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CORRELATES OF EXAM PERFORMANCE IN AN INTRODUCTORY STATISTICS COURSE: BASIC MATH SKILLS ALONG WITH SELF-REPORTED PSYCHOLOGICAL/BEHAVIORAL AND DEMOGRAPHIC VARIABLES

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ABSTRACT

This study investigated whether basic mathematics skills are associated with undergraduate psychology statistics course performance while simultaneously considering self-reported psychological/behavioral and demographic variables. Participants (n = 460) completed a Math Assessment for College Students (MACS), which included questions ranging from calculating percentages to graphical interpretation. The researchers used a discriminant correspondence analysis to reveal differences in course performance evaluated as the average of three exam grades. For the variation in the average exam scores accounted for by our model, the MACS scores provided the largest contribution. Other variables associated with better exam grades included white ethnicity, non-transfer status, lower year in school, and low procrastination. The researchers discuss the implications for helping instructors identify areas of basic mathematical deficiency and strength.

Keywords: *Statistics education research; Math Assessment for College Students; Self-efficacy; Self-reported procrastination; Discriminant correspondence analysis*

1. INTRODUCTION

1.1. OVERVIEW

In the United States and in other countries, undergraduates in social science programs share a common requirement and perceived obstacle in their education: the introductory statistics course (Barron & Apple, 2014; Blumberg, 2001; Bourne, 2018; Stoloff et al., 2010). Competency in statistics is essential for becoming an educated consumer of information, both within and beyond the classroom. Statistical knowledge is necessary for understanding and being able to evaluate research encountered in textbooks, articles, and book chapters. A foundation in statistics is a prerequisite for working in a research setting where data are collected, managed, analyzed, and interpreted, and where results are prepared for dissemination. Statistical literacy is also beneficial for critical thinking, decision-making, competency in diverse work settings, and being informed and engaged citizens (Chew & Dillon, 2014;

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Gal, 2002). On a practical level, most graduate programs in psychology and the social and health sciences require at least one statistics course as a prerequisite requirement.

Unfortunately, many students perceive statistics as a difficult subject that should be approached with trepidation and anxiety (Chew & Dillon, 2014; Gal & Ginsburg, 1994; Onwuegbuzie et al., 1997; Onwuegbuzie & Wilson, 2003; Zeidner, 1991). Additionally, fail rates are high for undergraduate statistics courses relative to other courses within psychology and social science majors (Bushway & Flower, 2002; Conners et al., 1998; Ferrandino, 2016). Given the importance of statistics to various academic disciplines, to understanding the scientific method, and to navigating the world, it is critical to identify factors associated with performance in introductory courses.

1.2. LITERATURE REVIEW

Several types of variables have been examined in relation to performance in undergraduate introductory statistics courses. For example, studies have examined demographic variables such as gender with mixed results. While some studies reported that women outperform men in terms of overall performance or class exams in undergraduate statistics courses (Lester, 2016; Sibulkin & Butler, 2008), other studies reported no gender differences (e.g., Fenster, 1992; Lalonde & Gardner, 1993; Lester, 2007; van Es & Weaver, 2018) or an advantage for male students (Feinberg & Halperin, 1978). In a meta-analysis on gender differences in statistics achievement in applied psychology courses at the undergraduate or graduate levels in departments of psychology, education, or business, there was a trivial, average effect size of −0.08 standard deviation units favoring females (Schram, 1996). These results also indicated that males outscored females when the outcome was exams but females outscored males when the outcome was total course performance (Schram, 1996). Overall, a clear pattern of sex differences in statistics courses has not yet been discerned and may depend on how course success is determined (e.g., exam scores versus overall course performance; Halpern et al., 2007; Niederle & Vesterlund, 2010; Voyer & Voyer, 2014).

There is limited literature and inconsistent findings for other demographic variables. Better course performance in psychology statistics was associated with lower age (Lester, 2007), but later work by the same author failed to replicate this result (Lester, 2016). Fenster (1992) found that college juniors outperformed seniors in a statistics course for behavioral social science majors. In another study, Asian students earned higher grades in an introductory statistics course compared to other racial/ethnic groups (van Es & Weaver, 2018). Despite these findings, overall, age and number of years in school, along with other demographic variables, such as race/ethnicity and transfer student status, have not been systematically explored in relation to undergraduate statistics courses.

Research has also examined psychological/behavioral variables in relation to statistics course performance including student expectancy beliefs such as self-efficacy, which play a role in academic motivation. Self-efficacy describes an individual’s perceived capability to execute behaviors that will produce an outcome (Bandura, 1977). A related construct is outcome expectancy, which is a belief about the likelihood that an outcome will follow a given behavior. Outcome expectancy is thought to emerge from self-efficacy and either increase or decrease the likelihood of behavior (Williams et al., 2005). Thus, students with low-self efficacy hold negative perceptions of their capability and may invest less effort and persistence in academic tasks or use less effective study strategies, leading to lower performance than their actual skill levels (Bandura, 1997; Pajares, 1996). Academic self-efficacy has been positively related to academic achievement in multiple studies (Chemers et al., 2001; Choi, 2005; Vuong et al., 2010). A few studies investigated self-efficacy in relation to performance in statistics courses. Consistent with research in other subjects, including mathematics, self-efficacy for introductory statistics was positively associated with course achievement, as was students’ self-efficacy for learning statistics (Finney & Schraw, 2003). Additionally, statistics self-efficacy increased over a 12-week instructional period as students engaged with statistical concepts and computations (Finney & Schraw, 2003). Another study found that self-efficacy was not associated with course grade for students in an introductory psychology statistics course (Walker & Brakke, 2017). With regard to outcome expectancy, one study reported that negative outcome expectancy was associated with students’ attitudes and behavior (i.e., in terms of low effort and persistence), which was then associated with lower exam grades in introductory statistics (Budé et al., 2007). Additional research is required to elucidate how self-efficacy and related constructs operate among diverse students in specific academic disciplines and courses.

