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Self-regulation and STEM persistence in minority and non-minority students across the first year of college

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Abstract

Psychological factors have been implicated in STEM persistence but remain poorly understood. In particular, the role of self-regulation--the cognitive, behavioral, and emotional skills that allow individuals to work efficiently toward their desired goals, especially when under stress--has received minimal attention. Psychological factors may be particularly important for persistence by underrepresented minority (URM) students, many of whom face significant barriers to success in STEM. We examined the extent to which self-regulation predicts STEM persistence in 732 STEM students and whether minority status moderated self-regulation's associations with STEM persistence. We found minimal differences in self-regulation styles between URM and nonunderrepresented minority students. Baseline cognitive-emotional self-regulation predicted intentions to persist in a science career, using alcohol and drugs to cope with stress predicted less persistence in STEM major across the year, and only URM status predicted end-of-year GPA. Minority status did not moderate these associations. Future research is needed on self-regulation skills and students' trajectories of STEM success.

Keywords

Self-regulation; STEM; Persistence; Student success; Minorities

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1. Introduction

Attrition throughout the Science-Technology-Engineering-Mathematics (STEM) pipeline remains a national concern (PCAST, 2012), driving considerable research to identify factors that predict and/or facilitate student success and persistence in STEM fields. Despite early intentions to pursue a STEM career, the percentage of college students who start off in a STEM field and go on to earn a STEM degree within five years ranges from 33% to 46% (Hurtado, Eagan, and Chang, 2010; Huang et al., 2000). Some loss in STEM degree attainment is understandable as there is likely some disconnect between the appeal of a STEM career (e.g., job opportunities, career status) and the challenges associated with many STEM majors (e.g., academic preparation, additional requirements) as well as the potentially negative experiences associated with STEM curricula (e.g., weed out/gateway courses). However, even high-achieving STEM students sustain significant losses in STEM degree attainment (Chen and Soldner, 2014).

1.1. STEM Persistence in Underrepresented Minority Groups

Understanding the lack of student persistence in STEM is important for all students, but particularly so for underrepresented minority (URM) groups, who comprise a growing percentage of the U.S. population but remain woefully underrepresented among STEM professionals (Estrada et al., 2016). These discrepancies in STEM degree attainment between URM and nonunderrepresented minority (NURM) groups are not due to a lack of interest in STEM. In fact, interest and intent to pursue a STEM career are comparable for college bound URMs and NURMs, yet NURMs are twice as likely to graduate with a bachelor's degree in STEM than are URMs (Hurtado, Eagan, and Hughes, 2012).

1.2 Predicting STEM Persistence

To date, factors shown to predict STEM persistence among college students include prior academic achievement (e.g., high school grades and standardized test scores; Hurtado et al., 2012; Swail, Redd, and Perna, 2003), science-related experiences (e.g., research experience and science identification; Hurtado et al., 2008; Schultz et al., 2011), goal-directed behaviors and mastery orientation (Harackiewicz, Barron, Tauer, and Elliot, 2002; Hernandez, Schultz, Woodcock, and Chance, 2013), and institutional supports (Chang, Cerna, Han, and Saenz, 2008; Estrada et al., 2016; Hurtado et al., 2012). Many of these same factors also predict URM success in STEM, but the relative strength of their predictive associations may differ for URMs compared to NURMs. For instance, research experiences benefit students in general, but the benefits for URMs may be much broader, including not only STEM persistence but lower overall attrition (Barlow and Villarejo, 2004) and higher graduation rates (Maton, Hrabowski, and Schmitt, 2000); further, research experiences may have greater impact on less academically prepared URM students than other groups (Kinkead, 2003).

In more recent years, greater emphasis has been placed on psychological variables such as identity threat (Cohen, Garcia, Apfel, and Master, 2006; Walton and Cohen, 2007), academic and science self-efficacy (Larson et al, 2015; MacPhee, Farro, and Canetto, 2013), values orientation (Hrackiewicz, Canning, Tibbetts, Priniski, and Hyde, 2015), and

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motivation (Eccles, 2004; Estrada, Woodcock, Hernandez, and Schultz, 2011), and their impact on STEM persistence. Some of these psychological variables have been shown to be especially impactful on URM persistence (Espinoza, 2011; Estrada et al., 2016). One potentially important individual- level variable that is receiving increasing attention in psychology—*self-regulatory processes*— has not received wide attention in the STEM literature.

1.3 Self-Regulation and STEM Persistence

Self-regulation refers to processes by which individuals purposefully expend effort monitoring, managing, controlling or otherwise altering their responses and impulses in order to pursue focal or valued objectives (Carver and Scheier, 1998, 2013; Luszczynska, Diehl, Gutiérrez-Doña, Kuusinen, and Schwarzer, 2004; Zell and Baumeister, 2013). Self-regulatory processes can take the form of more cognitive skills such as attention, concentration, goal awareness, self-monitoring vis-à-vis goal progress, and problem-solving to better attain goals (for reviews, see Carver and Scheier, 1998; Sitzmann and Ely, 2011). Self-regulation also involves managing positive and negative emotions, controlling impulses, effectively channeling emotional energy, and expressing and reading emotions appropriately (see Gross and Thompson, 2007; Koole, 2009; Web, Miles, and Sheeran, 2012). Other self-regulation skills involve using adaptive behaviors (e.g., seeking information, talking about one’s problems, minimizing distractions, improving study skills, and appropriate self-care) to effectively reach one’s desired goals rather than engaging in more avoidant or less effective strategies (e.g., playing video games, using alcohol) (see Carver and Connor-Smith, 2010; Skinner and Zimmer-Gembeck, 2007).

