THE ACCOUNTING EDUCATORS' JOURNAL
Volume XXX
2020
pp. 115-135

Data Analytics in The Financial Statement Audit: Assessing Its Active Learning Effects on Student Performance

Ouadie Akaaboune
Sam Houston State University

Leslie Blix
Sam Houston State University

Ronald Daigle
Sam Houston State University

Ross Quarles
Sam Houston State University

Abstract

The objective of this study is to determine if there is a beneficial effect derived from the inclusion of a data analytics (DA) active learning assignment on student learning beyond the direct benefit of students developing skills in the use and application of DA. Two groups of students are compared for their exam performance in a financial statement audit course, with one group completing an IDEA assignment after the first exam and the other group not doing so. All other course matters are the same between the groups. Results show that student performance on the second and third exams improved for those who completed the assignment, but there was no similar improvement for those who did not. Our results suggest that there is value in using DA in a financial statement audit course in addition to the direct benefit of developing skills in the use of DA. This insight makes our study timely and relevant by appealing both to accounting education and the audit profession in that graduates would be better prepared to meet the growing demands for higher-order thinking as well as possess increasingly important skills in data analytics.

1. Introduction

The growing implementation of data analytics (DA) within the financial statement audit has caused major changes in the profession. As the amount of data, the speed at which it is received, and its different types all increase (Gartner 2013), auditors must quickly become familiar with new software that becomes available for use in analysis. Results from a survey of accounting alumni show that most new auditors are analyzing and processing data on a large scale using software like IDEA (Pelzer and DeLaurell 2018). The use of DA in the financial statement audit has been discussed in the literature, and the capabilities and techniques these applications (such as IDEA Data Analysis) contribute to the process have been noted (Liddy 2014). As technological advances such as Big Data and DA gain momentum, the auditors' role is evolving from a manual to an automated environment.

Big Data consists of datasets so large with both unstructured and structured data that they cannot be analyzed by traditional software programs (Warren Jr, Moffitt, and Byrnes 2015). While traditional software programs enable the acceleration of existing manual processes, DA can profoundly change the underlying audit process by allowing auditors to handle data through various applications to discover and communicate useful information and patterns, suggest conclusions, and support decision making (Cao, Chychyla, and Stewart 2015; KPMG 2012; Setty and Bakhshi 2013; Titera 2013; Brown-Liburd, Issa, and Lombardi 2015). As such, the role of auditors will expand beyond sample-based testing and require more thorough risk assessments for tailoring each audit plan (EY Reporting 2015).

DA implementation in the financial statement audit is in the early stages of development, and transition to this automated environment will take time. The ultimate goal is to add value to the audit process, but this transition has highlighted a number of difficulties that audit firms encounter when using DA applications (Appelbaum, Kogan, and Vasarhelyi 2017). For example, a survey conducted by KPMG found that 85% of managers acknowledge a struggle in learning how to analyze the vast amounts of data being collected (2014). Other problematic issues faced when using DA in audits include difficulty in acquiring appropriate data, not knowing where to start, and, perhaps most importantly, a lack of adequately trained staff (Wang and Cuthbertson 2015; Earley 2015). If staff are not properly trained to use DA techniques, they will not be able to decipher the outputs or interpret their impact on the audit plan. Offsetting these problematic issues are the numerous benefits that result from the use of DA, including working with larger data sets, proactive risk assessment, and improved efficiency of evaluating control procedures (Wang and Cuthbertson 2015).

As significant as the impact of DA has been on the audit profession, it has similarly important repercussions for the academic community. Schools have modified their programs to implement a focus on data analytics to address the need in the profession (Briggs 2013). Auditors who completed their undergraduate or master's programs before big data was recognized as an influence are expected to understand the risk assessments made during an audit despite not being taught how to analyze and understand big data (Earley 2015).

As DA becomes a permanent part of the auditing environment, established practitioners need to learn new skills that they did not initially learn through their accounting programs. Regulators have voiced concerns that auditors lack the skills to properly apply DA techniques (Earley 2015; Katz 2014). In the near future, students may be concerned that they lack the DA skills which accounting firms will increasingly require. The problem of inadequately trained staff as noted by auditing firms should be addressed before individuals even enter the accounting profession. By exposing students to DA as part of their accounting curriculum, educators can address the concerns of regulators by increasing student understanding of DA applications. Such exposure will also address student concerns that may arise regarding skills required by accounting firms.

