Toward data-driven instruction in the first course in accounting

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ABSTRACT

This study takes a step toward using data-driven instruction (i.e., using data to guide instructional choices) in the accounting classroom: Evaluating which students are most likely to struggle in the first course of accounting. More specifically, it evaluates the correlations between four constructs (i.e., academic background, grit, attendance, and study habits, skills, and attitudes [SHSA]) and course learning outcomes. Each construct was associated with learning outcomes in the context of this study. However, both prior semester cumulative Grade Point Average (GPA), a measure of average grades earned in college, and SHSA appear to offer the most promise for instructional intervention at the institution under study. Caveats for using correlational findings with significant, but imperfect associations with learning outcomes are provided. Using this study as a flexible blueprint tailored for other contextual settings is also described.

Keywords: the first course in accounting, learning outcomes, academic background, grit, study skills, course absences

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INTRODUCTION

The first course in accounting is critical for both accounting majors and other business majors alike (Accounting Education Change Commission [AECC], 1992; Pathways Commission, 2012). Introductory coursework is highly connected to the decision to major in accounting (Mauldin, Crain, & Mounce, 2000) and 'shapes . . . [majors'] perceptions of (1) the profession, (2) the aptitudes and skills needed for successful careers in accounting, and (3) the nature of career opportunities in accounting' (AECC, 1992, 1). The importance of this introductory course for other business majors is encapsulated by the catchphrase: Accounting is the language of business. In other words, business majors cannot hope to operate successfully in the business world without fundamental accounting knowledge.

Unfortunately, the first course in accounting is also widely recognized as a stumbling block for students. Faculty members generally cannot pinpoint which students might struggle at the onset of the class. Consequently, students' downhill trajectories may go undetected until the situation is no longer salvageable as a result of this lag in identifying students in need of intervention.

This exploratory study is built on the preceding joint considerations of the importance of the first course in accounting and the difficulty of predicting which students will struggle in the course. Reminiscent of the Pathways Commission's (2012, 78) Action Item 4.2.3, the purpose of this study is 'to gather, through pilots, measurable data for the first course' and to 'establish open communication and feedback channels' through informal discussions between colleagues, through formal presentations on and off campus, and through publication. This study adopts the data collection effort the Pathways Commission suggests as a step toward data-driven instruction (i.e., using data to guide instructional choices). More specifically, it assesses effect sizes regarding the relationships among learning outcomes in the first course in accounting and four factors that researchers in higher education and educational psychology have determined may be correlated with learning. These factors are academic background (Geiser & Santelices, 2007; DeBerard, Spielmans, & Julka, 2004), grit (Duckworth, Peterson, Matthews, & Kelly, 2007; Duckworth & Quinn, 2009), attendance (Credé, Roch, & Kieszczynka, 2010), and study habits, skills, and attitudes (SHSA) (Credé & Kuncel, 2008).

In the future, factors that are correlated with learning outcomes will be used as data at the institution under study to develop educational interventions targeted to assist those who may be most likely to struggle in the first course in accounting. For example, if a measure of academic background is highly correlated with student success, faculty can try to prevent the needs of academically stronger students from overshadowing the needs of students who are most likely to fail the course. Outreach to students who appear to have a greater chance of failure might include assuring that students are included in class discussions, connecting them with institutional tutors, and initiating early invitations to office hours or problem sessions. Even the power of expressing expectations has long been known to have a significant impact on learning outcomes (Rosenthal & Jacobson, 1968; Steele, 1997). This data-driven approach will require a change in institutional practices at universities that do not currently provide instructors with assessment data before classes begin.

The remainder of this paper is organized as follows. The next section provides an overview of data-driven instruction and the study's research questions. Then, background literature related to the study is presented. A description of the research design follows along with a summary of study results. The final sections provide a discussion of findings, limitations, and implications.

CONCEPTUAL FRAMEWORK: DATA-DRIVEN INSTRUCTION

Data-driven instruction is an approach that classroom teachers and administrators, rather than traditional researchers, use to inform instructional choices (Marsh, Pane, & Hamilton, 2006). In the United States, primary educators (who teach students in grades Kindergarten-6) and secondary educators (who teach students in grades 7-12)—rather than educators in higher education—typically use this approach. Data sources may include the results of standardized tests, surveys, or data collected during classroom activities or course assessments. It may also rely on an approach similar to a single subject design (Kratochwill, 2013; Mertler, 2014). Originating from the fields of educational psychology and special education (e.g., education for those with a learning disability or mental delay), single subject designs evaluate the impact of instructional choices on small samples, often consisting of one learner or a small group of learners (Kratochwill, 2013). Hence, data-driven research is often contextual and, related to an individual, a course, instructor, school, or school district.

The general strategy in data-driven instruction is to use a continuous feedback loop involving three steps: (1) collecting data, (2) analyzing the data, and (3) implementing a decision based on data analysis (Data driven instruction, engage^{NY}, 2019). Data analysis is not necessarily advanced in a statistical sense because it is conducted by classroom teachers or administrators who may have competing priorities and limited understandings of statistics. Analysis may consist primarily of frequency counts, benchmarking, and graphing (Datnow & Hubbard, 2015; Mertler, 2014).

This study explores the possibility of using data-driven instruction for evaluating which students may be most likely to struggle in the first course in accounting. Given its conceptual framework, the study is rooted in context (i.e., a specific institutional setting). Data analysis is not centered on advanced modeling, but on analysis appropriate for small groups, where the objective is to identify measures that may have large enough associations with learning outcomes that teachers may be able to impact meaningful change in those small groups. Accordingly, the research questions for this study are as follows:

1. Are students' academic backgrounds correlated with learning outcomes in the first course of accounting at the university under study?
2. Is grit correlated with learning outcomes in the first course of accounting at the university under study?
3. Is course attendance correlated with learning outcomes in the first course of accounting at the university under study?
4. Is SHSA correlated with learning outcomes in the first course of accounting at the university under study?

Hypotheses for each research question are provided in the next section.

