such rankings and no agreed upon standard method exists for their generation (Thomas et al., 1998).

The reported relative importance of independent variables generated by the random forest analysis applies to the sample population of students, as such it may mask potential heterogeneity among student sub-populations. To explore this potential, as a second step we implemented a clustering analysis to group students. This ensemble method of random forest followed by cluster analysis has been successfully used to resolve a given population into subgroups with significantly different explanatory factors; for example, Shi et al. (2005) successfully grouped patients with tumors into clinically meaningful clusters based only on their protein expression profiles. Applying this same approach to our data, we sought to successfully separate our students into different clusters and discover significant differences between the clusters on a multitude of variables, including those that would normally mask heterogeneity. Our intention was to reveal within and across learning community differences as well as potentially identifying equity gaps.

The third and final step involved using traditional multiple linear regression analysis as a mean to explore and estimate the strength of the relationships among independent variables identified in the random forest analysis with respect to end-of-semester GPA. While random forest analysis identifies factors that predict selected outcomes, it does not provide an estimate of the strength of the relationships in comparison with one another that is like regression weights. More specifically, in our study, after clustering students into different groups and identifying factors that predicted end of term GPA within the clusters, we used a traditional multiple regression analysis to estimate the strength of the relationship between the variables to GPA within the clusters (See Figure 1).

Figure 1. Visualization of relationships between processes. The analysis process has three steps, where methods are displayed in gray boxes and the results from the previous process are in white boxes.



Analysis

For the first step of the analysis, the random forest was implemented by growing many trees based on a random vector, where such vectors serve as a tree predictor with numerical values (Breiman, 2001). The random forest predictor was then used to calculate mean-squared generalization error, which helped compute the out-of-bag error rate. Meanwhile, the out-of-bag data determined the variable importance for each feature from the data set. As mentioned, the primary goal of the study was to explore the effectiveness of intrapersonal competency cultivation, and its correlation with or prediction of end-of-semester GPA for students with varying backgrounds and demographics. Without the random forest method, some variables that relate to the dependent variable of GPA would have been ignored, as is often the case with traditional inferential analytics.

The random forest analysis does not only provide variable importance but also calculates a proximity matrix which measures the 'nearness' or 'adjacency' between pairs of subjects. After all such distances are measured, their values are standardized and stored in a proximity matrix, and this matrix can represent dissimilarity by subtracting their values from one. This data was then used to create clusters by sampling at random from the univariate distribution of the original data. When clustering using random forest, the matrix generated from the random forest creates the clusters. More specifically, for clustering, the partitioning around medoids (PAM) method took dissimilarity (1-proximity) into the measurement of class partitioning. (R, Library: cluster). The purpose of the PAM algorithm is to track k, which represents the number of indicative objects or medoids within the data (Kassambara, 2017). When k medoids are located, the number of clusters will also be assigned around the medoids. To determine k, this study utilized R using package called 'NbClust', which takes Silhouette index that indicates dissimilarities of subjects within each cluster (Charrad et al., 2014; R Packages: NbClust, 2014). The value of the Silhouette index is related to k, an optimal number of clusters (k) generally is preferred when the Silhouette index is high (Kaufman and Rousseeuw, 1990). For the current data set, k = 2 and k = 3 groupings were recommended for consideration, since the top two highest Silhouette index scores when k = 2 and k = 3 were almost identical.

Multiple regression analysis is often used to estimate the strength of the relationships among variables (Neter, 1996). Once subjects are grouped into recommended clusters, the correlations among important variables and regression coefficients were compared to further explore the importance of each of the identified variables for each group. Thus, for the n-clusters identifies (k = n), the data was disaggregated into the n suggested groups and n multiple linear regression equations were established, compared, and checked across each group.

For our study, considering the Silhouette index scores for k = 2 and k = 3 were almost identical, selecting either situation would be representative enough. By checking and comparing the distribution of subjects within each cluster for these two cases, k = 2 is a special case of k =3. Thus, the following results would focus more on the k= 3 case, as it contains more groups which potentially includes more inference. We also chose to use k=3 to align with our intention to identify any students that needed additional intrapersonal competency cultivation support. Thus, using k=3, three distinct clusters of students and therefore three multiple linear regression equations were established, compared, and checked crossing each group.

Results

Following the designated process in Figure 1, the importance plot (Figure 2) indicated that in addition to academic measures such as incoming GPA and demographic variables such as ethnicity, intrapersonal competency variables such as environmental mastery, purpose in life, perceived stress, personal growth, etc., were predictive of EOT GPA. The top twelve most important variables from the random forest analysis (see Table 2) were considered as potential predictors for the regression analysis process. Interestingly, the learning community grouping was the 21st variable listed. As such, our quasi-experimental design was no longer in play.

