

A Comparative Study of Self-Regulation Levels and Academic Performance among STEM and Non-STEM University Students Using Multivariate Analysis of Variance

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ABSTRACT

Based on the assumption that STEM students may exhibit higher self-regulation levels than non-STEM students, this study compared the levels of self-regulation variable across four fields of study. By employing multivariate analysis, it was found that differences in self-regulation levels among STEM and non-STEM students predict students' GPA. STEM students reported higher self-regulation levels than non-STEM students. However, among the STEM fields, only engineering students displayed statistically significant difference in self-regulation levels when compared to non-STEM fields of study. Computer science students displayed a significantly higher GPA than law and business administration students, with engineering students displaying the second-highest and statistically non-significant GPA. A regression analysis revealed that students' self-regulation levels significantly predicted students' GPA. The findings add value to the psychological concept as an important element in the context of learning in higher education. It was concluded that self-regulation remains an essential skill that enhances students' effectiveness and needs to be emphasized in the orientation for life in College.

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Introduction

Academic performance has long been associated with successful learning and studying strategies that are governed by cognitive processes. Self-regulation has been identified as the most common cognitive process that learners employ to achieve high academic performance (Li et al., 2018). As a cognitive process, self-regulation enables learners to monitor their thinking, motivation, and emotions during learning in ways that allow them to adapt to the demands of a given teaching and learning environment (Pintrich, 2004). However, self-regulation skills are not limited to the learning context in higher education. Students are expected to master lifelong learning skills to be able to regulate their own learning once they start working in their fields of expertise (Van Eekelen et al., 2005). Researchers have oftentimes defined self-regulated learning as a function of students' motivation,

cognitive strategies, and metacognition (Wolters, 2003). While this view may be viable, a social cognitive approach considers context-related elements that may impact learners' self-regulation.

Zimmerman (2000) refers to self-regulation as context-specific processes that individuals utilize intermittently to accomplish their own objectives. Zimmerman argued that the self-regulatory processes include metacognitive thinking and abilities that influence emotional and behavioral processes. The theory of self-regulation emphasizes self-efficacy-related resilience. The belief about one's own ability to master a particular act defines self-efficacy, a construct that was proposed and expanded by Bandura (Bandura et al., 1999). Self-efficacy plays an essential role in motivation because a person must have a certain degree of confidence in initiating and completing a given task or act before acting on it (Ozer & Bandura, 1990).

A substantial number of studies have focused on students' self-regulation pertaining to teaching and learning contexts (Artino Jr., 2008; Hodges & Kim, 2010; Shea & Bidjerano, 2010). While studies assessing self-regulation among university students from a variety of majors exist, comparisons of self-regulation levels based on the type of majors, particularly STEM and non-STEM majors, were either vague or scarce (Ajisuksmo & Vermunt, 1999; Shell, & Soh, 2013). Equally important is research that explores potential effects stemming from academic disciplines on levels of self-regulation and the effect self-regulation has on students' Grade Point Average (GPA). It is possible that employed self-regulation paired with academic content stimulates and improves students' use of these self-regulatory processes in a given learning context (Miller et al., 2013). Specifically, the challenging and demanding subject matter of STEM majors may also pressure university students to perform well in order to continue and complete their chosen STEM field of study. Kokkelenberg and Sinha (2010) found that STEM departments usually had much stricter grading systems in place than many non-STEM departments.

While STEM majors are particularly challenging, attrition rates among them tend to be higher than non-STEM majors (Chen & Soldner, 2014, Park et al., 2019). A report by Northern Virginia Community College (NOVA) presents observations in support of the proposed relationships. According to the report, STEM students at the community college level went on to be more successful in college compared to non-STEM students. Additionally, the report states that STEM students were retained at a higher rate and were more likely to graduate within four years than non-STEM students. A more important finding of this report states that STEM-oriented students (i.e., students who switched from a non-STEM to a STEM major or students who remained in STEM) had a higher GPA compared to non-STEM students (Northern Virginia Community College, 2016). It is thus possible that STEM students are under higher pressure than non-STEM students to respond to the academic demands and challenges imposed on them in order to prevail in their chosen STEM fields of study. However, while the above report points to relationships between STEM majors and GPA, research that explains the relationships between STEM majors, self-regulation levels, and GPA remains scarce.

Literature review shows that STEM-based courses require precision learning, which offers specificity and objective analyses. These involve a high level of procedural and step-by-step approaches. In this light, STEM students face more challenges and have more pressure to succeed. Due to the emphasis on precision and critical procedures, STEM-related courses require organized and highly self-controlled tendencies. Therefore, it can be conceptualized that these may probably result in the use of more self-regulation strategies and enhance performances.

Self-regulation, Self-efficacy, And Motivation In Academic Settings

When discussing the effects of self-regulation, it is important to consider the roles of self-efficacy in the context of self-regulation and performance. For example, research confirms that self-regulation precedes self-efficacy. To acquire a high level of self-efficacy, self-regulation, resilience, and self-esteem play crucial roles in a person's cognitive repertoire of mechanisms (Yang, et al., 2019). Other studies show strong positive associations between self-regulation and self-efficacy beliefs. Both constructs reciprocally affect each other in that strong self-efficacy beliefs contribute to students' motivation and their goal-setting activities. They help regulate learning and increase their engagement and performance (Räsänen et al., 2016; Zimmerman, 2002). Bandura posited that while self-efficacy varies across

domains, its pivotal and distinct characteristic involves a persons' beliefs about their performance and abilities. Therefore, self-efficacy is a context-specific construct that focuses on learners' beliefs in their ability to execute a given task, rather than on general performance. More importantly, highly self-efficacious individuals are more likely to resist negative thoughts and other negative cognitive patterns that may inhibit their perseverance during a task or project (Ozer & Bandura, 1990).