LITERATURE REVIEW AND HYPOTHESES

The accounting literature offers a variety of empirically-tested innovations for improving outcomes in the first course in accounting. Some research suggests adopting interactive and otherwise more engaging technologies (Premuroso, Tong, & Beed, 2011; Spiceland, Spiceland,

& Schaeffer, 2015). It also points out the utility of pedagogical styles such as active learning (Warren & Young, 2012) and of refocused curriculum (Spiceland et al., 2015). Other research suggests modifying assessment styles to increase motivation (Braun & Sellers, 2012), to inform instructional design (Curtis, 2011), or to evaluate student ability more effectively (Bergner, Filzen, & Simkin, 2016).

Despite these innovations, Pincus, Stout, Sorensen, Stocks and Lawson (2017) recently lamented that course design and accounting instruction are largely unchanged as a whole. They believe this situation is particularly dire due to changes in higher education (e.g., increased financial strains on students) and the need to prepare students for survival in a world of increased automation. The current study seeks to identify additional practical and time efficient pathways for addressing the challenges Pincus et al. (2017) describe from the fields of educational psychology and higher education. Subsequent subsections discuss salient empirical findings on academic background, grit, attendance, SHSA and teacher effects from those external literatures. They also include information on relevant, extant studies in the accounting literature, if these studies were uncovered.

Academic Background and Student Learning

After decades of public and empirical debate, the higher education literature appears to have concluded that standardized test scores and high school grade point average (HSGPA) may not have generalizable predictive power. More specifically, Aguinis et al. (2016) report that neither metric has generalizable predictive power in terms of first year college grades based on College Board data collected from about 475,000 students at 176 colleges in the United States from 2006 to 2008. Instead, the researchers point to the role of institutional context in evaluating whether HSGPA and standardized test scores have predictive power, although they are unable to quantify this role due to data limitations. Other research indicates that prior cumulative college grade point average (GPA) is a key predictor of future college success. For example, DeBerard et al. (2004) report that cumulative freshman GPA more than doubled the predictive power of their model of college grades. Data for this study were collected at a university on the west coast of the United States.

Studies on the first course in accounting with measures most similar to Aguinis et al.'s (2016) are largely limited to older, institution-specific samples. More specifically, Doran, Bouillon, and Smith (1991) and Eskew and Faley (1988) indicate that grades in the first course in accounting are, in part, a function of standardized test scores and prior college grades at Iowa State in 1987 and at Purdue in 1983, respectively. Eskew and Faley (1988) also explore the impact of high school grades and report that they have a significant correlation with learning outcomes. At the time these studies were conducted, these researchers believed their findings were somewhat generalizable. However, institutions today might consider contextualizing their evaluations of correlates with learning outcomes, given the potpourri of institutions in higher education and Aguinis et al. (2016)'s findings.

Based on recent research in higher education (Aguinis et al., 2016) and prior accounting literature (Doran et al., 1991; Eskew & Faley, 1988), Hypothesis 1 is formulated as follows:
H_1: Academic background is correlated with learning outcomes in the first course in accounting, where the specific pattern of correlation is institutionally dependent.

Grit and Student Learning

Grit is a popular psychological construct that attributes much of any type of success to perseverance and consistent interests (Duckworth, Peterson, Matthews, & Kelly, 2007). Grit has been reported to be associated with a wide array of positive outcomes including retention at West Point, GPA, watching less television, and success in national spelling bee competitions (Duckworth & Quinn, 2009). Although it is usually studied as a single factor, grit is sometimes evaluated as two separate subscales—perseverance of effort and consistency of interest (e.g., Datu, Valdez, & King, 2015).

Credé, Tynan, and Harms's (2017) meta-analysis of 584 effect sizes from 88 independent samples of 66,807 participants calls much of the earlier evidence about grit into question. In particular, findings indicate that grit has a lower correlation with success than previously thought. For example, grit's correlation with overall academic performance has been downgraded to .18, compared to prior notions that Grit has more explanatory power than cognitive ability (Duckworth, 2013)—which would have required grit to have an effect size larger than .50 (Credé et al., 2017). Additionally, Credé et al. (2017, 502) conclude that "grit may be redundant with conscientiousness," with the two constructs having an overall correlation of .84. This finding may be particularly problematic because conscientiousness is a personality trait. Personality traits are not generally considered to be malleable (McCrae, & Costa, 1994), and, thus, not widely considered as useful for educational intervention.

Credé et al (2017) also determine that perseverance of effort has more predictive power than consistency of interest, with the former subscale having predictive power beyond conscientiousness. This finding suggests that grit might be studied better as two-factors rather than as a single factor.

Based on recent research in higher education that suggests that the predictive power of grit is low (Credé et al., 2017), Hypothesis 2 is formulated as follows:

H_2: There is no detectable correlation between grit and learning outcomes in the first course in accounting in the context of data-driven instruction.

Course Absences and Student Learning

Credé et al.'s (2010) meta-analysis of 90 independent samples of 28,034 student participants from 1927 to 2009 suggests that attendance is a better predictor of college grades ($\rho = .44$) than standardized tests scores, high school GPA, or SHSA. Only three studies included in the analysis contained sufficient data for examining mandatory attendance policies. These mandatory policies are associated with better grades, where the effect size was Cohen's $d = .20$. Credé et al. (2010) also concludes that attendance is a unique predictor of student success, being largely independent of HSGPA and standardized test scores.

Research on the relationship between absenteeism and course performance is relatively sparse in the accounting literature itself. One exception is Luke (2015), which provides a qualitative reflection on the connection between absenteeism and learning outcomes. In their discussion about how to construct a course attendance policy, Robinson and Fink (1991) reflect on their belief that attendance will improve course learning.

Based on research in higher education (Credé et al., 2010) and in accounting (Luke, 2015; Robinson & Fink, 1991), Hypothesis 3 is formulated as follows:

H3: There is a negative correlation between course absences and learning outcomes in the first course in accounting.