Utilizing the proximity matrix from the random forest, subjects from the data set were identified using the PAM clustering method which divided them into two or three groups (Figure 3). Across the different clusters, institutional performance indicators and many other variables differed. For example, when k = 3, the average GPA among those three groups differed as illustrated in the boxplot (Figure 4). An Analysis of Variance (ANOVA) for the three cluster groups indicated the difference in GPA was statistically significant differences , $F(2, 782) = 578.6$, $p<.001$.

Table 3 shows the correlation between a selection of the variables identified from the Random forest and end-of-term cumulative GPA for the sample as a whole and for the three clusters. The results show that the relationship between these variables and GPA differed across the clusters. We note, with particular interest, that incoming GPA and incoming units did not significantly correlate with GPA for students in Cluster 2. To explore additional differences between the groups, we compared the averages and distributions of the 12 most important variables identified from the random forest across the three

Figure 2. Variable importance plot indicating the strength of the effectiveness of each variable

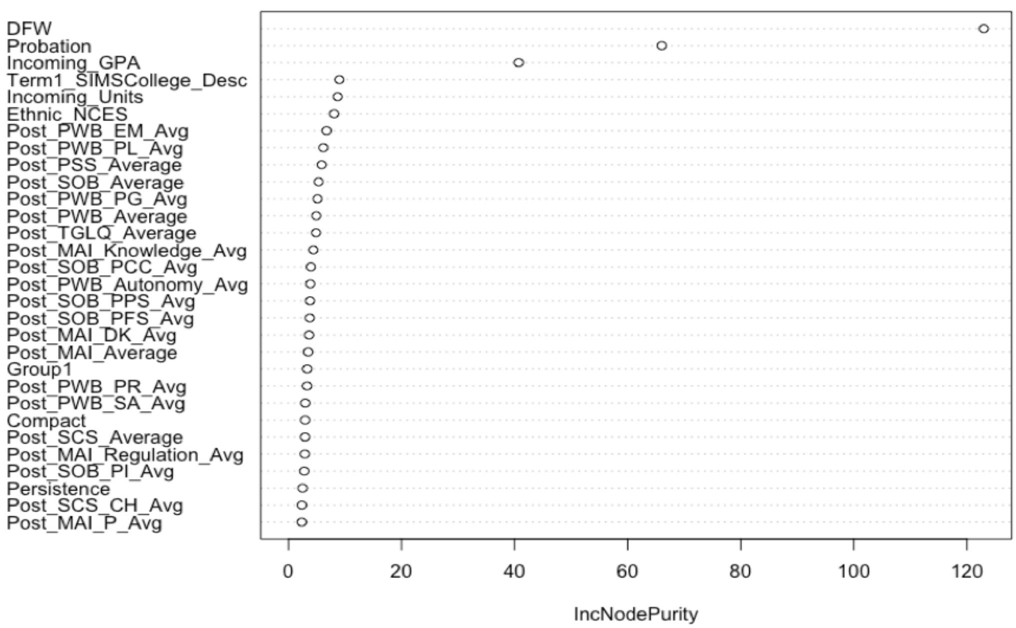
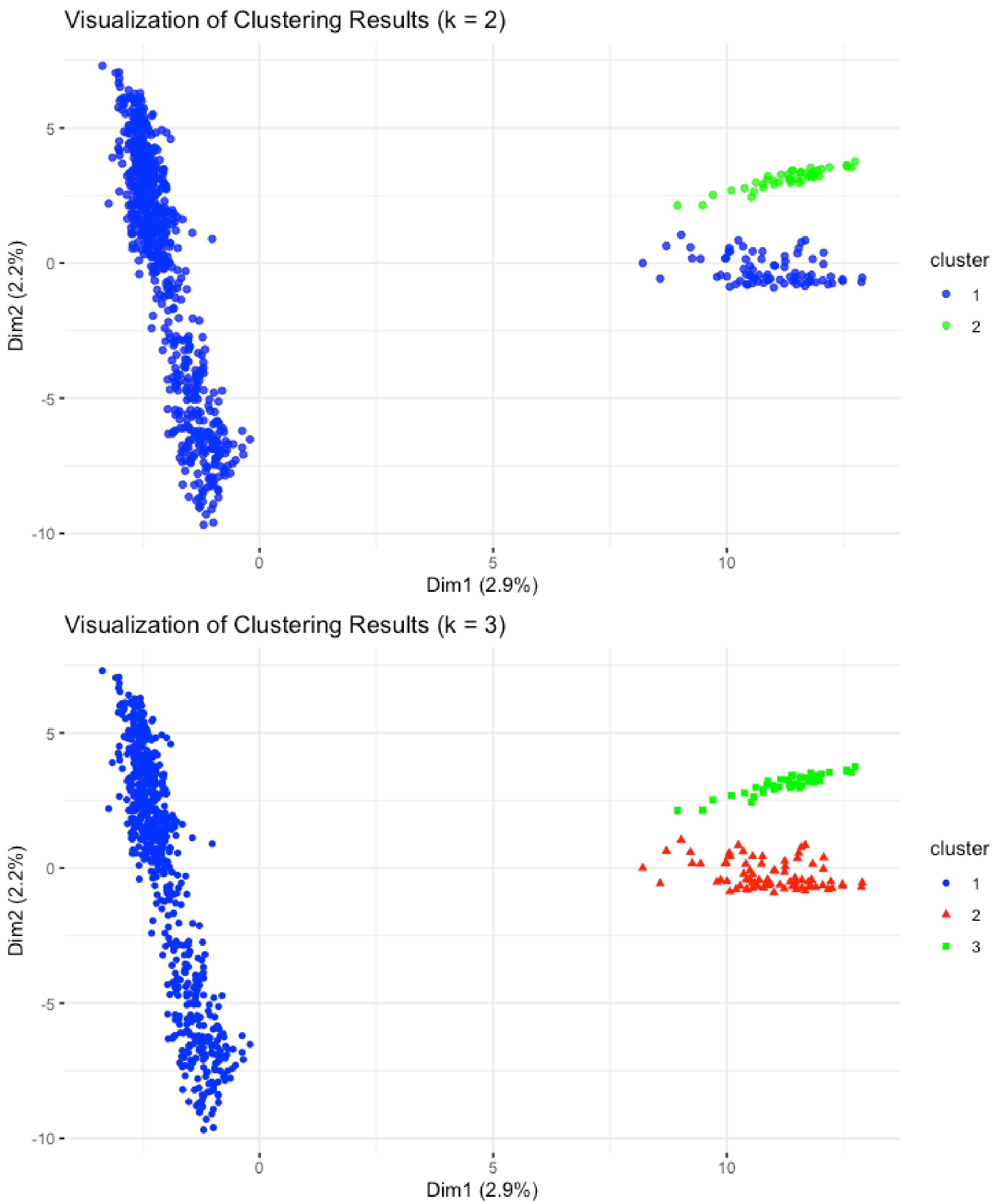


