Salient Factors in Predicting Student Success, Including Course Modality

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Much discussion in higher education has focused upon predicting student learning, and how to identify students who may be at particular risk of failure. Little research has actually tackled that challenge, and research on the scholarship of teaching and learning (SoTL) in this areas is scarce; this study does so by measuring students across three semester of study in a variety of courses and course formats. Our results indicate that a set of characteristics predicting student success can be identified, and that course modality affects overall student success rate. Our results are discussed in terms of how they might inform faculty and administrators how best to identify at-risk groups of students, and who other researchers might expand on these results to produce a more nuanced interactive understanding of the interplay among students, courses, course modalities, and other characteristics to identify ideal combinations of those factors leading to student success.

BACKGROUND ON STUDYING STUDENT LEARNING

There has long been a need to assess students' performance in courses, as assessment has long been a weak point in the educational sphere, with more claims than evidence that students are learning in their courses. In addition, there are increasing demands for more accountability in terms of demonstrations (vs. mere claims) of student learning, and those demands have led to greater calls for a heavier emphasis on the scholarship of teaching and learning (SoTL; Applegate, 2006; Godbold et al., 2021; Rhem, 2018). Thus, instructors and researchers are researching the best method to improve student learning, as the unforeseen worldwide pandemic beginning in 2020 worsened the situation and as all institutions shut their doors for in-person business. During the COVID-19 pandemic shutdown, all students in universities transitioned to an online platform, which is a new method for many students. In light of the COVID-19 pandemic, when the question was raised whether students were learning anything at all given the challenges of online-only learning, the need to examine which course modalities are best suited for particular students took on greater urgency, as most colleges and universities shut down their face-to-face learning in spring 2020 (Adedoyin & Soykan, 2020; Bawa, 2016; Pokhrel & Chhetri, 2021), moving all instruction online, and expected to see (and did see) significant declines in student learning (Engzell et al., 2021). By fall 2021, much teaching had returned to face-to-face (or at least hybrid) learning. Going forward, the increasing use of online courses (Garrett, 2007), and the proliferation of diverse teaching modalities (face-to-face, hybrid, virtual live lecture, distance learning) has not been accompanied by empirical evidence as to which of these modalities leads to the best student learning, and (presumably) which is best suited for particular students, assuming an interaction between student characteristics and student success in different modalities. This study aims to address that gap in the literature by examining student success across various modalities.

As the pandemic restrictions continued, there was concern that the continued reliance on remote teaching would hurt instructors and students alike. For example, Klusmann et al. (2016) found that teachers' emotional exhaustion was significantly negatively related to students' performance in math classes, even after controlling for several other characteristics. Similarly, it may be that heavy reliance on Zoom classes due to the pandemic may produce such emotional exhaustion, and thus hurt student performance. Likewise, in 2020, Serhan's findings on the effects of lecture via the Zoom platform revealed negative impact on student's performances; however, participants in the study affirmed they enjoyed the flexibility of Zoom lectures (Serhan, 2020).

Garrett (2007) found that there is greater demand than supply for online courses, although this preference was moderated by age, as younger and older students preferred on-campus classes, whereas middle-aged students were more inclined toward online courses. However, respondents also had more questions about the quality of online than on-campus courses.

Specifics on Student Learning

Chu and Tsai (2009) got responses from 541 computer applications students (67% women, 33% men; age range = 32-87; age mean = 50.7) enrolled in adult education institutions in Taiwan, and reported that they placed highest value in terms of Internet-based learning environments on relevance to life and reflecting thinking, and least value on critical judgment, ease of use, and student negotiation. Thus, these students preferred course learning environments that demonstrated authentic and reflective experiences.

Day et al. (2010), using a sample of 129 undergraduate students in the UK (60% women, 40% men; age range = 18-21) found that trait hope significantly predicted future academic achievement three years later.

Growth mindset, first identified by Dweck (2008), reflects a malleable sense of being able to learn and grow, as opposed to a fixed mindset, which reflects a sense that one has an innate sense of intelligence that is largely unchangeable; having a growth (vs. a fixed) mindset has been shown to lead to greater academic achievement. Shorter versions of the original growth mindset scale, including a 6-item version by Ingebrigtsen (2018), have shown satisfactory reliability.

