ISSN: 2690-0726

Research Article

Journal of Educational and Psychological Research

Illuminating Differences in The Psychological Predictors of Academic Performance for First- And Continuing-Generation Students

Amber Carmen Arroyo*, Sonja D Winter, Sarah Depaoli, Matthew J Zawadzki

Psychological Sciences, University of California, Merced, CA, USA

***Corresponding author:**
Amber Carmen Arroyo, 5200 North Lake Road, Merced, CA 95343, United States of America

Submitted: 16 July 2021; **Accepted:** 21 July 2021; **Published:** 25 July 2021

Citation: *Amber Carmen Arroyo, Sonja D Winter, Sarah Depaoli, Matthew J Zawadzki (2021) Illuminating Differences in The Psychological Predictors of Academic Performance for First- And Continuing-Generation Students. J Edu Psyc Res 3(2): 234-246.*

Abstract

First-generation college students experience a disproportionate rate of challenges on college campuses, reflected by lower academic performance. Research has identified academic self-efficacy, optimism, goal orientation, and academic stress all as psychological factors associated with academic performance. However, this research rarely distinguishes between first- and continuing-generation students, and there may be unique effects for each group. We investigated whether the previously identified psychological factors associated with academic performance hold the same relationships for first- and continuing-generation college students. A sample of 143 undergraduate students self-reported levels of academic self-efficacy, optimism, goal orientation, and academic stress. Academic performance was measured using their midterm exam grade. There were differences found in the mean levels of psychological factors and their associations with academic performance for first- and continuing-generation students. Overall, the psychological factors explained a very small portion of the variance in academic performance among first-generation students (13.4%) with none of the psychological factors holding an independent association with academic performance. Conversely, psychological factors explained considerably more of the variance in academic performance for continuing-generation students (60.5%), with domains of goal orientation and academic stress being independently associated with academic performance. Our findings suggest that new pathways to improving first-generation students' academic performance should be identified, and that the current literature knows very little about the psychological factors that play a role in their academic performance.

Keywords: First-Generation College Student, Academic Self-Efficacy, Optimism, Goal Orientation, Academic Stress, Academic Performance

INTRODUCTION

First-generation students are defined as students who do not have a college-educated parent [1–4] and currently makeup 56% of the undergraduate student body of college campuses nationwide [4]. Compared to their continuing-generation peers, first-generation students tend to be more disadvantaged in college [1]: they are more likely to work full-time, experience food insecurity, homelessness, come from low-socioeconomic status (SES) backgrounds and have less familial support throughout college [1, 5, 6]. They are also less academically prepared for college on average and may lack the basic knowledge of how to navigate the college system [1, 5-7]. These barriers may partly explain why first-generations students are more likely to leave a four-year institution after their first year and are at increased risk of dropout throughout their college career [2, 3, 8]. A key indicator of vulnerability for dropout is academic performance (the degree to which students reach their academic goals [9, 10]). Indeed, the disadvantages first-generation students experience make them more susceptible to low academic performance [7, 12]. This disparity in academic performance and subsequent increased vulnerability for dropout is worrisome considering college graduation is especially important for first-generation students, as it is the most reliable method of upward economic and social mobility for this already disadvantaged group [11].

Due to the importance of college graduation, universities dedicate resources for interventions targeting psychological factors known to improve academic performance. The psychological factors academic self-efficacy, optimism, goal orientation, and academic stress appear repeatedly in the literature on academic performance and have been tested among several age groups, cultures, and measures of academic performance [12-16]. However, research rarely disentangles first- and continuing-generation students in these studies. The aforementioned psychological factors may play a different role within the college experience of first- and continuing-generation students, and thus potentially differentially relate to academic performance. The current study aims to understand

whether the known psychological factors (academic self-efficacy, optimism, goal orientation, and academic stress) associated with academic performance among a general student population holds when disentangling first- and continuing-generation college students.

Generational Status, Psychological Factors and Academic Performance

Academic Self-Efficacy

Academic self-efficacy is the belief in one's own capabilities to organize and execute courses of action to achieve one's academic goals [17, 18]. Academic self-efficacy is one of the most consistent predictors of academic performance [14, 15, 19-22]. It has shown its predictive ability across geographically diverse samples [19], ethnic groups [23, 24], genders [23-26], age groups [12, 13, 15, 21, 22, 27], and SES [23, 24]. However, there is some inconsistency in the literature on academic self-efficacy, college generational status, and academic performance. While many studies have found first-generation students have significantly lower levels of academic self-efficacy compared to their continuing-generation peers [30-32], there are some studies that have not found an association between these two variables [33]. Given that interventions targeting self-efficacy are proposed to narrow the achievement gap among university's most vulnerable students [29, 30], it is informative to understand if the relationship between self-efficacy and academic performance exists for both first- and continuing-generation students.

Optimism

Optimism is the dispositional tendency to expect favorable outcomes (e.g., high academic performance) in the future [12, 31]. Optimism is often thought of in contrast to pessimism, which is the dispositional tendency to expect undesirable outcomes [31]. Research has demonstrated a significant positive association between optimism and academic performance [14, 37]. Optimistic students exhibit higher expectations of available resources to deal with academic challenges, which in turn are associated with better academic performance [14]. Thus, interventions to improve academic performance could shape students' beliefs about their academic standing and requirements for academic success [38]. Although there is limited research on optimism for first-generation students, we may be able to extrapolate from research on SES and optimism. Specifically, first-generation students are often from a low-SES background, and low-SES independently predicts increased risk of dropout [1]. Optimism has been identified as a method to overcome the power of socioeconomic factors that impede students' academic performance [39] and therefore may also benefit first-generation students' academic performance.

Goal Orientation

In academic contexts, goal orientation is the source of motivation for students to engage in academic tasks [16]. There are four types of goal orientation: mastery-approach (focused on acquiring knowledge), mastery-avoidance (focused on circumventing missed educational opportunities), performance-approach (focused on the appearance of knowledge), and performance-avoidance (focused on avoiding the appearance of educational incompetence; [40, 41]). Previous research has found inconsistent associations between goal orientations and academic performance among college students, which could be attributed to variability in college generational status (e.g., [41-44]). Highlighting this variability, continuing-generation students' academic performance has been associated with performance-approach goal orientations, whereas first-generation students' academic performance has associated with mastery-approach goal orientations [44]. The variability between generational statuses continues while examining subgroups of students, such as college students with high academic performance. Within this sub-group of students, high performing first-generation students use more 'performance-avoidance' goals compared to high performing continuing- generation students [43]. Given the inconsistent findings between generational statuses, it is unclear which goal orientations will be related to academic performance for each group in the current study. However, it is likely that generational status will differentially predict the association between goal orientation and academic performance.

Academic stress

Academic stress can be defined as a student's perception of the knowledge required to perform well academically, and the perception of inadequate time to develop this knowledge [45, 46]. Academic stress is negatively associated with a college student's academic performance [47-51]. Academic stress can manifest in students affectively (feeling emotionally drained by school), behaviorally (procrastinating school work), physiologically (trouble sleeping), and cognitively (worrying about school; [47]). First-generation students may have higher levels of stress compared to continuing-generation students due to the aforementioned disproportionate challenges they face on college campuses compared to continuing-generation students [3, 48]. Due to the known adverse effects of academic stress on academic performance among college students, it could be a primary contributor to the disparity in academic performance among first and continuing-generation college students.

