Thriving in University: Leveraging Psychosocial Characteristics to Predict Persistence

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Abstract: The purpose of this study was to examine the effect of adding psychosocial measures of student well-being to a predictive model of student success. Traditionally, student success research has relied heavily on behavioural measures of student well-being, resulting in predictive models that implicitly suggest that behavioural intervention should be a central feature of student services. Instead, the present research focuses on student *thriving*, a construct that expands the idea of student well-being to include the psychosocial factors of engaged learning, academic determination, diverse citizenship, positive perspective, and social connectedness. In other words, student thriving suggests that student beliefs, motivations, and attitudes are just as important to their overall success as behavioural indicators. The main finding of this study revealed that a robust prediction model of student success was meaningfully improved by the inclusion of psychosocial data features. Specifically, a binary logistic prediction model of student persistence was enhanced by adding student responses on the *Thriving Quotient* (TQ). Overall, the additional data features improved the model's AUC from .637 to .665, an indication that psychosocial variables may enhance our ability to predict student persistence from term to term.

keywords: thriving, predictive analytics

Introduction

The most basic definition of student success focuses on enabling students to gain access to college and complete a certificate or degree. Thus, the importance of degree completion has become an article of faith in higher education research. This degree-oriented definition of student success is the basis of arguments that emphasise increasing access, enrollment, and persistence (Bowen, Chingos, & McPherson, 2009; Hauptman, 2007). Student success is therefore implicitly equated with graduation; as a result, theories of student success that have arisen from this definition are primarily based on persistence models (Braxton, 2000; St. John, Cabrera, Nora, & Asker, 2000; Tinto, 1975, 1993). Because persistence rates are time definite, they are not only easier to measure than graduation rates, but are an effective shadow of measuring degree completion itself (students cannot ultimately graduate if they do not continuously persist). Using this perspective, student behaviours predictive of persistence have been outlined as the target of student success initiatives; such behaviours include, among other things, campus involvement (Astin, 1984, 1993) and interaction with faculty (Chickering & Gamson, 1987; Kuh & Hu, 2001).

In recent years, research exploring student success has emerged in ways that expand

beyond the fundamental benchmarks of college completion rates and grades into more holistic domains. Such expanded foci have included learning gains (Barr & Tagg, 1995), talent development (Kuh, Kinzie, Schuh, Whitt, & Associates, 2005), satisfaction (Schreiner, 2004), sense of belonging (Hurtado & Carter, 1997), and student engagement (Kuh, 2001). Within this paradigm, Kuh, Kinzie, Buckley, Bridges, and Hayek (2007) created perhaps the broadest conceptualization of student success as having multiple, crucial elements: academic achievement, engagement in educationally purposeful activities, satisfaction, acquisition of desired knowledge, skills and competencies, persistence, attainment of educational objectives, and post-college performance. Such elements are often critical features of predictive models that institutions use to forecast student persistence.

However, most of the focus in current student success research and predictive modeling is on student engagement. The concept of student engagement originates from Pace's (1980) measures of quality of effort and Astin's (1984) theory of involvement and represents two key components. The first is the amount of time and effort students put into their studies and additional activities that lead to the experiences and outcomes that characterise student success. The second component of this perspective of student engagement is how institutions of higher education allocate their human and other resources and organise learning opportunities and services to encourage students to participate in and benefit from such activities (Kuh, 2001). These two components, taken together, lay a nice foundation for an expanded view of the importance of student engagement as it relates to student success.

Higher education research, specifically research based theoretically in engagement theory (Kinzie & Kuh, 2004; Kuh et al., 2005), has informed the field of higher education about the behaviours that are indicative of student success. Successful students are more engaged in campus life and academic studies, interact regularly with faculty, and are generally satisfied with their college experience (Kuh, 2003). Engagement theory has grown in scope over the past 30 plus years, framing much of the recent research in higher education. Large-scale behavioural research in higher education began with involvement-based studies of the Cooperative Institutional Research Program (CIRP) at the University of California Los Angeles (UCLA), an ongoing study of student behaviour, and has expanded to include the National Survey of Student Engagement (NSSE) research at Indiana University.