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Perceived competence, or the perception of one's ability to learn, is measured via a 5-item Competence sub-scale of the Intrinsic Motivation Inventory (Ryan, 1982).

Yu et al. (2018) used a large sample (*N* = 13,570) to assess the psychometric properties of the Learning Climate Questionnaire's short (6-item) version. It was shown to be adequately reliable, but there were some concerns about one item.

Student Learning in Distance Learning Contexts

Bawa (2016) reviewed the literature on retention in online courses, with a focus on identifying possible causes of the high attrition rate in such courses, and identified several key factors: (1) misperceptions about online course difficulty; (2) social, family, attitudinal, and motivational factors; (3) technological constraints; (4) lack of instructor understanding of online students; and (5) faculty and institutional limits in using technology.

Bolliger and Inan (2012) developed and validated the Online Student Connectedness Survey (OSCS) using a sample of 146 Turkish students (73% male; age range = 19-14; age mean = 27.6) enrolled in synchronous and asynchronous delivery methods in a computer engineering course. The OSCS measure is reliable (overall Cronbach's alpha = .97; Cronbach's alphas for sub-scales ranged from .94 to .97) and contained four factors (explaining 84% of the variance): comfort, community, facilitation, interaction and collaboration.

In a study of 1401 students, Bradford (2011) explained about 25% of the variance in student satisfaction with online learning with a measure of cognitive load. A three-component solution revealed three main components: awareness of criteria for course success, challenge required to meet course requirements, and engagement-supporting elements.

In a study of 262 students in online programs, Chen and Jang (2010) tested a model of self-determination theory. They found that contextual support predicted course satisfaction but not perceived learning or final grade earned; that need satisfaction predicted motivation perceived learning but not course satisfaction or final grade earned; and that motivation did not significantly predict course satisfaction, perceived learning, or final grade earned.

Hachey et al. (2015), in a study of 1566 online STEM course students, found that, even after controlling for GPA, prior experience taking an online course was a significant predictor of future online STEM course outcomes.

Hao (2004) identified four types of student interactions (instructional, affective, collaborative, and vicarious), and found that students' attitudes toward instructional interactions, positively, and vicarious interactions negatively, related to course satisfaction.

In a literature review aimed at identifying factors predicting success among online students, Kauffman (2015) identified several key factors: high emotional intelligence, organizational skills (including time management, self-discipline, and planning), reflective or visual learning styles, and having an internal locus of control. Helms (2018), in a study of face-to-face versus online students, found that the latter earned lower GPAs, missed more opportunities to earn good grades, and were more likely to fail the course. Similarly, Patterson and McFadden (2009) found that students in online programs were more likely to drop out than students in campus-based (face-to-face) programs. Levy (2004) reported that student satisfaction with e-learning was significantly related to decision to drop out from such courses, with eventual drop-outs reporting lower satisfaction than persisters, and no effect of academic locus of control on student retention rates. Such results indicate the potential challenge to student success posed by online courses and programs.

Rovai (2003) developed a composite persistence model to identify factors that predict student retention in online programs. The model included (1) student characteristics and student skills (such as academic preparation and time management), external factors (such as finances and life crises), and internal factors (such as study habits and goal commitment).

Jones (2013) implemented a mandatory student orientation for online students, and found that it produced higher confidence in students' technological and academic success perceptions, and improved retention among students enrolled in it compared to non-enrolled controls. Similarly, Gilmore and Lyons (2012) reported that, after implementation of a face-to-face orientation for an online RN-to-BSN nursing program, revision and expansion of the initial orientation program, including reviews of student support services, computer technology services and applications, and virtual environment interactions, led to significant increases in student satisfaction with the orientation (from 78% to 98%).