Many undergraduate students engage in academic help-seeking behavior, in an attempt to increase understanding of class material and improve their academic performance. This includes seeking assistance from an instructor, classmate, or academic advisor. Research on help-seeking among students of various ages has identified variables associated with a lower tendency to seek assistance including feeling threatened by help seeking (Karabenick, 2003), being at risk of failing grades (Karabenick & Knapp, 1988), and having low perceived cognitive competence (Ryan & Pintrich, 1997). In contrast, college students who are more motivated and strategic learners may be more likely to engage in help-seeking behaviors (Karabenick, 2003). There is limited research in terms of help-seeking specifically in statistics courses. One study found that meeting with a psychology statistics professor and assessing one's progress in the course (e.g., emailing questions prior to the meeting and submitting a learning reflection form after the meeting) improved test scores (McGrath, 2014). It was unclear, however, whether the benefits were driven by the in-person meeting or reflection or a combination of both. Another study found that anxiety related to asking for course-related help was common and that such anxiety was related to final exam scores in an undergraduate psychology statistics course (Cantinotti, et al., 2017). Further research on the relationship of help-seeking behavior to performance in undergraduate statistics courses is warranted.

Finally, academic procrastination, or the intentional delaying of tasks and activities related to learning and studying (Steel & Klingsieck, 2016), is a widespread phenomenon in college settings, with negative consequences for student learning and achievement, self-efficacy, emotional functioning, and overall quality of life (Kim & Seo, 2015; Steel, 2007; Rothblum et al., 1986; Solomon & Rothblum, 1984; Tice & Baumeister, 1997). Despite the sizable literature on academic procrastination, few studies have investigated its impact on performance in specific courses, including undergraduate statistics. One study found that self-reported studying procrastination was negatively associated with final exam grade in an undergraduate social science course on statistical inference (Goroshit, 2018). Another study found that for students in an undergraduate business statistics course, two types of procrastination, (1) *submission* of completed homework assignments and an online midterm exam relative to the available time once the task had been initiated, and (2) *initiation* of homework assignments and the midterm examination, were associated with course outcomes including homework grades and mid-term score (Wang & Englander, 2010). Furthermore, a study that investigated the impact of statistics anxiety and mathematics anxiety on academic performance in an undergraduate psychology statistics course revealed that statistics anxiety led to higher procrastination and therefore contributed indirectly and negatively to final examination score (Paechter et al., 2017). Overall, there is some support for the idea that students' delay behaviors can negatively impact statistics course performance. Additional research is required to establish the role and relative importance of procrastination in relation to other variables.

A potential contributing factor to success in undergraduate statistics courses is basic mathematics skills. Some social science students struggle with mathematical concepts and operations (e.g., negative numbers, square roots, probability), which may interfere with learning statistics (Greer & Semrau 1984; Johnson & Kuennen 2006; Mulhern & Wylie, 2006). Additionally, several studies reported moderate positive correlations between basic mathematics skills tests and overall statistics course performance within psychology and business departments (Adams & Holcomb, 1986; Feinberg & Halperin, 1978; Harlow et al., 2002; Lalonde & Gardner, 1993; Lester, 2007, 2016; Noser et al., 2008).

Research has also assessed the relationship of mathematics skills tests to course performance, with overall positive results and modest effect sizes. One study examined basic and more advanced mathematics skills and other math-related, academic, and demographic variables in relation to final course grades of approximately 300 students in an introductory business statistics course. Scores on a multiple-choice mathematics quiz were associated with course grades, while other variables such as the mathematics portion of the ACT college entrance exam and completion of a calculus course were not associated with course grades. Mathematics questions with the strongest relationship to course outcomes dealt with basic concepts in arithmetic, algebra, and geometry, including understanding simple equations, manipulating ratios, dividing fractions, estimating square roots, and finding the area of a rectangle. Higher GPA, being female, and higher scores on the ACT science exam were also associated with better course performance, although these explanatory variables together accounted for less than 22% of the total variance in statistics grades (Johnson & Kuennen, 2006).

In additional research, two mathematics tests, (1) fractions, proportions and percentages and (2) interpreting simple data displays and descriptive statistics, were both related to end of course undergraduate psychology students' statistical knowledge, but basic level of mathematics skills upon college entry was not associated with end of course statistical knowledge (Gnaldi, 2006). Similarly, scores on a basic mathematics test, such as numerical knowledge, decimals, fractions, and percentages, were associated with passing a statistics course by psychology and educational science students (Fonteyne et al., 2015). Psychology students with low mathematics skill, based on a multiple-choice measure, as compared to medium-high skill, were more likely to have a low level of final examination performance, not take the final examination, or fail the final examination. Also, higher mathematics skills were associated with positive attitudes toward statistics and lower anxiety about statistics (Galli et al., 2011).

Another study analyzed data from over 3,700 students enrolled in an introductory psychology statistics course over a 21-year period (taught by the same instructor, using the same mathematics test). The test required students to perform a range of operations manually, including arithmetic, operations with fractions, exponents, and inequalities and algebraic equations. The results showed that the mathematics test scores were associated with total number of points earned on exams, quizzes, and assignments, and had a stronger association with course performance than scores on the SAT mathematics college entry exam (Carpenter & Kirk, 2017). Another longitudinal study evaluated the mathematics skills required to complete a 3-year psychology undergraduate degree program. Interpretation of graphical information was related to performance in first-year research methods and statistical analysis modules, but only for some course outcomes; there were no relationships when considering performance in the second or third years (Bourne, 2018).

In summary, previous research shows consistent relationships between basic mathematics skills and undergraduate statistics course performance. The magnitude of this relationship, however, tends to be modest and while the specific mathematics skills related to course performance vary, the research suggests that basic as opposed to high-level, complex skills are most relevant. Also, other ways of capturing and quantifying mathematics skills, such as college admission scores or completion of advanced college courses, may be less useful than basic mathematics tests. Although studies have included psychological/behavioral and academic variables in their analytic models, the relative value of basic mathematics skills as compared to other variables warrants clarification.