SHSA and Student Learning

Credé and Kuncel's (2008) metanalysis examines the correlations among academic performance in higher education and 10 dimensions of SHSA via a sample of 344 studies with a total of 72,431 participants. The ten dimensions of SHSA examined are study skills, study habits, study attitudes, student anxiety, study motivation, deep processing, surface processing, strategic processing, metacognitive skills, and aggregate measures. Grades in individual classes are most highly correlated with study skills and motivation ($\rho = .20$ for each dimension) and least correlated with having a strategic approach to learning ($\rho = .02$). The authors also conclude that SHSA is relatively unique among data elements typically collected for college admissions, given that SHSA is largely independent of HSGPA and standardized test scores.

Additionally, Credé and Kuncel report (2008, 425) that "scores on traditional study habit and attitude inventories are the most predictive of performance, whereas scores on inventories based on the popular depth-of-processing perspective are shown to be least predictive of the examined criteria." Traditional inventories include the Learning and Study Strategies Inventory (LASSI) (Weinstein, Palmer, & Acee, 2016) and the Survey of Study Habits and Attitudes (SSHA) (Brown & Holtzman, 1967). Depth-of-processing inventories include the Approaches and Study Skills Inventory for Students (ASSIST, 1996).

In the accounting literature itself, Yu (2011) reports limited support for SHSA in predicting course grades in introductory accounting in the Philippines. However, a validated instrument was not used to measure SHSA. Consequently, although the study marks an important conceptual step, it is not clear whether the strength of the results is a function of this limitation in study design. Other accounting education researchers have examined some aspects of SHSA, where a portion (but not all) of the students in their samples were in their first course in accounting. For example, Byrne, Flood, and Willis (2004) identify the presence of deep, strategic, and surface learning via ASSIST. Schleifer and Dull (2009) detect a correlation between metacognition and course grade with the Metacognitive Awareness Inventory (MAI) (Schraw & Dennison, 1994).

Based on research in higher education (Credé & Kuncel, 2008) and in accounting (Byrne et al., 2004; Schleifer & Dull, 2009; Schraw & Dennison, 1994), Hypothesis 4 is formulated as follows:

H4: There is a positive correlation between SHSA and learning outcomes in the first course in accounting.

Instructor Effects on Learning Outcomes

Not only might instructor effects complicate evaluating student-level correlates with learning outcomes, but also the literature documents a considerable array of potentially impactful instructor effects in a wide variety of educational settings. For example, Rosenthal's (1991) meta-analysis finds that teachers' expressed beliefs and expectations have an impact on learning outcomes. Elikai and Schumann (2007) review the potential impacts of grading policies on course grades and provide evidence pointing to the efficacy of a stricter grading scale on learning outcomes in upper-level accounting coursework. Hattie (2003) provides a host of instructor effects that may have an impact on learning outcomes such as the effective use of feedback, selection of homework assignments, and promotion of an appropriate classroom environment.

Possibly particularly germane to the present study are differing impacts of fulltime faculty and adjunct faculty outcomes. Researchers commonly report longitudinal evidence of grade inflation among adjunct professors relative to fulltime faculty (Kezim, Pariseau & Quinn, 2005; Sonner, 2000). Sooner (2000) suggests the reason for this problem is that the tenuous nature of adjuncts' employment status triggers the need to avoid student complaints. Research that attempts to investigate actual student learning has reported not only evidence of grade inflation, but also evidence that students actually learn less from adjunct faculty (Kirk & Spector, 2009).

Some research, though, does report positive findings about the impact of adjunct professors. Figlio, Schapiro, and Soter (2015) conclude that first-semester students at Northwestern actually learn more after taking introductory coursework from adjunct faculty. Figlio et al. discuss possible institutional level characteristics, such as university quality and longer-term adjunct contracting, as possible causal factors for their findings and express doubt about whether their findings generalize to other universities. In fact, though, research that reports contrary results to Figlio et al. is also centered at a particular institutional setting (Kezim et al., 2005; Kirk & Spector, 2009; Sonner, 2000). Hence, the literature suggests the possibility that context may matter in terms of the direction of adjunct professors' impacts on learning outcomes.

MATERIALS AND METHOD

Student Sample

The analytical sample consists of data on students at a public university in the United States who enrolled in Introduction to Financial Accounting in Fall 2017 and who consented to participate in this study ($N = 47$). Eighty-two percent of eligible students consented to participate. The sample reflects the university's enrollment of about 90% males each year. The university provides a rigorous education designed to prepare most of its students for military careers. All coursework at the university is taught face-to-face. In addition, students tend to make very limited email contact with faculty about specific instructional issues. They are required to live on campus and thus, generally, are in the habit of discussing detailed questions in person.

Given its focus on military preparation, the university has a host of relatively stringent rules including prohibitions on unexcused course absences. Students admitted to the university are generally traditional students in terms of age, dependency status, and not having had previous professional employment. The institution offers a major in business and economics, but not a major or a concentration in accounting. Introduction to Financial Accounting is students' first exposure to accounting. The university's Institutional Review Board (IRB) approved the research protocols used in the study.

Instructors

Two faculty members provided accounting instruction during Fall 2017. These faculty members are masked as Instructor 1 (a full-time faculty member) and Instructor 2 (an adjunct faculty member). Over time, about two-thirds of students have successfully met course requirements (i.e., earning a C or better) when a fulltime faculty member has taught the class. Volatility in the number of students meeting requirements has been greater when the course instructor has been an adjunct faculty member. This volatility has generally been the case regardless of the identity of the fulltime and adjunct instructors. Historically, on the whole, students of adjunct faculty members have earned higher grades as is consistent with much of the literature (Kezim et al., 2005; Sonner, 2000). Thus, these students have been more likely to meet course requirements.

All instructors at the university have the academic freedom to design their own courses, syllabi, and assessments (which they grade). Faculty who teach the same course use the same textbook; there is no requirement about the extent of textbook coverage. The only common assessment requirement is that the final exam must be cumulative and represent at least 30 percent of course grades. Each instructor in this study arrived at similar weightings of their assessments: homework and quizzes (10%), four tests during the semester (60% total, 15% each), and one final exam (30% of the final exam grade).