Notwithstanding the important contributions of this prior work, much of the research surrounding student success in higher education has been conceptually based on behaviour theory, meaning that little research has focused on the psychologically motivating factors of engagement. Accordingly, researchers (Schreiner, 2010, 2016; Schreiner, McIntosh, Nelson, & Pothoven 2009) have explored these psychosocial factors through the construct of *thriving*. As in prior work, this approach includes academic factors but also acknowledges the importance of personal well-being and healthy relationships as vital components of a successful student experience.

For example, by 2004 researchers were exploring what it meant for students to be psychologically engaged in classroom learning (Schreiner & Louis, 2006). Qualitative interviews with faculty sought to determine the psychological factors that faculty believed corresponded with the kind of deep learning referenced by Tagg (2004). Following the qualitative analysis, a quantitative tool was developed and tested to measure students' engaged learning (Schreiner & Louis, 2006, 2011). By 2007, the researchers had broadened the focus from engaged learning to a focus on student *thriving*. The researchers expanded the emphasis on student success beyond 'satisfaction, persistence, and high levels of learning and personal development' (Kuh et al.,

2005, p. xiv) to encompass some of the psychological processes evident in the construct of human flourishing (Schreiner, 2010, 2016). Subsequent research has confirmed a measurement model of thriving and has articulated success outcomes that thriving predicts, along with structural models of the significant experiences that contribute to thriving (Schreiner, Kammer, Vetter, Primrose, & Quick, 2011; Schreiner, Nelson, Edens & McIntosh, 2011; Schreiner, Pothoven, Nelson, & McIntosh 2009). Overall, the construct of thriving has emerged as a promising measure of student success as it relates to persistence and graduation.

Importantly. the construct of thriving was derived from research on flourishing within adult populations that emerged from the positive psychology movement. Human flourishing is conceptualised as positive emotions and optimal well-being (Keyes, 2002). Flourishing 'exemplifies mental health' (Keyes & Haidt, 2003, p. 6) and is evident in individuals who are experiencing life to its fullest rather than simply existing. Flourishing individuals are resilient to the challenges presented in life and demonstrate personal growth and optimism through adversity. Goal setting, the active pursuit of valued objectives and fulfillment through creatively reaching such objectives, is another sign of a flourishing individuals actively engage with their world. Lastly, flourishing individuals are connected to the world through emotion (Haidt, 2003); flourishing individuals display moral emotions such as charity, gratitude, and awe toward others and the world around them. Haidt also identified compassion, empathy, courage, and loyalty as positive moral emotions. Individuals who flourish bring flourishing into the world around them, positively and indelibly changing their world.

The construct of thriving builds on these concepts and the psychological well-being implied in flourishing. Thriving encompasses elements critical to college students' success: academic engagement, effort regulation, citizenship, openness to diversity, goal-setting, optimism, and self-regulated learning (Schreiner, McIntosh et al., 2009). Not only do aspects of thriving positively impact the student, but, because of the communal-benefits of the construct, they also positively impact the college or university in which the student enrolls (Schreiner, Hulme, Hetzel, & Lopez, 2009). Students who thrive are actively involved in their community and give back in service to the others within the community. Indeed, thriving is based on a conceptualization of student behaviour, including engagement and persistence, as psychologically motivated (Bean & Eaton, 2002). Thriving students are fully engaged intellectually, socially, and emotionally, which facilitates students' overall success and wellbeing (Schreiner, Pothoven et al., 2009).