Not only is self-efficacy a key factor in students' motivational beliefs but it also influences their choices of academic tasks (Pajares, 2008). Furthermore, self-efficacy predicts the use of effective self-regulatory learning strategies (Greene et al., 2004) and plays an important role in academic performance (Chemers et al., 2001). More importantly, self-regulation predicts academic achievement above and beyond other motivational concepts, such as task value and affective components, such as test anxiety (Robbins et al., 2004). For example, Robbins and colleagues' meta-analysis of 109 studies revealed that self-efficacy along with self-regulatory processes were best at predicting GPA and college outcomes. Considering the above, the relationship between self-regulation and self-efficacy highlights the importance of investigating self-regulation in academic settings.

Effects Of Student Self-regulation On Academic Performance

From a social cognitive perspective, individuals learn as they orientate themselves by external factors through modeling and imitating before they advance into using internal self-regulated learning strategies to achieve set goals. Learners become self-controlled in their learning through previously acquired standards for performance and regular self-reinforcing feedback (Schraw et al., 2006). Contemporary self-regulation theories emphasize meta-cognitive processes and intrinsic motivation to execute goal-oriented tasks (Schraw et al., 2006). For example, Zimmerman's (2000) self-regulation theory points to motivation in the form of self-efficacy and self-reflection as crucial factors in self-regulated learning. Further, self-regulation consists of four cyclical operational definitions as proposed by Zimmerman and Schunk (2008). Setting specific goals and using task-focused techniques that may involve elaborating, organizing, and rehearsing are the first two self-regulatory actions. Exhibiting high levels of self-efficacy and reflecting on the entire learning process and performance outcomes are the other two self-regulatory operational procedures (Zimmerman & Schunk, 2008). There is a major metacognitive component in Zimmerman's theory of self-regulation. Self-regulatory processes include metacognitive thinking and abilities coupled with self-efficacy-related resilience that impact emotional and behavioral processes. According to Zimmermann, a learner who demonstrates a high degree of self-regulation skills will first use forethought, followed by performance and self-reflection. The social-cognitive approach strongly supports the view that teachers, peers, or parents serve as socializing agents, modeling self-regulation in the presence of younger learners who reciprocally strengthen their own and others' self-regulation (Zimmerman, 2000).

Paying special attention to the role of context in self-regulation research is crucial because self-regulation involves modulating systems of emotion, attention, and behavior in response to a given situation or stimulus (Calkins & Fox, 2002; Carlson, 2003; Eisenberg et al., 2004). For instance, certain forms of didactic and instructional models that promote self-regulated learning have been found to be effective in increasing students' motivational, cognitive, and metacognitive self-regulatory approaches to learning (Leutwyler & Maag Merki, 2009). In this light, it is also important to include GPA as another crucial factor to see whether differences in self-regulation attributable to disciplines have an impact on academic success as indicated by GPA. Therefore, academic self-regulation involves students' level of independent and self-initiated learning with the ability to use a variety of learning strategies (e.g., organizing, transforming, note-taking) to accomplish specific learning goals (Kitsantas, 2002; Zimmerman, 2008). Over time, self-regulation has been of interest to educational researchers whose goal is to improve academic performance among students in demanding fields of study, such as law and legal education (Bloom, 2013; Schwartz, 2003). Hyytinen and colleagues (2019) demonstrated that self-regulation among law students is best fostered in student-centered learning environments that require independent learning and less direction from instructors. An important finding in Hyytinen et al.'s

(2019) study is that students with higher self-regulation view their learning experiences more positively. Thus, positive learning experiences may impact learners' motivation and self-efficacy levels.

Several studies have examined the effect of college students' self-regulation on their success as indicated by their GPA. In a past pre- and post-measure study with 227 participants by Kitsantas et al. (2008), self-regulation measured by time management skills predicted student GPA a year later above and beyond previous academic performance (e.g. SAT and ACT scores). An important finding of this study was that metacognitive self-regulation defined by planning and adjusting one's learning processes did not display statistically significant predictive value (Kitsantas et al., 2008). It is possible that the metacognitive dimensions of planning and adjustment may show a predictive role if measured separately. Another explanation is that time management skills may be (1) conceptually closely related to self-regulation, (2) behavioral in nature rather than cognitive, (3) less abstract than metacognition, and (4) are not limited to students' perceptions but can be tracked via regular logs in journals. A more recent study by Zimmerman and Kitsantas (2014) with 507 high school student participants revealed that self-regulation (SR) was a significant predictor of academic achievement compared to other related constructs, such as self-discipline (SD). SD was defined by regulating one's impulsive behaviors and refraining from distractive behaviors. They distinguished SD from SR by emphasizing the focus on performance as inherent in SD that stands in contrast to learning processes as inherent in SR. Using structural equation modeling, SR was a stronger predictor than SD implying that concentrating on one's learning is more effective rather than focusing on mitigating impulses and immediate reward. Assuming responsibility for one's learning coupled with self-efficacy during the learning process are the defining characteristics of the SR construct that explained a total of 64% of GPA alone in the SEM procedure. When SD was added to the SR factor, the variance increased to only 69% that explained GPA.

The mentioned findings above are in line with several cross-sectional studies that have shown college students' high self-regulation levels are more strongly correlated with GPA than with standardized tests (SAT, ACT scores) (Conard, 2005; Nofle & Robins, 2007). Although Zimmerman and Kitsantas' sample (2014) included high school students, self-regulation levels can extend to subsequent schooling phases (e.g., various grade levels, college, university). Additionally, the long-term effects of self-regulation can certainly be promoted when combined with self-regulation strategies and teacher consultation during adolescent education (Minnaert et al., 2017). A longitudinal study by McClelland and colleagues (2013) confirmed that self-regulation measured at an early age is a strong long-term predictor for college completion. While controlling for socio-economic factors, math and reading skills, and gender in their structural equation modeling analysis, children rated by their parents one standard deviation above the mean on attention span/persistence at age 4 had 48.7% higher chances of completing university by the age of 25 (McClelland et al., 2013). Despite the empirically established links between self-regulation and academic performance, there is evidence showing rather weak positive effects of self-regulation on academic performance. Peverly et al. (2003) evaluated college students' ability to monitor their test preparation and explored the relationships among self-regulation, background knowledge, study time, and note-taking activities. While results indicated that note-taking and background knowledge were generally better predictors of test performance than self-regulation, it is important to note that the means, instruments, and tools used in Peverly's study were different from the instruments used in the present study. This makes it difficult to compare findings. Considering the literature reviewed above, self-regulation seems to be a better predictor of academic outcomes than other achievement-related constructs, such as IQ. In a comparison of STEM and non-STEM students, self-regulation may significantly predict differences in their performance.