Although self-regulatory processes include cognitive, emotional, and behavioral skill sets, there is currently no consensus on how specific self-regulation skills should be categorized (Augustine and Hemenover, 2009). Self-regulation can take place through cognitive, behavioral and emotional strategies, but any one of these strategies can also target the regulation of cognitions, behaviors, or emotions, and often more than one type simultaneously (Gard, Noggle, Park, Vago, and Wilson, 2014; Kelley, Wagner, and Heatherton, 2015). For instance, positive reframing is often categorized as a cognitive strategy (i.e., reappraising a negative event in a more positive light) but can also function as an emotional strategy (i.e., doing so reduces negative affect), and/or behavioral strategy (i.e., talking about the event differently). Thus, the “self-regulation” umbrella includes multiple and overlapping constructs.

Despite difficulties in conceptualization, self-regulation has been related to success in many domains (Carver and Scheier, 1998; Heatherton, 2011), especially in stressful situations (Eisenberg, Smith, and Spinrad, 2016; Skinner and Zimmer-Gembeck, 2007; Wood, 2016) and in contexts of performance and ability challenge (Davis, DiStefano, and Schultz, 2008). Such stresses and challenges are commonly experienced in and around classrooms and other educational settings (Vermetten, Vermunt, and Lodewijks, 1999; Zimmerman and Bandura, 1994) including academic success in general undergraduate samples (e.g., Tangney, Baumeister, and Boone, 2004). For example, one meta-analysis found self-regulation predicted academic performance and retention over and above traditional and other

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psychosocial indicators (e.g., Robbins et al., 2004). Moreover, self-regulatory processes reliably predict or account for several key behavioral factors (e.g., beneficial habit formation, organizing material, note-taking, choosing study-conducive environments) that, in turn, explain long-term and sustained academic achievement (e.g., Galla and Duckworth, 2015; Robbins et al., 2004; Robbins, Le, and Oh, 2009). To date, none of this work has examined its specific role in minority student success or in STEM persistence or success.

We assert that students majoring in STEM fields deal with many academic challenges and stressors above and beyond those faced by all college students. Self-regulation processes may be particularly important for persisting in and achieving success in biomedical science/STEM fields, especially for URM college students who intend to pursue STEM careers. . To our knowledge, self-regulation has not yet been examined in terms of URM success in STEM or biomedical research careers. If self-regulation is found to promote STEM persistence and success, it will provide a useful target for interventions beyond existing curricular and institutional interventions.

1.4 Current Study: Self-Regulation Predicting Persistence and Success in STEM

We examined three separate indicators of success in the first year of college for STEM students. A few studies have examined academic performance (e.g., GPA) and persistence (e.g., retention in STEM major), reporting different patterns of predictors for each (e.g., Hurtado et al., 2008: Espinoza, 2011; Robbins et al., 2004); however, very few studies have compared these institutional outcomes in the context of self-regulatory processes. In the present study, we examined both (a) institution-reported outcomes of students’ GPAs and majors and (b) self- reported intentions to pursue a science career as our indicators of academic success in the first year. We asked three research questions: (1) Do URM and NURM students bound toward STEM degrees and careers possess different levels of self-regulation skills at entry into college? (2) Do self-regulation skills predict success for URM and NURM students in STEM majors, over and above background characteristics at the end of the first year of college? and (3) Is self-regulation particularly important for URM success in STEM (i.e., are associations with self-regulation moderated by URM status)?

2. Method

2.1 Participants

A sample of 755 first year students in STEM majors was drawn from a larger study of student success – *The UConn Success Study*, an ongoing longitudinal panel study primarily comprising first year students enrolled at the University of Connecticut (UConn) in the fall of 2015. This study was designed to examine the role of self-regulation skills as potential determinants of academic success, with a particular focus on URM and non-URM students in STEM majors. The study began in the spring/summer of 2015 (baseline) and surveyed 1,839 students accepted for fall admission who participated in orientation prior to fall enrollment. Of that number, 11% (n = 210) were nonfreshmen (i.e., transfer students) and less than 1% (n = 11) ultimately did not enroll despite participating in the summer orientation. Here we report STEM success and persistence outcomes from the first year of data collection. The study sample was restricted to freshmen who enrolled at the university

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(i.e., n = 1,618) and the current analytic sample consists of those students who declared a STEM major at any point within the first year of college (n = 755).

At baseline, the analytic sample was approximately evenly split by gender (51.9% male). Regarding the sample's race/ethnicity, 63.1% self-identified as White, 19.9% were Asian, 6.9% were Hispanic/Latino, 3.9% were Black/African American, 2.9% were 2-or-more races, and 3.5% did not self-report race/ethnicity. Most (87.3%) identified English as their first/native language, 9.3% reported English and another language as their first language, and 3.5% reported a language other than English as their first language. Finally, 87.7% of the analytic sample were admitted to the university in a STEM major.

There were few demographic differences between freshmen who participated in the study (n = 1618) and those who did not (n = 2193). Similar to students who participated, less than 1% (n = 20) of nonparticipants did not enroll despite participating in orientation and paying an enrollment fee. In addition, gender was comparable between groups, with males constituting 53.6% of nonparticipants. Self-reported race/ethnicity via institutional records indicated that nonparticipant freshmen were 57% White, 6.3% Black, 3.0% Hispanic/Latino, 21.3% Asian, .6% two or more races, and 11.6% unknown. While there were some differences in the representation of race/ethnicity between participating and nonparticipating groups, these differences may be explained in part by the higher number of nonparticipants who did not report their race/ethnicity on their admissions forms as well as differences in how race versus ethnicity were assessed on the survey measures versus admissions records. The overall racial/ethnic composition of the Fall 2015 cohort at UConn was comparable to previous years at the university.

At baseline (i.e., prior to fall enrollment), 670 students were STEM majors and 85 were non-STEM majors. In the fall semester, 672 students were STEM majors and 43 were non-STEM majors. In the fall semester, 672 students were STEM majors and 43 were non-STEM majors. By the spring semester, 637 students were STEM majors and 78 were non-STEM majors. Cross-tabulation analysis of fall and spring STEM majors showed that 43 (6%) non- STEM students switched into a STEM major from fall to spring, 78 (11%) STEM students switched to a non-STEM major from fall to spring, and 594 (83%) students started and remained STEM majors from fall to spring.