Instructor 1 designed and conducted this study. Instructor 2 supported the study by promoting the study to students and providing access to students. Instructor 2 and Instructor 1 discussed their thoughts about teaching a few times during the semester that the study took place, and during several meetings following the end of the semester (after the study was over). These discussions took place as part of their employment obligations to the university and were not part of this study itself. Other than satisfying IRB-required consent processes, the instructors did not discuss the study or study instrument with students while the study was taking place. Instructor roles in the study are in keeping with data-driven instruction’s orientation of teacher-as-researcher.

Measures

Study outcomes

Learning outcomes are assessed as meeting program requirements, as a letter grade, and as the numerical course grade (0-100). These choices were made based on their salience to the educational program and based on the continuum they may represent about the impact of educational interventions. Currently, whether students meet course requirements is perhaps, the most salient measure to the university and to instructors. There are two means by which students can fail to meet course requirements at this institution: (1) they can earn a grade of record lower than a C (i.e., a D or F) or (2) they can be failing to earn at least a C and withdraw from the course prior to the last week of classes. Consequently, students who dropped the course (n = 3) are included in the measure of meeting course requirements. No students withdrew from the class for reasons other than not meeting course requirements. A clear course grade letter grade or numerical grade cannot be computed for students who withdrew because they did not complete all course assessments. Thus, those who withdrew do have these outcome measures.

Letter grades provide information about wider intervals of grade distributions (i.e., A = 90 to 100; B = 80 to 89; C = 70 to 79; D = 60 to 69; F = below 60). They are important to the educational program because grades are on the students’ permanent record. Additionally, meeting expectations, letter grades, and numerical grades may form an insightful continuum for prioritizing interventions. If one of the four constructs under examination is correlated with meeting course requirements, then intervening based on that construct would be have the highest priority. Interventions that are most likely to impact letter grade would be ranked as having the next highest priority followed by interventions most likely to impact numerical grades only.

Academic background

Measures of academic background are composite SAT[1] (0-1600), math SAT (0-800), high school GPA (4.0 scale), and prior semester college cumulative GPA (4.0 scale). Rather than being self-reported, these measures were obtained from the office of admissions. The office of admissions calculates an unweighted high school GPA that includes only academic coursework. Academic coursework includes such courses as math, English, science, social studies, and foreign languages, but excludes courses such as physical education, marching band, choral music, and other courses that are associated with extracurricular activities in the United States.

GPA is a summary measure adopted in the United States used to calculate average grades earned, while taking into consideration differences in time investments in each course and total course load, as proxied by credit hours. All GPAs in this study are calculated on a 4-point scale as grade points divided by total credit hours attempted. Grade points are further calculated as the sum of credit hours for each course times a quantitative rating for each letter grade, where A = 4, B = 3, C = 2, D = 1, F = 0. For example, if a student took one 2-credit-hour course and earned an A and one 3-credit-hour course and earned a C, his GPA for this coursework would be the sum of credit hours* quantitative grade ratings/total credit hours = $(2*4+ 3*2)/(2+3) = 2.8$. Cumulative GPAs include all coursework taken at an institution, rather than just coursework taken for a shorter period of time such as a semester or a year. High school GPAs are cumulative over students' high school years.

Attendance

Attendance is assessed as the number of excused absences for each student in the course. The university permits students to miss up to 30% of course meetings as long as the absences are excused. Unexcused absences are not permitted. Attendance is closely monitored at the university by a designated student—who initially takes the roll—and by the instructor who reviews this record for correctness and turns it in to his or her department after each class period. The department record of attendance has been used for this study.

Grit

GRIT-S (Duckworth & Quinn, 2009) was used to measure grit. Duckworth distributes a comparable, free grit instrument at https://angeladuckworth.com/grit-scale/. Duckworth and Quinn report Cronbach's alpha for GRIT-S as ranging from .73 to .83 for the full grit scale, .73 to .79 for consistency of interest, and .60 to .78 for perseverance of effort. (Cronbach alphas for this study are provided in the results section.) Items that measure consistency of interest relate to being able to work toward the same set of goals over time, where the time interval may be unnamed, measured in months, or years. Items that measure perseverance of effort relate to

[1]The SAT is the most common college admissions exam in the United States. This exam was named the Scholastic Aptitude Test prior to 1993, but has been renamed SAT.

industriousness, overcoming obstacles, and project completion. Responses on the grit scale range from 5 (very much like me) to 1 (not at all like me) for items that indicate the presence of grit. Scores on GRIT-S are the average of items related to the scale, so that 5 is the highest possible score (i.e., highest level of grit) and 1 is the lowest possible score (i.e., lowest level of grit). In the present study, grit was measured pre and post to ascertain its stability over the semester. The correlations between pre-measures of grit and learning outcomes were evaluated. Grit was also evaluated as a unitary scale and as a 2-factor scale (i.e., perseverance of effort and consistency of interest).

SHSA

SHSA was measured via the Learning and Study Strategies Inventory (LASSI), third edition (Weinstein et al., 2016). The LASSI is used at over 3,000 institutions (LASSI, 2018). LASSI is administered online for a fee through a contract with H&H Publishing, which reports results and provides comparisons with national norms. The LASSI has 60 items that measure 10 dimensions of SHSA. Students respond to each item by selecting one of five responses that range from 1 (not at all like me) to 5 (very much typical of me). Dimensions are created as the sum of 6 items, so that the highest possible score for any dimension is 30 and the lowest possible score is 6. Higher scores represent the positive aspects of each dimension of SHSA. For example, measures closer to 30 for anxiety are associated with lower levels of anxiety about coursework (i.e., stronger coping skills). Each of the 10 dimensions of LASSI is a separate construct.[2] LASSI was not developed to provide a single, composite measure of SHSA. Because LASSI is a proprietary instrument, and, thus, classified as intellectual property, underlying items cannot be released. Only results for each dimension can be presented.

Table 1 (Appendix) describes LASSI's ten dimensions, and the publisher's reported Cronbach's alphas (Weinstein et al., 2016). In the current study, pre and post measures of SHSA were collected to evaluate the stability of SHSA over the semester. Pretest and posttest comparisons of SHSA (and grit) were conducted for 44 students because three students had either dropped the course or were absent when posttest measures were collected.[3] The

[2]The term "study habits, skills, and attitudes" was developed in the context of the larger body of extant literature to describe a host of pre-existing instruments. Each dimension of LASSI was developed as a standalone dimension; dimensions were not developed to be further categorized in to one of three subgroupings: as a study habit, skill, or attitude.