Aims

Despite first-generation students being a vulnerable group, and a current majority of all current undergraduates, limited research has been dedicated to understanding the psychological factors associated with their academic performance, and how it could differ from their continuing-generation peers. Given the identification of academic self-efficacy, optimism, goal orientation, and academic stress as important factors for predicting academic performance in college student samples, and the likely differences in the endorsement and association of these psychological factors for first- and continuing-generation students, our study has two aims. Aim 1 tests if there are group differences in mean levels of psychological factors academic self-efficacy, optimism, goal orientation, and academic stress between first- and continuing-generation college students. Aim 2 examines the psychological factors known to predict academic performance while distinguishing between first and continuing-generation students.

MATERIALS AND METHODS

Instruments

Academic Self-Efficacy

The College Self-Efficacy Inventory [16] was used to measure perceptions of academic self-efficacy. Out of the three subscales (course, roommate, social) the current study focused on the course

self-efficacy subscale (7 items) as it most closely represents the construct of academic self-efficacy previously found to relate to academic performance [22]. This subscale was found to be reliable in the original validation study (Cronbach's α = .88) [16].

The course self-efficacy subscale asked students to indicate how confident they were in their ability to successfully complete academic tasks such as "research a term paper", "do well on your exams", and "manage time effectively" [16]. Items were rated by respondents on an 11-point Likert-type scale ranging from 0 (not at all confident) to 10 (extremely confident). The College Self-Efficacy Inventory has been validated with Hispanic samples and was also deemed valid across genders and class levels in school [16].

Optimism

The Life Orientation Test [49] was used to measure levels of optimism. Respondents were asked to rate how much they agreed or disagreed with 8-items on a 4-point Likert-type scale ranging from 1 (disagree) to 4 (strongly agree). In line with the psychometric properties of the scale [50-54], the two-factor structure was used, in which four items measured optimism (e.g., "In uncertain times, I usually expect the best"), and four measured pessimisms (e.g., "If something can go wrong for me, it will"). These subscales optimism (Cronbach's α =.70) and pessimism (Cronbach's α =.80) have demonstrated internal validity in previous research [53].

Goal Orientation

The Achievement Goal Questionnaire [55] was used to measure participants' goal orientation for academic achievements. The 12-item scale consisted of four goal orientation subscales, each measured by three items: mastery-approach (e.g., "I want to learn as much as possible from this class"), mastery-avoidance (e.g., "I worry that I may not learn all that I possibly could in this class"), performance-approach (e.g., "It is important for me to do better than others in this class"), and performance-avoidance (e.g., "I just want to avoid doing poorly in this class"). Response options were on a 7-point Likert-type scale ranging from 1 (not at all true of me) to 7 (very true of me). The intended four-factor model was used to represent the four types of goal orientation as indicated by previous research (Cronbach's α ranging from .83 to .92) [55].

Academic stress

The Lakaev Academic Stress Response Scale [47] was used to measure students' levels of academic stress. The scale's 21-items were divided into four subscales: affective (4 items; e.g., "My work built up so much that I felt like crying"), behavioral (8 items; e.g., "I felt lazy when it came to university work"), physiological (5 items; e.g., "I had headaches"), and cognitive (4 items; e.g., "I felt overwhelmed by the demands of study"). Respondents rated how often they experienced each item in the past three days on a 5-point Likert-type scale ranging from 1 (none of the time) to 5 (all of the time). The intended four factor structure of the Lakaev Academic Stress Response Scale was used for its sound psychometric properties measuring academic stress with a cross-cultural sample (Cronbach's α ranging from .82 to .89) [47].

Academic Performance

Academic performance was measured using total points earned on students' second midterm exam in a general education course. General education courses are often taken during a student's first year of college, a crucial time for establishing patterns of success [56]. Midterm exams in general education courses in particular serve as a powerful measure of academic performance due to their predictive relationship with final course grades and overall college success [56, 57]. The exam consisted of 50 multiple choice questions. Exam scores were originally out of 100 points; however, a 3-point curve was added by the instructor resulting in a range from 23 to 103 points.

Procedure

All study procedures were approved by the university's Institutional Review Board, and all participants provided written informed consent prior to participating. Participants were enrolled in a section of a general education Introduction to Psychology course at a designated Hispanic serving institution located in Central California. Participants were recruited with a listing posted on the campus online research participation system and an announcement during their class lecture. All students enrolled in that section of the course (n = 348) were eligible to participate voluntarily. Participants completed an online survey during the 48-hour period between the end of their in-class review session and the start of their midterm exam. Additional follow-up surveys were administered after the midterm exam, but are not relevant to the current study. Finally, all students' grades on the midterm exam were recorded with no additional data stored if they did not participate in the full study (thus was treated as archival data).

Participants

Participants were 143 undergraduate students (41.1% of all students enrolled in the course). The academic performance of students who participated in the study did not differ from students who did not participate in the study, t [373.81] = 0.34, p = .732, d = .04, 95% CI [-2.78, 3.96]. Five additional students were excluded from the study because they did not report their college generational status; their grades did not differ significantly from students included in the current study, t [4.56] = -0.59, p = .581, d = .20, 95% CI [-17.02, 10.79]. The average age of the eligible sample was 18.41 (SD = 0.94, range = 17 to 25). There were 95 females (66.4%), 47 males (32.9%), and one gender fluid participant (0.7%). The majority of participants (n = 99; 69.2%) were first-generation college students. The ethnic breakdown of our sample was similar in composition to the university where data were collected. From a list of force-choice options, the largest self-identified ethnic group was Hispanic (n = 92; 64.3%), followed by Asian or Pacific Islander (n = 18; 12.2%), White (n = 14; 9.5%), African-American (n = 6; 4.1%), Multi-ethnic (n = 9; 6.1%), and Other (n = 4; 2.7%).

Data Analytic Plan

All analyses were performed in the R programming environment [58], and scripts are available on the Open Science Framework: https://osf.io/jqz8d/. The Lavaan package [59] was used to estimate confirmatory factor analyses (CFA) and (multiple-group) regression analyses. To maintain full transparency in our analysis methods per recommendations by the American Psychological Association [60] technical implementation for estimation methods are provided in S1 Appendix.

In preliminary analyses, we first tested for measurement invari-

ance in order to ensure that we could make meaningful comparison between first- and continuing-generation students. If measurement invariance is not assessed, then a mean difference between two groups could reflect differential interpretation of items across groups and not a true difference in the underlying construct. Thus, for each of the scales used in the current study, all three levels of measurement invariance (configural, metric, and scalar) were assessed before making comparisons between first- and continuing-generation students (as recommended by [61]).

To minimize the influence of measurement error [62], we used latent. An additional benefit is that latent factor scores take into account the weight of each item, instead of weighing all items equally as do observe scale means [63]. Thus, latent factor scores allow for the items that are more strongly related to an underlying latent construct to contribute more to the latent factor score values. Latent factor scores were exported from the measurement invariance analyses. To be succinct and focus on the primary analyses, details about each step of measurement invariance and the creation and interpretation of the latent factor scores are provided in S2 Appendix.