Given the increased recognition of data analytics as a skill needed by accounting professionals, there can be little argument that the inclusion of data analytics assignments in accounting coursework will provide a direct value-added effect for students. Learning and developing data analytics skills will enhance the overall knowledge base of students to include this new area of importance to the profession and help meet employer expectations of the skills required for new graduates.

While accounting programs may be enhancing and improving course content to include data analytics for this direct skill set purpose, there may also be an indirect value-added effect for student learning related to these enhancements. A data analytics assignment included in accounting coursework can be readily structured as an active learning activity. Active learning activities have been suggested as a means of improving retention of all material studied in coursework. Therefore, there may be a "bonus" outcome derived from the inclusion of data analytics assignments in coursework over and above the direct enhancement of the students' skill set to include proficiency in the application of data analytics.

The objective of this study is, therefore, to examine whether the inclusion of a data analytics assignment in accounting coursework provides an indirect value-added effect on student learning and understanding. This study examines a data analytics assignment structured as an active learning activity included in the coursework for an undergraduate audit class to determine if there is an effect on overall student course performance. Our premise is that the inclusion of the active learning DA assignment will have a positive effect on overall student course performance beyond the direct benefit of students developing skills in the use and application of DA.

Our study tested for any potential indirect value-added effect derived from including an active learning assignment (DA) in an undergraduate auditing course. One group of students (treatment group) was given a general introduction to IDEA and an IDEA assignment to be completed outside of class. Another group of students which did not receive this IDEA exposure served as a control group. To test for any potential "bonus" effect, the performance of each group on identical course content examinations was compared. Results show that the treatment group performance on examinations following the completion of the IDEA assignment improved, but there was no similar improvement for the control group. Our results imply that there may be beneficial effects on overall performance of using DA in a financial statement audit course in addition to the direct benefit of developing skills in the use of DA.

2. Literature Review and Motivation

Accounting Education Reform

Skills such as recognizing patterns within data and how to evaluate anomalies have not traditionally been a major element of accounting education. Currently only six percent of undergraduate courses and two percent of graduate courses require students to use database software, even though database skills are in high demand by employers (Blankley, Kerr, and Wiggins 2018). However, with the professional shift toward an environment driven by DA, accounting education will need to make changes at all levels of the curriculum (Earley 2015; EY Reporting 2015). Accounting firms are calling for educators to equip students with an expanded skill set that enables them to perform DA effectively upon entering the profession. Such an educational expansion would address the gaps that firms face in their employees' skills and expertise with DA (PwC 2015). The American Institute of Certified Public Accountants (AICPA) has heard this call from accounting firms and now requires students to successfully demonstrate higher-order thinking skills (analysis and evaluation of information) in order to pass the CPA exam (Freeman 2018).

For many years, accounting practitioners and the American Accounting Association (AAA) have made it their goal to ensure that accounting curricula match the needs of students' career paths (Accounting Education Change Commission 1990). In particular, the AAA has expressed concern with course content, content delivery, how students learn, and recommended that accounting courses include a form of computer-assisted instruction within the educational environment (Lux 2000). The mode of delivery is increasingly important as the learning preferences of the current generation evolve and as educators struggle to gain the attention of millennial students - a generation that depends on technologies and demonstrates a decreased tolerance for lecture-style teaching (Prensky 2001). Through the use of educational technology, students may develop higher-order thinking skills that they can apply both in the classroom and in their future workplaces (Roehl, Reddy, and Shannon 2013). These higher-order thinking skills encompass students' skills of analysis, synthesis, evaluation, comprehension, and application (Ennis 1985).

Educational reform can be approached by gaining an understanding of the students and the optimal environments in which they learn (Frederickson and Pratt 1995). Students have different learning methods so changes to accounting programs require the gathering of data about how participants learn, how they process information, and how they can use what they have learned to improve future knowledge (Monsanto, Cardoso, and Joyce 2004). Efforts to reform education should include an evaluation component to measure how interventions (in this case, including DA assignments in coursework) enhance student learning and improve academic results more significantly than traditional approaches (Chu and Libby 2010). Educators can assess students' grades, attrition rates, and their perceptions of a learning approach (e.g. DA) utilized in the curriculum to determine if positive results are produced (Elias 2011).