[3]In the past, LASSI has sometimes been implemented as a pretest and a posttest to measure the impact of educational interventions, such as academic coaching (Swartz, Prevatt, & Proctor, 2005). LASSI developers report high test-retest correlations (approaching .90) between pre and posttest results over short intervals, such as 3 to 4 weeks, in the absence of a specific educational intervention (Weinstein et al., 2016). The purpose of pre- and posttesting of LASSI in this study differs from these prior investigations. Here, the issue being examined is whether LASSI results fluctuate over longer periods (i.e., an academic semester) in the absence of a specific educational intervention. This examination provides evidence about whether SHSAs are malleable in a naturalistic, education setting—where instructors are trying to improve learning outcomes without a specific strategy. Accordingly, it provides a baseline for fluctuations in LASSI over a semester in the absence of either an intervention or the use of data-driven instruction. No similar pre- and post-testing of LASSI appear to be available for comparisons to study findings.

correlations between pre-measures of SHSA and learning outcomes were evaluated. Students are informed of their results after each administration of the LASSI in its typical format. However, H&H Publishing customized LASSI for this study for an additional fee—so that students did not receive their LASSI results until after the study had concluded.

Instructor effects

Due to anecdotal observations about instructor differences at the university under study and findings about possible instructor effects on learning outcomes in the literature (Figlio et al., 2015; Kezim, et al., 2005; Sonner, 2000), the sample is evaluated both as a full sample and as subsamples broken down by instructor. It is not the purpose of this study to research instructor effects, however. The analysis is designed to control for instructor effects, so that they do not confound the study focus.

Segmenting the sample by instructor also provides insight about the level of segmentation at which a future intervention might be noticeable to administrators and instructors. For example, if a measure is determined to have a significant impact on learning outcomes at the course level (i.e., for the full sample) but not at the instructor level, instructors can be more confident that not observing the impact of an intervention while teaching does not mean there is no impact at a higher level of aggregation (i.e., at the course level). Because of data-driven instruction's orientation toward teacher-as-researcher, this information can be of greater relevance than traditional experiments where instructors may not have a role in the research.

Analysis

Due to the sample size, data analysis was limited to univariate analysis. Effect sizes were measured as bivariate correlations (i.e., point biserial correlations or Pearson's correlations depending on the specification of each set of variables being compared). T-tests were calculated for comparisons of learning outcomes between instructors' students and for evaluating differences in pre and post measurements of grit and SHSA. T-tests included an assessment of Levene's test for equality of variances. Cronbach's alphas were computed to evaluate the internal consistency of grit and SHSA. Alpha for two-sided significance testing was set at 0.05.

Power analysis indicates that the full sample and each subsample by instructor is sufficiently large to detect a medium effect size in the neighborhoods established by Cohen (1988) for a two-sided test of significance, with alpha = .05 and power set to the conventional levels of .80. The results in the next section reveal 18 statistically significant correlations between student-level measures and learning outcomes for the full sample, and 12 such significant correlations for subsamples segmented by instructor. Although a test of statistical significance is not a required element for data-driven instruction, the study is sufficiently powered to provide statistical results that are likely to be impactful. While not necessarily unimportant in driving learning outcomes, a measure with a small effect size is arguably less likely to reveal an approach that instructors can use to have a high impact on learning outcomes. Due to the participation rates in the study, any significant correlations detected are reflective of the actual sample sizes that the institution and instructors manage on an annual basis. It is these class sizes that instructors are attempting to impact.

RESULTS

Descriptive Statistics for Learning Outcomes

Table 2 (Appendix) provides information on learning outcomes. For the full sample, the mean course grade was 78; 9 out of 47 students (19%) did not complete the course with at least a C. Furthermore, the mean numerical course outcome was significantly different between instructors (Mean difference = 9.82, $t(43) = 3.85$, $p < .000$). Specific information about the distribution of letter grades cannot be provided because IRB policies require the aggregation of student data. To allow for sufficient masking of student data required under these policies, it is disclosed that fewer than 10% of Instructor 2's students did not meet course requirements of earning a C or better. More than a third of Instructor 1's students (35%) did not meet these requirements. Due to distributional differences in learning outcomes for each instructor, results were evaluated for both the full sample and for each subsample by instructor, except that an insufficient number of data points were available for evaluating whether Instructor 2's students met course requirements.

Academic Background

Table 3 (Appendix) provides descriptive statistics for students' academic backgrounds for the full sample and for subsamples by instructor. There were no significant mean differences in measures by instructor, except for composite SAT score (Mean difference = 73.29, $t(42) = 2.05$, $p = .047$).

Correlations were evaluated to test Hypothesis 1, which asserted that academic background is correlated with learning outcomes in the first course in accounting, where the specific pattern of correlation is institutionally dependent. The only significant correlation with learning outcomes was prior semester cumulative GPA. The correlations between numerical grade and letter grade for the full sample were 0.40 ($p = .009$) and 0.42 ($p = .006$), respectively. There were no significant correlations between prior semester cumulative GPA and satisfying course requirements for the full sample or by instructor.

Grit

Cronbach's alpha for Grit-S was .73 for the full sample when grit was measured as a single scale (Table 4, Appendix). When grit was assessed as a 2-factor construct, Cronbach's alpha was .59 for consistency of interest and .53 for perseverance of effort. Mean scores on each scale ranged from 3.62 to 3.67 for the full sample, with the possible range being from 1 (lowest level of grit) to 5 (highest level of grit). There were no significant differences in the changes in pre-post measures of grit for the full sample. However, the pre-test measure of consistency of interest was significantly different between instructors (Mean difference = .34, $t(45) = 2.21$, $p = .03$). No post-test measurements of grit were significantly different between instructors.

Correlations were evaluated to assess Hypothesis 2, which asserted that there is no detectable correlation between grit and learning outcomes in the first course in accounting in the context of data-driven instruction. Consistency of interest was significantly correlated with meeting course requirements for the full sample ($\rho = .31$, $p = .03$). There were no other significant correlations between grit and learning outcomes for the full sample or by instructor.