For the final preliminary analysis, we used an independent samples *t*-test using the Welch correction [64] to test for group differences in academic performance between first and continuing-generation students.

To test aim 1, latent factor means of academic self-efficacy, optimism (optimism and pessimism), goal orientation (mastery-approach, mastery-avoidance, performance-approach, performance-avoidance), and academic stress (affective, behavioral, physiological, cognitive) were compared for first- and continuing-generation students to identify potential group differences in their endorsement. The first-generation group was used as the reference group for the multiple-group analysis.

Aim 2 was divided into two parts to examine the psychological factors known to predict academic performance while distinguishing between first- and continuing-generation students. To test the first part of aim 2, bivariate correlations were estimated to test the association between academic performance and the psychological factors academic self-efficacy, optimism, goal orientation, and academic stress, across first- and continuing-generation students. To test the second part of aim 2, a multiple-group regression model was run for all psychosocial factors together predicting academic performance to test if each psychosocial factor had its own independent relationship with academic performance, and whether these relationships were consistent across first- and continuing-generation students.

RESULTS

Preliminary Analyses

We found configural, metric, and scalar invariance between first- and continuing-generation students on all scales, thus assuring that there were no significant differences in how the groups interpreted the items, and we could therefore make meaningful comparisons between groups (see S2 Appendix for a detailed report and interpretation).

The average level of academic performance derived from midterm grades was 72.68 (*SD* = 15.57, range = 23-103). The two lowest midterm grades were flagged as outliers on a boxplot (i.e., 1.5 times the interquartile range above or below the upper or lower quartiles). However, the results were not affected with and without these outliers and thus we included all participants (*n*= 143) in subsequent analyses.

For the final preliminary analysis, we examined group differences in academic performance between first- and continuing-generation students, finding unexpectedly that they did not significantly differ, t (82.552) = -0.95, p = .347, d = -0.17; 95% CI [-8.32, 2.96]. First-generation students had an average academic performance of 71.85 (*SD* = 15.68, range = 23-103), while continuing-generation students had an average of 74.53 (*SD* = 15.34, range = 45-101). To assess if demographic characteristics could account for this unexpected non-significant difference, follow-up analyses were run, finding that first- and continuing-generation students did not differ in age [t (108.38) = 1.48, p = .141, d =, 95% CI [-0.08, 0.53]], gender [χ^2 (1) = 0.48, p = .788], high school city [comparing most often reported city to all others; χ^2 (1) = 2.02, p = .155], or year in school [χ^2 (2) = 3.13, p = .209]. First-generation students, however, were more likely to be Hispanic [χ^2 (1) = 8.72, p = .003], but Hispanic ethnicity was unrelated to academic performance for the entire sample [t (87.99) = 0.03, p = .978, d = 0.005, 95% CI [-5.66, 5.82]] nor for first-generation students alone [t (36.73) = 0.003, p = .998, d = 0.001, 95% CI [-8.23, 8.25]]. Thus, it was unlikely that demographic characteristics accounted for the non-significant difference in academic performance.

Aim 1: Group Differences in Psychological Factors

Aim 1 examined if first- and continuing-generation students differed in their endorsement of academic self-efficacy, optimism (and pessimism), goal orientation (mastery-approach, mastery-avoidance, performance-approach, performance-avoidance), and academic stress (affective, behavioral, physiological, cognitive). Compared to first-generation students, continuing-generation students reported significantly lower levels of academic affective stress (β = -0.58, *SE*= .22, p = .008), behavioral stress (β = -0.64, *SE* = .21, p = .002), and physiological stress (β = - 0.53, *SE* = .25, p = .032). To further contextualize, compared to first-generation students, continuing-generation students were on average 0.58 standard deviations lower in affective stress, 0.64 standard deviations lower in behavioral stress, and 0.53 standard deviations lower in physiological stress. There were no other significant differences between first- and continuing-generation students in their mean levels of the psychological factors (see Table 1 final column). To support interpretation of results, Table 1 also provides the traditional mean composite scores for each scale. Assessing this aim with traditional mean scores did not change results.

Table 1: Composite Score Means (*SDs*), Welch Corrected *t*-test Statistics, and Latent Mean Difference Estimates (β) for First-Generation (*n* = 96) and Continuing-Generation (*n* = 43) Students.

	Composite Mean				Latent Mean
	First-Generation *M (SD)*	Continuing-Generation M (*SD*)	Difference	*t* (df)	Difference β (*SE*)
Academic Self-Efficacy	6.35 (1.39)	6.77 (1.42)	0.42	1.65 (80.99)	0.37 (.21)
Life Orientation					
Optimism	10.57 (2.60)	10.16 (2.56)	-0.41	-0.88 (83.72)	-0.16 (.21)
Pessimism	9.59 (3.01)	9.02 (2.98)	-0.57	-1.04 (83.41)	-0.20 (.20)
Goal Orientation					
Mastery-Approach	5.72 (1.12)	5.68 (1.08)	-0.04	-0.14 (85.37)	-0.04 (.19)
Mastery-Avoidance	5.03 (1.24)	4.73 (1.41)	-0.30	-1.21 (73.60)	-0.21 (.20)
Performance-Approach	4.90 (1.32)	5.01 (1.32)	0.11	0.45 (82.26)	0.06 (.19)
Performance-Avoidance	5.99 (0.81)	5.83 (0.96)	-0.16	-0.97 (71.54)	-0.19 (.19)
Academic Stress					
Affective	9.08 (3.33)	7.43 (3.12)	-1.65	-2.85 (87.78)**	-0.58** (.22)
Behavioral	18.67 (4.33)	15.95 (4.70)	-2.72	-3.30 (76.86)**	-0.64** (.21)
Physiological	11.78 (4.28)	10.00 (3.85)	-1.78	-2.46 (91.28)*	-0.53* (.25)
Cognitive	11.67 (3.34)	10.45 (3.67)	-1.22	-1.67 (76.06)	-0.39 (.20)

Note. Scale Ranges are: Academic Self-Efficacy = 0 – 10; Optimism/Pessimism = 4 – 16; Goal Orientation subscales = 1 – 7; Affective stress = 4 – 16; Behavioral stress = 7 – 28; Physiological stress = 5 – 20; Cognitive stress = 4 – 16.
*$p < .05$, **$p < .01$.

Aim 2: Psychological Factors and Academic Performance by Group

The first part of aim 2 examined how academic performance correlated with academic self-efficacy, optimism (and pessimism), goal orientation (mastery-approach, mastery-avoidance, performance-approach, performance-avoidance), and academic stress (affective, behavioral, physiological, cognitive; Table 2, column 1) among first- and continuing-generation students. Academic performance was positively associated with academic self-efficacy for both first- and continuing-generation students ($p = .031$, $p = .015$ respectively). However, only continuing-generation students had a significant positive association between academic performance and mastery-approach ($p < .001$) and performance-avoidance ($p < .001$) goals. In contrast, only first-generation students had a significant negative association between their academic performance and academic behavioral ($p = .016$) and cognitive ($p = .009$) stress. The remaining psychological factors (optimism and pessimism, mastery-avoidance and performance-approach goal orientations, and academic affective and physiological stress) were not significantly associated with academic performance for either group.