THEORETICAL MODEL

Our theoretical model is based on the model used by Lalonde and Gardner (1993), who predicted performance among psychology students in a statistics course. Their model contained five major factors, and were related in the following manner: Mathematical Aptitude predicted Situational Anxiety and Achievement; Situational Anxiety predicted Attitude-Motivation Index, which in turn predicted Effort, which in turn also predicted Achievement. Although our sample will include students from a variety of disciplines and courses, we adapted and modified this model, as it received strong support for each of the proposed connections between factors. In order to adapt that model to a more general set of courses, we adopted a stepwise regression approach, adding sets of variables in three steps (those measuring situational anxiety, attitude/motivation, and effort), with four distinct measures of achievement as the outcome variable.

HYPOTHESES

Consistent with the work of Lalonde and Gardner (1993), we set out to test a set of hypotheses regarding what would predict student achievement. However, we modified their approach somewhat, primarily in using a stepwise (hierarchical) regression approach as opposed to a structural equation modeling approach, primarily due to not having the rather large sample sizes often required for the latter approach. Our hypotheses were that each of the following sets of predictors would significantly predict student achievement:

1. measures of situational anxiety;
2. measures of attitude/motivation;
3. measures of effort; and
4. measures of perceived student achievement.

In addition, we sought to predict student success as a function of course modality. Consistent with past research, our fifth hypothesis predicted that students would perform better in face-to-face courses than in other formats.

METHOD

Participants

Across three semesters (Spring and Fall 2021, Spring 2022), we recruited students at a comprehensive mid-sized public university in the Midwest. There were a total of 336 student responses, of which there were 248 fully linked responses (i.e., including both the survey response and the final course average earned). Of these, there were 223 cases with complete information on all variables.

Response rates were roughly even across the three semesters (88 for Spring 2021, 76 for Fall 2021, 84 for Spring 2022). Age of respondents ranged from 18 to 58 (M = 22.6, Mdn = 21.0, SD = 6.3), but consisted primarily (79%) of those aged 18 to 23. Students' course formats were predominantly either face-to-face (44%) or online (41%), with fewer students reporting virtual live lectures (14%) or hybrid (2%). Students' final course average ranged from 40.4 to 100.7 (M = 86.9, Mdn = 89.6, SD = 10.3), and were positively skewed, with 91% of students earning at least a 70% final average. Students reported a wide range of work hours per week (M = 19.5, Mdn = 20.0, SD = 14.1), with the vast majority (79%) of students reporting at least some work. In terms of reported gender, most respondents (63%) were female, 35% were male, and relatively few (2%) reported being transgender, non-binary, or other. The vast majority of respondents (85%) did not report having any children or other dependents; of those who did report dependents (15%), most (13%) reported having 1 or 2, with 1% each reporting 3 and 5 dependents. Marital status of respondents likely reflected their relative youth, with the vast majority being single (87%), with far fewer respondents reporting being married (7%), cohabiting (5%), divorced (1%), and widowed (<1%). In terms of job stress, there was considerable variability (M = 2.68 on a 5-point scale, Mdn = 3.0, SD = 1.3).

Materials

A survey containing each of the major variables of this study, as well as demographic characteristics, was presented to each student who clicked on the survey link or QR code. Each variable is described in detail below. Unless otherwise noted, each scale used a 7-point Likert response scale ranging from 1 (*Strongly disagree*) to 7 (*Strongly agree*).

Situational anxiety

Four measures of situational anxiety were used. *Satisfaction with technology* was measured with the Online Student Connectedness Survey (Bolliger & Inan, 2012), a 23-item measure that assesses thoughts, feelings, and behaviors toward technology and learning (sample item: "I feel comfortable in the online learning environment provided by my program"). Internal consistency reliability, as measured by Cronbach's alpha, was .95. *Satisfaction with online courses* was measured with 12 items taken from Powers (2008) (FIND, or Bolliger & Halupa, 2012), which assesses one's perception of one's academic abilities (sample item: "I am satisfied with my interaction with the instructor"). Internal consistency reliability, as measured by Cronbach's alpha, was .89. *Satisfaction with Brightspace* was measured with 6 items (2 of which were reverse-coded) using a 5-point Likert scale ranging from 1 (*Strongly disagree*) to 5 (*Strongly agree*), created to assess students' perception of the value of the course management system (sample item: "Learning to use Brightspace was easy"). Internal consistency reliability, as measured by Cronbach's alpha, was .81. *Learning climate* was measured with 6 items taken from Yu et al. (2018), which assesses one's views toward the learning climate (sample item: "I feel that my instructor provides me choices and options"). Internal consistency reliability, as measured by Cronbach's alpha, was .92.