Active Learning

In order for students to develop higher-order thinking skills, they must be actively involved in their learning and engaged in higher-order thinking tasks rather than just listening to a lecture (Chickering and Gamson 1987). Active learning can support such involvement and engagement. Active learning, as described by Bonwell and Eison (1991), involves five strategies: 1) students are involved in more than just listening; 2) less emphasis is placed on transmitting information and more on developing skills; 3) students are involved in higher-order thinking; 4) students are engaged in activities; and 5) greater emphasis is placed on student exploration of attitudes and values. This framework engages students in the learning process and requires that they think about what they are doing (Prince 2004). Research has shown that students are better able to understand and retain information and improve their academic results through an active learning approach (Yoder and Hochevar 2005).

Prior studies of active learning techniques have examined numerous areas from student skills to education reform. For example, Hermanson (1994) found active learning to be a major contributor to a student's ability to formulate relevant responses in a business setting. Springer and Borthick's (2007) results indicate that an active learning approach allows students to decipher what they are learning, reflect on the methods that work for their own learning style, and discover improvements for themselves. Elsewhere, Chu and Libby (2010) suggest that active learning encourages students to take control of their knowledge and improves how they apply it in the future.

A number of direct benefits of incorporating active learning into accounting courses content have been identified. Cottell and Mills (1993) report an active approach that allows faculty to address accounting education reform through the implementation of new teaching methods (e.g. small group work) that ultimately produced positive results. Matherly and Burney (2013) found that students in a managerial accounting class perceived active learning activities (e.g. hands-on, in-class experiences) to have a positive impact on their knowledge as well as on their attitude and interest in the material. Similarly, Gainor et al. (2014) found that accounting students were able to more effectively focus on their experience, increase their confidence, and work in a competitive environment through the use of an active learning in-class competition. Diaz (2016) was able to increase student knowledge of audit reporting by working in small-group active learning exercises. Edmonds and Edmonds (2010) report that the use of technology enables students to recognize an active learning environment and, in their study, it was deemed efficient. Although educators are implementing active learning techniques in their course content, varying opinions remain regarding the effectiveness of this approach and more research is therefore warranted (Blankley, Kerr, and Wiggins 2017).

The AICPA has identified a critical role that technology and related IT skills should play in accounting education. That body suggests, "all professional accountants, irrespective of their primary work domain or role, must acquire both relevant theoretical knowledge and practical IT skills." (AICPA 1996, para. 12). Given this identified need for practical IT skills, educators should consider the role that active learning can play in providing those skills to accounting students.

Prior research shows that active learning can be accomplished through many different forms. Technology (desktops, laptops, software applications, electronic whiteboards, projectors, and work processing application, etc.) in the classroom and in the curriculum is commonly used as a technique within the active learning framework; it can be used as a tool that adds value to the learning process. Du and Wagner (2005) found the use of technology provides educators with an opportunity to move beyond traditional instruction and gives students new outlets for learning. Using technologies in the curriculum allows students to work directly with different kinds of information, samples, and data to improve their skills and learning outcomes (Anderson et al 2007). Since the great majority of business processes rely on computer applications, auditing is carried out in a computerized and automated environment (Coffey 2018). The inclusion of DA technology, such as IDEA, as an active learning approach can expose students through hands-on practice to business-related technologically based activities relevant to the profession.

As indicated by Weidenmier and Herron (2004), utilizing data analytics software such as IDEA outside of the classroom can reinforce understanding of audit concepts. Students can filter and extract data, summarize, stratify, age, and calculate data statistics. IDEA also allows the selection of samples using a number of different methods. IDEA allows the identification of duplicates, gaps, and proper sequences to aid the identification of areas that require more extensive examination. Audit students can use the application to compare multiple files, create new files, customize reports, and document audit tasks through a number of varying processes. These powerful functions bring active learning to life through the actual application of concepts and procedures that, without such activities, are merely words contained in a textbook. This is the basic idea involved in active learning.