The current study builds upon previous research by combining demographic (gender, year in school, race/ethnicity, transfer status), psychological/behavioral (self-efficacy/outcome expectancy, self-reported help-seeking, and self-reported procrastination), and academic (basic mathematics skills) variables within a model that aims to explain the variance in undergraduate statistics course performance. As the data were a combination of categorical, numeric, and Likert Scale variables used to examine performance on an ordinal scale variable (treated as nominal for this study), and the research question was correlational rather than predictive in nature, the researchers chose to employ discriminant correspondence analysis (DiCA; Williams, et al., 2010; Abdi, 2007). Because of the incorporation of categorical variables, DiCA preserves the inherent nature of these multivariate data (as opposed to a traditional discriminant analysis, which is more suitable for quantitative data), and represents the relationship between variables in an intuitive component structure.

2. METHOD

2.1. PARTICIPANTS AND PROCEDURES

Students were recruited across five semesters of an undergraduate psychology statistics class at an urban public senior college located in the northeast United States. The only course prerequisite was Introductory Psychology. The statistics course was computationally-based, with students learning to calculate many tests manually (e.g., chi square, t-tests, ANOVA), in addition to using statistical software programs. The class met twice a week for 75-minute lectures (faculty instructor) and once a week for 110-minute laboratory sessions (graduate student instructors). The Math Assessment for College Students (MACS; Rabin et al., 2018) was administered during the first week of the semester, along with all self-reported psychological/behavioral and demographic variables, while the average of three exam grades was calculated at the end of the semetser. The MACS questions took approximately

40 minutes to complete. Students did not receive compensation for participation. Informed consent was obtained, and the study received ethical approval from the college Human Research Protection Program. Among 526 eligible participants across all five semesters, 66 were dropped due to missing data, resulting in a final sample of 460 participants (i.e., the response rate was 87.5%).

2.2. MEASURES

Participants were asked to report their gender, race/ethnicity, year in school, and whether or not they were a transfer student (i.e., had transferred to the current college from a two-year community college or other four-year senior college). Participants were asked a series of questions about their attitudes and behaviors. One question measured self-efficacy (*I am quite capable of mastering the material in this class*) and another measured outcome expectancy (*I will never do well in this class*). Possible responses to these questions were: *strongly agree*, *somewhat agree*, *somewhat disagree*, *strongly disagree*. For self-efficacy, responses of *strongly agree* and *somewhat agree* were classified as high self-efficacy (coded as 1), and responses of *somewhat disagree* and *strongly disagree* were classified as low self-efficacy (coded as 0). For outcome-expectancy, responses of *strongly agree* and *somewhat agree* were classified as low outcome-expectancy (coded as 0), and responses of *somewhat disagree* and *strongly disagree* were classified high outcome-expectancy (coded as 1).

Seven questions were related to help-seeking behaviors (see Appendix). Possible responses were: *very likely*, *somewhat likely*, *somewhat unlikely*, and *never would*. Responses of *very likely* and *somewhat likely* were classified as high help-seeking behavior (coded as 1), and responses of *somewhat unlikely* and *never would* were classified as low help-seeking behavior (coded as 0). Based on a preliminary examination using multiple correspondence analysis (Greenacre & Blasius, 2006), two questions that did not contribute to differences in help-seeking behavior (items 6 and 7) were eliminated from further analyses. The summed composite score for each participant for help-seeking ranged from 0 to 5. Internal consistency of the five help-seeking items was assessed using the Kuder-Richardson Formula 20 [KR-20] for dichotomous data. The KR-20 was 0.61 indicating adequate internal consistency (Aron & Aron, 1999; Hair et al., 2006).

Four questions were related to procrastinating behavior, each with five response options (see Appendix). Responses were classified as 0, 1, or 2 where 0 meant absence of the procrastinating behavior (e.g., reported *never* or *almost never* in response to the first procrastination question), 1 meant moderately procrastinating behavior (e.g., reported *sometimes* in response to the first procrastination question), and 2 meant highly procrastinating behavior (e.g., reported *nearly always* or *always* in response to the first procrastination question). The summed composite score for procrastination ranged from 0 to 8. Cronbach alpha reliability was 0.76 indicating good internal consistency.

Participants also completed an objective test—the Math Assessment for College Students (MACS; Rabin et al., 2018), a 30-item, paper-and pencil measure of basic mathematics skills. For the MACS, respondents calculated and reported responses within five general content domains: (1) basic arithmetic skills; (2) basic algebraic skills; (3) decimals, fractions, and percentages; (4) categorization and ranges; and (5) visual understanding (see Appendix for sample items). For all 30 MACS items no partial credit was awarded, and all items received a score of 0 = incorrect or 1 = correct, resulting in scores ranging from 0 to 30. Scoring of the MACS protocols was accomplished by a single rater and rescored by a second independent rater. This measure has previously shown strong interrater reliability ($k = 0.97$), internal consistency (KR-20 = 0.89), and other psychometric properties including concurrent validity through its correlation with the Wide Range Achievement Test-Fourth Edition, $r = 0.78$, item difficulty, and discrimination (Rabin et al., 2018). The distribution of MACS scores for the included 460 students was left skewed (skewness = −0.31). As the goal of this study was not to look at differences in individual MACS scores, but to have a more generalized indication of basic mathematics skills that could be comparable with other scales that measure such skills, the raw scores were converted to percent correct scores. Further, to examine MACS scores along with the other categorical variables in the same model, the original MACS scores, percent correct (a continuous variable), were converted to a nominal variable. The scores were left skewed (skewness = −0.29), so were binned into five groups in order to account for scores in the tails of the distribution: 0–19%; 20–39%; 40–59%; 60–79%; 80–100%. The KR-20 for the MACS items in the current sample was 0.88 indicating strong internal consistency.