Attitude/motivation

Six measures of attitude/motivation were used. *Academic control* was measured with 8 items (4 of which were reverse-coded) adapted from Perry et al. (2001), which assesses one's perception of control over one's academic success (sample item: "The more effort I put into my courses, the better I do in them"). Internal consistency reliability, as measured by Cronbach's alpha, was .83. *Academic orientation* was measured with 7 items adapted from Johansson (2008) (FIND), which assesses one's orientation toward academic success (sample item: "I get a sense of fulfillment merely by learning new information"). Internal consistency reliability, as measured by Cronbach's alpha, was .79. *Intrinsic motivation* was measured with 17 items adapted from Lepper et al. (2005), which assesses one's desire to face challenges for their own sake (sample item: "I like hard work because it's a challenge"). Internal consistency reliability, as measured by Cronbach's alpha, was .93. *Extrinsic motivation* was measured with 13 items adapted from Lepper et al. (2005), which assesses one's desire to face challenges to earn an external reward (sample item: "I don't like to figure out difficult problems"). Internal consistency reliability, as measured by Cronbach's alpha, was .87. *Entitlement* was measured with 8 items from the Academic Entitlement Questionnaire, which assesses students' views of themselves as customers (sample item: "Professors should only lecture on material covered in the textbook and assigned readings"). Internal consistency reliability, as measured by Cronbach's alpha, was .84. *Growth mindset* was measured with 6 items (3 of which were reverse-coded) adapted from Dweck (2008), which assesses one's sense of control over the ability to learn (sample item: "No matter who you are, you can significantly change your intelligence level"). Internal consistency reliability, as measured by Cronbach's alpha, was .88.

Effort

Three measures of effort were used. *Time management* was measured with 14 items taken from Trueman and Hartley (1996), measured with yes or no responses, which assesses one's use of time management strategies (sample item: "Do you make a list of things you have to do each day?"). Internal consistency reliability, as measured by Cronbach's alpha, was .94. *Study habits* was measured with 12 items taken from Gurung (2005), measured with a 5-point Likert scale ranging from 1 (*Never*) to 5 (*Always*), which assesses one's use of various study strategies (sample item: "For each chapter in a course, how often do you do each of the following while studying? Read the text"). Internal consistency reliability, as measured by Cronbach's alpha, was .83. *Active procrastination* was measured with 16 items taken from Choi and Moran (2009), which assesses one's tendency to engage in procrastination behaviors (sample item: "I don't do well if I have to rush through a task"). Internal consistency reliability, as measured by Cronbach's alpha, was .89.

Perceived student achievement

Three measures of perceived student achievement were used. *Perceived competence* was measured with 5 items taken from McAuley et al. (1989), which assesses one's perception of competence in one's ability to learn (sample item: "I think I am pretty good at learning in this course"). Internal consistency reliability, as measured by Cronbach's alpha, was .89. *Learning ability* was measured with 3 items taken from Gurung (2005), measured with a 5-point Likert scale ranging from 1 (*Never*) to 5 (*Always*), which assesses one's ability to acquire information (sample item: "For each exam in a course, how well do you think you… understood the material for the exam accurately?"). Internal consistency reliability, as measured by Cronbach's alpha, was .90. *Academic self-assessment* was measured with 5 items taken from Powers (2008) (FIND), which assesses one's perception of one's academic abilities (sample item: "I typically get better than average grades in this class"). Internal consistency reliability, as measured by Cronbach's alpha, was .89.

Student achievement

For this outcome variable, we extracted students' final course average after the semester was completed and linked it up (via students' provided names) to their survey data. If a student name was not provided, it was thus not possible to extract these data.

Demographics and course information

Additional measure of demographics and characteristics of the student's course were asked, including measures of students' total course load, types of courses taken (options included online, virtual live lecture, hybrid, or face-to-face, with the ability to select all that apply), name (to link up survey responses to final course average), hours worked per week, gender, number of dependents, marital status, and perceived job stress (measured using a 5-point Likert scale ranging from 1 [*None at all*] to 5 [*A great deal*]).

