The Influence of Anxiety and Self-Efficacy on Statistics Performance: A Path Analysis
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ABSTRACT. Numerous researchers have discussed the potentially detrimental role that anxiety can play in thwarting positive student outcomes in higher education. Statistics anxiety, in particular, has been shown to pose a threat to statistics achievement. Although some previous researchers have demonstrated that statistics anxiety was directly related to impaired statistics performance, other researchers failed to identify such a relationship. Building from these inconsistencies in the literature, the present exploratory study used path analysis to investigate whether anxiety directly or indirectly impairs performance and its relationship with self-efficacy. In this study, we replicated previous findings that self-efficacy can predict a significant amount of the variability in statistics performance ($\beta = .45, p = .001$, adjusted $R^2 = .21$), even after controlling for students’ prior GPAs. More importantly, through this study, we also demonstrated that anxiety did not directly impact performance ($\beta = .23, p = .102$), but instead altered students’ levels of self-efficacy ($\beta = -.65, p = .001$), and indirectly affected academic outcomes ($\beta = -.30, p = .001$). The results of this study provide evidence that students have the ability to gain the skills they need to succeed, even if they have a challenging academic history or heightened levels of anxiety. These results align with much of the previous literature, suggesting that classroom interventions at the undergraduate level should center less on decreasing student anxiety and more on instilling in students a sense of self-efficacy: the belief that, with effort and persistence, they can succeed in their statistics courses.

Many undergraduate students—particularly from nonmath majors such as psychology, nursing, social work, and the social sciences (Sesé, Jiménez, Montaño, & Palmer, 2015)—shudder at the mention of the word statistics and at the thought of enrolling in a statistics course (Chew & Dillon, 2014). Statistics and research methods are mandatory courses in these majors, yet many students tend to underperform in these courses (Chew & Dillon, 2014; Lester, 2016). Motivated by staggering figures documenting these underperforming behaviors in universities throughout the United States (Chew & Dillon, 2014; Lester, 2016), researchers have investigated the role of statistics anxiety on various performance measures in undergraduate statistics courses (Cruise, Cash, & Bolton, 1985; Griffith et al., 2014; Macher, Paechter, Papousek, & Ruggeri, 2012; Onwuegbuzie & Wilson, 2003). Statistics anxiety has been defined as “a negative state of emotional arousal experienced by individuals as a result of encountering statistics in any form and at any level” (Chew & Dillon, 2014, p. 9), which can significantly impair student learning during a statistics course (Macher, Papousek, Ruggeri, & Paechter, 2015; Onwuegbuzie, 2004).

Although some researchers have argued that lower performing students tend to have significantly greater levels of statistics anxiety than their high-performing classmates (Onwuegbuzie & Seaman,
1995), there are inconsistencies in the literature with respect to how, exactly, statistics anxiety is related to course outcomes (Chew & Dillon, 2014). However, if statistics anxiety has the capacity to debilitate students, then educators need to know exactly how it works so as to circumvent or at least reduce its negative impact. Although researchers such as Chew and Dillon (2014) have expressed the need to uncover exactly how statistics anxiety impacts academic performance, few empirical studies have involved a description of the mechanisms underlying statistics anxiety. Yet, there are at least two models, proposed by Macher et al. (2015), by which statistics anxiety is theorized to impact performance: the cognitive interference model and the deficit model.

According to the cognitive interference model, statistics anxiety directly affects a student’s performance on a statistics exam (Macher et al., 2015). This model says that anxiety overloads a student’s working memory during the exam and effectively disrupts the student’s performance on the exam. Both Macher et al. (2015) and Onweugbuzie (2004) stated that students often cite their high levels of anxiety as an explanation for why they did not perform as well as they anticipated. In support of this model, some researchers have reported that, as statistics anxiety increases, statistics performance decreases, illustrating a direct relationship between statistics anxiety and performance (Griffith et al., 2014). Although the results of this research support a direct negative effect of anxiety, according to Paechter, Macher, Martskvishvili, Wimmer, and Papousek (2017), “various studies have found no or only low, nonsignificant correlations between statistics anxiety and academic performance” (p. 2); these studies include Hamid and Sulaiman (2014) and de Vink (2017). One explanation for these inconsistencies may be due to the questionnaire used to measure anxiety. Hamid and Sulaiman (2014) and de Vink (2017) measured anxiety using the Statistics Anxiety Rating Scale (STARS; Cruise et al., 1985), and Griffith et al. (2014) used a different instrument, the Statistics Comprehensive Anxiety Response Evaluation (SCARE). Nonetheless, these inconsistencies still raise two questions: Does anxiety influence performance? If it does, is the relationship between anxiety and performance direct or indirect?