The second part of aim 2 combined all factors together into one model to compare if any of the psychological factors uniquely predicted academic performance, and to assess the amount of the variance explained in academic performance for first- and continuing-generation students (Table 2). For continuing-generation students, all factors explained 60.5% of the variance in academic performance, and mastery-approach (positive association, $p = .012$), performance- approach (negative association, $p = .037$), and academic behavioral stress (negative association, $p = .038$) all had significant independent associations with academic performance. In contrast, for first-generation students, all factors explained only 13.4% of the variance in academic performance, and none of the psychological factors were uniquely associated with academic performance.

Table 2: Bivariate correlations and regression model estimates predicting academic performance among first- and continuing generation students.

First-generation (*n* = 96)				
	r	***b (SE)***	***95% CI***	**β**
Academic Self-Efficacy	0.22*	3.10 (2.46)	-1.72, 7.92	.18
Life Orientation				
Optimism	0.09	-1.88 (2.61)	-7.01, 3.24	-.10
Pessimism	-0.09	-0.57 (2.36)	-5.19, 4.05	-.03
Goal Orientation				
Mastery-Approach	0.08	2.61 (1.91)	-1.14, 6.36	.17
Mastery-Avoidance	-0.11	-1.93 (2.04)	-5.93, 2.07	-.11
Performance-Approach	0.07	1.26 (2.06)	-2.78, 5.31	.07
Performance-Avoidance	-0.08	-2.95 (2.00)	-6.86, 0.97	-.18
Academic Stress				
Affective	-0.15	0.95 (2.96)	-4.85, 6.74	.05
Behavioral	-0.24*	-1.00 (2.71)	-6.30, 4.31	-.05
Physiological	-0.11	2.97 (2.50)	-2.94, 6.87	.11
Cognitive	-0.27**	-4.40 (2.87)	-10.01, 1.22	-.24
***F* (df1, df2)**		1.19	(11, 84)	
***R*-squared**		0.13		
Continuing-generation (*n* = 43)				
	r	***b (SE)***	***95% CI***	**β**
Academic Self-Efficacy	0.37*	1.85 (1.80)	-1.68, 5.38	.13
Life Orientation				
Optimism	0.13	-0.32 (1.69)	-3.64, 3.00	-.02
Pessimism	0.09	1.37 (1.91)	-2.37, 5.11	.09
Goal Orientation				
Mastery-Approach	0.60***	7.96** (2.53)	3.00, 12.93	.49
Mastery-Avoidance	-0.07	0.15 (1.78)	-3.34, 3.63	.01
Performance-Approach	0.14	-5.53* (2.16)	-9.76, -1.31	-.35
Performance-Avoidance	0.52***	3.13 (1.76)	-0.32, 6.57	.24
Academic Stress				
Affective	0.15	-0.39 (3.20)	-6.65, 5.87	-.02
Behavioral	-0.27	-5.69* (2.24)	-10.07, -1.32	-.35
Physiological	0.20	6.42 (3.81)	-1.05, 13.88	.33
Cognitive	-0.14	-3.28 (2.95)	-9.06, 2.50	-.19
***F* (df1, df2)**		4.32***	(11,31)	
***R*-squared**		0.61		

*Note. *p < .05, **p < .01, ***p < .001.*

DISCUSSION

Due to the large presence of first-generation students on college campuses [4], and their increased risk of dropout due to poor academic performance [2, 3, 6, 8], the current study examined if the psychological factors known to predict academic performance held the same relationship for first- and continuing-generation students. The first aim of our study examined if there were mean differences between first- and continuing-generation students in the psychological factors academic self-efficacy, optimism (and pessimism), goal orientation (mastery-approach, mastery-avoidance, performance-approach, performance-avoidance), and academic stress (affective, behavioral, physiological, cognitive). We found that first-generation college students had significantly higher levels of academic stress (affective, behavioral, physiological, but not cognitive) than continuing-generation students. This finding expands prior work showing first-generation students experience greater levels of stress in a variety of domains – financial [65, 66], work-related -71, 72], familial [71, 73, 74], and basic needs [1, 6, 7] – compared to their continuing-generation peers. The increased levels of academic stress could be compounded with these other sources of stress, which is worrisome considering the known effect stress has on academic performance in college [47-49]. Unfortunately, poor academic performance is associated with increased levels of academic stress; thus, continuing a cycle of high academic stress and poor academic performance [46, 75]. Our finding calls attention to the disproportionate levels of academic stress first-generation students experience compared to their peers, and could be an area to address on college campuses.

Perhaps surprisingly, we did not find a significant difference in the endorsement of the remaining psychological factors academic self-efficacy, optimism (and pessimism), and goal orientation (mastery-approach, mastery-avoidance, performance-approach, performance avoidance). These findings indicate that first-generation students do not always differ from their peers, and that looking at the endorsement of these psychological factors (with the exception of academic affective, behavioral, physiological stress) may not be a fruitful target for addressing educational disparities. Instead, differences between these two groups could arise in other areas, such as the relationship between psychological factors and academic performance.

Indeed, the first part of aim 2 revealed that the relationship between some psychological factors and academic performance differed for first- and continuing-generation students. Two goal orientations (mastery-approach and performance-avoidance) had a significant positive association with academic performance for continuing-generation students but not for first-generation students. Further, academic stress (behavioral, cognitive) had a significant negative association with academic performance for first-generation students but not for continuing-generation students. The results of aims 1 and 2 in conjunction suggest that not only do first-generation students have higher levels of academic behavioral stress (as shown in aim 1), the way academic behavioral stress associates with first-generation students' academic performance appears uniquely worse than it is for continuing-generation students. In addition, although first-generation students did not experience higher levels of cognitive stress (as shown in aim 1), their cognitive stress levels were independently associated with worse academic performance. This demonstrates the importance of looking at both the mean levels of psychological factors and their associations with academic performance, as each contributes a distinct piece of information.

In contrast to the differences we did find between these two groups, academic self-efficacy was a common denominator for first- and continuing-generation students. Specifically, academic self-efficacy was positively associated with academic performance for both groups of college students. This is in line with previous research indicating that academic self-efficacy is one of the most robust psychological predictors of academic performance among students regardless of age [14, 15, 17, 23, 24, 29], ethnicity [22, 25, 26], or country [17, 21]. It also suggests that if interventionists only had the resources to focus on one psychological factor in a diverse group of students, assessing academic self-efficacy to stratify who is most at risk, and targeting ways to promote academic self-efficacy may be the best option for improving academic performance (as prior research has suggested a causal relationship between self-efficacy and performance; [34, 35]).

We did not find a significant difference between first- and continuing-generation students in the way academic performance associated with optimism (and pessimism), goal orientation (mastery-avoidance, performance-approach), and academic stress (affective and physiological). This finding was surprising given previous literature suggesting that these psychological factors are associated with academic performance. As discussed in greater detail in our limitations section, it is possible that there was something uniquely different about our sample compared to those used in previous research.