Procedure

Potential classes of participants were identified by the researchers early in the semester. Consistent with IRB regulations (Purdue IRB protocol #2020-1628), we contacted the instructors of those (generally high-enrolled) courses to ask for permission to recruit students in those classes (either in person or via e-mail using Brightspace, our course management system); if permission was granted, we read or e-mailed our recruitment script to the students, and followed up 1-2 weeks later with an e-mail reminder. Students who chose to participate were directed (via weblink or a QR code) to the Qualtrics survey. At the end of that survey, they were also asked if they would like to be entered into a raffle to win a $25 gift card (via a separate survey) to Amazon or Starbucks, with odds of winning varying by semester (1 in 50, 1 in 25, and 1 in 5, respectively, for the spring 2021, fall 2021, and spring 2022 semesters). Those who did so were taken to a separate Qualtrics survey link (to maintain anonymity of their survey responses) to provide the requested information, from which winners were selected.

RESULTS

Data Screening and Cleaning

After data collection was completed, data screening occurred. For all scales, a similar procedure was used: (1) any items needed to be reversed-coded were so reversed, so that higher scores indicated a consistent response on each scale; (2) internal consistency reliability, as measured by Cronbach's alpha, was computed for each set of items on a scale; (3) a scale score was computed for each scale, defined as the mean of all items on that scale.

Next, data screening occurred on all primary variables, including examination for skewness, univariate and multivariate outliers, linearity, and multicollinearity. Several variables demonstrated significant skewness; the skewness was effectively remedied via a square root transformation (for variables Time Management and Entitlement) or via a reflect and square root transformation (for variables Academic Control, Learning Climate, Perceived Competence, Learn It, Academic Self-Assessment, and Satisfaction with Online Courses). A total of X cases were identified as outliers, and were excluded from further analysis.

Test of Hypotheses

In order to test the hypotheses, a hierarchical (stepwise) linear regression was conducted, using the following predictors: step 0: constant; step 1: measures of situational anxiety; step 2: measures of attitude/motivation; step 3: measures of effort; step 4: measures of perceived student achievement. The outcome variable was student achievement, as measured by course final average.

The results (see Table 1) reveal a few key findings. Each set of predictors added to the prediction, with later sets added more explanatory power, culminating in the measures of perceived student achievement, which predicted 12% of the variance in student achievement. In step 1, including only measures of situational anxiety, there were no significant predictors (except for the constant). In step 2, adding in measures of attitude/motivation, there were two significant predictors: academic control and intrinsic motivation. In step 3, adding in measures of effort, there were two significant predictors: time management and active procrastination. In step 4, adding measures of perceived student achievement, there were two significant predictors: perceived competence and academic self-assessment. Overall, students attained a higher final course average if they had greater perceived academic control, higher intrinsic motivation, better time manage-

Table 1. Results of Stepwise Regression Results

Step	Predictor	*B*	β	*t*	Adjusted R_2 Added
0	Constant	108.7	–	9.22***	
1	Situational Anxiety				.03*
	Satisfaction with technology	-0.27	-.03	-0.37	
	Satisfaction with online courses	-3.53	-.13	-1.34	
	Satisfaction with Brightspace	-0.60	-.07	-0.91	
	Learning climate	-4.00	-.15	-1.59	
2	Attitude/motivation				.04*
	Academic control	-7.31	-.23	-2.56*	
	Academic orientation	-0.79	-.08	-0.80	
	Intrinsic motivation	2.48	.25	2.44*	
	Extrinsic motivation	0.48	.05	0.67	
	Entitlement	3.90	.12	1.40	
	Growth mindset	-0.18	-.02	-0.30	
3	Effort				.05**
	Time management	-5.08	-.14	-2.03*	
	Study habits	0.39	.03	0.44	
	Active procrastination	-2.35	-.26	-3.42**	
4	Perceived student achievement				.12***
	Perceived competence	-5.13	-.19	-1.99*	
	Perceived learning	3.01	.08	1.04	
	Academic self-assessment	-8.96	-.32	-3.82***	

Note. *p < .05; **p < .01; ***p < .001. Outcome variable = student achievement.

ment, less procrastination, higher perceived competence, and a greater sense of their academic self-assessment. Thus, in terms of our hypotheses, our first hypothesis was not supported (in that no measure of situational anxiety significantly predicted student achievement), whereas our second, third, and fourth hypotheses were supported (in that two predictors each among the measures of attitude/motivation, effort, and perceived student achievement significantly predicted student achievement.