Course outcome was evaluated based on the average scores obtained on three exams conducted during each semester. Average exam grade was chosen as the basis of student performance because other aspects of students' overall course performance had greater subjectivity (i.e., attendance and participation scored by the instructor, homework scored by the lab instructor). Also, this approach aligns with previous research that uses exam score(s) as an indication of course outcome (e.g., Budé et al., 2007; Feinberg & Halperin, 1978; Lester, 2016). In the current sample, exam performance accounted for 75% of the course grade, so findings would likely be similar if overall course performance was used instead. Each of the three exams, administered during the lecture portion of the class, was semi-cumulative, covered approximately one-third of the course material, and was graded out of 100 points. The first exam consisted of multiple-choice questions that tested descriptive statistics, *Z*-scores, correlation, regression, fundamentals of the normal curve, and basic probability theory. The second exam consisted of multiple-choice and problem-solving questions on the principles and steps of hypothesis testing for single sample *t*-tests, dependent sample *t*-tests, *Z*-tests, decision errors, effect size, power, and confidence intervals. The third exam consisted of multiple-choice and problem-solving questions covering independent samples *t*-tests, analysis of variance, chi-square tests, rank-order tests, and other advanced statistical procedures. All exams involved mathematical computations and students were permitted to use handheld calculators. Examinations were graded objectively by the lecturing instructor and a graduate student instructor. Partial credit for hypothesis testing responses was awarded according to an objective scoring rubric. As the goal of the study was to examine the differences between participants based on their overall performance in the course (and not on individual differences in exam scores), the average exam score was then classified into corresponding letter grade levels, which are usually based on average performance throughout the semester and quite common to most undergraduate statistics courses. The normal definition of each letter grade was retained as follows: A = 90–100%; B = 80–89%; C = 70–79%; D = 60–69%; and F = below 60%.

2.3. STATISTICAL ANALYSES

As noted above, Discriminant Correspondence Analysis (DiCA) was used to identify differences between patterns of responses based on basic mathematics skills (i.e., MACS score) and the other study variables.

Discriminant Correspondence Analysis. DiCA (Abdi, 2007) is a factor analytic technique that is the discriminant version of correspondence analysis (Greenacre, 2007) and multiple correspondence analysis (Greenacre & Blasius, 2006). These techniques, which are related to principal component analysis (Abdi & Williams, 2010), are used to analyze categorical data such as those from self-assessments and surveys (Beaton et al., 2014; Humboldt et al., 2013). DiCA specifically analyzes the differences between categories or groups of observations based on multiple categorical variables, and represents these differences in the form of new, uncorrelated (or orthogonal) variables also known as components. Each component explains a certain percentage of variance in the data in a descending fashion, with the first component explaining the maximum amount of variance and so forth. Within the component space, the transformed values of the categories and variables for each component are known as component scores, and plots of these component scores (for each pair of components) reveal how different categories are related to each other, and which variables contribute to those differences. On a particular component, if two categories have oppositely signed component scores, then those two categories are dissimilar to each other, and vice versa. Additionally, if a category appears at the center or origin of the component space, then that category represents the average and does not contribute much to the variance of the data (see Beaton et al., 2014 for a more detailed application of DiCA). In addition, DiCA accounts for imbalances within categories where the underlying technique, correspondence analysis, analyzes data in the form of numerical frequencies. Therefore, any differences in the frequency distribution of variables can be interpreted within the context of the research question (Greenacre, 2007).

Inference Procedures. DiCA utilizes two non-parametric inference testing procedures, the permutation and bootstrap tests, both based on data-resampling techniques. For the permutation test, which is based on a null hypothesis approach (Berry et al., 2011), data were resampled 1,000 times without replacement in order to derive a sampling distribution under the null model. Actual *p*-values are reported for permutation tests (Beaton et al., 2014).

The goal of a bootstrap test is to identify the categories and variables that contribute to forming the component structure, based on bootstrap ratios (Chernick, 2008; Hesterberg, 2011; McIntosh & Lobaugh, 2004) and bootstrap-based confidence intervals (Abdi et al., 2009; Williams et al., 2010). Under standard assumptions, bootstrap ratios are distributed as a student's *t* statistic and variables with bootstrap ratios with a magnitude larger than a critical value (e.g., 1.96 for a large N corresponds to $p < 0.05$) are considered to be of interest. Bootstrap-based confidence intervals are computed with peeled convex hulls drawn around each category mean (e.g., 95% of the bootstrapped means will be contained within the interval), and indicate where the category mean falls within the component space. If the convex hulls of two categories do not overlap, then the two categories are more likely to be different from each other (Greenacre, 2007). For the bootstrap test, which is based on an effect size approach, data were resampled 1,000 times in order to generate confidence intervals based on multiple samples that closely resembled the original data. Bootstrap ratios greater than +1.96 or less than −1.96, corresponding to $p < 0.05$ for a two-tailed test, are reported for bootstrap tests (Beaton et al., 2014; Chernick, 2008). This approach was used on the study variables forming the component structure.

Data Organization and Recoding. For DiCA, responses to all variables were converted into disjunctive coding (Beaton et al., 2014). For example, a participant could respond to a question about his or her self-efficacy as being either high (H) or low (L). If {H, L} represents the two possible responses, a high response will be recoded as {1, 0}, whereas a low response will be recoded as {0, 1}. This format of disjunctive coding captures the patterns of response levels (Beaton et al., 2014). Recoding of all data yielded a total of 24 columns of 0s and 1s—as many columns for each variable as the number of possible responses. In addition, respective course grade category (i.e., A, B, C, D, or F) was also coded in a disjunctive fashion. The data table for DiCA contained the number of occurrences of each type of response for each variable per category of observation.

3. RESULTS

Overall, the sample was demographically diverse across race/ethnicity and year in college, with more than three-fourths being female (Table 1). The vast majority of students, greater than 93% and 94%, were classified as having high self-efficacy and high outcome expectancy, respectively. More than 75% reported being high help-seekers, while fewer than 20% reported being low procrastinators. The distribution of the MACS scores was left skewed, as was the distribution of grade levels.