The second part of aim 2 examined all psychological factors simultaneously in a model predicting academic performance to understand the extent to which these psychological factors were explaining the variance in academic performance for first- and continuing-generation students. Remarkably, for first-generation students, the model explained just 13.4% of the variance in academic performance, and none of the psychological factors were independently associated with academic performance. In contrast, for continuing-generation students, the model explained 60.5% of the variance in academic performance, with mastery-approach (positively associated), performance-approach (negatively associated), and academic behavioral stress (negatively associated) all being independent predictors of academic performance. This difference in explained variance is striking and highlights a problematic assumption in the field that the same factors would matter for all students. Yet, because first-generation college students have either been consistently underrepresented in research or this demographic has not been explicitly studied as a risk stratified, we know comparatively very little for a group of students so prominent on campuses [4] and vulnerable to drop out [2, 3, 4, 8].

Limitations and Future Directions

This study fills a gap in the literature by highlighting the importance of distinguishing between college generational statuses while examining psychological factors associated with academic performance. However, it is not without limitations. In our sample, college generational status was highly correlated with ethnici-

ty (i.e., most first-generation college students were also Hispanic). This was unique in that we had a chance to research a fast-growing but historically understudied group, yet we are limited in our ability to generalize to other racial and ethnic groups that also have historically shown relatively worse academic performance, including African-American students [71]. There is some evidence to suggest correlates of academic achievement vary across ethnic groups [72-74]. Therefore, it is unknown whether our findings would generalize to all first-generation students, or if they reflect something unique for first-generation Hispanic students. They also put a spotlight on the need to identify and address sample differences while attempting to replicate findings. Future research should employ stratified sampling methods to understand how academic performance is related to college generational status or ethnicity or if they interact with one another.

Our study was also one of the first to examine measurement invariance across first- and continuing-generation students on several scales of psychological factors. However, due to sample size restrictions, we did not have enough statistical power to examine a structural equation model that included latent factors for all of the psychological factors. To circumvent this issue, we exported latent factor scores from the measurement invariance results. Although common practice in the literature with small sample sizes [75], a potential limitation to this method is possible correlations between scales. Future research could expand on our study by obtaining a larger sample size to examine all latent factors in one model to account for possible correlations between scales.

Further, the current study is correlational allowing us to identify which students are at risk, but these data do not tell us why they are at risk. Experimental studies in educational settings are generally rare as many administrators do not want to withhold potential resources that could benefit vulnerable students. Yet, additional work is needed to better make causal inferences. For example, future research may wish to track a cohort of students over time measuring both within- and between-person variation in psychological factors and subsequent changes to academic performance. Moreover, it is important to control for a wide range of third variables that could be confounding effects, such as family income, early childhood trauma, and individual differences in professors.

Our measure of academic performance was well-informed; midterm exams predict final course grades [57] and is frequently used as a measure of academic performance [10, 76]. Nevertheless, this measure only represents one type of assessment and academic performance covers a wider range of possibilities (e.g., standardized assessments, cumulative GPA). It would be interesting to examine whether psychological factors differentially relate to these alternative measures of academic performance.

Conclusions

Earning a college degree is the most consistent way of improving economic and social mobility in the United States [11]. Yet, first-generation students drop out of universities at higher rates than their continuing-generation peers [77]. Investing in targeted interventions to help First-generation students graduate college would not only be beneficial to the individual, but also their future kin and society as a whole [78]. Nevertheless, a primary conclusion of this paper is that we do not understand what influences first-generation students' academic performance, and therefore do not understand a key indicator of vulnerability for dropout or how to help them. This is a pressing issue given that first-generation students make up over half of all students enrolled at college campuses in the US [4]. Due to the importance of graduating college, especially for first-generation students, we are doing them and ourselves a disservice by not knowing more about them.

References

1. Cataldi EF, Bennett CT, Chen X (2018) First-generation students: College access, persistence, and postbachelor's outcomes. National Center for Education Statistics. Washington DC, National Center for Education Statistics.
2. Choy SP (2001) Students whose parents did not go to college: Postsecondary access, persistence, and attainment. Washington DC: U.S. Department of Education, National Center for Educational Statistics.
3. Pascarella ET, Pierson CT, Wolniak GC, Terenzini PT (2004) First-generation college students: Additional evidence on college experiences and outcomes. The Journal of Higher Education. 75 :249-284.
4. Pamela Brown (2017) Institutional Research and Academic Planning. First-generation student success at the University of California.
5. RTI International (2019) First-generation college students: Demographic characteristics and postsecondary enrollment. Washington, DC: NASPA: Center for First Generation Student Success.
6. Allan BA, Garriott PO, Keene CN (2016) Outcomes of social class and classism in first and continuing generation college students. Journal of counseling psychology 63: 487-496.
7. Bui KVT (2002) First-generation college students at a four-year university: Background characteristics, reasons for pursuing higher education, and first year experiences. Project Innovation 36: 3-11.
8. Fallon MV (1997) The school counselor's role in First-generation students' college plans. The School Counselor 44: 384-393.
9. Lohfink MM, Paulsen MB (2005) Comparing the determinants of persistence for first-generation and continuing-generation students. Journal of College Student Development 46: 409-428.
10. Stinebrickner T, Stinebrickner R (2009) Learning about academic ability and the college dropout decision. Journal of Labor Economics. 30: 707-48.
11. Ward A, Stoker HW, Stoker H, Murray Ward M (1996) Educational Measurement: Theories and applications. University Press of America 1996: 384.
12. Riehl RJ (1994) The Academic Preparation, Aspirations, and First-Year Performance of First- Generation Students. College and University 70: 14-19.
13. Garriott PO, Hudyma A, Keene CN, Santiago D (2015) Social cognitive predictors of first and non-first-generation college students' academic and life satisfaction. Journal of Counseling Psychology 62: 253-263.
14. Chemers MM, Hu L, Garcia BF (2001) Academic self-efficacy and first year college student performance and adjustment. Journal of Educational Psychology 93: 55-64.