Accordingly, there is a opportunity for a perspective on student success that expands beyond student behaviourism, graduation rates, and academic performance to include psychological well-being and optimal functioning. This new approach is grounded in Bean and Eaton's (2002) psychological model of student retention. From this perspective, retention is not merely a function of student behaviour, but is rather an outward manifestation of what is happening in the minds of students. More importantly, these realities are becoming more desirable as elements of student success research and predictive modeling techniques that forecast student success. Students who are psychologically engaged in life and vibrantly connected to the world around them are engaged with all aspects of their learning and the community within which they learn, which makes thriving a valuable construct for anyone interested in researching student persistence.

In keeping with these theoretical innovations in student success research, this paper explores the utilization of a measure of student thriving at a large public university to examine student term-to-term persistence. While many universities employ large predictive models to predict student persistence, these models have characteristically been more behaviour-driven, passing over important psychological factors such as those central to the construct of thriving. As such, this study explores the extent to which a predictive model of student retention, informed by data elements from both the learning management system (LMS) and the student information system (SIS), was enhanced by the addition of psychosocial characteristics specific to student thriving.

Methods

In the fall of 2017, data were collected at Utah State University (USU) measuring the psychological and social characteristics of first-year students utilizing Schreiner's (2016) *Thriving Quotient* (TQ), a 24-item measurement of the interpersonal, intrapersonal, and academic characteristics of students. Thriving is comprised of five factors: Engaged Learning ($\alpha = .89$), Academic Determination ($\alpha = .81$), Diverse Citizenship ($\alpha = .78$), Social Connectedness ($\alpha = .78$), and Positive Perspective ($\alpha = .77$), all of which contribute to a secondary order factor of Overall Thriving ($\alpha = .89$) (Schreiner, 2016; Schreiner, Kalinkewicz, McIntosh, & Cueves, 2013). The five factor model of thriving demonstrates excellent overall structural fit ($\chi 2$ (114) = 1093.83, p < .001, CFI = .954; RMSEA = .054, with 90% confidence intervals from .052 to .058). Data from the TQ were tested to determine their predictive power in a model of student term-to-term persistence at USU, a public, four-year, research-oriented institution located in a rural mountain-valley of northern Utah. Surveys were sent to 3,030 first-year students to complete over the course of four weeks in the term; completed surveys were received from 816 students representing a 26.9% response rate.

USU partners with vendor Civitas Learning to create predictive models of student persistence. Leveraging information from the student information system (SIS), learning management system (LMS), and card-swipe data, the university is able to examine the predictive characteristics of both raw and derived data elements to predict the likelihood of student term-to-term persistence as generated via binary logistic regression. Individual data features are extracted from the source data and segmented via data segmentation availability.

Because of its value in applied research applications, student persistence from term to term was the sole dependent variable in this study. In order to examine the effect of multiple independent variables on the dependent variable, multiple siloed institutional data sources (e.g., student information system and learning management system) were federated into a single data structure. Through an Extract, Transform, and Load (ETL) process, all data points were integrated into a canonicalised data schema referencing each data point back to a common student identifier; all data points were therefore referenced to the same student regardless of database origin.

Each data element became either a continuous or categorical feature variable for each student. Students who do not have a given data element were provided an N/A characteristic and data were sorted by available element within a broad canonicalised data schema. Segmentation of data was performed both manually, to separate graduate students from undergraduate students, and through data availability segmentation (U.S. Patent No. 61/925,186, 2015). Features derived from the data, both in raw format and computed format, were competed for predictive variance through a model feature competition. A k-means clustering algorithm was employed to further

distinguish the common characteristics within each segment (MacKay, 2003). Modeling was employed for each cluster to determine the extent to which the included independent variables available for the segment predicted the dependent variable of persistence within the cluster.