Table 2. Top 12 Important Features/Top 10 Non-Institutional Performance Variable Importance

Variable Name	Variable Description
1. DFW	Dichotomous variable indicating whether student received D, F, or withdrawal in first semester
2. Probation	Dichotomous variable indicating whether the student was on academic probation at the end of the first semester
3. Incoming GPA	High School GPA
4. Term1 College	The college student was enrolled in based on their major
5. Incoming Units	The number of college credits the student had when they started their first semester
6. Ethnic NCES	Student self-reported race/ethnicity using NCES codes
7. Post PWB EM	Environmental Mastery Subscale
8. Post PWB PL	Purpose in Life Subscale
9. Post PSS	Perceived Stress
10. Post SOB	Overall Sense of Belonging
11. Post PWB PG	Personal Growth Subscale
12. Post PWB	Overall Psychological Well-Being

Figure 3. Cluster plots showing k= 2 and k = 3 cases. The cluster plot presents how subjects are distributed within each group. k = 2 is a special case of k =3, Cluster 2 (red) of k = 3 case was included in Cluster 1 (blue) of k = 2 case.



groups. Continuous variables including GPA, incoming units, and scores on the inventories were compared using ANOVA. Distributions on nominal scales, such as ethnicity and gender, were compared using Chi-square and Fisher exact tests.

Table 4 provides demographic data for each cluster. Distributions across the three groups were compared using Chi-square tests or Fisher exact tests when the expected values for any cells was less than five.

Figure 4. Boxplot of GPA for three-cluster case showing significant decreasing trend for the average GPA from Cluster 1 to Cluster 3.