15. Guay F, Boivin M, Hodges EVE. (1999) Social comparison processes and academic achievement: The dependence of the development of self-evaluations on friends' performance. Journal of Educational Psychology 91: 564-568.
16. Hsieh P, Sullivan JR, Guerra NS (2007) A closer look at college students: Self-efficacy and goal orientation. Journal of Advanced Academics 18: 454-476.
17. Ogunmakin AO, Akomolafe MJ (2013) Academic self-efficacy, locus of control and academic performance of secondary school students in Ondo State, Nigeria. Mediterranean Journal of Social Sciences 4: 570-576.
18. Solberg VS, O'Brien K, Villareal P, Kennel R, Davis B (1993) Self-efficacy and Hispanic college students: Validation of the college self-efficacy instrument. Hispanic Journal of Behavioral Sciences 15: 80-95.
19. Bandura A, Barbaranelli C, Caprara GV, Pastorelli C (1996) Multifaceted impact of self-efficacy beliefs on academic functioning. Child development 67: 1206-1222.
20. Bandura A (1997) Self-efficacy: The exercise of control. New York NY US: W H Freeman 1997: 604.
21. Adeyemo DA (2007) Moderating influence of emotional intelligence on the link between academic self-efficacy and achievement of university students. Psychology and Developing Societies 19: 199-213.
22. Bembenutty H (2007) Self-regulation of learning and academic delay of gratification: Gender and ethnic differences among college students. Journal of Advanced Academics 18: 586-616.
23. Greene BA, Miller RB, Crowson HM, Duke BL, Akey KL, et al. (2004) Predicting high school students' cognitive engagement and achievement: Contributions of classroom perceptions and motivation. Contemporary Educational Psychology 29: 462-482.
24. Klomegah RY (2007) Predictors of academic performance of university students: An application of the goal efficacy model. College Student Journal 41: 407-415.
25. Bondy JM, Peguero AA, Johnson BE (2017) The Children of Immigrants' Academic Self-Efficacy: The Significance of Gender, Race, Ethnicity, and Segmented Assimilation. Education and Urban Society 49: 486-517.
26. MacPhee D, Farro S, Canetto SS (2013) Academic Self-Efficacy and Performance of Underrepresented STEM Majors: Gender, Ethnic, and Social Class Patterns. Analyses of Social Issues and Public Policy 13: 347-369.
27. Schwery D, Hulac D, Schweinle A (2016) Understanding the Gender Gap in Mathematics Achievement: The Role of Self-Efficacy and Stereotype Threat. School Psychology Forum 10: 386-396.
28. Williams M, George Jackson C (2014) Using and doing science: gender, self-efficacy, and science identity of undergraduate students in STEM. Journal of Women and Minorities in Science and Engineering 20: 99-126.
29. Pajares F (1995) Self-Efficacy in Academic Settings. In San Francisco, CA.
30. Hellman CM (1996) Academic Self Efficacy: Highlighting the First-generation Student. Journal of Applied Research in the Community College 4: 69-75.
31. Wang C-CD, Castañeda-Sound C (2008) The Role of Generational Status, Self-Esteem, Academic Self-Efficacy, and Perceived Social Support in College Students' Psychological Well-Being. Journal of College Counseling 11: 101-118.
32. Ramos Sánchez L, Nichols L (2007) Self-Efficacy of First-Generation and Non-First-Generation College Students: The Relationship with Academic Performance and College Adjustment. Journal of College Counseling 10: 6-18.
33. Westbrook S, Scott J (2012) The Influence of Parents on the Persistence Decisions of First- Generation College Students.
34. Avalos MRA (2017) College self-efficacy and academic performance in Mexican American undergraduates. Arizona State University.
35. Bartsch RA, Case KA, Meerman H (2012) Increasing Academic Self-Efficacy in Statistics with a Live Vicarious Experience Presentation. Teaching of Psychology 39: 133-136.
36. Carver CS, Scheier MF, Segerstrom SC (2010) Optimism. Clinical Psychology Review 30: 879-889.
37. Segerstrom SC, Nes LS (2006) When goals conflict but people prosper: The case of dispositional optimism. J Res Pers 40: 675-693.
38. Lin-Siegler X, Dweck C, Cohen G (2016) Instructional interventions that motivate classroom learning. Journal of Educational Psychology 108 :295
39. Hoy WK, Tarter CJ, Hoy AW (2006) Academic optimism of schools: A force for student achievement. American Educational Research Journal. 43: 425-446.
40. Dweck, Carol S (1986) Motivational processes affecting learning. American Psychologist 41: 1040-1048.
41. Law W, Elliot AJ, Murayama K (2012) Perceived competence moderates the relation between performance-approach and performance-avoidance goals. Journal of Educational Psychology 104: 801-819.
42. Hadsell L (2009) Achievement goals, locus of control, and academic success and effort in introductory and intermediate microeconomics. In Atlanta GA.
43. Jury M, Smeding A, Court M, Darnon C (2015) When first-generation students succeed at university: On the link between social class, academic performance, and performance-avoidance goals. Contemporary Educational Psychology 41: 25-36.
44. Darnon C, Jury M, Aelenei C (2018) Who benefits from mastery-approach and performance- approach goals in college? Students' social class as a moderator of the link between goals and grade. Eur J Psychol Educ 33: 713-726.
45. Carveth JA, Gesse T, Moss N (1996) Survival strategies for nurse-midwifery students. Journal of Nurse-Midwifery 41: 50-54.
46. Misra R, Castillo LG (2004) Academic stress among college students: Comparison of American and international students. International Journal of Stress Management 11: 132-148.
47. Akgun S, Ciarrochi J (2003) Learned resourcefulness moderates the relationship between academic stress and academic performance. Educational Psychology 23: 287-294.
48. Felsten G, Wilcox K (1992) Influences of stress and situation-specific mastery beliefs and satisfaction with social support on well-being and academic performance. Psychol Rep 70: 291-303.
49. Pritchard ME, Wilson GS (2003) Using emotional and social factors to predict student success. Journal of College Student Development 44: 18-28.