Course Absences

The number of excused course absences ranged from 0 to 7, where the total number of class meetings was 42. The mean number of absences were 2.04 for the full sample (SD = 2.04), 1.83 (SD = 1.70) for Instructor 1's students, and 2.25 (SD = 2.35) for Instructor 2's students. The mean difference between the number of absences for Instructor 1's and Instructor 2's students was not significant.

Correlations were assessed to evaluate Hypothesis 3, which asserted that there is a negative correlational between course absences and learning outcomes in the first course in accounting. Number of absences was not significantly correlated with any learning outcomes (i.e., course letter grade, numerical grade, or meeting requirements) for the full sample.

SHSA

Cronbach's alphas for LASSI ranged from .66 for using academic resources for the analytical sample to .83 for information processing (Table 5, Appendix). Mean pre-test scores ranged from 18 for self-testing to 23 for motivation for the full sample (Table 5, Appendix). Supplemental analysis indicated that the mean difference between pretest and posttest scores did not differ for the full sample.

Correlations were used to assess Hypothesis 4, which asserted that there is a positive correlation between SHSA and learning outcomes in the first course in accounting. For the full sample, 6 out of 10 pre-measures of SHSA were significantly correlated with learning outcomes (Table 6, Appendix). Concentration, motivation, self-testing, and using academic resources were significantly correlated with all three learning outcomes with correlations ranging from .40 (p = .006) to .49 (p =.001) for numerical grade, .36 (p = .014) to .43 (p =.003) for letter grade, and .29 (p = .045) to .40 (p = .005) for meeting course requirements. Time management skills were significantly correlated with numerical grade (ρ = .37, p = .013) and letter grade (ρ = .33, p = .025). Anxiety was significantly correlated with numerical grade (ρ = .32, p = .034).

DISCUSSION

This study has explored a step toward using data-driven instruction to improve learning outcomes in the first course of accounting. The specific issue under study was to evaluate using four constructs that might help identify struggling learners. These constructs were academic background, grit, course absences, and SHSA. Each set of measures examined were correlated with learning outcomes in the context of this study. However, prior semester cumulative GPA at the university and SHSA appear to offer the most promise for instructional intervention. Thus, Hypotheses 1 and 4 were corroborated the most affirmatively.

More specifically, prior semester cumulative GPA, investigated under Research Question 1, was correlated with numerical grade (ρ = 0.40) and letter grade (ρ = 0.42) for the full sample. High school GPA and standardized tests scores were not correlated with learning outcomes. These findings are consistent with Hypothesis 1. They corroborate findings in higher education that conclude that the impact of academic background appears to be institutionally dependent (Aguinis et al., 2016), and appear to contextualize prior findings in the accounting literature (Doran et al., 1991; Eskew & Faley, 1988). These findings are also consistent with findings that prior cumulative GPA at the university level has significant predictive power (DeBerard et al., 2004).

Both the strength of the correlations detected and their accessibility at the institution under study are encouraging in terms of prior GPA serving as a benchmark for learning outcomes in the first course in accounting. Findings also help explain faculty's and administrators' anecdotal observations of students' confusion about the implications of their prior academic performance at the institution under study. For example, students with strong high school GPAs or standardized test scores often expect these performance measures will carry over to the first course of accounting, even when these students have done poorly in the past at the university. In reality, high school GPA and standardized test scores appear to act as "noise" that distracts students from recognizing obstacles to learning.

Additionally, the correlations among prior GPA at the university level and learning outcomes appear to offer room for optimism: Any improvement in one outcome may trigger improvement in the other. For example, improvements in learning strategies developed in the first course in accounting may result in overall improvement in cumulative GPA in the future, beyond the effect of the course grade in accounting itself. However, any optimism is tempered by the fact that GPA was not associated with the learning outcome that instructors would like to impact most: helping students meet course requirements in the first course of accounting (i.e., completing the course with at least a C).

Six out of ten dimensions of SHSA, investigated under Research Question 4, were significantly correlated with learning outcomes for the full sample. Thus, Hypothesis 4 was supported. These measures were concentration, motivation, self-testing, using academic resources, time management, and managing anxiety where correlations ranged from .29 to .49. Concentration, motivation, self-testing, and using academic resources were significantly correlated with all three learning outcomes. Time management skills significantly was associated with letter grade and numerical grade. Anxiety was correlated with numerical grade. These findings are consistent with the higher education literature in terms of SHSA being a key predictor of learning outcomes (Credé & Kuncel's, 2008).

Both the strength of the correlations and the number of significant dimensions detected for the sample are encouraging in terms of the role of SHSA in determining learning outcomes in the first course of accounting. Whether SHSA is malleable is unclear. On one hand, there were no statistically significant pre-post changes in SHSA for the full sample. On the other hand, there were a few significant changes for each instructor's students (i.e., motivation for Instructor 1's students, and concentration and self-testing for Instructor 2's students). Furthermore, although the instructors already suggest study strategies in their classes (such as reviewing course notes before the next class), they have done so without any knowledge of which SHSA dimensions are correlated with positive learning outcomes in the course. With paid LASSI materials, they are now able to drill down to specific study behaviors that are correlated with positive learning outcomes in the course. However, more empirical evidence is needed in terms of determining how to best intervene to encourage students to change their approaches to SHSA.

Number of course absences, investigated under Research Question 3, appeared to have limited usefulness in this context. Hence, Hypothesis 3 was not supported. This measure was not significantly correlated with learning outcomes for the full sample. However, findings of an exploratory study should be interpreted with care to avoid overgeneralizing them. At this juncture, this finding suggests that overall the university's mandatory attendance policy supports learning outcomes, which is consistent with the higher education literature (Credé et al., 2010).

In other words, the mandatory policy appears to have prevented absences from rising to a high enough level to impact either the learning outcomes for the full sample or for the subsample of Instructor 1's students.