Self-regulation Associated With STEM-related Disciplinary Fields Of Study.

In the present study, the researchers assume that there is a relationship between self-regulation and disciplinary fields of study, such as STEM and non-STEM college majors. It is presumed that STEM

majors may stimulate students' adaptive learning behaviors that enable them to regulate their learning and increase academic achievement (e.g., high GPA).

Although there is insufficient research confirming the relationship between STEM majors and higher GPA, a few studies point to link self-regulation, performance, and persistence in STEM majors. Denice's (2020) study involving 2,206 students showed that switching college major occurs predominately from STEM-related fields of study to non-STEM fields of study. The finding not only shows that switching college major is widespread, but it also indicates that adaptive learning behaviors such as self-regulation, is necessary in order to remain and succeed in a demanding STEM-related course (Denice, 2020). Other components of regulatory processes, such as emotional regulation, have also been considered in research on self-regulation. According to Park et al.'s (2019), cognitive-emotional self-regulation (e.g., regulating thinking and concentration as well as positive and negative emotions) was found to be more strongly related to persistence in STEM majors.

Perceptions of one's abilities are related to the person's choice of major. For example, Umarji et al. (2018) found that students who perceived themselves to be exclusively good at math, as opposed to being good at both math and other non-STEM subjects like English, had a higher math-related self-concept and were thus more likely to major in a math-intensive field of study. A learner's perception of their subject-related ability is an integral part of the concept of self-efficacy. While Umarji's study demonstrates that high self-efficacy influences their choice of major, the present study focuses on levels of self-regulation in students who already decided to major in STEM as well as non-STEM courses. It is intended to compare students' levels of self-regulation as they relate to their chosen majors in the university.

Self-regulation Differences Based On STEM vs. Non-STEM Fields

Few studies exist that compare self-regulation levels of post-secondary students who major in a variety of disciplines. Lin (2019) discovered that male students in STEM majors displayed better time and environment management skills, which are self-regulation strategies that involve regular review and exercise of the study material. In other words, male students in STEM fields spend more time studying and adjust their learning environment when compared to male students in non-STEM fields. The reasons for varying levels of self-regulation among students based on STEM vs non-STEM-related differences are yet to be explored. A previous study by Chen and Lin (2018) showed contradicting results with a large student sample from Taiwan. STEM- students (e.g., science, engineering) presented a lower level of self-regulation compared to students from non-STEM fields. Shell and Soh (2013) had previously demonstrated that STEM college students enrolled in required non-major courses relating indirectly to their field of the study exhibited lower engagement and higher rates of surface learning strategies than students from required courses that directly relate to their major. However, there were no differences in strategic self-regulation levels among STEM students in required computer science courses and students from other non-STEM fields of study. Given the differences in self-regulation levels among students within the STEM field (Shell & Soh, 2013), there may be course-related characteristics such as being required or non-required that contribute to self-regulation levels and motivation.

While these studies focused on the relationships among self-regulation and STEM majors with non-STEM majors, none of them revealed the non-STEM majors' specific fields of studies. Another study that shows differences in self-efficacy and diverse majors focused on context-driven factors, such as role model effects. Shin et al. (2016) experimented with 1035 STEM and non-STEM undergraduate students and explored the effects of role model biographies. These biographies challenged STEM clichés, such that STEM fields are only for gifted students who are European American and male. Also, Ülger and Çepni (2020) found that in recent years STEM education was drastically associated with students' innate abilities to learn successfully in the area, thus the importance of giftedness in STEM education. Further, students read about inspiring successful STEM professionals who succeeded through hard work. Shin

et al. showed that role model exposure had a positive impact on academic self-efficacy among STEM students, but not on non-STEM students.

Following exposure to the role model strategies, STEM students also demonstrated a higher interest in STEM and a greater perceived connection between self and STEM when compared to students who were not exposed to such models, while there was no effect on non-STEM interest. Varying levels of self-regulation have been compared to factors other than fields of study. For example, Ajisuksmo and Vermunt (1999) found differences in the use of self-regulation strategies between students from two different countries (the Netherlands and Malaysian students) but comparison across fields of studies was not part of the research. Age-related factors have also been associated with higher self-regulation levels. Graduate students demonstrated more adaptive self-regulation strategies compared to undergraduate students' learning profiles (Artino & Stephens, 2009). Artino and Stephens (2009) explained this difference between undergraduate and graduate students by showing lower levels of procrastination as reported by graduate students.

Zheng et al. (2020) also investigated the engineering design performances of students by utilizing principal component and cluster analyses. Participants were grouped as "competent, cognitive-oriented, reflective-oriented, and minimally self-regulated learners". The findings showed that the competent self-regulated students possessed a suitable self-evaluation that helped them to increase their knowledge. Furthermore, cognitive-oriented self-regulated participants undervalued themselves whereas reflective learners concentrated on the work outcomes. Finally, the minimally self-regulated students overrated their abilities and employed the smallest amount of effort. In another study, Johns (2020) found that self-regulatory abilities can predict students' results far beyond their mathematics skills. The study revealed that mathematics skill alone accounted for 32% of the variance in learners' final calculus scores. Furthermore, it was found that the model could have predicted up to 48% of variance if the measures of self-regulation were added to the model. In other fields of study, Sun and Wang (2020) studied how writing self-efficacy and writing self-regulated learning approaches could relate to writing proficiency among college students in an English as a foreign language class. Learners reported a moderate level of self-efficacy and occasional use of self-regulatory strategies. The results showed that self-efficacy and self-regulation contributed significantly to predicting students' writing aptitude. In other words, self-regulation had been implicated as a factor in performance among students in STEM. The various studies were however in settings that did not include the Arabian culture.