2.2. Procedure

The study protocol consisted of (a) an online survey administered to students in the summer prior to starting at the university and (b) administrative data provided by the institution (e.g., declared major, grade point average) gathered after the end of the first academic year. All study procedures were approved by the university Institutional Review Board and participants compensated $20 following each wave of data collection. All participants provided documented informed consent. No authors have a conflict of interest to declare.

2.3 Measures

2.3.1 Self-Regulation Skills.—Because self-regulation skills have been variously defined and there is no agreed-upon measurement strategy, we elected to cast a wide net by employing a range of self-regulation measures tapping cognitive, emotional and behavioral facets and testing whether an underlying factor structure emerged: (a) *Emotion Regulation Questionnaire* (ERQ: Gross and John, 2003) consists of two scales: the Cognitive Reappraisal scale comprises six items that measure the tendency to redirect or reinterpret negative emotional stimuli, and the Expressive Suppression scale comprises four items that measure the degree to which individuals manage their emotions by restricting emotional reactions and responses. Response options for each item range from 1 (*Strongly disagree*) to 7 (*Strongly agree*). (b) *Brief COPE* (Carver, 1997). The Brief COPE assesses 14 coping strategies employed over the past year in response to difficult or stressful events. We used nine scales from the Brief COPE that reflect self-regulating coping strategies ranging from cognitive approaches (Positive Reframing) to emotional approaches (Venting) to behavioral approaches (Active Coping). The remaining six COPE scales included were Instrumental Support Seeking, Emotional Support Seeking, Humor, Religious coping, Substance Use, and Planning. Each strategy consisted of two items and response options for each item range from 1 (*not at all*) to 4 (*a lot*). Scores are derived as a mean of the two items.

2.3.2 Control Variables/Demographics.

2.3.2.1 Demographics.: Students self-reported their gender (*Female, Male, or Other [Please specify]*), race/ethnicity (*American Indian/Alaskan Native, Asian, Black/African American, Hispanic/Latino, Native Hawaiian/Pacific Islander, Two or more races, White, or Prefer not to respond*), and first language spoken (*English, English and non-English, or non-English*). Demographic variables were transformed into dummy-coded indicators or demographic background for all analyses. We dummy-coded gender (0 = male, 1 = female), Race/ethnicity (0 = NURM (White or Asian), 1 = URM (American Indian/Alaskan Native, Black/African American, Hispanic/Latino, Native Hawaiian/Pacific Islander, or Two or more races), and first language spoken (0 = English, 1 = English and non-English, or non-English).

2.3.2.2 Precollege Enrichment Experiences.: Precollege enrichment experiences were measured using items developed from previous research (Chang et al., 2008; Hurtado, et al., 2006). Hurtado et al. (2006) found that specific precollege activities that reflect more enriched academic experiences (e.g., “participated in summer research programs”, “took advanced placement courses in science, math, or technology”), along with traditional academic success indicators (e.g., high school GPA, standardized test scores and background characteristics), predicted both aspirations and persistence in science-based careers and degree attainment. Additional enrichment activities unique to UConn students were also included (e.g., a summer bridge program for prospective engineering students and a program that allows students in Connecticut to earn UConn course credits while in high school). Students indicated whether they had participated in or experienced 15 enrichment experiences prior to enrolling in college. Response options were binary, scaled 1 (*Yes*) or 0 (*No*). Scale scores were derived as the sum of the 15 items. Prior research with similar scales has indicated that the scores were reliable with undergraduates (Hurtado et. al., 2006).

2.3.2.3 Ever a STEM Major.: Student administrative records were obtained to determine major at three time points during the first year of college: at time of admission, beginning of

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fall semester, and beginning of spring semester. Majors were categorized as STEM (1) or non-STEM (0) using the National Science Foundation STEM Classification (2016), which includes 137 STEM majors. Major was coded as STEM or non-STEM at each time point.

2.3.3 Outcomes.

2.3.3.1 Intentions to pursue a scientific research career.: Our proximal outcome measure was students' intention to pursue a scientific career at baseline (i.e., prior to entering college). Students were asked to respond to two questions: "To what extent do you plan to pursue a science-related research career?" and "What is the likelihood of you obtaining a science-related degree?" on a scale from 0 (*Definitely will not*) to 10 (*Definitely will*). Scale scores were derived as the mean of the two items.

2.3.3.2 Cumulative GPA (Spring 2016).: Student administrative records were obtained to determine cumulative grade point average (GPA) at the end of the spring semester of the first academic year.

2.3.3.3 Persistence in a STEM major.: Student administrative records were used to derive a measure of persistence. Students admitted as a STEM major and still a declared STEM major in the spring semester of their first year were categorized as having persisted (1). Students admitted as a non-STEM major, but who switched to a STEM major by the spring semester were also categorized as having persisted (1). Finally, students who were admitted as a STEM major or declared a STEM major in the fall semester, but switched to a non-STEM major by the spring semester were categorized as not having persisted (0).

3 Results

3.1 Statistical Assumptions and Analysis Details

Prior to conducting substantive analyses, we evaluated the distributional characteristics of the data (Table 1) and intercorrelations among the variables (see Table 2) in SPSS software version 23.). Because self-regulation skills were measured on different metrics, we transformed all self-regulation scale scores to put them on a common normalized metric (Blom, 1958) and used these scores in all subsequent analyses. Prior to conducting inferential tests with transformed variables, we examined the data for outliers and inspected the tenability of statistical assumptions. We found no evidence of extreme outliers (i.e., leverage and Cook's D values were all acceptably small; Judd, McClelland, and Ryan, 2009) and determined that the statistical assumptions were met (i.e., Box's $M = 66.67$, $F[66, 49681.90] = 0.95$, $p = .59$; the ratio of largest to smallest variance between URM and NURM groups did not exceed 3.0 for any of the self- regulation variables; and Q-Q plots showed only minor deviations from normality for most self- regulation variables). The only exception concerned the normality of the Religious Coping and Substance Use scale scores, which Q-Q plots showed to be positively skewed in both groups.