Table 1. Descriptive statistics for variables included in DiCA (n = 460)

Variables		Number of Levels: Name of Levels	% (*n*)
Gender		2: Male; Female	
	Female		78.48 (*361*)
Race		2: White; Non-White	
	Non-White		51.74 (*238*)
Transfer Status		2: Yes; No	
	No		55.22 (*254*)
Year in School		3: First-Second; Third; Other	
	First-Second		26.30 (*121*)
	Third		40.44 (*186*)
	Other		33.26 (*153*)
Self-Efficacy		2: High; Low	
	High		93.04 (*428*)
Outcome Expectancy		2: High; Low	
	High		94.57 (*435*)
Help-Seeking		3: High; Medium; Low	
	High		75.65 (*348*)
	Medium		14.13 (*65*)

Variables	Number of Levels: Name of Levels	% (*n*)
Low		10.22 (*47*)
Procrastination	3: High; Medium; Low	
High		27.61 (*127*)
Medium		52.61 (*242*)
Low		19.78 (*91*)
MACS Percent Correct	5: 0-19%; 20-39%; 40-59%; 60-79%; 80-100%	
0 to19%		4.35 (*20*)
20 to 39%		18.91 (*87*)
40 to 59%		24.78 (*114*)
60 to 79%		33.26 (*153*)
80 to 100%		18.70 (*86*)
Exam Grade (average of three exams)	5: A (90-100%); B (80-89%); C (70-79%); D (60-69%); F (0-59%)	
A (90 to100%)		13.70 (*63*)
B (80 to 89%)		25.43 (*117*)
C (70 to 79%)		28.70 (*132*)
D (60-69%)		20.65 (*95*)
F (0 to 59%)		11.52 (*53*)

Note. MACS=Math Assessment for College Students

DiCA produced four components, which were assessed via permutation tests. The overall variance (determined by the sum of eigenvalues), also known as *inertia*, was found to be $I = 0.057$, $p_{perm} < 0.001$. Additional permutation tests on individual components identified that the variance explained by the first two components together accounted for 89.51% of the total variance (Component 1 = 78.86%, $p_{perm} = 0.001$, Component 2 = 10.66%, $p_{perm} = 0.037$; see Figure 1). Finally, to determine the reliability of assignment of individuals to groups, an R^2-type statistic (i.e., the ratio of between-group inertia to total inertia), was found to be $R^2 = 0.11$, $p_{perm} < 0.001$.

Grades A, B, D, and F contributed more to Component 1 than grade C; grades A, C, and F contributed to more to Component 2 than grades B and D (determined via bootstrap tests, Table 2). These findings imply that the largest variance in the data (Component 1) was explained by the difference in the pattern of responses of students who earned grades of A or B as compared to students who earned grades of D or F, followed by the pattern of responses of students who earned a C (Component 2).

Table 2. Component scores and bootstrap ratios for each grade category (*n* = 460)

Grade Category	Component 1	Component 2
A	**0.29 (6.93)**	**−0.10 (−2.99)**
B	**0.21 (5.71)**	0.00 (0.00)
C	−0.03 (−0.97)	**0.10 (3.63)**
D	**−0.21 (−6.01)**	0.01 (0.14)
F	**−0.34 (−7.25)**	**−0.13 (−2.71)**

Note. **Bold** values above/below +/−1.96 indicate possible grade-levels of interest based on 1,000 bootstrap samples.

Figure 1 details the results from DiCA where the left panel shows the component scores reported in Table 2, with 95% peeled convex hulls representing the confidence intervals as determined by the bootstrap tests ($p_{\text{boot}} < 0.001$). On Component 1, A- and B-level students were more likely to perform differently from D- and F-level students. Performances of A- and B-level students, however, were less likely to differ from each other, as also the performances of D- and F-level students, indicating that Component 1 contrasted the high- from the low-performers in the course.

Variables that contributed to the difference between the high-performers and the low-performers in the course as represented by Component 1 (determined via bootstrap tests, Table 3) included scores on the MACS, transfer status, race/ethnicity, year in school, and tendency to seek-help and procrastinate. Additionally, MACS scores was the main variable associated with average exam grade on Component 1 and had a 48% contribution to the variance on that component. Next, transfer status alone had a 21%

contribution on Component 1, while year in school, gender, and race/ethnicity together had a 23% contribution. All psychological/behavioral variables together only had an 8% contribution on Component 1.