Predictive models were created, utilizing binary logistic regression, at the cluster level of each student grouping to determine the correlative strength of each independent variable on the dependent variable of student persistence (Milliron, Malcolm, & Kil, 2014). Students who reenrolled (i.e., persisted) and/or completed degree programs (i.e., graduated) were combined into one group. Multiple segments were created and at least one cluster existed within each segment. A sample of the data elements forming independent variables in the model are provided for perspective in Table 1. The final predictive model for USU employed 396 features across the

Table 1

Sample Variables Competed for USU Predictive Model
Variable Name
Sections Attempted (Cumulative)*
GPA (Prior Term)*
Standard Deviation of Online GPA (Cumulative)
Standard Deviation of On-ground GPA (Cumulative)
On-ground Credits Earned Ratio (Cumulative)
Loan Aid Per Attempted Credit Hour (Current Term)
Grade Count by Day Relative to Section Range
Change in Total Merit Based Aid (Current Term)
Degree Program Alignment Score

*Example of raw feature vs derived data feature

To assess the value of psychosocial variables (in comparison to exclusively relying on more traditional behaviour-oriented variables), data from the TQ were added to an existing predictive model of student retention for 816 undergraduate students at the university. A Random Forest (RF) model was built for the students who completed the survey using 17 derived items from the TQ (See Table 2) – including demographic characteristics and factor scores (Breiman, 2001). This step was repeated for new students, returning students, students taking courses on the physical campus (on-ground students), and online or blended modality students (i.e., students taking both on ground and online courses). Trees and tree depth were tuned for segments with low student population (e.g., returning students and online/blended).

Table 2Model Features Created from TQ Items

Feature Name	Feature MOM
Institutional Fit Item Score	0.845
Tuition a Worthwhile Investment Item Score	0.827
Intent to Re-enroll at USU Item Score	0.765
Intent to Graduate from USU Item Score	0.852
Major Certainty Item Score	0.854
Perceived Financial Difficulty Item Score	0.721
Academic Determination TQ Factor Mean Score	0.796
Engaged Learning TQ Factor Mean Score	0.861
Diverse Citizenship TQ Factor Mean Score	0.856
Positive Perspective TQ Factor Mean Score	0.853
Social Connectedness TQ Factor Mean Score	0.870
Spirituality Factor Mean Score	0.894
Psychological Sense of Community Factor Mean Score	0.846
Institutional Integrity Factor Mean Score	0.829
Thriving Quotient Factor Mean Score	0.772
	2

n=816 students with data available (785 persisters and 33 non-persisters)

To evaluate the models, areas under the curve (AUCs) were calculated for each model, and the top 50 features of the model were retrieved. AUCs are a critical element of assessing and optimizing predictive binary logistic models. Next, multimodal overlap measure (MOM) scores and correlations (Pearson) were calculated for each of the TQ survey-derived features to show relation to persistence. The calculation for MOM is shown in Figure 1. Correlations from the analyses are available in Table 3.

$$MOM = \sum_{i=1}^{N} min(p(x_i \mid y = 0), p(x_i \mid y = 1)), \text{ where } X \in \{x_1, \dots, x_N\}$$

where $p(x_i \mid y)$ represents the *i*-th value of the class-conditional PMF of X

Figure 1: MOM statistical calculation

Measure	1	2	3	4	5	9	٢	8	6	10	11	12	13	14	15	16
1. Institutional Fit	I															
2. Tuition Worthwhile	0.39	I														
3. Intent to Re-enroll	0.68	0.34	Ι													
4. Intent to Graduate	0.71	0.26	0.76	I												
5. Major Certainty	0.19	0.19	0.18	0.14	I											
6. Financial Difficulty	-0.21	-0.37	-0.19	-0.21	0.16	I										
7. Academic Determination	0.24	0.36	0.14	0.13	0.11	-0.18	I									
8. Engaged Learning	0.22	0.40	0.18	0.11	0.17	-0.10	0.70	Ι								
9. Diverse Citizenship	0.30	0.42	0.17	0.11	0.13	-0.17	0.51	0.49	Ι							
10. Positive Perspective	0.33	0.26	0.21	0.24	0.08	-0.09	0.50	0.41	0.56	I						
11. Social Connectedness	0.19	0.19	0.15	0.18	0.19	-0.08	0.30	0.12	0.31	0.34	Ι					
12. Spirituality	0.34	0.33	0.16	0.22	-0.01	-0.21	0.25	0.20	0.36	0.40	0.21	I				
13. Psychological Sense of Community	0.65	0.45	0.49	0.43	0.15	-0.23	0.37	0.39	0.58	0.45	0.34	0.40	I			
14. Institutional Integrity	0.62	0.45	0.45	0.46	0.07	-0.26	0.31	0.33	0.47	0.48	0.36	0.38	0.76	I		
15. TQ Mean	0.35	0.44	0.24	0.22	0.19	-0.16	0.80	0.72	0.74	0.76	0.63	0.39	0.57	0.53	Ι	
16. Persistence (actual)	0.05	0.03	-0.02	-0.03	0 00	-0.17	00.00	-0.04	0.09	0.08	0 04	-0.05	0.08	0.05	0 04	I