Structural equation modeling (SEM) was used to simultaneously predict the three outcomes from the self-regulation skills and control variables. Control variables included gender, first language status, precollege enrichment score, and URM status given that these variables

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have been shown to affect success and persistence in STEM (e.g., Han, Capraro, and Capraro, 2015; Wolniak, 2016). Because the STEM persistence outcome was binary, we used Weighted Least Squares (WLSMV) to estimate structural equation models in M*plus* version 8.01. Finally, consistent with recommendations for controlling Type-I error rate in complex SEMs, we adopted a Bonferroni adjusted alpha level of .017 (i.e., alpha level = .05/ #DVs = .05/3 = .017) when evaluating parameter estimates (Green and Babyak, 1997).

3.2 Differences in Levels of Self-Regulation Skills for URMs Versus NURMs

To address our first research question (i.e., degree to which URM and NURM students possess different levels of self-regulation skills), we conducted a one-way MANOVA to compare URMs and NURMs on the 11 measures of cognitive, emotional, and behavioral self- regulation skills. The resulting multivariate F test was nonsignificant, $Wilks' \lambda = .97$, $F(11, 512) = 1.67$, $p = .08$, $\eta^2_{partial} = .04$, indicating no differences in initial self-regulation skills were evident between URM and NURM groups, Table 1.

3.3 Self-Regulation Skills Predict Persistence and Academic Outcomes

3.3.1 Measuring self-regulation.—Prior to addressing our second and third research questions, we sought to discover if the 11 self-regulation skills could be more parsimoniously represented in terms of the expected cognitive, behavioral, and emotional self-regulation constructs. Therefore, we used exploratory factor analysis (EFA) with principal axis factoring to reveal the underlying number of latent factors. Pre-EFA diagnostics revealed that three of the self-regulation measures, Religious coping, Substance Use coping, and Expressive Suppression, had extremely low communalities (i.e., <.20) and thus were not retained in the EFA (Thompson, 2004). Robust factoring techniques such as parallel analysis (Horn, 1965; Hayton, Allen, Scarpello, 2004) and Velicer's minimum average partial revised test (Velicer, 1976; Velicer et al., 2000) indicated two factors explained the pattern of associations among the remaining eight measures of self-regulation skills.

We examined the pattern and structure matrices to determine the nature of the two underlying factors. The first factor, which we label Cognitive-Emotional self-regulation skills, had strong positive loadings with Active coping, Planning coping, Positive Reframing coping, and Cognitive Reappraisal (supplemental materials, Table S1), while the second factor, which we label Support-Seeking self-regulation skills, had strong positive loadings with Emotional Support Seeking coping, Instrumental Social Support Seeking coping, and Venting coping. Humor coping did not load strongly onto either factor and was therefore removed prior to reliability analyses. Reliability analyses indicated that the Cognitive-Emotional and Support- Seeking self-regulation factors exhibited acceptable reliability (α = .75 and .73, respectively).

Based on the EFA information, scale scores were created for Cognitive-Emotional and Support Seeking self-regulations skills for use as predictors in the following outcomes models. Self-regulation skills that did not load onto either factor, Humor coping, Religious coping, Substance Use coping, and Expressive Suppression coping, were included as individual predictors in the outcomes models.

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3.3.2 Predicting persistence and academic outcomes and testing moderation.

—To directly address our second and third research questions (i.e., predicting outcomes from self- regulation skills and moderating effect of URM status on self-regulation skills, respectively), we conducted a series of three nested structural equation models predicting the outcomes. Specifically, the first SEM predicted the outcomes of persistence intentions, end of first year cumulative GPA, and persistence in a STEM major from: a) control variables (i.e., gender, first language status, precollege enrichment score, and URM status), b) all self-regulation skills (i.e., Cognitive-Emotional, Support Seeking, Religious coping, Substance Use coping, Expressive Suppression coping, and Humor coping), and c) six multiplicative terms representing two-way interactions between URM status and each self-regulation skill. The first SEM provided adequate fit to the data, $\chi^2(28) = 113.81$, $p < .001$, CFI = .96, RMSEA = .06 with 90% *CI* [.05, .08]. The second SEM directly tested research question two (i.e., degree to which self-regulation skills predict success for students in STEM majors) by constraining the paths from self-regulation skills and multiplicative terms to the outcomes to zero. A comparison of fit in Model 1 versus Model 2 revealed that Model 2 significantly worsened fit, $\Delta\chi^2(48) = 68.65$, $p = .03$. The third SEM tested research question three (i.e., degree to which self-regulation skills are particularly important for URM success) by constraining the paths from multiplicative terms to the outcomes to zero. Again, a comparison of fit in Model 1 versus Model 3 revealed that Model 3 significantly worsened fit, $\Delta\chi^2(24) = 37.35$, $p = .04$. The model comparisons tests indicated that both self-regulation skills and differential effects of self-regulations skills across URM and NURM groups significantly contributed to the prediction of the outcomes.

We inspected the parameter estimates in order to determine the precise nature of the relationship between the self-regulation skills and outcomes (Table 3). Concerning *scientific persistence intentions*, the parameter estimates indicated a statistically significant URM by Cognitive-Emotional self-regulations skills moderation effect, as well as a significant positive effect of precollege enrichment experiences. A simple slopes analysis, depicted in Figure 1, revealed that Cognitive-Emotional self-regulation skills was a stronger predictor of scientific persistence intentions in the URM group (dotted black line) compared to the NURM group (solid black line).