The present study seeks to add to the existing knowledge base of the relationship between STEM and non-STEM majors, effective use of self-regulatory strategies in different fields of study, and academic achievement. By analyzing STEM and non-STEM students' self-regulatory strategies in academic settings, the salient variables of interest are being investigated in higher education. This study is pioneering the inclusion and comparison of the two major fields of study whose conclusions about motivational strategies that can impact learners in higher education have rarely included the Arabian sample. Specifically, the scope of the study that sets to cover a homogenous Arabian group of students would offer a possible new understanding of the roles of self-regulation to performance and the difference in STEM from non-STEM courses in a Middle Eastern sample.

Aim

Generally, the present study was designed to compare STEM and non-STEM students on self-regulation strategy and academic performance. Specifically, the study set to examine students' self-regulation levels as they concern different disciplinary fields categorized as STEM or non-STEM majors. It was also the aim of the study to investigate the role of self-regulation in STEM and non-STEM students' academic performance as indicated by their GPA. The literature shows that research that explains the relationships between STEM majors, self-regulation levels, and GPA are insufficient. Few studies exist that compared self-regulation levels of post-secondary students who major in a variety of specialties. Similarly, none of the previous studies focused on a homogeneous group such as the Arabs.

These necessitated the present study to compare university students on the variables being examined. Based on the literature, which was conceptualized, it was hypothesized that there would be significant differences between the fields of study and university students' levels of self-regulation. It was also assumed that students' levels of self-regulation will significantly predict their GPA scores.

Methods

Students' learning processes in higher education have been studied using a variety of research paradigms, such as quantitative and qualitative methodologies. Quantitative methods enable social science researchers to draw inferences based on sample characteristics representing certain populations. Group comparison designs are appropriate methods to test the effects of the variables of interest (Fraenkel et al., 2012). This study followed a causal-comparative research design to observe differences in self-regulation levels among the four student groups majoring in Business Administration, Engineering, Law, and Computer Science (Fraenkel et al., 2012). In addition to group comparison designs, psychometric techniques, such as factor analysis, have been used to develop diagnostic instruments for student learning (Ajisukmo, & Vermunt, 1999). In this study, the principal component analysis was used to test the robustness of the factor structure in the self-regulation questionnaire (Carey et al.'s 2004).

Participants

The sample size in the study was 150. Participants were drawn from a STEM and Non-STEM major student population. Participants' ages ranged from 18 to 30 ($M = 20.37$; $SD = 2.08$). All participants were male undergraduate students from several majors in the university. Participants were drawn from colleges of Business Administration with students majoring in Aviation, Marketing, Finance, and Accounting ($n = 57$); Computer Sciences with students majoring in Information Sciences and Software Engineering ($n = 28$); College of Engineering with participants majoring in Communication and Networking Engineering, Production, Construction, Engineering management ($n = 16$), and the College of Law with students majoring in law ($n = 49$). The responses of those whose fields of study were unknown or missing were not used in the data analysis. Participants provided information about age, GPA, and fields of study in addition to completing the two subscales of the self-regulation inventory. No female students were enrolled because the data were collected only from a male campus.

Measures And Procedure

Questionnaires were used for data collection. It contained the short version of the self-regulation questionnaire (SRQ) (Carey et al., 2004). It is a one-factor instrument that includes 31 items ($\alpha = .92$) and accounted for 43% of the total variance. The short version was found to be internally consistent and correlates significantly with the original longer version of 63 items ($r = .96$). The SRQ was originally created and validated to gauge individuals' overall ability to regulate their behaviors to attain set goals. Furthermore, the factor structure of the SRQ instrument and its internal consistency were ensured as indicated by Cronbach's alpha. To generate a parsimonious representation of the instrument's structure, principal component analysis of the 31 items using oblimin rotations were carried out. The analysis yielded two factors that explained 40% of the variance in total. These two factors were then labeled *Difficult times* and *positive actions*.

The subscale *Difficult Times* refers to experiencing difficulties or challenges in using self-regulatory techniques. For example, items 2. *I have a hard time setting goals for myself*, 17. *I don't seem to learn from my mistakes* and 1. *I have trouble making plans to help me reach goals* showing the highest loadings indicate problems with motivation to follow through with set goals and problems with awareness of consequences from actions. The other subscale, *Positive Actions*, centers on a respondents' successful use of self-regulation strategies to achieve set goals. This subscale exhibits highly motivational and self-

efficacy-related actions and was represented by items 13. *I'm able to accomplish the goals I set for myself*, 21. *As soon as I see a problem or challenge, I start looking for possible solutions*, and 18. *If I wanted to change, I am confident that I could do it*. All 31 items in this analysis provided loadings over 0.4. The component matrix displayed a cross-loading of 0.4 for item Q22 (*When it comes to deciding about a change, I feel overwhelmed by the choices*). Loadings for items ranged from 0.4 to 0.7 with most of the loadings showing a value of 0.6. Using Cronbach's alpha, we examined the internal consistency of the two subscales. The alpha values were 0.82 and 0.87 for the scales *Difficult Times* (14 items) and *Positive Actions* (17 items), respectively.

Data Collection

The researchers used both paper-based and digital versions of the SRQ to collect data from participants. Data collection was done at a private university in Riyadh through the convenience sampling technique. After receiving authorization from the institutional review board to proceed with the study, the investigators and other faculty members informed potential participants of their intent to conduct this study and explained the objectives. The students were then handed over the anonymous survey to complete. An online version of the same questionnaire was provided by other faculty members to their students using Google forms. Regardless of the format, each participant only took the survey once. Data collection was done from April 2019 to January 2020 and the data were continually entered into the SPSS datasheet to be screened and cleaned.