Although the cognitive interference model proposes a direct effect of anxiety, an alternative model, the deficit model, suggests that the negative effect of statistics anxiety on performance is primarily indirect (Macher et al., 2015). In the deficit model, students come into an exam ill-prepared because their anxiety prevented them from sufficiently studying for the exam. As Paechter et al., (2017) argued, statistics anxiety’s negative, indirect effects “mostly concern difficulties in time-management and procrastination during the preparation phase” of the learning process (p. 2). This model proposes that statistics anxiety inhibits learning before the exam by first prompting students to avoid the course material, leading to a decrease in appropriate studying behavior and diminished motivation (Macher et al., 2015). Paechter et al. (2017) and Sesé et al. (2015) also supported this argument with empirical evidence: These researchers found that anxiety had an indirect negative effect on academic performance. Macher et al. (2015), Paechter et al. (2017), and Sesé et al. (2015) provided support for the deficit model, each showing that statistics anxiety had an indirect negative effect on academic performance. These results suggest that statistics anxiety impairs the learning process, which in turn, impedes performance. That is, statistics anxiety may have a direct effect on learning behaviors, but an indirect effect on exam performance on statistics exams.

Several studies have provided additional support for the deficit model. For instance, researchers have reported that higher statistics anxiety was positively related to the utilization of maladaptive learning strategies (Onweugbuzie & Wilson, 2003), procrastination (Macher et al., 2012; Onweugbuzie, 2004; Paechter et al., 2017), low levels of statistics self-efficacy (McGrath, Ferns, Greiner, Wanamaker, & Brown, 2015), and was negatively related to the use of self-regulated learning strategies (Kesici, Baloglu, & Deniz, 2011). Each of these preceding variables were, in turn, related to statistics performance. These findings provide tentative evidence that statistics anxiety may have a negative, indirect effect on academic performance.

The cognitive interference model is a somewhat straightforward model because it focuses primarily on the direct effect of statistics anxiety on performance. Conversely, because the deficit model involves slightly more complex relationships between these variables, it seems there may be other variables and behaviors involved in this model, such as a students’ learning strategies, levels of procrastination, or self-efficacy. As such, it is necessary to examine the deficit model more closely and identify which variables are key components in the learning process. To identify other
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relevant variables, it is important to first establish a theoretical framework in which anxiety operates to influence performance, so as to help explain how and why statistics anxiety may disrupt the learning process in statistics courses.

Researchers have posited that anxiety may influence performance by preventing students from becoming active and self-regulating learners (Zimmerman, 2002). The results of several studies have shown that students with high levels of statistics anxiety were more likely to adopt maladaptive learning strategies (Onwuegbuzie & Wilson, 2003) and less likely to adopt more effective self-regulated learning strategies (Kesici et al., 2011). Self-regulated learning is one of the theoretical frameworks often used to explain the learning process (Bandura, 1986); it is described in three phases: forethought, performance, and self-reflection (Zimmerman, 2002). Self-regulation theorists such as Bandura (1991) and Zimmerman and Schunk (2004) have argued that anxiety can impair students during the early stages of learning by reducing their self-efficacy (e.g., during the forethought phase). Anxious students tend to have maladaptive beliefs about their statistics abilities that frequently lead them to struggle to keep up with class work from the beginning of the course (Onwuegbuzie & Wilson, 2003). They tend to procrastinate and avoid completing their homework because it gives them anxiety, and they often do not know how to help themselves to view the course material in a less threatening way so that they can study more productively (Onwuegbuzie, 2004; Paechter et al., 2017). Moreover, these students often are afraid of asking a professor for help (Cruise et al., 1985). Anxious students often find themselves experiencing repeated failures on exams, yet they cannot find a way to generate success out of their underperformance. This is due to the fact that students with heightened anxiety tend to have low levels of self-efficacy (Perepiczka, Chandler, & Becerra, 2011).

To be successful in their statistics courses, researchers argue that students must possess high levels of self-efficacy (McGrath et al., 2015). Having high self-efficacy helps students to feel that they can develop the skills they need to master a given concept, even if they have to work through setbacks (Bandura, 1986). These beliefs, in turn, prompt students to engage in effective studying and learning behaviors. For example, a self-efficacious student is one who approaches a statistics course with an analytical mindset, deciphers which skills are needed to meet a given learning objective, and knows that, with effort, the necessary skills can be achieved (Bandura, 1993). This student can set clear, challenging, but realistic goals that lead the student toward mastery of the learning objective through acquiring these needed skill sets (Artino, 2012). A self-efficacious student is, furthermore, able to use any underperformance as feedback, changing study strategies as needed, rather than seeing failure as final. Researchers have provided evidence that self-efficacy has a significant impact on students’ course performance (Byrne, Floor, & Griffin, 2014). For instance, Nelson, Gee, and Hoegler (2016) found that students’ statistics self-efficacy beliefs significantly predicted an additional 7% of the variability in their final exam scores, after controlling for prior GPA. Other researchers have similarly found self-efficacy to be a significant predictor of course performance in statistics (Byrne et al., 2014; McGrath et al., 2015).