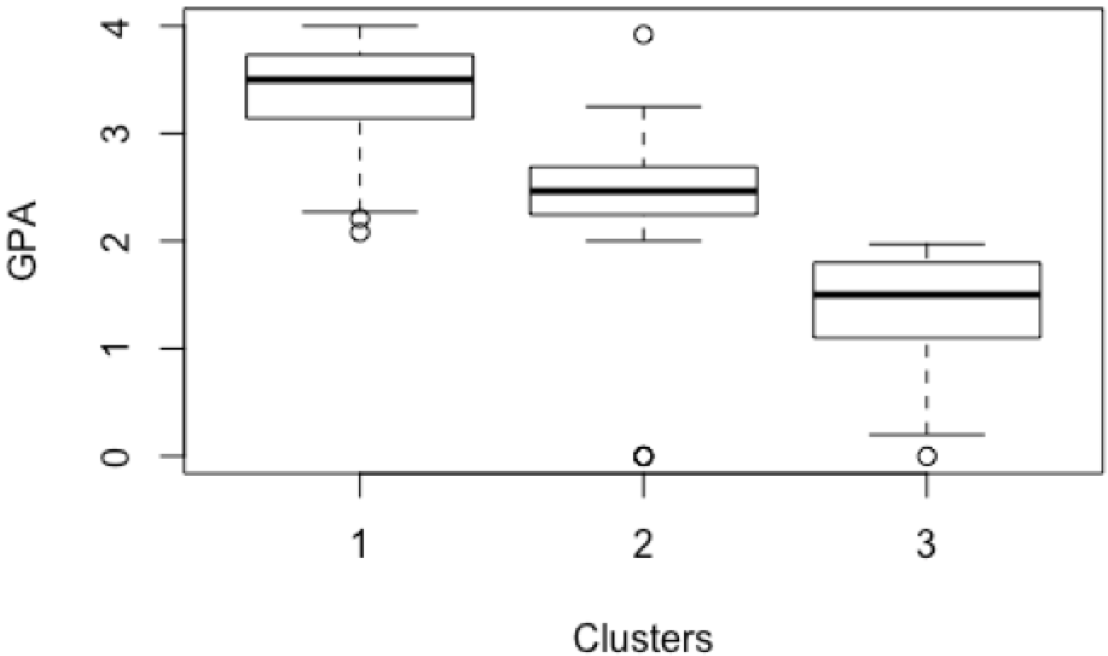


Table 3. Correlation to End of Term GPA for Complete Dataset and Three Clusters

Measures	Full Dataset (N=785)	Cluster 1 (N=663)	Cluster 2 (N=78)	Cluster 3 (N=44)
Incoming GPA	.495**	.444**	.148	.328*
Incoming Units	.245**	.249**	.197	.099
Perceived Stress	-.238**	-.151**	-.209	-.099
Psychological Well Being				
Purpose in Life	.231**	.167**	.262*	.159
Environmental Mastery	.241**	.138**	.282*	.083

*Correlation with End of Term GPA is significant at the 0.05 level (2-tailed). **Correlation with End of Term GPA is significant at the 0.01 level (2-tailed).

Students were distributed relatively evenly by first-generation status, intervention group/learning community grouping, housing, leadership course, STEM major and college. However, significant differences in distribution exists between the clusters for gender ($\chi^2(2,785)=15.482$, $p<.001$), race/ethnicity NCES categories ($p=.008$), underrepresented minority (URM) ($\chi^2(2,785)=18.769$, $p<.001$), and Pell Grant recipient status ($\chi^2(2,785)=11.233$, $p<.001$). Cluster 1 included a disproportionately high number of females, non-URM, non-Hispanic/Latinx, and non-Pell Grant recipients. Cluster 2 had a disproportionately high number of URM, Hispanic/Latinx, Pell Grant recipient, and female students. Cluster 3 included a disproportionately high number of Pell Grant recipient and male students.

Since the analysis represented in Figure 3 shows evidence of clear boundaries among these three clusters (k = 3) and Table 4 illustrates clear demographic differences between the clusters, we needed to explore how these three clusters differed based on the top 12 variables identified by the random forest analysis. This, we hoped, would provide us the important information of how we could repair inequities for specific identities of the students we serve. Table 5 illustrates the significant differences on continuous variables between the clusters. Incoming GPA and incoming units, both typical academic predictors, are significantly different across the clusters. The same is true for end-of-term GPA, the institutional performance indicator that we were trying to influence toward closing existing equity gaps. Also notable are the significant differences between the groups with respect to students' intrapersonal competencies of environmental mastery (i.e., the ability to navigate the university environment with confidence), purpose in life, perceived stress, sense of belonging, personal growth, and overall psychological well-being. The recognition of such differences reveals an opportunity and obligation, as an institution, to repair inequities through focusing on cultivating these skills among higher proportion identity groups represented in Clusters 2 and 3.

Table 4. Student Demographic Distributions for Three Clusters (k=3)

Demographic Category	Cluster 1		Cluster 2		Cluster 3	
	n	%	n	%	n	%
Race/Ethnicity (NCES)[a]						
International student	12	1.8%	2	2.6%	0	0.0%
Black/African American	18	2.7%	4	5.1%	0	0.0%
American Indian/Alaskan Native	1	0.2%	0	0.0%	0	0.0%
Asian/Pacific Islander	120	18.1%	16	20.5%	7	15.9%
Hispanic/Latinx	195	29.4%	37	47.4%	19	43.2%
2 or more races/ethnicities	55	8.3%	6	7.7%	6	13.6%
White	253	38.2%	12	15.4%	11	25.0%
Other/Decline to state	9	1.4%	1	1.3%	1	2.3%
Underrepresented Minority[b]						
Yes	328	49.5%	58	74.4%	27	61.4%
No	335	50.5%	20	25.6%	17	38.6%
Gender[c]						
Female	445	67.1%	47	60.3%	17	38.6%
Male	218	32.9%	31	39.7%	27	61.4%
Pell Grant recipient[d]						
Yes	173	26.1%	32	41.0%	18	40.9%
No	490	73.9%	46	59.0%	26	59.1%
First-generation student						
Yes	238	35.9%	37	47.4%	19	43.2%
No	425	64.1%	41	52.6%	25	56.8%
STEM Major						
Yes	210	31.7%	26	33.3%	12	27.3%
No	453	68.3%	52	66.7%	32	72.7%
College						
Business	62	9.4%	8	10.3%	9	20.5%
Arts and Letters	65	9.8%	10	12.8%	3	6.8%
Education	19	2.9%	2	2.6%	1	2.3%
Engineering	92	13.9%	11	14.1%	5	11.4%
Health and Human Services	94	14.2%	5	6.4%	3	6.8%
Professional Studies and Fine Arts	112	16.9%	14	17.9%	6	13.6%
Sciences	150	22.6%	19	24.4%	11	25.0%