Data Screening And Analysis

The MANOVA assumptions were tested prior to running the analyses. Regarding the first assumption, three dependent variables were included (*Difficult Times*, *Positive Actions*, and *GPA*) which are continuous variables measured using a scale of 1 to 5. Regarding Assumption 2, independent variables consisted of 4 categorical, independent groups which are Law, Computer science, Engineering, and Business administration students. On the third assumption, there was an independence of observations in that there was no relationship between the observations in each group or between the groups. Different participants in each group were observed without participating in more than one group. Assumption 4 showed that the sample size was considered adequate because there were more cases than the number of observed dependent variables. To test the remaining MANOVA assumptions, IBM SPSS software version 22, IBM Corp (2013) was employed.

Assumption 5 necessitated a check for univariate outliers by using boxplots. In checking for Multivariate outliers, a measure called Mahalanobis distance obtained from the regression analysis was utilized. A few outliers were found and removed from the data set. The decision was deemed appropriate because the sample size was large enough to conduct the analysis. Regarding assumption 6, the multivariate normality assumption was tested by using the Shapiro-Wilk test of normality involving SPSS. The data on the *Difficult Times* was normally distributed, $p = .23$ while those of the *Positive Actions* ($p = .01$) and the *GPA* ($p = .00$) were not normally distributed. To counteract the problem of non-normal distributions of both variables, the bootstrapping technique available in SPSS for smaller group samples of engineering ($n = 16$) and computer science ($n = 28$) students was applied. On assumption 7, the linear relationships between each pair of dependent variables for each group of the independent variable were tested by plotting a scatterplot matrix for each group of the independent variable. Visual interpretation of the plot showed a general pattern that the assumption of this linear relationship was not violated. For the next assumption, the homogeneity of variance-covariance matrices was tested by using Box's M test of equality of covariance. Data did not fail this assumption given $p = 0.95$. Finally, to check for assumption 9, we tested for the absence of multicollinearity. Based on the analysis, no correlations were greater than 0.9. In this regard, the assumption of multicollinearity was not violated.

Findings

Parametric analyses showed significant differences among Law students, Computer science students, Engineering students, and Business administration students when considered jointly on their self-regulation and GPA, Pillai's Trace = .125, $F(9, 438) = 2.11$, $p = .027$, partial $\eta^2 = .042$ (Table 1.). As a follow-up test to the MANOVA, the researchers subsequently conducted a series of one-way ANOVA tests for each dependent variable of *Positive Actions* and *Difficult Times*, which are subscales from the SRQ, as well as GPA at an alpha level of .05. The test produced two statistically significant values for the dependent variable GPA, ($F(3, 146) = 2.72$, $p = .047$, partial $\eta^2 = .053$; the subscale *Difficult Times*, $F(3, 146) = 3.63$, $p = .014$, partial $\eta^2 = .069$; and non-significant values for *Positive Actions*, $F(3, 146) = .798$, $p = .497$, partial $\eta^2 = .016$) (Table 2 & 3). Finally, a number of Post-Hoc analyses (Fisher's LSD) were conducted in order to examine individual mean difference comparisons across all four levels of college majors and all three dependent variables which included two subscales of self-regulatory behaviors and GPA.

The four Post-Hoc mean comparisons were shown to be statistically significant. When compared with Engineering ($M = 36.14$; $SD = 8.25$; CI 95% [31.74, 40.4]), Law ($M = 35.69$; $SD = 7.92$; CI [33.4, 37.95]), Business Administration students scored significantly higher ($M = 40.60$; $SD = 7.56$; CI [38.6, 42.6]) on the *Difficult Times* subscale of the SRQ. Results showed no significant differences on the *Difficult Times* subscale between Computer Science students ($M = 38.76$; $SD = 9.18$; CI [35.15, 42.37]) and the other field of studies. Further, Computer science students ($M = 3.06$; $SD = .82$; CI [2.74, 3.37]) displayed a significantly higher GPA compared to Business Administration students ($M = 2.58$; $SD = .75$; CI [2.38, 2.77]) and Law students ($M = 2.68$; $SD = .75$; CI [2.46, 2.89]). Engineering students' GPA ($M = 2.86$; $SD = .70$; CI [2.48, 3.24]) displayed no significant differences when compared with other fields of study in the data set although their GPA was higher than the non-STEM students' GPA. There were no statistically significant differences on the *Positive Actions* subscale of the self-regulation instrument across all university majors (Table 4.). The participants were grouped into STEM (computer science and engineering students) and non-STEM groups (Business and Law students) to see if STEM students' GPA significantly differs from students not majoring in the sciences. A one-way ANOVA with bootstrapping revealed a significant difference ($p = 0.009$) with an average GPA of 2.98 (CI 95% [2.75, 3.22]) for STEM students and 2.62 (CI 95% [2.48, 2.77]) for non-STEM students. Before initiating inferential analyses for main effects, we tested the groups for significant differences in participants' age demographic. A one-way ANOVA revealed significant age differences in the four groups. To rule out that the differences were due to unequal sample sizes in the four groups (i.e., the issue of small sample variance), we bootstrapped the test, which resulted in nonsignificant bias estimates for the unequal sample groups. Further, we ran supplemental ANCOVAs to test whether age as a covariate impacted the dependent variables significantly. The covariate analysis showed that age was not a significant covariate in the analyses for main effects between the independent and dependent variables in this study.

In order to test the second hypothesis which stated that self-regulation can significantly predict student GPA, we ran a multiple regression analysis. Results showed a significant, albeit small, effect of self-regulation subscales *Difficult Times* and *Positive Actions* on student GPA ($F(1, 252) = 13.17$), $p < .001$, with Adjusted $R^2 = .046$, suggesting that 5% of the variance is predicted by the listed factors. *Difficult times* was found to be a better predictor of student GPA ($p < .001$), followed by *Positive Actions* ($p = .059$). To address the non-normality problem of the variable GPA and *Positive Actions*, we used the bootstrapping technique in SPSS.