Grit—investigated under Research Question 2—had questionable usefulness. Thus, in the main, Hypothesis 2 was supported. Only consistency of interest was significantly correlated with meeting course requirements for the full sample ($\rho = .31$). This finding appears to be consistent with the literature in terms of the modest effect sizes detected for grit (Credé et al., 2017). On the positive side, this finding does suggest that a future educational intervention based on grit might impact the learning outcome that instructors hope to impact most (i.e., helping students to meet course requirements). Care should be taken before developing such an intervention, however. First, the effect sizes detected for consistency of interest are modest—with higher effect sizes being detected for SHSA. Second, the significance of consistency of interest might be an aberration in the data: Its significance, rather than that of perseverance of effort, is a departure from the literature. Perseverance of effort generally has the larger effect size in the literature as a whole (Credé et al., 2017). The finding that neither the full grit scale nor the perseverance of effort were significantly correlated with learning outcomes may be a function of the sample sizes available at this institution. Other explanations for the limited connection between grit and learning outcomes detected are certainly possible.

Furthermore, there was only one statistically significant change in grit over the course of the semester (i.e., consistency of interest was initially significantly different between instructors). Thus, findings are not necessarily encouraging in terms of grit being malleable. Like most accounting instructors, the accounting faculty at this university continuously encourage students to persevere and to study consistently before each class period. Additionally, the university's rigorous, military environment provides similar supports to this end. However, there was little evidence that these supports increase students' grit levels, suggesting that if grit is malleable, substantial interventions may be necessary to change it.

Although the concept of grit seems intuitively connected with learning outcomes in accounting, current instruments may not fully support the measurement of grit. More specifically, one might expect motivation and grit to be relatively synonymous. Yet, motivation (as measured by LASSI) was significant for all learning outcomes for the full sample, whereas one component of grit was significant for one learning outcome. Possibly, this is because LASSI identifies more specific behaviors (e.g., "when work is difficult, I either give up or study only the easy parts"), whereas the grit instrument is more nebulous (e.g., "I am a hard worker.")

Limitations, Caveats, and Obstacles

Limitations

Readers should be cautioned that the specific findings of this study are not intended to be generalizable. The sample size evaluated was small. Additionally, not only is the institution under study unique, all institutions have their ideocracies whether these ideocracies are rules about absences, unique academic resources and supports, substantial enrollments of nontraditional students, or institutional characteristics that may influence the predictive power of academic background. Rather than claiming to offer generalizable findings, this study provides a flexible blueprint for measures that faculty at other universities might consider when trying to predict student success in the first course in accounting at their universities.

Caveats

Additionally, the literature indicates that faculty should exercise extreme care when intervening based on any significant correlations identified for their institution. The literature has long demonstrated the power of teachers' expectations in influencing learning outcomes. In the seminal study, "Pygmalion in the Classroom" (Rosenthal, & Jacobson, 1968), teachers were told that some of their students were gifted when in fact, these students were simply selected at random. Yet, the selected students outperformed the other students in terms of gains in IQ scores. Steele's work (1994) shows that expressed beliefs can induce both the gender and the race achievement gaps in mathematics. Furthermore, although this study did identify correlations that generally had at least medium effect sizes, causal connections were not established; correlational findings indicate general associations that do not hold true for every individual, student. Consequently, rather than telling students that a certain set of measures indicate that they will struggle in the first course in accounting, faculty should seek an alternative strategy such as indicating to students that they expect them to modify a particular study strategy to maximize course success.

Obstacles

One of this study's overreaching messages is that correlations with learning outcomes in the first course in accounting may be institutionally specific or even instructor specific, ideally calling for accounting faculty to develop their own set of correlations and to monitor the strength of these measures on an ongoing basis. Accounting faculty may encounter a number of challenges when developing this set of correlations. For example, some universities regularly restrict teaching faculty's access to student records due to the Family Educational Rights and Privacy Act (FERPA). Hence, faculty may need to negotiate records access. Such negotiations may be aided by empirical demonstrations that knowledge of students' learning histories prior to beginning of the semester may help to improve learning outcomes via studies conducted under the auspices of stricter IRB permissions.

Additionally, even with access to student records, teaching faculty may find analyzing student records to be time prohibitive. Consequently, it may be necessary to negotiate automated reporting with the Office of Institutional Research. Furthermore, instruments like the LASSI may prove cost prohibitive without additional institutional funding. Cost benefit analysis and, initially, temporary faculty development grants might be useful in obtaining such funding.

Implications for Future Research

One avenue for future research is to expand the current study from its exploratory framework at the university under study. This research might emphasize more detailed explorations of academic background and SHSA, which appear to have the most promise for impact. Analysis might include using cohort data as a component of a longitudinal investigation, multivariate analysis, and—ultimately—trying to intervene to improve learning outcomes using the results of this exploratory study and subsequent research. Research on data-driven instruction is not limited to the use of assessment and survey data to identify potential struggling learners, however. It may have other uses in the accounting classroom in the context of collecting data during classroom activities and from course assessments. Such data may aid instructional decision-making about how to refine understandings of key course concepts and how to develop analytical reasoning skills. Other universities might consider conducting an exploratory study similar to the one described in this paper and then pursuing the thoughts for further research described in this subsection. Research at other universities might be particularly helpful in developing educational interventions via data-driven approaches that transfer across institutional settings at least to some degree.

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APPENDIX

Table 1
LASSI dimensions and publisher's reported Cronbach's alphas.

Dimensions	**Description**	**Cronbach's alpha**
Anxiety	coping with academic tasks	.87
Attitude	general perspectives about education	.76
Concentration	focus on school and school related tasks	.85
Information processing	strength of approaches for establishing meaning and organization	.81
Motivation	degree of responsibility, effort, and persistence	.77
Selecting main ideas	ability to identify important information	.86
Self-testing	strength of the student's approaches for reviewing and comprehending materials	.80
Test strategies	strength of preparation strategies for taking tests	.77
Time management	strength of scheduling time for academic tasks	.80
Using academic resources	knowing about and using resources on campus	.76

Source: Weinstein et al. (2016)

Table 2
Learning outcomes for the full sample and by instructor

	Full sample *N* = 47	Instructor 1 *n* = 23	Instructor 2 *n* =24
Mean numerical course grade, scale 0-100	78.07	73.05^{*}	82.87^{*}
Students who did not satisfy course requirements, %	19.15%	35%	≤ 10%

Note. Meeting course requirements = earning a C or better in the course. In compliance with the university's IRB policies, the exact percentage of students not meeting course requirements for Instructor 2 and the distribution of letter grades cannot be supplied. *Indicates that the means are significantly different where alpha = .05.