Demographic Category	Cluster 1		Cluster 2		Cluster 3	
	n	%	n	%	n	%
Undeclared	69	10.4%	9	11.5%	6	13.6%
Intervention Group						
GEN S 100A	79	11.9%	13	16.7%	5	11.4%
GEN S 100B	34	5.1%	3	3.8%	2	4.5%
Commuter	48	7.2%	10	12.8%	5	11.4%
Campus Resident	384	57.9%	35	44.9%	25	56.8%
ARP 296	12	1.8%	3	3.8%	1	2.3%
Other	106	16.0%	14	17.9%	6	13.6%
Housing						
Campus Resident	384	57.9%	35	44.9%	25	56.8%
Not Campus Resident	279	42.1%	43	55.1%	19	43.2%

[a] Fisher's exact test, $p=.008$.
[b] χ^2 $(2,785)=18.769$, $p<.001$.
[c] $\chi^2(2,785)=15.482$, $p<.001$.
[d] $\chi^2(2,785)=11.233$, $p=.004$.

Table 5. Comparison of Average Scores Between Three Cluster Groups

Measure	Cluster 1 (N=633)		Cluster 2 (N=78)		Cluster 3 (N=44)		One-way ANOVA
	M	SD	M	SD	M	SD	
End of Term GPA	3.41	0.41	2.38	0.65	1.36	0.54	$(F(2,782)=578.61, p<.001)$
Incoming GPA	3.88	0.27	3.67	0.30	3.52	0.35	$(F(2,782) = 52.64, p<.001)$
Incoming Units	15.39	12.98	11.01	12.96	9.30	10.54	$(F(2,782) = 8.04, p<.001)$
Perceived Stress	2.13	0.55	4.29	0.74	3.72	0.80	$(F(2,782) = 14.38, p<.001)$
Sense of Belonging	3.30	0.65	3.35	0.68	3.05	0.68	$(F(2,782) = 3.24, p=.040)$
Psychological Well Being	4.18	0.64	4.10	0.67	3.74	0.69	$(F(2,782) = 9.96, p<.001)$
Environmental Mastery	2.85	0.80	3.54	0.89	3.27	0.88	$(F(2,782) = 14.08, p<.001)$
Purpose in Life	4.35	0.82	4.29	0.74	3.72	0.80	$(F(2,782) = 12.59, p<.001)$
Personal Growth	4.62	0.76	4.63	0.79	4.09	0.76	$(F(2,782) = 10.31, p<.001)$

To prioritize limited institutional capacity and resources toward course improvement, regression analyses were explored for each cluster to ascertain what specifically we needed to focus upon improving for whom. The top 12 most important variables, as identified by the random forest analysis, were entered into a linear regression analysis with GPA as the dependent variable. Some of the variables, such as incoming GPA, DFW, and incoming units were highly correlated with one another, so we chose to include only one—incoming GPA—to avoid issues of collinearity. We also excluded the PWB overall score given the inclusion of two of the subscales from the PWB scale. A separate analysis was run for each group and the regression coefficients were compared across groups. A summary of the results is presented in Table 6. The regression analysis results indicated that the relationship between the intrapersonal competencies and GPA differed for specific students within different clusters.

Comparing the data amongst these clusters, it is important to note that, for Cluster 1, perceived heightened stress, enrollment in the College of Engineering, and identity with Hispanic/Latinx ethnicity were negative predictors of GPA. Positive predictors of GPA for Cluster 1 involved enrollment in the College of Professional Studies and Fine Arts, the College of Education, the College of Arts and

Table 6. Summary of Forward Stepwise Regression Analysis with EOT GPA as the Dependent Variable