On the contrary, when students do not develop self-efficacy beliefs, they often adopt maladaptive patterns of behavior that impair their ability to learn (Artino, 2012; Bandura, 1993). For instance, they are often unable to determine how to address an assignment or objective, leading to diminished motivation (Artino, 2012) and decreased performance (Nelson et al., 2016). This is often the case for students with high levels of statistics anxiety: They lack self-efficacy and fail to develop the skills they need to succeed in the course (McGrath et al., 2015). These students tend to internalize their failures and interpret their current situation as inescapable and overwhelming (Onwuegbuzie & Seaman, 1995), further raising their anxiety and decreasing their sense of self-efficacy (Schneider, 2011).

In many studies, researchers have reported a significant negative relationship between anxiety and self-efficacy (Chou, 2018; McGrath et al., 2015; Onwuegbuzie & Seaman, 1995; Perepiczka et al., 2011; Schneider, 2011). Bandura and Adams (1977) argued that anxiety contributes to the development of self-efficacy. They stated that one of the sources of self-efficacy is the “state of physiological arousal from which people judge their level of anxiety” (p. 288) and that stressful, anxiety-inducing, and otherwise emotionally arousing scenarios are “source[s] of information that can affect perceived self-efficacy in coping with threatening situations.” On the converse, Bandura (1993) has also argued that self-efficacy can predict the development of anxiety, remarking that one’s efficacy beliefs can influence one’s perception of stressors. According
to Bandura (1993), those who have high levels of self-efficacy tend to have low levels of anxiety because they believe they are in control of how they manage stressful situations.

However, theorists such as Pintrich and DeGroot (1990), Tremblay and Gardner (1995), and Zimmerman and Shunk (2004) argued for the former explanation—that anxiety primarily affects self-efficacy, not the other way around. Empirical studies have provided support for this argument (Chou, 2018; Perepiczka et al., 2011; Schneider, 2011). Perepiczka et al. (2011) showed that statistics anxiety was a significant predictor of statistics self-efficacy. Chou (2018) indicated that anxiety was a significant predictor of self-efficacy, although self-efficacy (but not anxiety) was a significant predictor of academic performance. Schneider (2011) revealed that, although self-efficacy and anxiety were significantly related to one another, anxiety had no significant relationship with performance. However, whether it is students’ self-efficacy that influences their anxiety, or vice versa, still remains to be further addressed.

In summary, statistics anxiety seems to play a role in student achievement in statistics, and thus appears to be an important variable for statistics educators to understand. If statistics anxiety is detrimental to student learning, then educators need to understand the mechanism by which anxiety impacts performance, either directly (in the case of the cognitive interference model) or indirectly (in the case of the deficit model). Although some researchers have identified a direct effect of anxiety on academic performance (Griffith et al., 2014), others have suggested that anxiety may instead impede performance indirectly (Macher et al., 2015; Paechter et al., 2017). One mechanism through which anxiety may be exerting its effect is by first influencing students’ self-efficacy beliefs, which then directly impact academic performance (Chou, 2018; Perepiczka et al., 2011; Schneider, 2011). In other words, anxiety may have a negative indirect effect on performance during the early stages of the learning process (Paechter et al., 2017; Zimmerman & Schunk, 2004). To date, few researchers have formally compared and analyzed models of how statistics anxiety affects learning and performance (Macher et al., 2015; Paechter et al., 2017).

The Current Study
Researchers have yet to identify the mechanism by which statistics anxiety influences course performance, as demonstrated by the conflicting evidence presented earlier. Yet, identifying this mechanism has important implications for statistics educators. If statistics anxiety directly impairs performance, then educational interventions should strive to directly reduce anxiety before exams. Conversely, if statistics anxiety works through other variables—namely self-efficacy—to exert an impact on academic performance, then it is important to examine how these other variables such as self-efficacy operate with anxiety to influence performance. Therefore, the current study aimed to fill in these gaps in the previous literature in order to help educators meet the needs of low-performing students in statistics courses. First, we investigated whether statistics self-efficacy could predict final exam performance, after controlling for prior GPA. Second, we compared which of the two models could best explain the role of statistics anxiety in final exam performance: (a) the cognitive interference model, in which prior GPA, self-efficacy, and anxiety would each have a direct effect on final exam performance; or (b) the deficit model, in which only prior GPA and self-efficacy would have a direct effect on final exam performance, but anxiety would have an indirect effect by working though students’ self-efficacy.

Method
Participants
Undergraduate psychology majors at a public university in the Northeast were recruited via e-mailed flyers as a convenience sample of students enrolled in two sequential statistics courses: Principles of Research Methods (covering descriptive statistics, the basics of hypothesis testing, and research design issues) or Psychological Statistics (focusing on inferential statistics from a one-sample t test through regression). Students were recruited from three sections of Psychological Statistics (n = 52) and two sections of Research Methods (n = 49). These courses were taught by the same two professors, who both used the same curriculum, teaching approach, and cumulative final exam questions and grading criteria for the sections of each course. A total of 101 students from both courses were asked to participate. Seventy-two students (71% of the initial sample) provided complete responses. Of these 72 respondents, nine were transfer students (all enrolled in psychological statistics) who did not have a prior semester cumulative GPA. Because prior GPA was a key variable for the study, these nine students were excluded from all analyses,
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Materials and Variables

Prior GPA. The university research office provided students’ cumulative GPAs from the semester prior to their enrollment in the Research Methods or Psychological Statistics courses; prior GPAs ranged from 1.59 to 4.00 (M = 2.93, SD = 0.58).