Figure 1. Results from DiCA

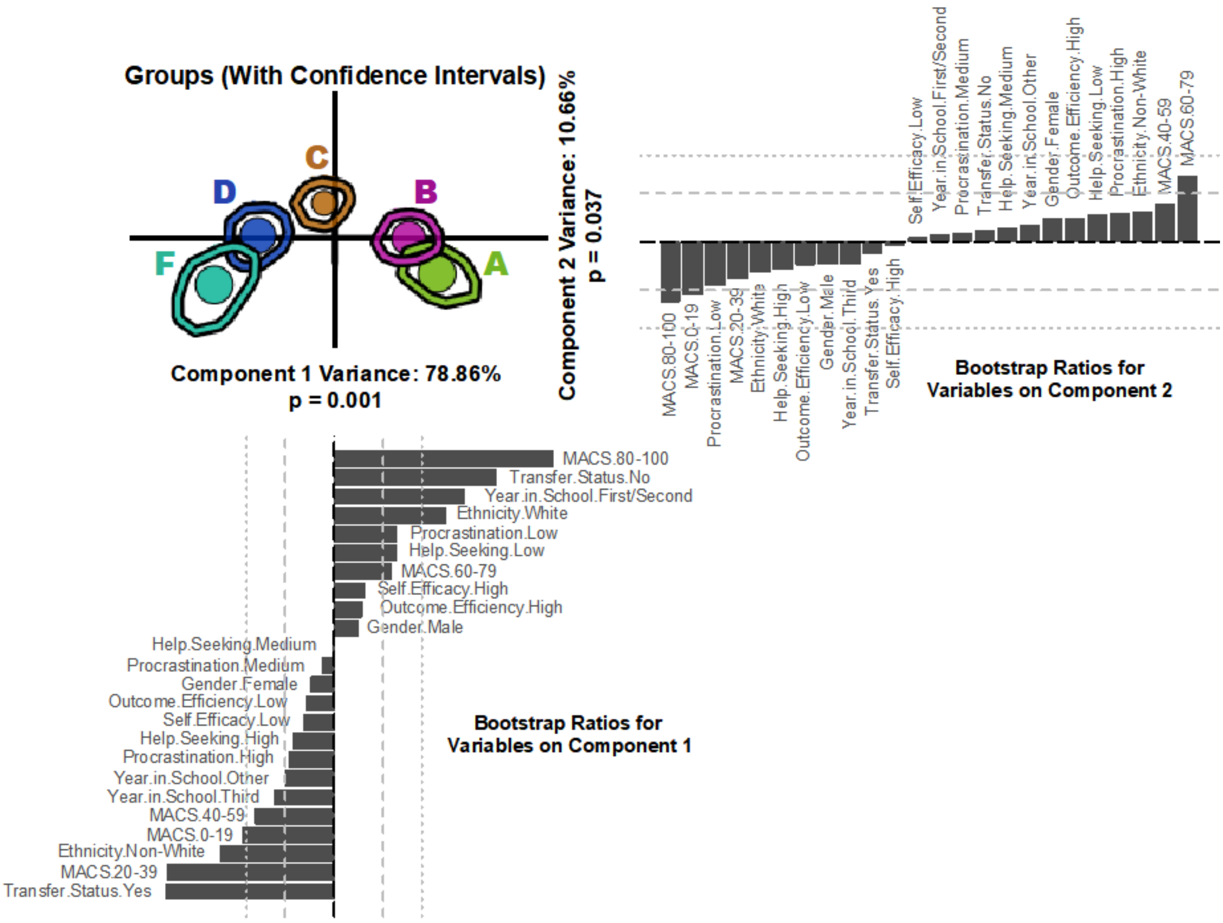

Figure 1: Results from DiCA showing bootstrap confidence intervals for the five grade categories (A, B, C, D, and F; top left), and bootstrap ratios for Component 1 (bottom left) and Component 2 (top right). The dashed lines represent a *p*=0.05 threshold and the dotted lines represent a *p*=0.0005 threshold (to account for multiple comparisons).

Figure 1 (bottom panel) shows the variables that contribute to the variance explained by Component 1 (based on the bootstrap ratios reported in Table 3), which revealed that A- and B-level students typically scored within the 60%−79% or 80%−100% range on the MACS, and were more likely to report being white, non-transfer students, with low procrastination and help-seeking behavior, who took the statistics course early in the first/second year in their undergraduate program. In contrast, D- and F-level students typically scored within the 0%−19%, 20%−39%, or 40%−59% range on the MACS, and were more likely to report being non-white, transfer students, who took the statistics course in the third year or later in their undergraduate program. All other variables did not reliably contribute to the variance explained by Component 1.

Table 3. Component scores and bootstrap ratios for every level for each variable (*n* = 460)

Variables	Component 1	Component 2
MACS Percent Correct*		
0−19	**−0.80 (−3.66)**	**−0.53 (−2.15)**
20−39	**−0.60 (−6.67)**	−0.15 (−1.48)
40−59	**−0.25 (−3.15)**	0.14 (1.53)
60−79	**0.15 (2.30)**	**0.17 (2.66)**
80−100	**0.60 (8.75)**	**−0.17 (−2.44)**
Self-Efficacy		
Low	−0.20 (−1.21)	0.02 (0.15)
High	0.01 (1.21)	0.00 (−0.16)
Outcome Expectancy		
Low	−0.23 (−1.11)	−0.20 (−0.93)
High	0.01 (1.11)	0.01 (0.93)
Help-Seeking		
Low	**0.30 (2.47)**	0.13 (1.08)
Med	−0.01 (−0.06)	0.07 (0.56)
High	−0.04 (−1.62)	−0.03 (−1.12)
Procrastination		
Low	**0.24 (2.50)**	−0.16 (−1.77)
Med	−0.02 (−0.49)	0.01 (0.36)
High	−0.13 (−1.79)	0.09 (1.16)
Year in School*		
First-Second	**0.35 (5.20)**	0.02 (0.29)
Third	**−0.13 (−2.35)**	−0.05 (−0.90)
Other	**−0.12 (−1.98)**	0.05 (0.65)
Transfer Status*		
Yes	**−0.33 (−6.70)**	−0.02 (−0.47)
No	**0.26 (6.48)**	0.02 (0.47)
Gender		
Male	0.09 (0.95)	−0.08 (−0.91)
Female	−0.02 (−0.95)	0.02 (0.92)
Race/Ethnicity*		
White	**0.22 (4.47)**	−0.05 (−1.22)
Non-White	**−0.21 (−4.54)**	0.05 (1.22)

Note. **Bold** values above/below +/−1.96 indicate possible variables of interest based on 1,000 bootstrap samples. Variables marked with an * indicate those that have levels with bootstrap ratios above/below +/−3.50, which corresponds to a two-tailed *p*-value below 0.0005, and provides strong evidence of association after accounting for multiple comparisons. MACS = Math Assessment for College Students.

Component 2 identified the C-level students as being different from students in other grade-categories [see Figure 1 (left panel), and Table 2], and this difference was driven by the MACS (60% contribution on Component 2) with no other variable reliably contributing to the variance [Figure 1 (right panel), and Table 3]. Specifically, the C students tended to score in the mid-range of 40%-59% on the MACS (and had variable patterns of correct and incorrect responses) and were different from the high-performing A- and B-level students, and low-performing D- and F-level students (who had more consistent patterns of correct and incorrect responses).

4. DISCUSSION

4.1. SUMMARY OF COMPONENT FINDINGS

The discriminant correspondence analysis revealed two main components that differentiated between students' average examination grades and explained 78.86% and 10.66% of the variance, respectively, accounting for approximately 90% of the total variance in course grades. Component 1 results showed that basic mathematics skills made the strongest contribution to course examination grades. This finding has implications for future research on educational interventions in statistics courses as will be discussed below.

Transfer status had high contribution to the variance accounted by Component 1. Other variables of year in school and race/ethnicity also contributed to the difference between A- & B-level students and D- & F-level students in terms of average exam scores. Traditional (non-transferred) students, white students, and/or those who took the course early in their college career tended to earn better exam grades. These findings are consistent with research showing that transfer students may be less academically prepared than traditional students (Dowd et al., 2008; Melguizo et al., 2011; Tipton & Bender, 2006; Nuñez & Yoshimi, 2017), as well as less integrated into their new college campus culture (Dougherty, 1992; Townsend & Wilson, 2006). With regard to academically "younger" students performing better, it is possible that students who more recently completed high school had better retention of basic mathematics knowledge that helped them in the course. Also, students who choose to take difficult courses, such as statistics, earlier in their college career may do so, in part, because they are more academically prepared and/or confident that they will succeed. Indeed, success in high school mathematics courses has been positively related to college statistics achievement (Dupuis et al., 2012).