Concerning *first year cumulative GPA*, the parameter estimates revealed a URM by Humor coping moderation effect, as well as effects of precollege enrichment experiences and URM status. A simple slopes analysis, depicted in Figure 2, revealed that Humor coping was a stronger negative predictor of first year cumulative GPA in the URM group (dotted black line) compared to the NURM group (solid black line). Concerning *persistence in a STEM major*, the parameter estimates indicated that Substance Use coping had a negative effect for both URM and NURMs.

4 Discussion

Overall, our study demonstrates that students come to college already using a range of self-regulatory strategies to manage stressful situations. Our results suggest that self-regulation plays an important role in persistence of STEM majors, both in *intentions* to persist in STEM and in their *actual* persistence in a STEM major across their first year of college.

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These results suggest fruitful new approaches to supporting students in their persistence in STEM despite the challenges and strains involved in these majors (Holland and Piper, 2016).

4.1 STEM Students and Self-Regulation

STEM students reported moderately high use of some self-regulatory strategies as evidenced by mean scores above the midpoint for both ERQ scales and five of the nine Brief COPE scales. At the beginning of college, students appear to rely on strategies that are more problem-focused (Planning, Active coping) and that help them manage their emotions (Cognitive Reappraisal)--all of which are generally considered adaptive strategies (Carver, Scheier, and Weintraub, 1989; Cheng and Cheung, 2005; Davis et al., 2008). It is possible that first year STEM students employ these strategies in anticipation of experiencing more academic challenges, but it is also possible that first year students in general are more likely to endorse these strategies as they are consistent with the messages and preparation students receive prior to enrolling in college and during orientation (e.g., problem solve, think positively).

We had hypothesized that URMs would differ from NURMs in their self-regulatory styles, but in fact, no differences emerged. That URMs arrive at college with reasonably strong self-regulation styles and are not disadvantaged in that regard relative to NURMs means that baseline self-regulation does not explain URMs' higher rates of attrition from STEM (Hurtado et al., 2012).

Our factor analysis of self-regulation styles yielded a large factor comprising multiple and diverse adaptive strategies, including cognitive reappraisal, positive reframing, and active coping, all aspects of self-regulation that have been shown to be associated with favorable outcomes, including college GPA (e.g., Casillas et al., 2012; Robbins et al., 2004; Tagney et al., 2004). While we had included cognitive, emotional and behavioral aspects of self-regulation, the fact that they loaded together rather than producing separate factors is consistent with theories of emotion generation and regulation that detail how these diverse aspects of regulation work together (e.g., Ellsworth and Scherer, 2003). The second self-regulation factor, seeking social support, is a common factor in studies of self-regulation in stressful situations (e.g., Lazarus and Folkman, 1984; Carver, et al., 1989; Skinner, Edge, Altman, and Sherwood, 2003). Although seeking social support typically predicts myriad positive aspects of adjustment (e.g., Aspinwall and Taylor, 1993; Ben-Zur, 2009), this factor was unrelated to our three indicators of success. Perhaps social support coping has a greater impact as STEM students progress through their college career or become more immersed in courses specific to their major. It may also be that seeking social support is more effective for some groups of students than others (e.g., women; Bonneville-Roussy, Evans, Verner-Filion, Vallerand, and Bouffard, 2017; Reevy and Maslach, 2001). We also found that many coping strategies did not fit into those two larger factors but rather are employed independently.

4.2 Self-Regulation Styles as Predictors of Success and Persistence in STEM

As assessed at baseline, cognitive-emotional self-regulation skills predicted students' intentions to persist in STEM, even when controlling for students' demographic

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characteristics, none of which predicted intentions to persist. In fact, students' precollege enrichment experiences were the only other predictor of student STEM intentions. Importantly, this positive effect of cognitive-emotional self-regulation skills on intentions to persist was stronger for URMs than for NURMs.

Curiously, the only aspect of self-regulation that predicted actual persistence was use of alcohol and other drugs to cope, which predicted actual lower persistence in a STEM major across the first year after controlling for gender, first language status, precollege enrichment score, and URM status. These findings are consistent with other studies. As in our sample, although this type of self-regulation is typically reported at low levels of use by college students (e.g., Ham and Hope, 2003), it tends to be strongly associated with a host of negative outcomes, including stress, less perceived academic achievement, personal injuries, and unplanned sexual activity (Wills, 1986; El Ansari, Stock, and Mills, 2013; Wechsler, Dowdall, Davenport, and Castillo, 1995).

Our third outcome, cumulative GPA, is obviously highly important; this objective measure of performance will strongly influence students' future prospects. The only aspect of baseline self-regulation that predicted cumulative first year GPA was using humor to cope. This type of coping has been inconsistently related to psychological well-being, with some studies finding that using humor in specific situations can be helpful (e.g., Martin and Lefcourt, 1983; Nezu, Wheeler, and Reis, 1988) while other studies have demonstrated its less positive or potentially adverse effects on well-being (e.g., Kuiper and Martin, 1998; Thorson, et al., 1997). These discrepancies may be due in part to the nature of the stressor (acute versus chronic) as well as situational context (benign versus threatening) (McGraw and Warren, 2010). In our study, using humor as a general way to cope with stress predicted lower academic performance in the first year, an effect that was stronger for URMs than for NURMs. These results suggest that a tendency to make light of potentially stressful situations might interfere with individuals' abilities to engage in more adaptive academic strategies (e.g., study skills, support seeking).

We expected that self-regulation would be particularly important in predicting first-year outcomes for URMs relative to NURMs, and we found some support for this hypothesis: Cognitive-emotional self-regulation was more strongly related to intentions to persist for URMs, and use of humor coping was related to lower GPA especially for URMs.