Statistics Anxiety Rating Scale (STARS). The STARS (Cruise et al., 1985) contains 51 items, comprising six subscales. The first three of these subscales measure statistics anxiety and the last three measure attitudes toward statistics (Baloglu, 2002). For the purposes of this study, we utilized only the three subscales measuring statistics anxiety: Interpretation Anxiety (11 items), Test and Class Anxiety (8 items), and Fear of Asking for Help (4 items), totaling 23 items. Participants responded to these questions on a 6-point Likert-type scale, with higher scores indicative of greater anxiety. In keeping with previous studies that have used this instrument (Baloglu, 2002; de Vink, 2017), we combined students’ scores on the three anxiety subscales into a total anxiety score. Researchers have previously demonstrated the construct and concurrent validity of this survey (Baloglu, 2002; Cruise et al., 1985). Cronbach’s α coefficients reported for the anxiety scale have ranged from .68 to .89 (Baloglu, 2002; Cruise et al., 1985). For the current sample, Cronbach’s α = .95.

Statistics self-efficacy. Statistics self-efficacy was measured using the eight-item Self-Efficacy subscale of Pintrich, Smith, Garcia, and McKeachie’s (1991) Motivated Strategies for Learning Questionnaire (MSLQ). This scale originally contained general wording (e.g., it referred to students’ beliefs about their college courses in general), but was adapted for the specific domain of statistics courses, in keeping with Nelson et al. (2016). Students responded to these items on a 6-point Likert-type scale, with higher scores indicative of greater self-efficacy. Researchers have established the construct and concurrent validity of this instrument (Ilker, Arslan, & Demirhan, 2014; Pintrich et al., 1991). Cronbach’s α for this instrument was reported as .93 by Pintrich et al. (1991) and was reported as .92 for the adapted version by Nelson et al. (2016). For the current sample, Cronbach’s α = .94.

Exam grade. Students’ scores on the final exam in their Research Methods or Psychological Statistics course were collected. The final exams for both professors’ courses and sections were cumulative and identical in format. All exams were cumulative, used a short answer format, were graded all-or-nothing (e.g., no partial credit was given for partially correct answers), and were graded out of a maximum score of 200 points. The content covered in the Research Methods final included descriptive statistics, introductory inferential statistics, and hypothesis testing concepts, and the content covered in the Psychological Statistics final covered descriptive and inferential statistics, focusing on a greater use of SPSS, while also including research methodology questions. Although the exams in these two sequential courses were not identical, there were similar numbers of statistics-related and research-related questions contained in each exam. After course grades were submitted, final exam scores were compiled by the supervising faculty member, and all identifying information was removed before any data was given to the student researcher. Final exam scores were converted to percentages before any analyses were conducted; in the literature, exam grades are often discussed in the form of percentages, so that the reader can more easily interpret the performance of students (Brookheart et al., 2016). Although these two required courses were sequential in nature, no student’s data was in both courses because data was collected during only a single semester.

Procedure

Before beginning this study, institutional review board approval was given by the Western Connecticut State University Institutional Review Board (#1617-138). Exploratory in nature, this study did not involve any experimental manipulation. As previously stated, students were recruited from two statistics courses for psychology majors. Several days before their final exam, students in both courses were recruited, via e-mailed flyers, to respond to a survey via Qualtrics® online survey platform. The survey included 40 questions (nine demographic and 31 items representing the self-efficacy and anxiety scales) and took approximately 10–15 minutes to complete. The flyers sent by e-mail contained a link to the survey website. If students decided to participate, they electronically signed the consent form on the survey website and then provided demographic information including age, sex, and the course and section in which they were enrolled. The survey questions were presented
to consenting participants one at a time and in a randomized order on Qualtrics. The presentation of the questions in a randomized order is a practice that has been investigated in prior literature (Schell & Oswald, 2013; Siminski, 2008). According to these sources, the order in which questions are presented can bias a respondent’s answers (e.g., the answer to one question is influenced by a previous answer) (Choi & Pak, 2005). To circumvent this potential bias, the current study followed the advice of these studies and randomized the order of the self-efficacy and anxiety questions. However, this practice has not been formally evaluated with these specific survey instruments, a potential limitation that is examined at length in the discussion.