Variable	B	β	t	p
Cluster 1 (N = 663, Average Incoming GPA = 3.41, Adjusted R^2 = .282				
Incoming GPA	.687	.447	13.029	<.001
Ethnicity = Hispanic/Latinx (N=195)	-.164	-.181	-5.424	<.001
College = Engineering (N=92)	-.101	-.085	-2.425	.016
Perceived Stress	-.077	-.103	-2.947	.003
College = Professional Studies/Fine Arts (N=112)	.124	.113	3.197	.001
Ethnicity = International Student (N=12)	.199	.064	1.884	.060
College = Undeclared (N=69)	.138	.102	2.921	.004
College = Education (N=19)	.207	.084	2.497	.013
College = Arts & Letters (N=65)	.039	.078	2.194	.022
PWB Purpose in Life Subscale	.039	.078	2.194	.029
Cluster 2 (N = 78, Average Incoming GPA = 2.38, Adjusted R^2 = .259)				
Ethnicity = Other/Not State (N = 1)	-2.459	-.430	-4.34	<.001
PWB Environmental Mastery Subscale	.192	.263	2.669	.009
Incoming GPA	.468	.216	2.178	.033
Cluster 3 (N = 44, Average Incoming GPA = 1.36, Adjusted R^2 = .087)				
Incoming GPA	.506	.328	2.253	.030

Letters, or identifying as undecided. In addition, positive predictors of GPA included identifying as an international student and having higher scores on the purpose in life measure—a proxy for the Purpose in Life intrapersonal competency. In essence, purpose in life was the only positive predictor of GPA for this already successful group of students—as defined by GPA.

For Cluster 2, the typical academic predictor of incoming GPA was a positive predictor of GPA, as was environmental mastery—a proxy for self-regulation. The negative predictor of GPA for this group was identification as an ethnicity that was labeled as "other."

Cluster 3's only predictive variable in this scenario was that of the traditional incoming GPA.

Discussion and Conclusions

We set out to examine the relationship between intrapersonal competency development and the student success performance indicator of EOT GPA in a first-year experience course by deploying random forest, cluster analysis, and regression analysis - methods not commonly used in educational settings (He et al., 2018; Yu et al., 2018). The results revealed that the first-year experience course that focused on cultivating intrapersonal competencies predicted EOT GPA for many but not all students. We chose this methodology to see whether we could identify specific students whose identities (as a proxy for culture) may be influencing gains or losses in certain intrapersonal competencies intended to be cultivated in a specific context (a 1-unit seminar course); competencies known to significantly correlate with and/or predict student success, such as EOT GPA (an equity indicator). This analysis revealed that students identifying ethnically as "other," experienced a significant decrease in EOT GPA. This signals to course designers that the course is working well for certain students and details for which students it is not working well, even when sample sizes are small. For example, for Cluster 1 (the group with the highest EOT GPA), the course showed that there is room for improvement for those who identify as Hispanic/LatinX. This same cluster illustrates that heightened perceived stress is also a negative predictor of EOT GPA. For course designers, this means that additional stress management resources that resonate with the Hispanic/LatinX culture will need to be provided within this course.

What we also discovered for Cluster 3 (the failing EOT GPA cluster) is that ethnic identity was not a significant finding, neither were any of the intrapersonal competency measures. However, all of the intrapersonal competency measures were descriptively lower within Cluster 3. Given the demographic make-up of Cluster 3, as illustrated in Table 4, and the lower scores on intrapersonal competencies, it is evident that intrapersonal competencies play a role in EOT GPA. As such, it is imperative that course design remained focused on their cultivation.

For example, for Clusters 1 and 2 (higher GPA clusters), aspects of psychological well-being—purpose in life for Cluster 1 and environmental mastery for Cluster 2—appear to be playing significant roles in EOT GPA. Cluster 1's perceived stress is also significant to their GPA success. This gives course designers information to make sure that with any course re-design or update, these aspects are kept in place or even emphasized.

This analysis (i.e., Cluster 3) revealed that one cannot assume that identities alone hold the key for closing achievement gaps for students. These findings made us more aware of the neurodiversity that exists within identity groups and as such, investigative work around how to cultivate intrapersonal competencies for all students must go beyond data disaggregation by identities. Analysis of first-person narrative is needed to better understand these students' experience in a manner where this course can be adjusted to better serve those students.

This analysis revealed a cluster of 44 students (i.e., Cluster 3) that could be contacted and invited into conversations to determine just what the institution can do to better support their success. When we consider how to manage limited resources to identify students who need to be provided something other than what the institution is currently providing to better cultivate student success for those being underserved (an equity practice) (Bresciani Ludvik, 2018; Bresciani Ludvik, et al., 2021), this kind of analysis proved beneficial to the course designers who have over 4,500 students in their care. Without engaging in random forest, cluster analysis, and regression analysis, we wouldn't have been able to identify which 44 of the 4,500 students the course designers needed to learn more about in order to improve their EOT GPA.