4.3 Limitations

Study limitations must be noted. First, although we endeavored to include a full cohort of incoming first year students (approximately 3800 students), less than half (43%) participated in the study. Although the percentage of men, URMs, and STEM majors was comparable between those who participated and those who did not (i.e., 51 vs. 53%, 10.8 vs. 9.3%, and 40.4 vs. 37%, respectively), other sample characteristics may have biased our results in unknown ways. Second, because there is no consensus regarding conceptualization or measurement of self- regulation, we may have omitted some important aspects of regulatory style or skill that promotes STEM student persistence and success. Further, our analyses include only the first year's metrics and only baseline self-regulation. Self-regulation strategies likely change across the college years and may have more meaningful

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relationships with persistence and success over time. Thus, self-regulation strategies may become more predictive of STEM student success as students delve deeper into their academic studies and the nature of their stressors evolves. Future analyses may reveal more about these developmental processes.

4.4 Strengths and Conclusions

This study has important strengths as well. Our sample of URM and NURM students is large enough to allow for in-depth examination of self-regulatory processes as they pertain to STEM persistence. Combining institutional data with self-report is very rare, yet illuminating (Linn et al., 2015). Our three outcomes were not strongly correlated—in fact, student intentions to persist in STEM and their actual persistence in a STEM major across the first year were correlated at $r = .09$. This lack of correspondence could be a result of the restricted range observed in both measures or it could suggest our measures tap into different aspects of STEM persistence and success. URM status and precollege enrichment experiences significantly predicted first year GPA, with lower first year GPAs for URMs and higher first year GPAs for STEM students with more precollege enrichment experiences. URMs also reported fewer precollege enrichment experiences which may have contributed to their lower first year GPA. Precollege enrichment may be especially impactful for URMs as these experiences not only provide opportunities for skill development but also facilitate self-regulation skills important for college success and STEM persistence (e.g., positive reframing, instrumental support). A focus on self-regulation skills is also a strength, given that these are highly amenable to change (Heatherton, 2011; Zimmerman, 1990) and can be measured early in students' course of study to provide clear avenues for interventions, including opportunities to tailor those interventions to the needs of particular students. For example, some types of research experiences or programs may be more helpful to students with strong self-regulation skills (e.g., independent study) while other types may be more helpful to students with self-regulation deficits (e.g., course-based research experiences).

Future research is needed to understand how self-regulation abilities that STEM students arrive with predict their trajectories across their college career, how they develop and change, and how they may best be promoted to optimize student persistence and success in STEM. The present study is a step in this direction, in highlighting the different ways that self-regulation may influence different indicators of STEM persistence and success.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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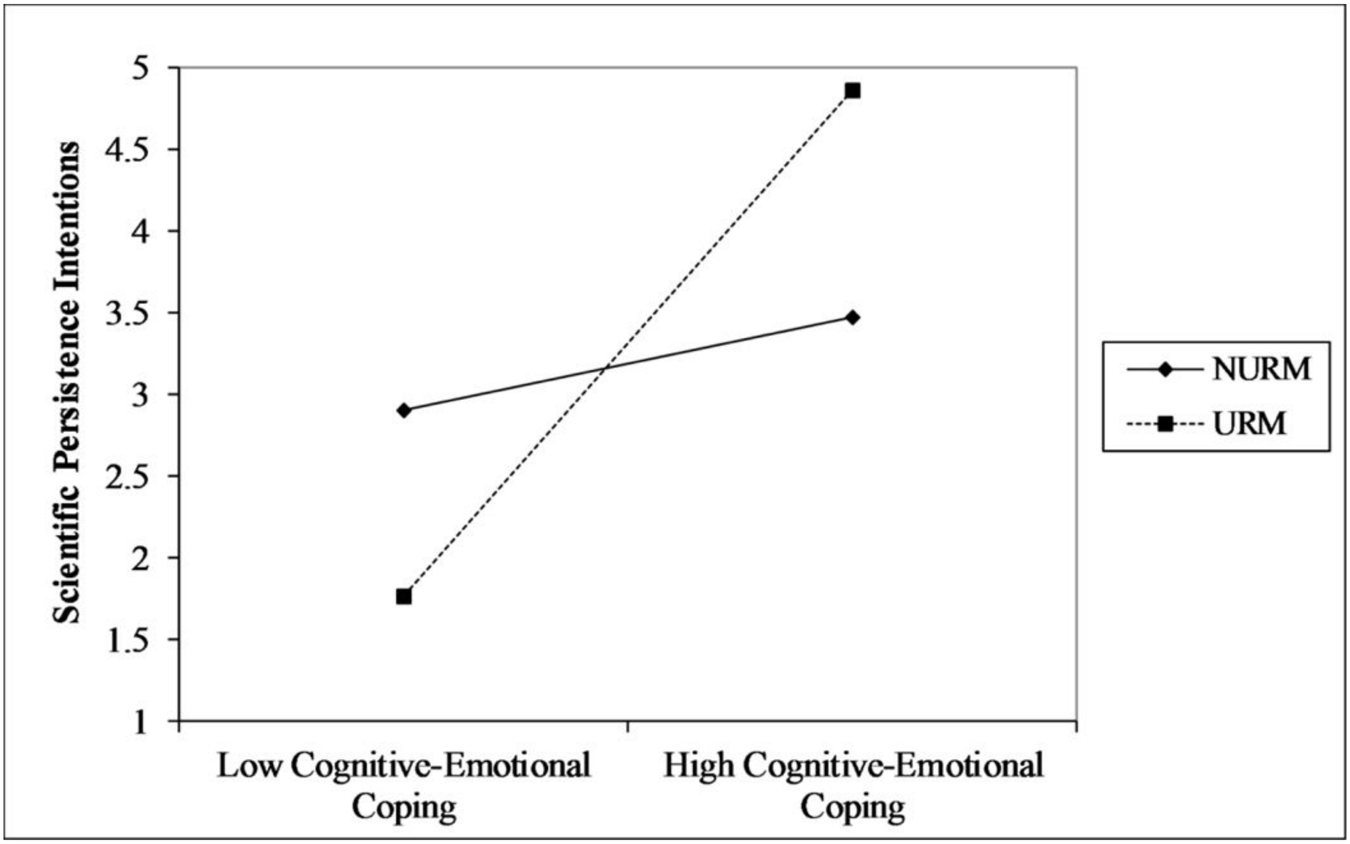

Figure 1.