Discussion

The first objective of this study focused on comparing STEM and non-STEM students' levels of self-regulation. The second objective focused on predicting students' GPA using self-regulation levels. Therefore, there were propositions that (1) there will be significant differences between fields of study

on students' self-regulation levels and (2) that students' self-regulation levels significantly predict their GPA.

The results showed that Business Administration students ($M = 40.60$; $SD = 7.56$) displayed significantly higher scores on the *Difficult Times* subscale of the SRQ than Engineering students ($M = 36.14$; $SD = 8.25$). Additionally, Business Administration students ($M = 40.60$; $SD = 7.56$) scored significantly higher than Law students ($M = 35.69$; $SD = 7.92$) on the SRQ subscale *Difficult Times*. Regarding the other dependent variable *GPA*, Computer science students ($M = 3.06$; $SD = .82$) demonstrated significantly higher GPAs compared to Business Administration ($M = 2.58$; $SD = .75$) and Law students ($M = 2.68$; $SD = .75$). Engineering students' GPA did not show significant differences when compared against the three majors. There were no statistically significant differences on the *Positive Actions* subscale of the self-regulation instrument across all university majors.

Self-Regulation And STEM vs Non-STEM Fields Of Study

The first hypothesis stating that there will be significant differences in self-regulation levels based on fields of study was confirmed. Students who are Business Administration majors face more difficulties than Engineering and Law students in using self-regulation strategies to be more successful in their college studies. Furthermore, those in Engineering have more difficulties in using self-regulation techniques than their counterparts in Law. These results were corroborated by the comparisons of the fields of studies on the GPA subscale. For example, Business administration students who face the highest level of difficulties also have the lowest GPA. Law students who face the third-highest level of difficulty also have the second-lowest GPA. There was no statistical difference between Engineering students' GPA and others. Computer science students, however, had the highest GPA, although their level of difficulties in using self-regulation strategies was not different from others.

The findings align with Shell and Soh (2013) that found differences in STEM students' self-regulation levels based on required non-major vs required major courses. In comparing self-regulation across different fields of study (i.e, STEM major, law, and business administration majors), Shell and Soh found that course-related aspects, such as required vs. non-required, impacted the self-regulation of learners. It is thus possible that external course-related aspects contribute to students' varying self-regulation levels. Further, Shell and Soh (2013) found no self-regulation differences between STEM and non-STEM majors. This did not align with the present study that shows differences based on the majors. STEM students reported higher self-regulation subscales than non-STEM in the present study. However, the previous study did not indicate the Non-STEM majors that they covered. Findings by Lin (2019) partially supported the present study. STEM male students exhibited better learning regulation strategies than non-STEM male students.

The present study is not supported by Chen and Lin (2018). They reported a contradicting pattern in a large-scale study with over a million Taiwanese STEM students who displayed lower levels of self-regulation than non-STEM students. While more researches are needed to examine self-regulatory behaviors and cognitive patterns in STEM and non-STEM students, possible explanations for the mixed findings could be related to internal (individual differences) as opposed to external (course-based, major-based) factors. There is evidence that student characteristics rather than STEM-related aspects that may include STEM course requirements, course structure, grading system, and other aspects specific to STEM majors – predict academic success. Wladis et al. (2015) provided evidence that showed age as a significant predictor of performance in STEM online courses compared to face-to-face courses. More importantly, this comparison is limited to online vs face-to-face learning media and is not focused on STEM vs non-STEM student differences. Despite such indication for student characteristics, academic preparation, and the ability for STEM-related studies, such as Advanced Placement course work, and college experience have been shown to significantly predict success in and graduation from college, particularly for STEM students (Kokkelenberg & Sinha, 2010). According to them, engineering students showed high levels of persistence than non-engineering ones. The researchers explained that the learning-by-doing structure of engineering majors promotes perseverance among the students.

Self-Regulation And GPA

Results of the multiple regression analysis that tested the second hypothesis showed that students' self-regulation strategies are good predictors of their GPA. *Difficult Times* was found to be a better predictor of student GPA than the subscale *Positive Actions*. Students who have less difficulty following through with set plans and learning from mistakes are better at regulating their learning and thus have a higher GPA. Surprisingly, the scores of the subscale *Positive Actions* appear to be relatively equal across all majors given the non-significant differences and its weaker ability to be a significant predictor of GPA. There is evidence that shares common elements with these findings. Park et al. (2019) found that having difficulty regulating negative behavioral patterns, such as alcohol and drug abuse, was significantly related to lower persistence in STEM majors while controlling for minority status, gender, and pre-college experience.

Given that *Difficulty Times* produced a significant difference in scores, it can be argued that fewer negative actions (i.e., less difficulty) are a better predictor than an increase in *positive actions*. The items on the *Positive Actions* subscale also do not specifically measure actions related to study habits and learning patterns. Therefore, another interpretation could be that fewer negative behaviors that bear negative consequences give rise to positive actions, which in turn could be self-regulatory learning and studying behaviors.

Considering these observations, it is possible that students' perceptions about their own employed actions that support their study habits and learning processes have no predictive value. Employing study habits or learning processes does not imply the effectiveness of respondents' actions. This is in line with Shin et al. (2016) and Shell et al.'s (2013) research that found facilitative learning processes, such as creative competency and implicit intelligence beliefs (i.e., that intelligence is a function of effort and can thus be developed), were associated with higher strategic self-regulation as well as knowledge retention in students enrolled in introductory computer science courses. However, both constructs were not directly linked to grades. Self-regulation, in turn, was associated with higher student grades, which is consistent with our findings. These links may explain how learning-oriented cognitive processes impact academic performance.