Planned Analyses and Power
The current exploratory study was designed to answer two research questions: (a) Can statistics self-efficacy predict final exam performance, after controlling for prior GPA, and (b) Which model best explains the role of statistics anxiety in final exam performance: cognitive interference or deficit? Based on these research questions, the planned analyses chosen for this study were hierarchical multiple regression and path analysis, for the first and second research questions, respectively. An a priori power analysis was performed using G*Power 3.1.9.2. Prior researchers have identified both large (McGrath et al., 2015; Perepicka et al., 2011) and medium effects (Chou, 2018; Schneider, 2011; Sesé et al., 2015) when investigating the relationships between these variables using these analyses; to err on the conservative side, a medium effect was used when conducting power analyses. Power analysis indicated that, to have power of .80 to detect a medium effect at the .05 level of alpha in a hierarchical multiple regression, the analysis required 68 people. For the path analysis, power analysis indicated that 77 people were required to detect a medium effect. Although we originally anticipated being able to utilize data from between 72 and 101 people (see participant section), the final sample was $n = 63$, slightly under the recommended minimum sample size. The fact that this study was slightly underpowered will be addressed in the discussion section.

Results
Preliminary Comparisons
Eighty-three percent ($n = 52$) of the sample was women, with women outnumbering men in the sample five to one, thereby making interpretation of comparisons between sexes tenuous at best. Nonetheless, these comparisons were conducted (see Appendix). Several comparisons between the two courses (Research Methods and Psychological Statistics) were also conducted. There were no significant differences between the two courses in terms of self-efficacy, anxiety, final exam performance, or prior GPA (see Appendix). The lack of significant differences between the two statistics courses justified combining the data into one sample for the remaining analyses.

Main Analyses
The assumptions of hierarchical multiple regression and path analysis were assessed and verified (see Appendix). Before the research questions were examined, correlations among the four variables were calculated. Anxiety ($M = 2.96$, $SD = 1.09$) and self-efficacy ($M = 4.61$, $SD = 0.87$) were significantly and negatively related, $r(61) = -.65$, $p < .001$. Final exam performance ($M = 82.83$, $SD = 13.20$) was also significantly and positively related to both self-efficacy, $r(61) = .45$, $p < .001$, and to prior GPA ($M = 2.93$, $SD = 0.58$), $r(61) = .27$, $p = .04$. In other words, final exam scores increased with an increase in self-efficacy, as well as an increase in prior GPA. However, prior GPA was not related to self-efficacy, $r(61) = .004$, $p = .98$, or anxiety, $r(61) = .01$, $p = .91$, and there was no relationship between anxiety and exam performance, $r(61) = -.16$, $p = .21$.

Research Question 1. Hierarchical multiple regression was conducted using SPSS 22 to assess the first research question: Can statistics self-efficacy predict final exam performance, after controlling for prior GPA? Because the correlations between prior GPA and final exam performance, and between self-efficacy and final exam performance were significant, a hierarchical multiple regression was performed to examine whether self-efficacy was a significant predictor of final exam performance, after accounting for prior GPA (see Table 1 for

| TABLE 1 |
|-------------|-------------|-------------|-------------|-------------|-------------|
| Prior GPA and Self-Efficacy as Predictors of Final Exam Performance | | | | | |
| | | | | | |
| **Step 1** | | | | | |
| Prior GPA | .27 | 2.15 | .035 | .27 | .07 |
| **Step 2** | | | | | |
| Prior GPA | .26 | 4.50 | .019 | .53 | .28 | .21 |
| Self-Efficacy | .45 | 4.14 | .001 | | | |

Note. $N = 63$. 

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results summary). Students’ prior cumulative GPA was entered into Step 1 of the model, so as to control for past performance; prior GPA explained 7% of the variance in exam performance. Self-efficacy was entered into Step 2 of the model, accounting for an additional 21% of the variability. The entire model was significant, accounting for 27.7% of the variability in final exam grades. This analysis replicated the results of a previous study (Nelson et al., 2016), which also found that self-efficacy was a significant predictor of exam performance, even after controlling for prior GPA.

**Research Question 2.** Path analysis was performed using the AMOS 22 plug-in for SPSS 22 in order to assess the second research question. Model fit was assessed by using the Chi-Square, Root Mean Square Error of Approximation (RMSEA), Comparative Fit Index (CFI), Normed Fit Index (NFI), and Incremental Fit Index (IFI) following the suggestions of McDonald and Ho (2002) and Schreiber, Nora, Stage, Barlow, and King (2006). A nonsignificant chi-square value indicates that the current model is not a bad fit for the data (Sheskin, 2011). CFI, NFI, and IFI values greater than or equal to .95 are considered representative of a “good” fit; an RMSEA value less than or equal to .05 is indicative of a “good” model fit (Sheskin, 2011).

The results of the path analysis including standardized path coefficients are depicted in Figure 1. The model was a good fit, as evidenced by \( \chi^2(2, N = 63) = .032, p = .98, \) RMSEA = .00, CFI = 1.00, NFI = .99, and IFI = 1.04. Prior GPA (\( \beta = .26, p = .006 \)) and self-efficacy (\( \beta = .60, p < .001 \)) each had a significant direct effect on final exam performance. As evidenced by the standardized path coefficients, self-efficacy had a medium effect on exam performance, and prior GPA had a small effect (Sheskin, 2011). There was also a significant inverse relationship between anxiety and self-efficacy (\( \beta = -.65, p < .001 \)). However, contrary to the hypothesized model, there was no significant direct effect of anxiety on exam performance (\( \beta = .23, p = .102 \)). The entire model accounted for 30% of the variability in final exam scores (\( R^2 = .30 \)).