In terms of white students performing better on statistics exams in this study, it is worth noting that the vast majority of the undergraduate students in this study come from New York City public high schools (Chellman & Truelsch, 2017). In recent years, the quality of mathematics education in New York public high schools, particularly schools with a majority of under-represented students, has been called into question (Hemphill et al., 2015). In a recent survey of approximately 1,000 New York public high school graduates, 67% of Latino and 70% of African-American respondents reported having to take a remedial course in college, compared to 34% of white students. Notably, mathematics was the top academic subject in which students expressed a desire for more preparation (Shelter, 2018). This survey came shortly after a report by the New York Equity Coalition (2018) that indicated, state-wide, schools enroll white students nearly three times more often in critical advanced courses in mathematics and science than non-white students.

Together, these results suggest that there may be opportunities to offer support to undergraduate statistics students. For example, a qualitative study on transfer students' experiences highlighted the importance of positive, personal interactions with faculty members for transfer students' successful transition to four-year colleges (Nuñez & Yoshimi, 2017). If feasible, statistics course instructors could attempt to get to know students individually, which could influence students' excitement about the course and motivation to succeed. There could be ongoing communication with local high school and community colleges about curriculum issues to ensure adequate preparation of students for rigorous college-level mathematics and statistics courses (Bragg, 2012). Also, students could be encouraged to take statistics earlier in their college career, when basic mathematics skills are "fresh", rather than delaying until late in college, which is common among psychology majors (Onwuegbuzie & Wilson, 2003).

All of the self-reported psychological/behavioral variables contributed to only 8% of Component 1, and only procrastination and help-seeking contributed to the difference between A- & B-level students and D- & F-level students. Specifically, consistent with previous literature demonstrating that academic procrastination is negatively associated with academic outcomes (Kim & Seo, 2015; Solomon & Rothblum, 1984), in the current study, A- and B-level students were more likely to report lower levels of procrastination. This finding has potential implications for course design, which will be discussed below. In terms of help-seeking, again, the A- and B-level students were less likely to report that they would seek help if they were to experience difficulty with the course material. Although it is possible that A- and B-level students felt more confident about their potential to succeed in the course, these findings should be interpreted with caution. Notably, help-seeking behavior was reported at the beginning of the semester, and it is possible that students could not accurately estimate this tendency before being exposed to course material and/or they may have been prone to over-estimation (as most students were self-reported high help seekers). A better metric may have been responses at the end of the semester or use of an objective behavioral measure.

The self-efficacy and outcome expectancy items did not reliably differentiate students across exam grade categories. The relatively unspecific and limited nature of our items, coupled with students' unfamiliarity with statistical concepts during week 1 of the semester, may have resulted in tapping students' general, academic, or mathematical self-efficacy, rather than efficacy for the statistics course itself. Given that non-mathematics majors are unlikely to be familiar with specific statistical concepts, it is recommended that future studies implement task-specific measures of self-efficacy and outcome expectancy after a statistical concept is introduced (but before the specific task is to be attempted).

Gender also did not have an impact on differentiating students across exam grade categories. Previous research failed to identify a clear pattern of gender differences in course grades for statistics, and the current findings are consistent with some research that did not find any differences between males and females (e.g., Fenster, 1992; Lalonde & Gardner, 1993; Lester, 2007). Among studies that have reported gender differences, effect sizes tended to be small. Together, these findings suggest that the practical significance of any gender differences in performance in undergraduate statistics courses might be small.

Component 2 results revealed that the only variable that contributed to the separation of C-level students from all other students is MACS performance. Specifically, the C students tended to score in the mid-range (i.e., the 40%−59%) on the MACS (and had variable patterns of correct and incorrect responses) and scored differently from the high-performing A- and B-level students, and low-performing D- and F-level students (who had more consistent patterns of correct and incorrect responses). None of the other study variables contributed to the differences between these groups.

4.2. STUDY LIMITATIONS

This study has several limitations that warrant mention. First, given logistical and cost issues, the researchers were not able to randomly select students for participation. Second, as data were collected from a single institution in a single country, results may not generalize beyond social-science based undergraduate statistics courses in the U.S. with similar content and assessed learning goals. In future research, it will be important to determine whether undergraduate students from different types of colleges (e.g., private, rural settings) and different countries show similar associations between basic mathematics skills and statistics course performance. Third, the course was computationally-based and may not generalize to those statistics courses that primarily focus on use of statistical software programs. Future research would be useful to determine whether basic mathematics skills are less important in courses where students primarily use statistical software programs for computations. Fourth, while the findings suggested that certain student groups (e.g., non-white, transfer) may be under-prepared in basic mathematics skills, it is also possible that there was an inherent bias in the MACS. In future work, the researchers plan to investigate whether MACS items are comparatively more difficult for specific subgroups of students (content validity bias) and whether MACS scores predict future academic performance equally well for student subgroups (predictive validity bias). Fifth, although the MACS was objective, other study variables relied upon self-report of attitudes and behaviors—latent variables that are admittedly difficult to quantify. Future research might re-examine these constructs using actual behavioral measures of help-seeking and procrastination in conjunction with improved self-report measures (e.g., lengthier, validated, contain task-specific items). As students' self-efficacy is subject to change in response to feedback from the environment (e.g., classroom), authority (e.g., professor), experience (e.g., homework or quiz scores), and/or physiology (e.g., anxiety), it may be necessary to assess efficacy/expectancy beliefs at several time points over the course of a semester. Sixth, although this study included many variables in its statistical model, there could be other variables that have an important impact on the observed relationship between mathematics skills tests and statistics exam scores. For example, the researchers were unable to include participant course load (due to lack of access to these data) or statistics anxiety and general attitudes toward statistics (due to concerns about making the questionnaire too lengthy and burdensome). Seventh, it is possible that the timeframe of data collection over five semesters may have included different types of students with different backgrounds. Eighth, future research with different data collection methods can provide triangulation to validate the current research results and provide more in-depth meaning on the quantitative results obtained from the current study.