50. Struthers CW, Perry RP, Menec VH (2000) An examination of the relationship among academic stress, coping, motivation, and performance in college. Research in Higher Education 41: 581-592.
51. Van Heyninge, Julie J (1997) Academic achievement in college students: What factors predict success? Indiana University of Pennsylvania 1997: 1-24.
52. Lakaev N (2009) Validation of an Australian academic stress questionnaire. Australian Journal of Guidance & Counselling 19: 56-70.
53. Barry LM, Hudley C, Kelly M, Cho SJ (2009) Differences in self-reported disclosure of college experiences by first-generation college student status. Adolescence 44: 55-68.
54. Scheier MF, Carver CS (1985) Optimism, coping, and health: Assessment and implications of generalized outcome expectancies. Health Psychology 4: 219-247.
55. Allan MM, Giles M (2008) Psychometric properties of Scheier and Carver's life orientation test in a sample of Australian prisoners. Psychol Rep 103: 305-322.
56. Chang L (1995) Connotatively inconsistent test items. Applied Measurement in Education 8: 199-209.
57. Chang L, McBride Chang C (1996) The factor structure of the life orientation test. Educational and Psychological Measurement 56: 325-329.
58. Kubzansky LD, Kubzansky PE, Maselko J (2004) Optimism and pessimism in the context of health: Bipolar opposites or separate constructs? Pers Soc Psychol Bull 30: 943-956.
59. McPherson J, Mohr P (2005) The role of item extremity in the emergence of keying-related factors: An exploration with the Life Orientation Test. Psychological Methods 10: 120-131.
60. Elliot AJ, McGregor HA (2001) A 2 × 2 achievement goal framework. Journal of Personality and Social Psychology 80: 501-519.
61. Reason RD, Terenzini PT, Domingo RJ (2006) First things first: Developing academic competence in the first year of college. Research in Higher Education 47: 149-175.
62. Jensen PA, Barron JN (2014) Midterm and first-exam grades predict final grades in biology courses. Journal of College Science Teaching 44: 82-89.
63. R Core, Team R (2019) A language and environment for statistical computing. R Foundation for Statistical Computing.
64. Rosseel Y, Lavaan (2012) An R package for structural equation modeling and more. Journal of Statistical Software 48: 1-36.
65. Appelbaum M, Cooper H, Kline RB, Mayo-Wilson E, Nezu AM, et al. (2018) Journal article reporting standards for quantitative research in psychology: The APA Publications and Communications Board task force report. American Psychologist 73: 3-25.
66. Vandenberg RJ, Lance CE (2000) A review and synthesis of the measurement invariance literature: Suggestions, practices, and recommendations for organizational research. Organizational Research Methods 3: 4-70.
67. Brown TA, Moore MT (2012) Comfirmatory factor analysis. In: Hoyle RH, editor. Handbook of structural equation modeling. New York: Guilford Press 2012: 361-379.
68. Brown, Timothy (2006) A Confirmatory factor analysis for applied research. New York, NY, US: The Guilford Press 2006: 1-475.
69. Welch BL (1947) The generalization of student's' problem when several different population variances are involved. Biometrika 34: 28-35.
70. Lombardi AR, Murray C, Gerdes H (2012) Academic performance of first-generation college students with disabilities. Journal of College Student Development 53: 811-826.
71. Phinney JS, Haas K (2003) The process of coping among ethnic minority first-generation college freshmen: A narrative approach. The Journal of Social Psychology 143: 707-726.
72. Stebleton MJ, Soria KM, Huesman RL (2014) First-generation students' sense of belonging, mental health, and use of counseling services at public research universities. Journal of College Counseling 17: 6-20.
73. Covarrubias R, Valle I, Laiduc G, Azmitia M (2014) "You Never Become Fully Independent": Family Roles and Independence in First-Generation College Students. Journal of Adolescent Research 34: 381-410.
74. Covarrubias R, Fryberg SA (2015) Movin' on up (to college): First-generation college students' experiences with family achievement guilt. Cultural Diversity and Ethnic Minority Psychology 21: 420-429.
75. Essandoh PK (1995) Counseling issues with African college students in US colleges and universities. The Counseling Psychologist 23: 348-360.
76. Greene TG, Marti CN, McClenney K (2008) The effort outcome gap: Differences for African American and Hispanic community college students in student engagement and academic achievement. The Journal of Higher Education 79: 513-539.
77. Valencia AA (1994) The attributes of academically successful Mexican-American university male and female students. Journal of Multicultural Counseling and Development 22: 227-238.
78. Walker KL, Satterwhite T (2002) Academic performance among African American and Caucasian college students: Is the family still important? College Student Journal 36: 113-129.
79. Yazedjian A, Michelle TL, Navarro A (2009) Exploring parental factors, adjustment, and academic achievement among White and Hispanic college students. Journal of College Student Development 50: 458-467.
80. Devlieger I, Rosseel Y (2017) Factor Score Path Analysis. Methodology 13: 31-38.
81. Von Stumm S, Hell B, Chamorro-Premuzic T (2011) The hungry mind: Intellectual curiosity is the third pillar of academic performance. Perspect Psychol Sci 6: 574-588.
82. Ishitani TT, DesJardins SL A (2002) longitudinal investigation of dropout from college in the United States. Journal of College Student Retention 4: 173-201.
83. Ma J, Pender M, Welch M (2016) Education pays The benefits of higher education for individuals and society. Trends in higher education series. Washington, DC College Board.

Supporting Information

S1 Appendix. Technical Implementation of Model Estimation.

S2 Appendix. Details about Measurement Invariance Analyses and Latent Factors.

S1 Appendix: Technical Implementation of Model Estimation

In the current study, CFAs with continuous items (including categorical items with at least 7 answer categories) were estimated through robust maximum likelihood (MLR) using full information maximum likelihood (FIML) to handle missing data. Analyses with categorical items were estimated through the mean- and variance-adjusted weighted least squares (WLSMV) estimator with Delta parameterization, using pairwise deletion to handle missing data. Robust or scaled fit indices were reported for all analyses. Specifically, for chi-squared estimates, the Satorra-Bentler [1] Chi-square was used for models estimated with MLR, and the Satorra approximation was used for models estimated with WLSMV [2]. Analysis scripts can be found on the Open Science Framework: https://osf.io/jqz8d.

S1 References

1. Satorra A, Bentler PM (2001) A scaled difference chi-square test statistic for moment structure analysis. Psychometrika 66: 507-514.

2. Satorra A (2000) Scaled and adjusted restricted tests in multi-sample analysis of moment structures. Innovations in Multivariate Statistical Analysis 2000: 233-247.

S2 Appendix: Details about Measurement Invariance Analyses and Latent Factors Methods of Measurement Invariance Analyses

The three levels of measurement invariance were: configural (Step 1, assesses the factor model), metric (Step 2, examines the individual factor loadings), and scalar (Step 3, assesses the intercepts or thresholds present in the model). These three steps were followed in a conventional manner according to measurement invariance testing [1].

For configural invariance, the same items were related to the same latent factors across groups, creating an equal CFA structure, but all measurement parameters (i.e., factor loadings, intercepts) were estimated freely. If previous psychometric research was inconclusive about the expected factor structure of a scale, then multiple factor solutions were compared x^2 using difference tests [2]. A lower x^2 statistic implies that the data fit the model better. In addition, we report the comparative fit index (CFI; [3,4]) and root mean squared error of approximation (RMSEA; [5]) to assess the fit of each model. The CFI is a goodness-of-fit measure, where higher values (i.e., closer to 1) indicate better model fit. The RMSEA is a badness-of-fit measure, meaning larger values imply worse model fit. For metric invariance, factor loadings were constrained to be equal across groups. In other words, the relationship between each item and the underlying latent factor is the same strength across groups. For scalar invariance, the intercepts and thresholds were constrained to be equal across groups. This implies that for each item, the observed answer value is associated with the same score on the latent factor across groups. After each level was estimated, a x^2 difference test was used to assess whether the more restrained model (e.g., metric) significantly worsened model fit compared to a less restrained model (e.g., configural). If either the metric or scalar model significantly worsened model fit, then further group comparison for that measure was discontinued because a significant x^2 implies that the two groups interpreted the items in the scale in fundamentally different ways. In addition, the CFI was also reported to provide additional information about the fit of each model.

Results of Measurement Invariance Analyses

Configural Model

Establishing how many latent factors underlie a set of scale items and whether this structure is the same across groups is the first step of invariance testing. CFA results of the configural models are discussed below. Whenever possible, we have included a comparison of multiple factor models that have been used in previous research.

Academic Self-Efficacy

A one-factor model of course self-efficacy, with a residual covariance between two similarly worded items, fit the data well, χ^2 (13) = 16.44, p = .226, CFI = .986, RMSEA = .043, 95% CI [.000, .093]. Cronbach's α for the scale was .82.

Optimism

A two-factor model of optimism and pessimism fit the data significantly better than a one-factor model of general optimism, $\Delta\chi^2$ (1) = 31.20, p < .001, and fit the data well, χ^2 (19) = 21.74, p = .297, CFI = .996, RMSEA = .032, 95% CI [.000, .083]. Cronbach's alphas for the optimism and pessimism subscales were .70 and .81, respectively. The subscales were moderately correlated, r = -0.45 (SE = 0.10), p < .001.