Because no direct effect of anxiety on final exam performance was identified, resulting in a nonsignificant path, the second proposed model was subsequently evaluated using path analysis. Model fit was again assessed with the Chi-Square, RMSEA, CFI, NFI, and IFI. The path analysis including standardized path coefficients is shown in Figure 2. Good model fit was evidenced by \( \chi^2(2, N = 63) = 2.64, p = .45, \) RMSEA = .00, CFI = 1.00, NFI = .95, and IFI = 1.01. As shown in Figure 2, both self-efficacy (\( \beta = .45, p = .001 \)) and prior GPA (\( \beta = .26, p = .008 \)) had significant direct effects on final exam performance. The standardized path coefficients indicate that self-efficacy had a medium effect on exam performance, and prior GPA had a small effect. There was also a significant large direct effect of anxiety on self-efficacy (\( \beta = -.65, p = .001, R^2 = .42 \)). Finally, there was a significant indirect
effect of anxiety on exam performance ($\beta = -.30$, $p = .001$), in that anxiety appeared to indirectly affect exam performance by first influencing self-efficacy. This indirect effect was medium in size. The entire path model explained 28% of the variability in final exam performance ($R^2 = .28$). Because the direct effect of anxiety on final exam was nonsignificant in the previous model, this second model seems to best explain the role of anxiety in statistics performance. It not only was a good fit for the data and explained a large portion of the variability in final exam performance, but it also did not have any nonsignificant paths. Jöreskog and Sörbom (1996) argued that, when comparing models that both are a good fit for the data, the model that significantly explains all or most of the effects (e.g., paths) should be chosen to interpret the findings.

Upon further consideration, we also decided to analyze and report an alternative model, in which statistics self-efficacy is proposed to directly affect statistics anxiety, which in turn influences performance. Although this alternative model does not exemplify either a cognitive interference or deficit model, it was tested as a means of examining an alternative explanation for the relationship between self-efficacy and anxiety (as described in some of Bandura’s (1993) work). The purpose in proposing this model was to assess any alternative explanations for the finding that Model 2, the deficit model, was the best explanation for the relationship between self-efficacy, anxiety, and exam performance. The alternative model was analyzed using path analysis. The chi square value, $\chi^2 (3, N=63) = 16.36, p = .001$, suggested that the data was not a good fit for the model; this was substantiated by RMSEA = .27, CFI = .74, NFI = .71, and IFI = .75. Therefore, this alternative model was eliminated as a potential alternative explanation for the finding that Model 2, the deficit model, appeared to be the best explanation for the relationship between self-efficacy, anxiety, and performance.

### Discussion

The purpose of this study was to investigate the relationships between students’ prior academic performance, self-efficacy beliefs, levels of anxiety, and their performance in statistics courses. Framed within this overall purpose, this study had two specific aims: to replicate the results of a previous study (Nelson et al., 2016) and to identify which model best explained the relationships between prior GPA, statistics anxiety, statistics self-efficacy, and final exam performance.

#### Research Question 1

Using a sample that was almost twice as large as the previous study ($N = 63$ vs. $N = 39$), we replicated Nelson et al.’s (2016) finding that self-efficacy is a significant predictor of final exam performance in a psychological statistics course, after accounting for prior GPA. These findings again revealed that self-efficacy could explain more of the variability (21%) in final exam performance than prior GPA (which explained 7.1% of the variance), suggesting that students’ beliefs in their ability to succeed may actually play a larger role in influencing their exam performance than their prior GPAs. This finding is particularly noteworthy because it suggests that students do have the potential to succeed if given the correct learning tools, even if they lack a strong academic history (Artino, 2012; Bandura, 1993; Nelson et al., 2016).

#### Research Question 2

The primary focus of this study was to identify a model that best explains the relationships between prior GPA, self-efficacy, anxiety, and statistics performance. Findings from both path analyses demonstrated that, although prior GPA played a small direct role in exam performance, it was not related to anxiety or self-efficacy. This is interesting considering the prior literature, as prior successes (i.e., a high prior GPA) are theorized to be related to increased self-efficacy, while prior failures (i.e., a low previous GPA) are theorized to be related to increased anxiety (Artino, 2012). However, prior literature has also remarked on the importance of keeping domain-specificity in mind when examining the role of non-cognitive variables in performance (Nelson et al., 2016; Pacheter et al., 2017). As such, it may be that one’s domain-specific statistics anxiety and statistics self-efficacy are not related to one’s general, nondomain-specific GPA (Pacheter et al., 2017).