 Table 3

 Correlations Retween 15 TO Characteristics and Actual Student Term-to-term

Results

Table 4

For the overall student segment (n=816), there was a slight AUC improvement (See Table 4 for student segment AUC deltas), and a TQ mean MOM score of 0.772, which demonstrates slight signal improvement. Due to sample size constraints, the segmented populations demonstrated less clear results. Nonetheless, these results appear promising relative to the value of including psychosocial features in predictive student success research.

Student Segment	Delta AUC	п	TQ MOM
All	0.028	816	0.772
New	-0.004	644	0.797
Continuing*	0.063	172	0.69
On-ground (courses taken)	0.048	703	0.782
Online/Blended (courses taken)*	0.07	113	0.683

AUC Delta for Models by Student Segment

*small n samples were susceptible to training despite using cross-validation

Discussion

The purpose of this study was to examine the effect of adding psychosocial measures of student well-being to a predictive model of student success. Traditionally, student success research has relied heavily on behavioural measures of student well-being, resulting in predictive models that implicitly suggest that behavioural intervention should be a central feature of student services. Instead, the present research focuses on student *thriving*, a construct that expands the idea of student well-being to include the psychosocial factors of engaged learning, academic determination, diverse citizenship, positive perspective, and social connectedness. In other words, student thriving suggests that student beliefs, motivations, and attitudes are just as important to their overall success as behavioural indicators.

The main finding of this study revealed that a robust prediction model of student success was meaningfully improved by the inclusion of psychosocial data features. Specifically, a binary logistic prediction model of student persistence was enhanced by adding student responses on the *Thriving Quotient* (TQ). Overall, the additional data features improved the model's AUC from .637 to .665, an indication that psychosocial variables may enhance our ability to predict student persistence from term to term. Since any binary prediction system begins with a 50% likelihood of accuracy and can never plausibly reach 100% accuracy, the 2.8% increase manifest in this study is promising.

Notwithstanding this encouraging finding, these results must be necessarily interpreted with caution. The value of adding any data feature to a post-secondary persistence prediction model must be assessed across multiple academic terms and using substantially greater numbers of participants. Given this relatively isolated sample, the increase could plausibly be an anomaly related to the institution itself, the particular academic term, or other potentially unknown idiosyncrasies. The sensitivity of prediction models to such insults warrants additional data collection over multiple semesters and across a more substantial sample of students. Nonetheless, these results are promising and speak to the recently emergent prospect of conceptualizing student success using more holistic lenses.

These results also highlight the possibility that an expanded view of student well-being could meaningful shape institutional design of student interventions. If the predictive capacity of the TQ characteristics remains consistent with increased data collection, the implications for practice are abundant. Notably, the psychological attributes of student thriving are amenable to intervention, underscoring their value in predictive early-alert systems designed to foreground opportunities for student growth and development. For example, an academic advisor might reach out to a student with low levels of self-reported social connectedness to offer a recommendation about an upcoming program-related student event. Alternatively, a faculty member might notice an inordinate number of class members have reported relatively low levels of engaged learning, prompting the faculty to replace the week's lecture with place-based field-trip related to the course content. When educators have the right information at the right juncture in time, opportunities for improving their level of service to students increase.