Simple slopes showing the relationship between cognitive-emotional self-regulation skills and scientific persistence intentions moderated by URM status.

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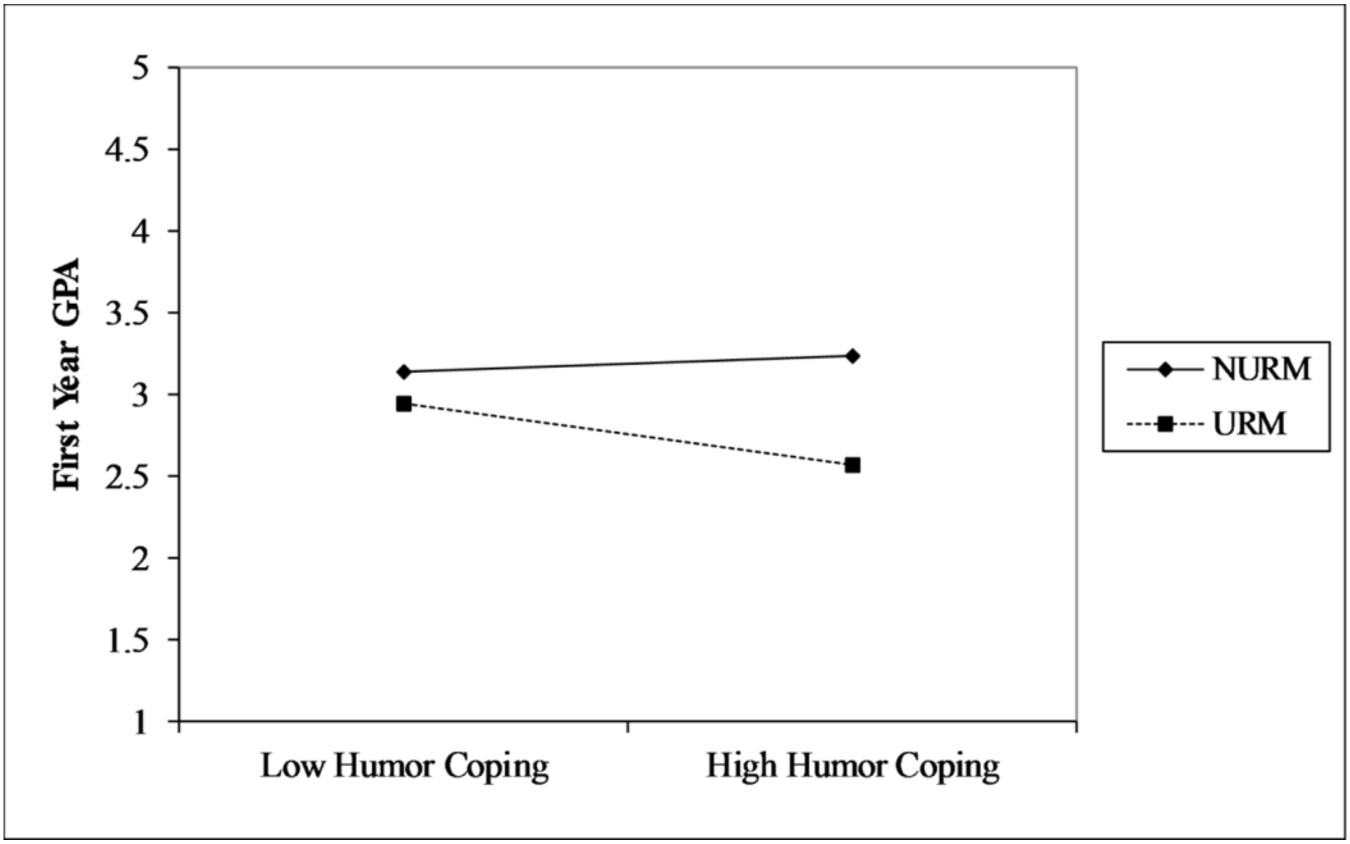

Figure 2.
Simple slopes showing the relationship between Humor coping and GPA moderated by URM status.

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Table 1.

Summary of descriptive statistics for outcomes, predictors and control variables

Variable	*N*	Standardized *M (SD)*	Unstandardized *M (SD)*	Skew	Kurtosis
Female	755	0.49 (0.5)	0.49 (0.50)	0.06	−2.00
Precollege Enrichment Experiences	755	0.00 (1.94)	2.54 (1.94)	0.28	−0.61
URM Status	755	0.15 (0.35)	0.15 (0.36)	1.98	1.92
First Language Status	755	0.14 (0.35)	0.18 (0.47)	2.09	2.35
Religious Coping	532	0.00 (0.83)	1.73 (0.94)	0.69	−0.79
Humor Coping	532	0.00 (0.85)	2.11 (0.92)	0.24	−0.82
Substance Use Coping	532	0.00 (0.54)	1.10 (0.38)	3.13	8.61
Emotional Suppression	525	0.00 (1.01)	3.72 (1.25)	0.04	−0.2
Cognitive Reappraisal	525	0.00 (0.99)	5.00 (1.03)	−0.07	−0.23
Positive Reframing	531	0.00 (0.91)	2.96 (0.80)	−0.29	−0.55
Planning Coping	531	0.00 (0.89)	3.01 (0.76)	−0.23	−0.61
Active Coping	622	0.00 (0.92)	3.10 (0.74)	−0.1	−0.13
Instrumental Support Seeking	624	0.00 (0.96)	2.69 (0.93)	0.09	−0.45
Emotional Support Seeking	531	0.00 (0.93)	2.56 (0.91)	−0.01	−0.79
Venting	531	0.00 (0.91)	1.98 (0.73)	0.28	−0.45
Scientific Career Persistence Intentions	518	8.67 (2.51)	8.67 (2.52)	−1.33	1.08
First Year Cumulative GPA	683	3.17 (0.66)	3.17 (0.67)	−1.18	1.72
Persistence in a STEM Major	691	0.89 (0.31)	0.89 (0.31)	−2.49	4.22

Notes: Standardized variables derived using the Blom transformation.