The main concern of this study was to use path analysis to evaluate the two different proposed models: the cognitive interference model (in which prior GPA, self-efficacy, and anxiety directly affect performance) and the deficit model (in which prior GPA and self-efficacy directly affect performance, and anxiety has an indirect effect). The analysis of the first model revealed that anxiety had no direct effect on performance. However, the analysis of the second model revealed that anxiety had a significant indirect effect on performance by altering students’ levels of self-efficacy. Evaluation of an alternative model, which proposed that
self-efficacy indirectly influenced statistics anxiety, and that anxiety in turn influenced performance, was not a good fit for the data. The results of the analyses of the two primary models, as well as the alternative model, provide evidence that anxiety may have an indirect influence on statistics achievement. This is vital information for any statistics instructor because it provides tentative evidence for the idea that, no matter how anxious statistics can make students, their anxiety may not have the final say in performance in the course.

These results contradict the cognitive interference model (Macher et al., 2015), which suggests that anxiety directly interrupts performance by disrupting and distracting students in the midst of their exams. The results of this study align with other studies, including Hamid and Sulaiman (2014) and de Vink (2017), which found that students’ anxiety, measured via their responses to Cruise et al.’s (1985) STARS scale, were not significantly related to their performance. Some previous studies, namely Griffith et al. (2014), identified a direct relationship between performance and anxiety. They measured anxiety with an instrument called the SCARE, which could have contributed to the differences in findings. The STARS was utilized in this study because it appears to be the most commonly used instrument to measure statistics anxiety (de Vink, 2017; Hamid & Sulaiman, 2014; Onwegbuzie, 2004; Paechter et al., 2017; Schneider, 2011), and a search of the literature shows that SCARE has only yet been utilized by Griffith et al. (2014).

The results of the current study lend support for Macher et al.’s (2015) deficit model, which says that anxiety indirectly impedes performance by first impacting students’ learning and motivational behaviors. In other words, statistics anxiety may prompt students to avoid the course material (Onwegbuzie & Wilson, 2003), which may lead them to not engage in effective, distributed study strategies (Zimmerman, 2002); it may prevent students from learning the material in the first place (Macher et al., 2015).

These results also provide insight into one of the potential mechanisms through which anxiety may indirectly influence performance. These findings contribute tentative evidence that supports explanations in the existing literature that anxiety during learning may prevent students from developing the self-efficacy they need to persist as they continue through the learning process (Perepiczka et al., 2011; Schneider, 2011), leading to an indirect effect of anxiety on exam performance (Macher et al., 2015). To more precisely examine what stage of the learning process is affected by anxiety, future research should focus on the relationship between anxiety and smaller, local assessments such as quiz, activity, and test performance over the semester. These smaller assessments may better reflect students’ learning progress throughout the course.

The results provide support for the argument that self-efficacy explains more of students’ statistics performance than prior GPA or anxiety alone. The extent to which students believe that they have the skills to master statistics seems to be a major predictor of their final exam performance. These findings are in line with existing literature, which suggests that high levels of self-efficacy can help motivate students during the early phases of learning (Zimmerman & Schunk, 2004) and help prevent them from succumbing to hardships or failures (Artino, 2012). Self-efficacy may specifically do so by instilling in students the “belief that failure is not permanent and that with effort and resilience they can succeed” (Nelson et al., 2016, p. 8).

Limitations and Suggestions for Future Research
This study was not without its limitations. First, some researchers have posited that the order in which the questions in a survey are presented can influence responses (Choi & Pak, 2005). In this study, we randomized the order of the items in the two survey instruments, as a means of guarding against learning bias (Choi & Pak, 2005, p. 9). These researchers have suggested “completing a questionnaire can be a learning experience for the respondent about the hypotheses and expected answers in a study” (p. 9), such that a participant’s response to one question may shape their responses to the questions that follow. Choi and Pak (2005) argued that, to prevent this type of bias, “it may be necessary to randomize the order of the questions” (p. 9). Several researchers assessed this type of randomization as a means of guarding against learning bias (Schell & Oswald, 2013; Siminski, 2008). These researchers found that randomizing the surveys items did not reduce the reliability of their instruments. However, no researchers have formally assessed the effects of this practice on the reliability of the Statistics Anxiety Rating Scale (STARS) or the Self-Efficacy subscale of the MSLQ. In our own prior research, we found no significant differences in reliability for these scales when the items were presented in their original order (Nelson, Gee, Heath, & McAndrew, 2015).
as compared to a randomized order (Nelson et al., 2016). Nonetheless, further research is needed to determine whether randomization of survey items reduces the reliability of these survey instruments.