4.3. FUTURE DIRECTIONS

Given modest positive findings for help seeking intentions, a future direction is to assess the benefits of a relatively non-threatening form of academic help seeking of peer tutoring. Peer tutoring is known to positively impact academic achievement (Carlson et al., 2016; Laher et al., 2007; Leung, 2015), and could be a cost-effective way to assist with basic mathematics skills and course material in introductory statistics classes. For example, in future research the MACS or a similar measure, could be used to identify areas of student weakness in mathematics, and statistics students could be paired with other students who have mastered specific skills. Tutors could be undergraduate statistics students from previous semesters who are motivated to gain valuable instructional and mentoring experiences. Alternatively, tutors could be students from the statistics course itself who volunteer their time. Regardless of the model adopted, course instructors and/or graduate teaching assistants should be responsible for selecting qualified tutors, providing them with resource materials to facilitate structured instruction, and offering ongoing feedback and support. Such a coordinated approach might benefit both the tutees, who are taught by peers and potentially easier to learn from than formal instructors, as well as the tutors, who could hone their own mathematics and statistics knowledge while improving basic teaching and communication skills.

This study found that high procrastinators were more likely to earn lower course grades than low procrastinators. Research on the antecedents of academic procrastination has identified various cognitive, emotional, and motivational factors, with recent work highlighting self-regulated learning skills as a major contributor (Pychyl & Flett, 2012; Steel & Klingsieck, 2016). Qualitative work has identified additional personal and situational variables that may underlie academic procrastination including competencies (e.g., lack of study and organizational skills), task characteristics (e.g., difficult, aversive), and instructor characteristics (e.g., disorganized, not supportive) (Grunschel et al., 2013; Patrzek et al., 2012). These contributors to academic procrastination suggest possible intervention efforts (Zacks & Hen, 2018). From a course development perspective, the undergraduate statistics syllabus could be organized by week of the semester with specified guidelines and point values, structured assignments that have concrete deadlines, and clear implications for late work. Instructors could assign weekly quizzes and/or frequent graded assignments to motivate students to keep up with course material and reduce the opportunity to leave studying for the last minute (Tuckman, 1998). Perrin and colleagues (2011) suggested making access to important study material contingent upon completing previous study material to reduce the tendency for bursts of studying right before a class quiz or exam. Another study (Strunk & Spencer, 2012), found that a personal meeting with the instructor, immediately following the failure to turn in a course assignment on time, led to improved on-time assignments and course grades (relative to students with similar late assignment tendencies who did not receive the intervention). Future research is required to determine which of these strategies are associated with reduced procrastination and/or higher course grades for statistics students.

Finally, this study found that basic mathematics skills, assessed during the first week of an undergraduate psychology statistics class, had the highest association with course examination grades. This was the main result, and while correlational, raises ideas for mathematics training efforts. For example, recent research promotes the use of support structures to broaden access to and success in introductory statistics courses for students who are diverse in terms of demographics and/or mathematics preparation (Peck, 2019). Many such students benefit from placement in an *accelerated statistics pathway* that enables completion of statistics within a single semester or within the first year of study, instead of having to undertake several remedial classes or traditional developmental mathematics courses over numerous semesters (Cullinane & Treisman, 2010; Peck, 2019). In this model, students receive support structures including co-requisite or pre-statistics courses that emphasize the mathematics needed for success in introductory statistics (Peck, 2019; Richardson & Dorsey, 2019), or specialized course sequences that combine developmental mathematics and college-level statistics (Norman et al., 2018). Institutions that have implemented statistics pathway models, which essentially offer the opportunity to enroll directly into introductory statistics with various forms of additional mathematics support offered, have reported positive results (Henson et al., 2017; Logue et al., 2016; Norman et al., 2018).

A related approach is to provide other forms of assistance for entering college students, who may present with wide discrepancies in mathematics proficiency (Atuahene & Russell, 2016; Flores, 2007). Lalonde and Gardner (1993) recommended creating short workshops to help students master basic mathematics skills relevant to introductory statistics. Indeed, most of the topics targeted by the MACS (e.g., arithmetic, fractions, exponents, simple equations) are essentially middle school mathematics (Common Core Standards, 2010), and the very skills with which many college students struggle (McGowen, 2017). Such training could occur prior to (or at the beginning of) the semester or as part of the class itself—at one community college, for example, a three-credit-hour statistics course was paired with three hours of support, with positive results (Richardson & Dorsey, 2019). Given the recent need for online instructional platforms due to the COVID-19 pandemic, training could be done in-person (e.g., instructed by a graduate student during college common hours or in the evenings) or via internet-based resources with assignments completed independently or with members of a small learning group. Ideally, these various efforts would provide opportunities for early and ongoing success in statistics courses, as students master relevant mathematics skills.

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APPENDIX

Help-Seeking Questions

If you don't understand something in class or get stuck when working on problems outside of class, how likely are you to:

Item stems:

1. Ask a friend or classmate for assistance?
2. Attend a peer tutor session?
3. Seek out your lab instructor and ask for assistance?
4. Seek out your course instructor or attend your instructor's office hours?
5. Go to the learning center?
6. Look up information online?
7. Look up information in a book?

Response options for all item stems:
very likely, somewhat likely, somewhat unlikely, never would

Procrastination Questions

With regard to academic tasks (e.g., reading for class, completing homework assignments, preparing for exams):

1. To what degree do you tend to delay or procrastinate?
   never procrastinate, almost never, sometimes, nearly always, always procrastinate
2. To what degree do you typically have to rush to complete academic tasks on time?
   never rush, almost never, sometimes, nearly always, always rush
3. How often do you begin assignments shortly after they are assigned?
   never begin shortly after they are assigned, almost never, sometimes, nearly always, always begin shortly after they are assigned
4. To what degree is procrastination on academic tasks a problem for you?
   not at all a problem, a small problem, a moderate problem, a large problem, a very large problem

Note: Item 3 is reverse coded

Math Assessment for College Students (MACS) Sample Items

1. (12–2) × 3 – 8 ÷ 2 =
2. Convert 100 ± 15 to a range:
3. What percent of 80 is 100?
4. Put the numbers 0 to 99 into 10 uniform categories (for example 0-3, 4-6, …)
5. State whether the fraction on the left is less than or greater than the fraction on the right. Use > or <
   1/3   2/5