Future Research

More data and analyses are needed in order to verify the value of using a Thriving Quotient score in a persistence model. Future recommendations include a need for more records of survey completion across multiple academic terms. Additionally, given that students completed the TQ survey across several weeks within the fall term, feature leakage may have occurred, reducing our ability to properly assess the predictive value of the survey; it would be useful to have students complete the survey within a shorter time period, either closer to term census date, or closer to the end of the term. The use of a random forest technique may have overfit the model to the train data, especially among smaller segments. Future iterations of this approach should compare the outcomes of an approach like random forest with simple binary linear regression. Lastly, it would also be useful to explore 'Null' values for TQ survey features among the total student population when adding to the current model to account for any selection bias given survey participation is voluntary. Overall, the results of this study are meaningful and promising, but prompt a need for additional investigation and continued support for innovation in student development research.

References

- Astin, A. W. (1984). Student involvement: A developmental theory for higher education. *Journal* of College Student Personnel, 25, 297-308.
- Astin, A. W. (1993). *What matters in college? Four critical years revisited*. San Francisco, CA: Jossey-Bass.
- Barr, R., & Tagg, J. (1995). From teaching to learning: A new paradigm for undergraduate education. *Change*, 27(6), 12.
- Bean, J. P., & Eaton, S. B. (2002). A psychological model of college student retention. In J. M. Braxton (Ed.), *Reworking the student departure puzzle* (pp. 48-61). Nashville, TN, : Vanderbilt UP.
- Bowen, W. G., Chingos, M. M., & McPherson, M. S. (2009). *Crossing the finish line: Completing college at America's public universities*. Princeton, NJ: Princeton University Press.
- Braxton, J. M. (2000). *Reworking the student departure puzzle: New theory and research on college student retention*. Nashville, TN: Vanderbilt University Press.
- Breiman, L. (2001) Random forests. *Machine Learning*, 45, 5–32.
- Chickering, A. W., & Gamson, Z. F. (1987, March). Seven principles for good practice in undergraduate education. *AAHE Bulletin*, 3-7.
- Haidt, J. (2003). Elevation and the positive psychology of morality. In C. L. M. Keyes & J. Haidt (Eds.), *Flourishing: Positive psychology and the life well-lived* (pp. 275-289).
 Washington DC: American Psychological Association.
- Hauptman, A. M. (2007). Strategies for improving student success in postsecondary education. Boulder, CO: Western Interstate Commission for Higher Education.
- Hurtado, S., & Carter, D. F. (1997). Effects of college transition and perceptions of the campus racial climate on Latino college students' sense of belonging. *Sociology of Education, 70*, 324-345.
- Keyes, C. L. M. (2002). The mental health continuum: From languishing to flourishing in life. Journal of Health & Social Behavior, 43(2), 207-222.
- Keyes, C. L. M., & Haidt, J. (Eds.). (2003). *Flourishing: Positive psychology and the life welllived* (1st ed.). Washington, DC: American Psychological Association.
- Kinzie, J., & Kuh, G. D. (2004). Learning from campuses that share responsibility for student success. *About Campus*, 9(5), 2-8.
- Kuh, G. D. (2003). What we're learning about student engagement from NSSE. *Change*, 35, 24-32
- Kuh, G. D. (2001). The National Survey of Student Engagement: Conceptual framework and overview of psychometric properties. Bloomington, IN: Indiana University Center for Postsecondary Research.
- Kuh, G. D., & Hu, S. (2001). The effects of student-faculty interaction in the 1990s. *Review of Higher Education*, 24, 309-332.
- Kuh, G. D., Kinzie, J., Buckley, J. A., Bridges, B. K., & Hayek, J. C. (2007). Piecing together the student success puzzle: Research, propositions, and recommendations. ASHE Higher Education Report, 32, 5.
- Kuh, G. D., Kinzie, J., Schuh, J. H., Whitt, E. J., & Associates. (2005). *Student success in college: Creating conditions that matter*. San Francisco, CA: Jossey-Bass.
- MacKay, D. J. (2003). Information theory, inference and learning algorithms. Cambridge UP.