This study's findings are grounded in the impact of one first-year experience course and have implications for the need to elevate the importance of foundational intrapersonal competency practices embedded into course design and programming efforts across disciplines (c.f., Prince et al., 2015). Further, by focusing on intrapersonal competencies, and measuring their increase or decrease using methods such as random forest, cluster analysis, and regression analysis, we can develop support that is more personalized to students' needs based on data gathered on malleable intrapersonal skills that can be taught. And rather than assuming that all students in a demographic group need the same support, using this kind of analysis on courses designed to cultivate such intrapersonal competencies, course designers can discover who needs more support regardless of how small the numbers are within their identity grouping. Without this kind of analysis, the course designers would not have become aware of how much neurodiversity there is within demographic groups, thereby revealing the complexities that exist both within and between demographic groups (as proxies for culture).

In closing, we invite our reader colleagues to explore how random forest, cluster analysis, and linear regression may reveal how intrapersonal competency development in curricula is working for their students. Doing so may be a strategy for identifying equity gaps and making course improvements for specific identity groups who are not being served by existing institutional structures. And/or, this analysis may reveal that the institution needs to dive deeper into other types of student narrative analysis if findings reveal no significant differences in disaggregated identities yet still have students not experiencing success. In doing so, each institution may be able to harness resources and focus them on specific students who need different types of learning support than that which is currently being offered so that all students can succeed even when institutional resources are limited.

Reference

Akos, P., & Kretchmar, J. (2017). Investigating grit at a non-cognitive predictor of college success. *Review of Higher Education*, 40(2), 163-186.

Altermatt, E. R. (2019). Academic support from peers as a predictor of academic self-efficacy among college students. *Journal of College Student Retention: Research, Theory & Practice*, 21(1), 21-37.

Berryman, M., SooHoo, S., Nevin, A., Ford, T., Nodelman, D. J., Valenzuela, N., & Wilson, A. (2013). Culturally responsive methodologies at work in education settings. *International Journal for Researcher Development.*

Bowers, A. J. (2010). Analyzing the longitudinal K-12 grading histories of entire cohorts of students: Grades, data driven decision making, dropping out and hierarchical cluster analysis. *Practical Assessment, Research, and Evaluation*, *15* (7). DOI: https://doi.org/10.7275/r4zq-9c31

Brecht, A. A., & Burnett, D. D. (2019). Advising student-athletes for success: Predicting the academic success and persistence of collegiate student-athletes. *NACADA Journal*, 39(1), 49-59.

Breiman, L. (1984). *Classification and regression trees* (Wadsworth statistics/probability series). Belmont, Calif.: Wadsworth International Group.

Bresciani Ludvik, M.J., Schellenberg, S., Potter, N. Kahn, S., Monzon, R., & Timm, R. (2021). Improving Performance Indicators with Outcomes-Based Assessment: A Theoretical Model. *Assessment Update.*

Bresciani Ludvik, M. J. (2018a). *Outcomes-based program review: Closing achievement gaps in and outside the classroom with alignment to predictive analytics and performance metrics* (2nd ed.). Sterling, VA: Stylus.

Bresciani Ludvik, M.J. (2018b, July/August). The neuroscience of learning and development: What does that mean for assessment and evaluation? *Assessment Update* 30(4), 13-15.

Bresciani Ludvik, M.J. (2019, November/December). Looking below the surface to close achievement gaps and improve career readiness skills. *Change: The Magazine of Higher Learning,* 51(6), 34-44.

Chevalier, T. M., Parrila, R., Ritchie, K. C., & Deacon, S. H. (2017). The role of metacognitive reading strategies, metacognitive study and learning strategies, and behavioral study and learning strategies in predicting academic success in students with and without a history of reading difficulties. *Journal of Learning Disabilities*, 50(1), 34-48.

D'Amico Guthrie, D., & Fruiht, V. (2020). On-campus social support and hope as unique predictors of perceived ability to persist in college. *Journal of College Student Retention: Research, Theory & Practice*, 22(3), 522-543.

Goyer, J. P., Walton, G. M., & Yeager, D. S. (2021). The role of psychological factors and institutional channels in predicting the attainment of postsecondary goals. *Developmental Psychology*, 57(1), 73-86.

Heller, M. L., & Cassady, J. C. (2017). Predicting community college and university student success: A test of the triadic reciprocal model for two populations. *Journal of College Student Retention: Research, Theory & Practice*, 18(4), 431-456.

Hepworth, D., Littlepage, B., & Hancock, K. (2018). Factors influencing university student academic success. *Educational Research Quarterly*, 42(1), 45-61.Kassambara, A. (2017). *Practical guide to cluster analysis in R: Unsupervised machine learning.* Create Space Independent Publishing Platform.

Katrevich, A. V., & Aruguete, M. S. (2017). Recognizing challenges and predicting success in first-generation university students. *Journal of STEM Education: Innovations and Research*, 18(2), 40-44.

Kaufman L, & Rousseeuw P. J. (1990). *Finding Groups in Data: An Introduction to Cluster Analysis*. John Wiley & Sons, New York.