Additionally, the a priori power analyses described in the Method section indicated that this study was slightly underpowered. As such, it is important to interpret these findings with caution until they can be replicated with a larger sample. Likewise, for this study, data was only collected during one semester, and it may be instructive to establish whether the effect of anxiety on academic performance is replicable over multiple semesters (Simons, Shoda, & Lindsay, 2017). Another study, currently in progress, is directed toward addressing the need for increased power and data collection over multiple semesters. Another limitation was the fact that two courses were used in this study, meaning that final exams were not identical in format. Despite the fact that both exams contained similar percentages of research methods-related and statistics-related concepts, a goal of future research should be to analyze each course individually to see if the present findings hold true. Furthermore, it is important to note the “constraints of generality” (Simons et al., 2017, p. 1124) that are present when interpreting these findings. Specifically, this study took place at a public university with open enrollment policies. As such, these findings may only be relevant to similar populations. Additional research at different types of institutions is necessary to determine whether the observed statistical relationships in this study are relevant to students at other types of institutions. Finally, we collected demographic information on participant age and sex, but not on race/ethnicity. In future studies, researchers should expand the collected demographic data to provide more information on the generality of these findings.

**Implications for Intervention**

Despite the need for further research, the current study can provide several important, albeit tentative implications for interventions. The results of this study, in addition to others, provide evidence that students’ anxiety may primarily inhibit their performance by working through self-efficacy (Chou, 2018; Perepiczka et al., 2011; Schneider, 2011). These findings are aligned with Bandura’s (1993) argument that students’ self-efficacy is one of the best predictors of whether or not they succeed academically, while students’ “level[s] of scholastic anxiety bear little or no [direct]

relationship to their academic performance” (pp. 133–134). Accordingly, Bandura suggests that educational interventions should focus on promoting students’ self-efficacy, rather than on creating “anxiety palliatives” (p. 134). In other words, it might be more effective for classroom interventions, activities, and general structure to focus primarily on promoting self-efficacy, rather than decreasing student anxiety.

An example of an intervention that can be used to improve self-efficacy is the exam wrapper (Achacoso, 2004). Exam wrappers are post-exam reflection exercises that help students to reflect on their exam performance, distinguish between the concepts they mastered and those they did not, and between which study methods were and were not effective (Achacoso, 2004; Nelson et al., 2015). When used in our statistics courses, exam wrappers help students to view their errors as an opportunity for growth, better preparing them to identify the concepts about which they need to develop a deeper understanding. This is one intervention that has been shown to raise students’ levels of self-efficacy over the course of a semester (Nelson et al., 2015). Another relevant classroom intervention is the preclass activity, assigned with readings from the textbook. These low-stakes activities are short learning exercises that teach the basic, factual information for a given topic. The preactivities have students answer mostly low-level (i.e., remembering and understanding from Bloom’s Revised Taxonomy) practice problems that require them to use the basic material from the assigned readings (Nelson & Hoegler, 2018). These activities were designed to teach students that they have the capability to master the basic concepts—reinforcing their self-efficacy.

Although it seems reasonable to design interventions directed at promoting self-efficacy, researchers must begin by replicating the current study with a larger and more diverse sample. If replicated, these results would support the continued evaluation of interventions such as the exam wrapper or the preactivity, and the design and development of similarly structured interventions. Although additional research is needed, two practical pieces of advice can be gained from this study and the related literature. First, statistics instructors must instill in their students an understanding that they will likely experience mistakes and suffer setbacks as they work through a statistics course. Second, and perhaps more importantly, statistics instructors must emphasize that, with effort and
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APPENDIX

Course Comparisons, Gender Comparisons, and Evaluation of Assumptions

The two courses did not differ in prior GPA, t(61) = -1.00, p = .32, d = 0.26, self-efficacy, t(61) = -3.83, p = .009, anxiety, t(60.93) = 0.58, p = .56, d = 0.15, or final exam scores, t(61) = -0.32, p = .75, d = 0.08. Men and women did not differ in self-efficacy, t(61) = 0.27, p = .79, d = .08, anxiety, t(29.20) = 1.11, p = .28, or final exam scores, t(61) = -0.32, p = .75, d = .10. Women had significantly higher prior GPAs than men, t(61) = 3.14, p = .003, d = 1.08; this finding is likely due to the fact that female participants (N = 52) outnumbered male participants (N = 11) five to one.

The assumptions of hierarchical multiple regression and path analysis were assessed (Field, 2017; Laerd, 2017). Independence of observations/residuals was verified for each model, as all Durbin-Watson statistics were near 2.00. There was no evidence of multicollinearity (tolerance values were greater than 0.1). Studentized deleted residuals fell between -3 and +3, no leverage values exceeded 0.2, and no values for Cook’s distance exceeded 1.0. The Shapiro-Wilk test indicated that prior GPA (p = .54), self-efficacy (p = .13), and statistics anxiety (p = .10) were normally distributed; the distribution of final exam scores violated normality (p = .001). Probability-probability (P-P) plots suggested that final exam scores were positively skewed, which is often the case for final course exams. These two analyses are considered robust to some violations of normality (Field, 2017). Visual inspection of P-P plots and scatterplots of each dependent variable and of studentized residuals plotted against predicted values for each dependent variable did not suggest any violations of linearity. Visual inspection of plotted studentized residuals and unstandardized predicted values suggested some small violations of homoscedasticity; these analyses are robust to minor violations of this assumption (Field, 2017).
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