Goal Orientation

We compared the intended four-factor model of goal orientation to four alternative factor models examined in previous research [6]. The expected four-factor model fit the data significantly better than a two-factor approach-avoidance model, $\Delta\chi^2$ (5) = 118.70, p <.001, a two-factor mastery-performance model, $\Delta\chi^2$ (5) = 152.03, p < .001, a three-factor specific approach-general avoidance model $\Delta\chi^2$ (3) = 19.52, p < .001, and a three-factor specific performance-general mastery model, (3) = 228.41, p < .001. The four-factor model fit the data well, χ^2 (48) = 86.41, p = .001, CFI = .936, RMSEA = .075, 95% CI [.050, .099].

Cronbach's alphas for the mastery-approach, mastery-avoidance, performance-approach, and performance-avoidance subscales were .82, and .87, .85, .58, respectively. The four subscales were positively correlated with each other, with correlation coefficients ranging from r = 0.28 (SE =.10), p = .003 (mastery-avoidance with performance-approach) to r = .56 (SE = .12), p <.001 (performance-approach with performance-avoidance).

Academic Stress

We compared the intended four-factor model of the LASRS to a general one- factor model of academic stress that has been used in previous research (e.g., [7, 8]). The four- factor model, modeling affective, behavioral, physiological, and cognitive stress separately, fit the data significantly better than a one-factor model, $\Delta\chi^2$ (6)

= 58.48, $p < .001$. It should be noted that Item 2 ("I used alcohol or drugs") in the behavioral stress scale was removed because 97.2% of participants were under the legal drinking age at the time of the study. The four-factor model fit the data well, χ^2 (43) = 256.82, $p < .001$, CFI = .972, RMSEA = .063, 95% CI [.048, .078]. Cronbach's alphas for the affective, behavioral, physiological, and cognitive subscales were .75, .80, .77, and .85, respectively. The four subscales were strongly correlated with each other, with correlation coefficients ranging from $r = 0.72$ (SE =.06), $p < .001$ (physiological with cognitive stress) to $r = .92$ (SE = .04), $p < .001$ (physiological with affective stress).

Metric and Scalar Models

Results of step 2 and 3 invariance testing are reported in Table 1. For all included measures, we found that scalar invariance did not decrease model fit significantly. In addition, the CFI values for all tested models indicate that good model fit was retained. Due to our relatively small sample size and larger number of items included in the LASRS, it was not computationally possible to examine measurement invariance for all the subscales in one analysis. Instead, each subscale of the LASRS was analyzed separately. Based on the results reported in Table 1, we conclude that all included scales reached the scalar level of measurement invariance.

Table 1: Multiple-group CFA Measurement Invariance Results.

		χ^2(df)	*p*	$\Delta\chi^2$(df)	*p*	CFI
Academic Self-Efficacy	Configural	28.65 (26)	.327			.991
	Metric	40.95 (33)	.161	12.43 (7)	.087	.972
	Scalar	46.96 (39)	.178	5.73 (6)	.454	.972
Life Orientation (Optimism and Pessimism)	Configural	46.23 (38)	.169			.989
	Metric	62.87 (46)	.050	12.79 (8)	.119	.977
	Scalar	69.10 (60)	.197	3.71 (14)	.997	.987
Goal Orientation[1]	Configural	166.50 (99)	< .001			.903
	Metric	180.40 (111)	< .001	15.14 (12)	.234	.901
	Scalar	184.37 (119)	< .001	4.54 (8)	.806	.907
Academic Stress: Affective[2]	Configural	6.27 (4)	.180			.995
	Metric	7.22 (8)	.513	2.91 (4)	.573	1.000
	Scalar	14.01 (15)	.525	5.71 (7)	.574	1.000
Academic Stress: Behavioral[2]	Configural	40.29 (28)	.062			.976
	Metric	37.06 (35)	.374	3.16 (7)	.869	.996
	Scalar	55.54 (48)	.212	16.77 (13)	.210	.986
Academic Stress: Physiological[2]	Configural	7.28 (10)	.699			1.000
	Metric	9.44 (15)	.854	3.40 (5)	.639	1.000
	Scalar	21.58 (24)	.605	11.44 (9)	.247	1.000
Academic Stress: Cognitive[2]	Configural	11.96 (4)	.018			.991
	Metric	14.26 (8)	.075	3.62 (4)	.461	.993
	Scalar	25.05 (15)	.049	6.67 (7)	.464	.989

Note. $\Delta\chi^2$ is based on uncorrected χ^2 estimates and may not match up when compared to values in χ^2 column. [1]Two non-significant negative residual variances (of item 6 and item 9) needed to be constrained to 0 for meaningful comparison. [2]The two highest response categories within this scale had to be collapsed as the highest response option was not chosen in at least one of the groups included.

Latent Factors Scores Extraction and Interpretation

As the sample size of the current study is limited, it is not possible to estimate a model that includes all latent factors representing the various constructs of interest. Instead, latent factor scores were exported from the invariance models and used for further analyses. Using latent factor scores instead of the more often used sum-scores or averages across all items has several advantages: First, factor scores take into account the weight of each item, instead of weighing all items equally [9]. This means that items more strongly related to the underlying latent construct contribute more to the factor score values. Second, CFA separates systematic variations in item responses that are related to the underlying latent factor from unsystematic measurement error [10]. Latent factor scores only reflect the systematic part of the variation in item responses and are thus less noisy than traditional composite scores such as total scores or averages across all items. Latent factor variables do not have an intrinsic scale, and thus need to be explicitly specified

by the researcher through the CFA model. In the current study, this was achieved by fixing the mean of the latent factor to 0 for the reference group (here, first-generation) and fixing the standard deviation to 1 for both groups. This allows for freely estimating the latent factor mean of the other group (here, continuing-generation). Through this method, the estimate of the continuing-generation group denotes the difference (in standard deviation units) between itself and the first-generation group. For example, if the estimate of the continuing-generation student group is 2, it indicates that their mean is two standard deviations higher than the mean for first- generation students.

S2 References

Vandenberg RJ, Lance CE (2000) A review and synthesis of the measurement invariance literature: Suggestions, practices, and recommendations for organizational research. Organizational research methods 3: 4-70.

1. Gregorich SE (2006) Do self-report instruments allow meaningful comparisons across diverse population groups? Testing measurement invariance using the confirmatory factor analysis framework. Medical Care 4: 78-94.
2. Bentler (1990) Comparative fit indexes in structural models. Psychological Bulletin 107: 238-246.
3. Cheung GW, Rensvold RB (2002) Evaluating goodness-of-fit indexes for testing measurement invariance. Structural Equation Modeling 9: 233-255.
4. Steiger JH (1990) Structural model evaluation and modification: An interval estimation approach. Multivariate Behavioral Research 25: 173-180.
5. Elliot AJ, McGregor HA (2001) A 2x2 achievement goal framework. Journal of Personality and Social Psychology 80: 501-519.
6. Bernstein C, Chemaly C (2016) Sex role identity, academic stress and wellbeing of first-year university students. Gender and Behaviour 14: 7547-7573.
7. Van der Werf D (2013) Effects of group inequality on perceived group processes and individual outcomes. Master's thesis, The University of Guelph, Ontario, Canada.
8. Brown TA (2006) Confirmatory factor analysis for applied research. New York: Guilford Press.
9. Brown TA, Moore MT, RH Hoyle (2012) Handbook of Structural Equation Modeling 2012: 740.