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Table 2.

Correlation matrix.

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1. Gender	1.00																	
2. Precollege Enrichment Experiences	−.02	1.00																
3. URM	.02	−.12**	1.00															
4. First Language Status	.05	−.12**	.04	1.00														
5. Religious Coping	.17***	.11*	.14**	.13**	1.00													
6. Humor Coping	−.09*	.02	−.05	−.01	−.06	1.00												
7. Substance Use Coping	−.01	−.10*	.06	−.01	.03	.15***	1.00											
8. Expressive Suppression	−.19***	.07	−.03	.06	−.08	.05	−.01	1.00										
9. Cognitive Reappraisal	.17***	−.04	.01	.04	.13**	−.02	−.06	−.16***	1.00									
10. Positive Reframing	.11*	−.12*	−.01	.07	.24***	.21***	.12**	−.22***	.42***	1.00								
11. Planning Coping	.00	.00	.02	.08	.21***	.16***	.00	−.07	.26***	.47***	1.00							
12. Active Coping	.06	−.07	.00	.09*	.18***	.15**	.02	−.10*	.35***	.55***	.68***	1.00						
13. Instrumental Support Seeking	.20***	−.09*	−.01	.08*	.22***	.18***	.04	−.28***	.24***	.47***	.49***	.49***	1.00					
14. Emotional Support Seeking	.23***	−.08	.05	.04	.18***	.14**	.04	−.33***	.25***	.44***	.40***	.41***	.75***	1.00				
15. Venting	.17***	−.03	.02	.02	.16***	.23***	.07	−.20***	.07	.22***	.27***	.18***	.35***	.37***	1.00			
16. Intentions to Pursue a Scientific Career	.05	.19***	−.02	.03	.05	−.01	−.10*	−.05	.17***	.02	.06	.07	.04	.06	−.01	1.00		
17. First Year Cumulative GPA	.06	.26***	−.26***	−.07	.08	.02	−.08	.02	.04	−.01	−.00	.02	−.03	−.02	.04	.03	1.00	
18. Persistence in a STEM Major	.00	.06	−.06	.00	−.04	−.00	−.14**	−.05	−.02	−.02	−.02	.00	.02	.02	.05	.09*	.05	1.00

* p<.05

** p<.01

*** p<.001

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Table 3.

Summary of final Structural Equation Model predicting Outcomes from Self−Regulation, Moderation, and Control variables

Predictor	Scientific Career Persistence Intentions		First Year Cumulative GPA		Persistence in a STEM Major	
	***b* (*SE*)**	***β***	***b* (*SE*)**	***β***	***b* (*SE*)**	***β***
Intercept	8.54 (.21) ***		3.19 (.16) ***		1.26 (.12) ***	
Female status	0.22 (.23)	.04	0.11 (.05)	.08	0.00 (.13)	.00
English first language status	0.22 (.36)	.03	−0.12 (.09)	−.06	−0.02 (.19)	−.01
Precollege Enrichment Experiences	**0.25 (.06)** ***	**.19**	**0.07 (.02)** ***	**.21**	0.06 (.04)	.11
URM Status (U)	0.13 (.30)	.02	**−0.48 (.08)** ***	**−.26**	−0.23 (.18)	−.08
Cognitive−Emotional SRS (CE)	0.36 (.20)	.11	0.04 (.04)	.04	−0.09 (.12)	−.07
Support-Seeking SRS (SS)	−0.04 (.21)	−.01	−0.04 (.04)	−.05	0.10 (.14)	.08
Religious Coping (RC)	−0.09 (.16)	−.03	0.07 (.05)	.09	−0.10 (.12)	−.08
Humor Coping (HC)	−0.08 (.15)	−.03	0.06 (.04)	.08	0.04 (.10)	.03
Substance Use Coping (SU)	−0.34 (.21)	−.07	−0.1 (.06)	−.08	**−0.34 (.12)** **	**−.18**
Emotional Suppression (ES)	−0.13 (.13)	−.05	−0.01 (.04)	−.02	−0.13 (.11)	−.13
U×CE	**1.61 (.61)** **	.18	0.00 (.13)	.00	0.18 (.44)	.05
U×SS	−0.49 (.58)	−.06	0.00 (.11)	.00	0.02 (.42)	.01
U×RC	−0.06 (.37)	−.01	−0.01 (.12)	.00	0.06 (.28)	.02
U×HC	0.39 (.36)	.05	**−0.31 (.08)** ***	−.14	−0.32 (.21)	−.10
U×SU	−0.68 (.40)	−.06	0.14 (.14)	.05	0.13 (.29)	.03
U×ES	0.23 (.32)	.04	0.13 (.07)	.09	0.21 (.29)	.09

Notes: Female status and first language status (control variables) were nonsignificant predictors and thus were constrained to zero in all models; therefore female status and first language status variables do not appear in the table above. All continuous self-regulation skills were grand-mean centered for analysis and all covariances were estimated among the continuous predictors (including multiplicative terms).

* $p<.017$

** $p<.01$

*** $p<.001$