Studies that show conflicting findings of college students' self-regulation not related to their academic success used different approaches to defining and measuring self-regulation to predict students' GPA. Kitsantas et al. (2008) distinguished explicitly from metacognitive self-regulation strategies. They found that explicit strategies of time management predicted student GPA a year later above and beyond previous academic performance such as SAT and ACT scores whereas metacognitive self-regulation defined by planning and adjusting one's learning processes did not display statistically significant predictive value (Kitsantas et al., 2008). The authors speculate that the metacognitive dimensions of planning and adjustment may show a predictive role if measured separately. Another possible explanation is that time management skills may be (1) conceptually closer related to self-regulation, (2) behavioral in nature rather than cognitive, (3) less abstract than metacognition, and (4) are not limited to students' perceptions but can be tracked via regular logs in journals. Peverly et al. (2003) have demonstrated similar disconnections between GPA and self-regulation strategies. For example, note-taking, an explicit learning strategy, and background knowledge were generally better predictors of test performance than were self-regulation strategies. However, it is important to note that the instruments and tools used by Peverly et al. (2003) and Kitsantas et al. (2008) were different from the instrument used in this study, making it more difficult to compare findings. The way self-regulation strategies were defined and distinguished may also differ from our definitions of self-regulation strategies.

A more recent study by Zimmerman and Kitsantas (2014) revealed a contrasting finding that points to self-regulation (SR) as a significant predictor of academic achievement compared to the related construct of self-discipline (SD). They distinguished SD from SR by emphasizing the focus on performance as inherent in SD that stands in contrast to learning processes, which is inherent in SR.

Their structural equation modeling procedure showed that SR was a stronger predictor of academic achievement, explaining a full 64% of the variance in high GPA. These findings imply that concentrating on one's learning is more effective than focusing on mitigating impulses and immediate reward.

In the study of Zheng et al. (2020) engineering design performances of students that utilized principal component and cluster analyses found that self-regulated students possessed a suitable self-evaluation that helped them to increase their knowledge. Furthermore, cognitive-oriented self-regulated participants undervalued themselves whereas reflective learners concentrated on the work outcomes. Finally, the minimally self-regulated students overrated their abilities and employed the smallest amount of effort. In another study, Johns (2020) found self-regulatory abilities to predict students' results far beyond their mathematics skill, and that the model could have predicted up to 48% of variance if the measures of self-regulation were added to the model. Both studies of Johns and Zheng et al. support the present study that found a significant difference between STEM and non-STEM students in the level of self-regulation and performance. However, the various studies were conducted in settings that did not include the Arabian culture.

Significance And Interpretation Of Effect Sizes

Based on the analysis, it is important to interpret the results according to specific effect size magnitudes. According to Miles and Shevlin (2001) effect size guidelines, medium effect sizes for ANOVA and MANOVA tests start at 0.06 and large effect sizes start at 0.13. Despite the statistical significance that is guided by the given cut-off values, the effect size of partial $\eta^2 = 0.042$ for the joint group comparison of self-regulation and GPA between law students, computer science students, engineering students, and business administration students was somewhat lower than the medium effect size (Miles & Shevlin, 2001). The one-way ANOVA tests for each dependent variable of self-regulation (*Positive Actions* and *Difficult Times*) and GPA produced two statistically significant values for the dependent variable GPA with a nearly medium effect size of partial $\eta^2 = .053$ and medium effect size for the self-regulation subscale *Difficult Times* as depicted by partial $\eta^2 = .069$. Regarding the effect size of the significant predictive relationship between students' self-regulation and GPA, the self-regulation subscale *Difficult Times* significantly predicted the criterion variable student GPA with an adjusted $R^2 = .046$, suggesting that 5% of the variance is predicted by less *difficult times* in students' higher GPA. While the adjusted R^2 value falls below the medium effect size magnitude of 0.09, it is substantially above the small magnitude of 0.01 (Cohen et al., 2003). The effect sizes are fairly small compared to some of the literature on self-regulation and academic performance. Although Zimmerman and Kitsantas (2014) obtained higher variances explained by self-regulation in students' GPA (variance explained > 60%), our effect sizes are limited to the research design parameters as well as sample size and sample characteristics we employed in this study. It is thus recommended not to generalize the effect sizes beyond the parameters of the research design (Olejnik & Algina, 2003). In other words, research with larger samples and controlled covariates may have produced different effect sizes.

An important perspective surrounding this issue is offered by Prentice and Miller (1992) who argued that small effect sizes have value if they surface and persist under flawed or adverse conditions, such as research designs with inappropriate samples or inadequate sample sizes. Their argument that "the size of an effect depends not just on the relationship between the independent and dependent variables but also the operations used to generate the data" (Prentice & Miller, 1992, p. 163) accentuates our argument that relatively small effect sizes do not imply low practical value. It is therefore essential to consider effect size in the context of an applied research design and the associated characteristics. The validated version of the self-regulation questionnaire by Carey et al. (2004) was adopted in the present study. Design characteristics, such as the type of instruments administered and the way exposure to stimuli occurs are factors that impact effect sizes.

The small effect sizes found may have practical implications in a real-life context. That is, the statistical analyses applied have not captured the practical effects. Small effect sizes may also accumulate and increase over time leading to larger effect sizes. For example, the student participants

in our study may exhibit higher self-regulation levels after prolonged exposure to STEM majors. From a critical standpoint, the small effect sizes could have implications on the theory of self-regulation and its connection to learning and performance (Abelson, 1985). Self-regulation may account for more than just learning and educational performance. Other aspects of life can benefit from self-regulation. Given that it is a limited cognitive resource that is at its lowest, learners may use it for learning and studying at various levels and amounts (Molden et al., 2016). It is difficult to know how much self-regulation the student has used up to the point of completing the questionnaire. In other words, students' perceptions about their own self-regulation may fluctuate with the level of self-regulation they may have at the time of completing the self-regulation scale. Nonetheless, effect sizes of any magnitude also add value to the existing literature on the topic.

Conclusion

The comparative study of self-regulation and academic performance among STEM and non-STEM university students found a significant difference between the students. The students of STEM majors utilized self-regulation strategy more in learning than the non-STEM majors. Their academic performance as measured by their GPA was also superior. It was therefore concluded that significant differences exist between students of both majors in their use of self-regulation strategy and academic performance. However, among the STEM fields, engineering students had the most self-regulation levels when compared to non-STEM fields of study. Computer science students showed higher performances based on their GPA than law and business administration students. Engineering students were the next most performing students based on their GPA.