Table 3
Descriptive statistics for students' academic background for the full sample and by instructor.

	Full Sample	Instructor 1	Instructor 2
Composite SAT			
N	44	23	21
Mean	1145.45	1180.43*	1107.14*
SD	123.01	134.82	97.94
Range (0-1600)	940 - 1400	980 - 1400	940 – 1360
Math SAT			
N	43	22	21
Mean	562.56	570.45	554.29
SD	67.01	67.58	67.05
Range (0-800)	430 - 730	430 – 680	460 – 730
High school GPA			
N	43	22	21
Mean	3.12	3.21	3.02
SD	0.47	0.51	0.42
Range (0-4.0)	2.19 - 4.0	2.25 – 4.0	2.19 - 3.69
Prior semester GPA			
N	44	21	23
Mean	2.70	2.75	2.66
SD	0.59	0.66	0.53
Range (0-4.0)	1.56 - 3.92	1.56 – 3.73	1.73 - 3.92

High school GPA reflects only academic coursework and is on an unweighted 4.0 scale. N is the number of data points on file at the university's administrative offices. *Indicates that the means are significantly different where alpha = .05.

Table 4
Cronbach's alpha (α), mean, standard deviation (SD), and range for grit.

Measure	Full sample $N = 47$	Instructor 1 $n = 23$	Instructor 2 $n = 24$
Grit, single scale			
α	.73	.73	.71
Mean	3.66	3.54	3.78
SD	0.51	0.49	0.51
Range	2.50 - 4.88	2.63 - 4.38	2.50 - 4.88
Perseverance of effort			
α	.59	.32	.62
Mean	3.62	3.58	3.66
SD	0.64	0.60	0.68
Range	2.33 - 5.00	2.33 - 4.33	2.33 - 5.0
Consistency of interest			
α	.53	.64	.50
Mean	3.67	3.50*	3.84*
SD	0.53	0.53	0.50
Range	2.50 - 4.80	2.50 - 4.60	2.60 - 4.80

Measures of grit can range from 1 (lowest level of grit) to 5 (highest level of grit).
* Indicates that the means are significantly different with significance level = .05.

Table 5
Cronbach's alpha (α), mean, standard deviation (SD), and range for LASSI pre-test.

Dimension	**Full sample** *N* **= 47**	**Instructor 1** *n* **= 23**	**Instructor 2** *n* **= 24**
Anxiety			
α	.81	.79	.82
Mean	19.62	18.30	20.88
SD	5.16	4.61	5.44
Range	10-30	10-28	10-30
Attitude			
α	.71	.72	.71
Mean	21.55	21.39	21.71
SD	4.34	4.24	4.53
Range	13-30	14-28	13-30
Concentration			
α	.73	.69	.68
Mean	19.06	17.65*	20.42*
SD	3.94	3.75	3.69
Range	11-30	11-24	15-30
Information processing			
α	.83	.82	.81
Mean	21.11	20.83	21.38
SD	4.59	4.93	4.32
Range	12-30	12-29	13-30
Motivation			
α	.71	.70	.75
Mean	22.87	20.52	23.21
SD	3.51	3.18	3.83
Range	16-29	17-29	16-26
Selecting main ideas			
α	.82	.78	.87
Mean	20.28	20.13	20.42
SD	4.64	4.52	4.85
Range	13-30	13-30	14-30
Self-testing			
α	.77	.84	.69
Mean	18.00	17.04	18.92
SD	4.64	4.86	4.23
Range	7-30	7-27	11-30

Table 5 (continued)
Cronbach's alpha (α), mean, standard deviation (SD), and range for LASSI pre-test.

Test strategies			
α	.75	.63	.80
Mean	20.32	19.26	21.33
SD	4.06	3.52	4.35
Range	12-29	12-25	15-29
Time management			
α	.69	.65	.74
Mean	18.43	17.43	19.38
SD	4.42	4.07	4.62
Range	9-30	9-28	10-30
Using academic resources			
α	.66	.59	.72
Mean	19.40	19.04	19.75
SD	4.29	4.17	4.47
Range	10-29	10-29	12-28

Note**.** Dimensions are constructed so that high scores represent the positive aspects of each SHSA. For example, a higher measure on anxiety means that the student has lower levels of anxiety about coursework (i.e., better coping skills). The highest possible score for each dimension is 30; the lowest possible score is 6; * indicates that the means are significantly different where significance level = .05.

Table 6
Correlations between learning outcomes and SHSA dimensions for the full sample and by instructor.

	Full sample		
	Numerical grade	Letter grade	Meeting course requirement
Anxiety			
Correlation	**.318**	.275	.038
p value	**.034**	.067	.802
Attention			
Correlation	.177	.130	.063
p value	.244	.396	.676
Concentration			
Correlation	**.429**	**.433**	**.355**
p value	**.003**	**.003**	**.014**
Information Processing	.053	.073	.154
Correlation			
p value	.729	.636	.300
Motivation			
Correlation	**.404**	**.364**	**.294**
p value	**.006**	**.014**	**.045**
Selecting main ideas	.039	.031	-.159
Correlation			
p value	.800	.838	.286
Self-testing			
Correlation	**.432**	**.407**	**.369**
p value	**.003**	**.006**	**.011**
Testing Strategies			
Correlation	.163	.168	.012
p value	.285	.271	.938
Time management	**.369**	**.334**	.233
Correlation			
p value	**.013**	**.025**	.115
Using academic resources			
Correlation	**.488**	**.422**	**.403**
p value	**.001**	**.004**	**.005**

Significant correlations are bolded. Correlations with meeting course requirements cannot be calculated for the subsample of Instructor 2's students because of insufficient sample size of students who did not meet requirements for this instructor.