Our fifth hypothesis predicted differences in student success (as measured by student final average) as a function of course modality, and found that course modality had a significant effect on students' final average, Brown-Forsythe F (3,241) = 3.52, p = .016. Contrary to our expectations, post-hoc Tamhane T2 tests revealed that face-to-face students (M = 84.6, SD = 11.2) performed significantly worse than online students (M = 88.7, SD = 10.3); neither of those groups different significantly from students taking virtual live learning (M = 87.8, SD = 8.0) or hybrid (M = 93.5, SD = 4.5) courses, the latter group likely due to its small sub-sample size (n = 4). Thus, our fifth hypothesis was not supported, in that our results supported stronger learning online than in face-to-face contexts.

An exploratory cluster analysis was run to examine patterns in the data that might reflect general tendencies among groups of students. A 3-cluster solution was most informative, and indicated several enlightening findings. The largest cluster (n = 130), labeled High Achievers, contained students who were most satisfied with online courses; used the most study techniques; procrastinated the least; were highest in academic control, intrinsic motivation, perceived competence, learning confidence, and academic self-assessment; and had the highest final course average (M = 93.9). The smallest cluster (n = 22), labeled Low Achievers, contained students who were least satisfied with online courses; used the fewest study techniques; procrastinated the most; were lowest in academic control, intrinsic motivation, perceived competence, learning confidence, and academic self-assessment; and had the lowest final course average (M = 66.9). A third cluster (n = 71), labeled the Moderate Achievers, generally fell between the High and Low Achievers, and had an intermediate final course average (M = 82.9). These exploratory results are consistent with the regression results. Students who demonstrated good characteristics (e.g., good study habits, less procrastination, more intrinsic motivation) tended to have higher perceived student achievement, as well as higher actual achievement.

DISCUSSION

Overall, the results supported three of our four hypotheses predicting overall student achievement, in that measures of attitude/motivation, effort, and perceived student achievement were significant predictors of student achievement. Further, the results demonstrated that six of our variables (academic control, intrinsic motivation, time management, perceived competence, and academic self-assessment) were significant predictors of student achievement. That the first hypothesis was not supported, in contrast to the results of Lalonde and Gardner (1993), may be a function of what was measured: whereas they examined performance in statistics courses, we examined a wider range of courses, and it may be that situational anxiety is particularly acute in statistics courses (as reported by Nalbone & Georgeff, 2019).

Our findings regarding modality (that online students outperformed face-to-face students in terms of final course average) are surprising. Past research has tended to indicate that online students are at a particular disadvantage, and are likely to earn lower final grades (Helms, 2014; Xu & Jaggars, 2014). Our results, pointing in the opposite direction, may indicate unique aspects of our sample, a shift toward higher student performance in online environments, or unique aspects of the pandemic, during which many instructors devoted considerable time and energy to ensuring that their (pandemic-required) online courses were of high quality (for some evidence of better instructor performance, see Chakraborty et al., 2021). Further research will be required to discern which of these competing explanations works best.

Much of our results replicated results from past research. In particular, our results are consistent with past research that has found that online learning contexts are important predictors of perceived and actual learning (Chen & Jang, 2010; Hachey et al., 2014), that successful (online) students are intrinsically motivated (Kauffman, 2015; Lepper et al., 2005) and experience academic control (Kauffman, 2015), and that skills with and attitudes toward technology predict academic success (Kerr et al., 2006). However, we did not find support for several other variables we thought would predict student success (such as growth mindset); such non-significant may indicate that several of these variables are in the same "space," and thus that overlapping of variance may explain why some are significant whereas others are not. Replication of this study would help to demonstrate whether that is the case, or whether there were unique factors in this study that produced idiosyncratic results.