Implications For Higher Education

The need for more post-secondary students to major and graduate in STEM fields is widely recognized (Valerio, 2014). In a study conducted by Uğur et al. (2020), students stated a constructive attitude about STEM education. They argued that STEM education offered the advancement of scientific method abilities and improved their behavior and interest in the field. Students' motivation and strategic self-regulation have been identified as playing crucial roles in their success in STEM classes. It was found that the incorporation of STEM disciplines into Toulmin's argumentation model was effective in improving the students' academic accomplishment, the growth of their deep thinking, and detecting the expansion of students' psychomotor abilities when constructing opinions in the classroom settings (Gülen & Yaman, 2019). For a while, self-regulation has been an interest of educational researchers whose goal is to improve academic performance among students in demanding fields of study beyond STEM, such as law and legal education (Bloom, 2013; Schwartz, 2003). A study with law students by Hyytinen et al. (2019) has shown that self-regulation is best fostered in student-centered learning environments that require independent learning and less direction from instructors. Considering the above, there are various learner-centered techniques and strategies that higher education institutions may employ to foster self-regulation among students in STEM fields.

A common learner-centered strategy that fosters independent learning is problem-based learning. Galand and colleagues (2010) successfully increased engineering students' adaptive self-regulation levels after employing problem-based learning strategies. Based on a comparison with traditional lecture, engineering students exposed to problem-based learning strategies also reported higher academic support, deep processing strategies as opposed to surface processing strategies, longer study time, all of which are elements linked to self-regulation. In addition to problem-based learning, employing role model biographies to increase motivation and facilitate the use of self-regulation strategies among STEM students is another method that universities and colleges should integrate into their student development programs and curriculum. Shin et al. (2016) presented the method of role model biographies as an effective technique that integrates motivational strategies for STEM students. These biographies, centering on prominent scientists, were shown to be effective in improving STEM students' self-efficacy levels and strengthening the connection between their identity and STEM.

Additionally, role model biographies may potentially increase STEM interest and retention rates (Shin et al., 2016). Equally effective are learning community participation and GPA for both groups from STEM and non-STEM majors (Whalen & Shelley, 2010).

A combination of various learning techniques embedded into a course structure has also proven to be effective in promoting self-regulation in students. Cazan (2020) developed an intervention that is comprised of learning journals, concept maps, error analysis tasks, self-and peer-assessment tasks. In that study, students were trained to use techniques through implicit training as these techniques were part of the coursework. For example, learning journals and concept maps required students to record planning and forethought activities. Students were also expected to monitor activities of their cognition and their progress toward their goals. Further, the main elements of the error analysis tasks, and the self and peer-assessment tasks are students' reflections on their performance based on their selection and use of various cognitive strategies that they have adopted for memory, learning, reasoning, problem-solving, and thinking. Strategies to promote self-regulation in students are not limited to the ones reported in this section. Universities and colleges are encouraged to explore evidence-based strategies and techniques that are best suited for their specific higher education system and STEM curricula.

Limitations

A major limitation of the study lies in its scope which makes it difficult for generalization across settings and fields. For example, the sample in this study consists exclusively of male participants from one university, thereby limiting the findings to male students and the setting. Given that only two majors (engineering and computer science) from the STEM fields were included in this study, the findings can be generalized mainly to engineering and computer science majors in STEM and a few non-STEM courses that were covered in an all-male campus of a Middle Eastern university. The inability to have female students was a major limitation in the study as well. However, this was not deliberate. It was the researchers' sensitivity to the cultural norms.

The design adopted in our present study limits the generalization of the conclusions. For instance, the variables already existed before the initiation of the study and thus were not manipulated in real-time. Moreover, there may be other unmeasured or unobserved factors that may explain the differences between groups based on fields of study. For example, certain classroom characteristics in STEM courses could be factors that were not considered in the present study.

According to Fraenkel et al. (2012), the inferences are rather associational in nature and are to be interpreted as reflecting the Arabian male sample. Because the design is associational, self-regulation levels in STEM students may have existed before they chose to enroll in STEM fields of study due to prior exposure to STEM preparation programs or advancement courses in high school.

Nevertheless, the findings have offered more insight that can stimulate further researches in the continuous quest for academic performance improvement among STEM and non-STEM students. For instance, when some dispositional and situational variables are examined along with self-regulation, new insights may emerge other than what self-regulation alone found. More importantly, the findings have added an Arabian sample to the existing literature in the area of self-regulation in STEM and non-STEM students' academic performance. Despite the unavoidable limitations, this study has offered new insight in the area of focus that could expand the literature on STEM-related self-regulation levels and performance as evidenced by students' GPA. STEM students were found to show more self-regulation than the non-STEM students, and it predicted students' GPA in the Middle Eastern sample. STEM students reported higher self-regulation levels than non-STEM students.

The findings have helped to increase understanding of self-regulation as an important element in the context of learning and performance in higher education. We argue that self-regulation remains an essential skill for students both in and out of the classroom. In addition to academic performance, higher self-regulation in STEM students has also been associated with significantly lower substance use to cope with stress (Park et al., 2019). Further, Hyttinen et al. (2019) have shown that students with higher self-

regulation view their learning experiences in a positive light. We believe that this connection between self-regulation and perception of the learning experience is salient in preparing students for success in college.

It was suggested that future comparative researches on self-regulation levels across fields of study need to expand the STEM and non-STEM student groups and include more variables that have been implicated in cognitive learning processes and other related constructs. When considered in future researches, the generalization of conclusions could be enhanced. Based on the significant difference in performance due to the level of self-regulation between STEM and non-STEM students, it is recommended that higher education instructions need to integrate strategies and techniques that promote self-regulation into their student development programs and curricula.

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