- Milliron, M. D., Malcolm, L., & Kil, D. (2014). Insight and action analytics: Three case studies to consider. *Research & Practice in Assessment, 9*, 70-89.
- Pace, C. R. (1980). Measuring the quality of student effort. *Current Issues in Higher Education*, 2, 10-16.
- Schreiner, L. A. (2004). The role of student satisfaction in the assessment of institutional effectiveness. In T. W. Banta (Ed.), *Hallmarks of effective assessment programs* (pp. 50-55). San Francisco, CA: Jossey-Bass.
- Schreiner, L. A. (2010). The "Thriving Quotient": A new vision for student success. *About Campus*, 15(2), 2-10.
- Schreiner, L. A. (2016). Thriving: Expanding the goal of higher education. In D. W. Harward (Ed.), Well-Being and Higher Education: A Strategy for Change and the Realization of Education's Greater Purpose (pp. 135-148). Washington, DC: American Association of Colleges and Universities.
- Schreiner, L. A., Hulme, E., Hetzel, R., & Lopez, S. J. (2009). Positive psychology on campus. In C. R. Snyder & S. J. Lopez (Eds.), Oxford handbook of positive psychology (pp. 569-578). New York, NY: Oxford University Press.
- Schreiner, L. A., Kalinkewicz, L., McIntosh, E., & Cuevas, A. (2013, November). *Measuring the malleable: Expanding the assessment of student success*. Paper presented at the annual meeting of the Association for the Study of Higher Education, St. Louis, MO.
- Schreiner, L. A., Kammer, R., Vetter, D., Primrose, B., & Quick, D. (2011). *Pathways to thriving among students of color*. Paper presented at the National Association of Student Personnel Administrators, Philadelphia, PA.
- Schreiner, L. A., & Louis, M. C. (2006). *Measuring engaged learning in college students: Beyond the borders of NSSE*. Paper presented at the Association for the Study of Higher Education, Anaheim, CA.
- Schreiner, L. A., & Louis, M. C. (2011). The Engaged Learning Index: Implications for faculty development. *Journal of Excellence in College Teaching*, 22(1), 5-28.
- Schreiner, L. A., McIntosh, E. J., Nelson, D., & Pothoven, S. (2009). *The Thriving Quotient: Advancing the assessment of student success*. Paper presented at the Association for the Study of Higher Education, Vancouver, BC, Canada.
- Schreiner, L. A., Nelson, D., Edens, D., & McIntosh, E. J. (2011). *The Thriving Quotient: A new vision for student success*. Paper presented at the National Association of Student Personnel Administrators, Philadelphia, PA.
- Schreiner, L. A., Pothoven, S., Nelson, D., & McIntosh, E. J. (2009). College student thriving: Predictors of success and retention. Paper presented at the Association for the Study of Higher Education, Vancouver, BC.
- St. John, E. P., Cabrera, A. E., Nora, A., & Asker, E. H. (2000). Economic influences on persistence reconsidered: How can finance research inform the reconceptualization of persistence models? In J. M. Braxton (Ed.), *Reworking the student departure puzzle: New theory and research on college student retention* (pp. 29-47). Nashville, TN: Vanderbilt University Press.
- Tagg, J. (2004). Alignment for learning: Reorganizing classrooms and campuses. *About Campus*, 9(2), 8-18.
- Tinto, V. (1975). Dropout from higher education: A theoretical synthesis of recent research. *Review of Educational Research, 45*, 89-125.

Tinto, V. (1993). *Leaving college: Rethinking the causes and cures of student attrition* (2nd ed.). Chicago, IL: The University of Chicago Press.