Data Analytics in Accounting Coursework

Including DA, such as an IDEA assignment, as an element of accounting coursework would allow students to engage in certain previously identified strategies of the active learning framework. First, to engage in more than just passive listening, students would be required to engage in related activities using IDEA. Second, utilizing IDEA would allow students to develop skills that will likely improve their reactions in business settings which accounting firms increasingly demand within the audit profession. Third, students are involved in higher-order thinking when using IDEA as they perform procedures to analyze, synthesize, evaluate, and comprehend data to conclude on financial aspects of a business. Lastly, using IDEA as an element of coursework forces students to learn and engage in technology related activities.

As noted by Chickering and Gamson (1987) in their third principle of good practice in undergraduate education, active learning techniques should be effective both inside and outside the classroom. Encouraging students to use the IDEA software on their laptops during and/or between classes would allow them to do more than internalize the information provided as they apply what they have learned to analyze the course content. Institutions can use data analysis tools at a minimal cost to meet the AACSB requirement that students develop skills and knowledge related to the integration of information technology in accounting (Pelzer and DeLaurell 2018). Perhaps most importantly, using this technique of active learning will provide students with an easier transition from academic life to the workforce.

3. Research Method

This study addresses whether there is a beneficial effect derived from the inclusion of a DA active learning assignment on overall student course performance beyond the direct benefit of students developing skills in the use and application of DA. An active learning assignment (DA) was implemented in the course content for one group of students (treatment group) by giving those students a general introduction to IDEA and an IDEA assignment to be completed outside of class. The general introduction showed students how to download the software on their computers and how to import files into the software. Students received a guide from the IDEA software and completed all remaining steps on their own.

Students then learned substantive auditing procedures over Accounts Payable, Accounts Receivable, and Inventory through lecture and textbook resources.[1] Students utilized IDEA to complement the traditional course content and completed substantive procedures within the data analytics software. Students completed procedures to verify the completeness, existence, and accuracy of the account balances. Specifically, students received cases and supporting files for each account balance. They were required to import the case files into IDEA and verify the file was imported correctly. Utilizing the Accounts Payable files students were required to determine trends among the payments and identify any high, unusual, or duplicate amounts. Utilizing the Accounts Receivable files students were required to select a random sample of customer payments for detail testing with the support of confirmations to verify existence of these balances. Lastly, utilizing the Inventory files students were required to identify obsolete inventory items and compute usage ratios. The assignment came with solutions that were used by the instructor to grade the accuracy of each respective student's results generated. The timing of the assignment followed the lecture of the subject material. For example, once the instructor lectured on Accounts Payable, the students had one week to complete the supporting IDEA assignment. Students were required to export and submit final reports from the system to verify they had completed all required steps.

This IDEA assignment was treated as an additional assignment, specifically a DA assignment, to improve the understanding of the course content. Another group of students (the control group) did not receive the assignment. Therefore, this study was designed to test the additional benefits of including the active learning DA assignment on overall student course performance beyond the direct benefit of students developing skills in the use and application of DA.

---

[1] Whittington and Pany (2019) auditing textbook was used to teach Chapter 11 (Accounts Receivable), Chapter 12 (Inventory), and Chapter 14 (Accounts Payable).

These benefits were measured through exam grades in the financial statement audit course over two semesters in the same school year (fall and spring semester). Exams 2 and 3 in the course tested the topics covered which were reflected in the DA assignment (Accounts Payable, Accounts Receivable, and Inventory, sampling, ratios, and assertions). These exams were identical both in the fall and spring semester for each student. The treatment group (spring) and control group (fall) classes had no significant variation. The classes were approximately the same size (between 20-30 students) and were held at the same time, same day of the week, in the same classroom, and taught by the same instructor at a large state university in the southwestern United States. Having the same instructor teach all students participating in the study avoided partiality caused by different teaching quality. Therefore, the only difference between participant groups was the completion of an active learning DA assignment; all other course matters were the same between both groups. We recognize that inclusion of the assignment in only the treatment group presents a limitation of our study. The treatment group did complete more work and gained an overall knowledge of DA through IDEA, thereby having an opportunity to apply to other course work. In comparison, the control group did less work and obtained the knowledge of DA only through course lecture.