Lingjun, H., Levine, R. A., Fan, J., Beemer, J., and Stronach, J. (2018). Random forest as a Predictive Analytics Alternative to Regression in Institutional Research. *Practical Assessment, Research, and Evaluation*, *23*(1). DOI: https://doi.org/10.7275/1wpr-m024

National Academies of Sciences, Engineering, and Medicine. (2018). *How people learn II: Learners, contexts, and cultures.* Washington, DC: The National Academies Press. DOI: https://doi.org/10.17226/24783.

National Academies of Sciences, Engineering, and Medicine. (2017). *Supporting students' college success: The role of assessment of intrapersonal and interpersonal competencies.* Washington, DC: The National Academies Press. DOIi: https://doi.org/10.17226/24697.

Neter, J. (1996). *Instructor solutions manual to accompany applied linear regression models, third edition and applied* *linear statistical models, fourth edition.* McGraw-Hill Europe.

Charrad, M., Ghazzali, N., Boiteau, V., & Niknafs, A. (2014). NbClust: An R Package for Determining the Relevant Number of Clusters in a Data Set. Journal of Statistical Software, 61(6), 1–36.

Santos, K., Menezes, A., Carvalho, A., & Montesco, C. (2019). *Supervised Learning in the Context of Educational Data Mining to Avoid University Students Dropout*. In 2019 IEEE 19th International Conference on Advanced Learning Technologies (ICALT) (pp. 207-208).

Petkovic, D., Sosnick-Pérez, M., Okada, K., Todtenhoefer, R., Shihong Huang, Miglani, N., & Vigil, A. (2016). *Using the random forest classifier to assess and predict student learning of Software Engineering Teamwork*. In 2016 IEEE Frontiers in Education Conference (FIE) (pp. 1-7). Frontiers in Education Conference (FIE), 2016, pp. 1-7, doi: 10.1109/FIE.2016.7757406.

Prince, K., Saveri, A., & Swanson, J. (2015). The future of learning: Redefining readiness from the inside out. KnowledgeWorks. Retrieved from https://knowledgeworks.org/wp-content/uploads/2018/01/redefining-readiness.pdf

RStudio Team (2021). RStudio: Integrated Development for R. RStudio, PBC, Boston, MA URL http://www.rstudio.com/.

Sass, D. A., Castro-Villarreal, F., Wilkerson, S., Guerra, N., & Sullivan, J. (2018). A structural model for predicting student retention. *Review of Higher Education*, 42(1), 103-135.

Shi, T., Seligson, D., Belldegrun, A., Palotie, A., & Horvath, S. (2005). Tumor classification by tissue microarray profiling: random forest clustering applied to renal cell carcinoma. *Modern Pathology*, 18(4), 547–557.

Thomas, D.R., Hughes, E. & Zumbo, B.D. (1998). On Variable Importance in Linear Regression. *Social Indicators Research, 45*, 253–275. https://doi.org/10.1023/A:1006954016433

Trainor, A. A., & Bal, A. (2014). Development and preliminary analysis of a rubric for culturally responsive research. *The Journal of Special Education*, 47(4), 203-216.

Trinidad, J. E. (2019). Stable, unstable, and later self-expectations' influence on educational outcomes. *Educational Research and Evaluation*, 25(3-4), 163-178.

Wells, R. S., Kolek, E. A., Williams, E. A., & Saunders, D. B. (2015). How we know what we know: A systematic comparison of research methods employed in higher education journals, 1996-2000 v. 2006-2010. *Journal of Higher Education*, 86(2), 171-198. Retrieved from http://libproxy.sdsu.edu/login?url=https://www-proquest-com.libproxy.sdsu.edu/scholarly-journals/how-we-know-what-systematic-comparison-research/docview/1697493472/se-2?accountid=13758

Wells, R. S., & Stage, F. K. (2014). Past, present, and future of critical quantitative research in higher education. New Directions for Institutional Research, (163), 103-112. DOI: http://dx.doi.org.libproxy.sdsu.edu/10.1002/ir.20089

Yu, C. H.; Lee, H. S.; Lara, E.; and Gan, S. (2018). The Ensemble and Model Comparison Approaches for Big Data Analytics in Social Sciences. *Practical Assessment, Research, and Evaluation*, *23* (17). DOI: https://doi.org/10.7275/hq8a-f262

Citation:
Bresciani Ludvik, M., Zhang, S., Kahn, S., Potter, N., Richardson-Gates, L., Schellenberg, S., Saiki, R., Subedi, N., Harmata, R., Monzon, R., Timm, R., Stronach, J., & Jost, A. (2022). Building intrapersonal competencies in the first-year experience: Utilizing random forest, cluster analysis, and linear regression to identify students' strengths and opportunities for institutional improvement. *Practical Assessment, Research, & Evaluation*, 27(21). Available online: https://scholarworks.umass.edu/pare/vol27/iss1/21/

Corresponding Author:
Marilee Bresciani Ludvik
San Diego State University
San Diego, CA USA

Email: Marilee.Ludvik [at] uta.edu