Implications

These results reinforce the message that contextual factors are important, especially when online learning is concerned, and that success in online learning often hinges on motivational factors and perceptions of being in control (or out of control, for negative learning experiences). Further, these results demonstrate that familiarity with and attitudes toward the elements intrinsic to online learning (i.e., technology) are predictive of academic success, and are consistent with numerous findings that older adults may experience greater difficulties with online classes due to deficits related to technology more than the course material *per se*.

Our cluster analysis results indicated that a set of characteristics were predictive of success (or its lack) across students: those who were least satisfied with online courses, used the fewest study techniques, procrastinated the most, and were lowest in academic control, intrinsic motivation, perceived competence, learning confidence, and academic self-assessment performed the worst. Such results indicate that paying attention to students' technology skills or comfort, study and procrastination behaviors, and motivational characteristics may help educators to better predict which students will achieve academic success. These results are somewhat akin to those of Babick-Wirkus et al. (2021), who found a 2-cluster solution among Polish university students, with the two clusters largely differentiated by the use of active vs. passive strategies of coping, and suggests that more active and useful strategies (e.g., using more study techniques, having intrinsic motivation) will lead to more success than less active or useful strategies (e.g., procrastination). Our cluster analysis results in particular demonstrate that a subset of students can be identified as at-risk, and additional resources can then be devoted to improving their odds of successful completion of their courses.

Overall, our results suggest a few key strategies that instructors can use to increase the likelihood of student success in their courses. First, emphasizing aspects over which students have direct control–including better time management, less procrastination, and exerting greater academic control generally–should lead to better student outcomes. Second, encouraging students to develop or nurture an intrinsic interest in the subject matter (admittedly, a challenge for some subjects) should also boost student performance. Finally, engaging in activities that foster student self-confidence in their abilities in the course (and thus report greater perceived competence and high academic self-assessment) should lead to better student achievement.

Limitations

As with all studies, this project had its limitations. First, data were collected in the midst of a pandemic, during which–especially at the outset–instruction was massively diverted away from face-to-face instruction, with as-yet-unknown consequences. As noted above, instructors devoted considerable effort into improving their (now-mandated online) courses, and it is unclear if such efforts were successful, and if so, if they will last as the pandemic winds down. In addition, data were collected at a mostly commuter campus, so these results may not apply similarly to more residential campuses–although as noted above during the height of the pandemic "residential" was a relative term, and few face-to-face interactions occurred, including on campus. Further research would help to identify what long-term effects the pandemic had on instruction as well as on student performance. In addition, we were limited (by sample size) to a regression analysis for our examination of course performance; future studies ought to obtain larger samples to enable tests of more complicated (structural equation) models. For example, our cluster analysis results identified a set of at-risk students; however, such students may be at risk only for a sub-set of courses, or a different (or overlapping) set of students might be at-risk only for certain courses (e.g., organic chemistry, statistics), as opposed to being at-risk for all courses. Further exploration of students being at-risk would require a more nuanced approach than that employed here, as it would (in analytical terms) go beyond the main effects of being at-risk to identify the interactive factors (such as particular courses) that might make particular groups of students at-risk in particular contexts (such as in distance learning courses).

CONCLUSION

In line with the aims to be more reflective of our teaching as laid out by adherents of the scholarship of teaching and learning (SoTL), our results demonstrate that it is possible to identify a set of characteristics that predict student success across various modalities. Future research can expand on the risk factors (and interactive terms) that predict student success in various courses and formats, by crossing up students, courses, and formats (and other relevant characteristics) to discern a more fine-grained pattern for specific combinations of those variables. Our (surprising) finding that online students performed better may indicate a tectonic shift around online teaching and learning, or may have been a result of unique factors related to the massive shift to online learning (and accompanying administrative support of faculty efforts in that regard, which may not continue); further inquiry is required to decide which of these two explanations is more plausible. As online learning is here to stay, it behooves researchers and educators to better gauge when students are likely to succeed or fail as a result of the characteristics of students, instructors, courses, and course modalities; this study was a first step in attempting to provide answers to some of those questions.

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