Understanding the role DA can play in improving the effectiveness of accounting pedagogy is warranted. However, examining this link by focusing solely on the presence of DA is not complete but, rather, must be done holistically and must include the interactions of DA and other variables that have traditionally been part of the education production function. In our analysis, we follow previous research by assessing the effects of DA on student performance over time in the presence of control variables known to impact performance (Byrne and Flood 2008; Eikner and Montondon 2001; Frakes 1977; Turner, Holmes, and Wiggins 1997; Didia and Hasnat 1998). Therefore, we designed our study based on the Frederickson and Pratt (1995) model by considering aspects associated with student performance such as curriculum content, course content, instructional methods, student effort, and faculty ability.

Data

The implementation of active learning in classrooms has been found to encourage exploration of attitudes and values, increase confidence, and promote critical thinking skills that have been linked to improved information retention and enhanced performance (Prince 2004). As a form of active learning, a DA assignment allows students to actively experience the application of substantive procedures that are covered in lectures and textbook materials; therefore, the outcomes related to active learning could be realized or enhanced through the implementation of the DA assignment. This study captures the effects of including a DA assignment on student performance over time.

This study draws on one data source; all demographic variables used in this study are obtained from the Office of Institutional Effectiveness. Following the model used by Morris, Burnett, Skousen, and Author (2015) student performance is captured through exam grades. The instructor of the audit course administered three exams throughout the semester, Exam 1 (E1), Exam 2 (E2), and Exam 3 (E3) which were identical between semesters. Furthermore, to capture the change in performance over time, we align with Morris et al. (2015) and employ the difference in exam scores between two consecutive exams. Therefore, the difference between E2 and E1 is referred to as EC1, the difference between E3 and E2 is referred to as EC2, and, just as importantly, EC3 represents the difference between E3 and E1. Finally, previous literature suggests that any analysis of student performance must take under consideration the individual attributes of each student (Byrne and Flood 2008). Therefore, we employ a vector of individual characteristics control variables for gender, age, cumulative grade point average, course load, and race (Morris et al. 2015; Eikner and Montondon 2001; Frakes 1997; Turner 1997; Didia and Hasnat 1998).[2]

Figure 1 Goes About Here

The objective of this study is to assess the effects of including a DA assignment in the coursework required in an undergraduate financial audit course on overall student performance over time. In doing so, we identified six sections of an audit course that were taught by the same instructor and had the same requirements. Three of the

---

[2] We also ran our model without the race variable, as well as with different versions of it. The results were the same as those shown in Table 5 (no significance).

sections (i.e. Control Group) used a traditional format where the instructor delivered in-class lectures and worked in-class problems with the students. Students in the other three sections of our sample (i.e. Test Group) were required to complete a data analytics project using IDEA.[3] The use of IDEA as an application of data analytics in auditing has proven to add value (Liddy 2014). Therefore, a dichotomous variable, IDEA, is used as an instrument for the employment of DA and takes a value of 1 for the test group and 0 for the control group.

Methodology

Following Morris et al. (2015), this study employs two different analyses. First, we use a univariate testing to assess variation within each group and compare between the two groups. Accordingly, we conduct both a within and between two-sample t-test analysis to compare the difference in performance between the test and control group. Next, we run multiple regression testing, by employing an ordinary least square (OLS) model that captures the different effects on student performance over time. We follow previous literature (Morris et al 2015) by using EC3 (the difference between exam 3 and exam 1) as a measure of change in performance over time. Given these observations, we propose the following model to capture the effects of DA on student performance over time:

$$EC3 = \beta_0+\beta_1 E1+ \beta_2 E2+ \beta_3 GPA+ \beta_4 AGE+ \beta_5 LOAD+ \beta_6 GENDER+ \beta_7 RACE+ \beta_8 IDEA+ \varepsilon$$

The coefficient of interest in the model is β_8. Aligning with previous studies, control variables such as age, gender, and race represent demographics in our sample. Cumulative grade point average at the start of the semester in which the audit course was taken and course load in semester hours to represent expected student efforts is used to control for individual attributes of each student and isolate the effect of DA, which will be identified by β_8. All the variables used and their definitions are shown in Appendix 1. Finally, we align with Monem (2007) by including E1 (exam 1 grade) and E2 (exam 2 grade) in our model, as prior academic performance could affect long-term performance.

Results

Table 1 provides summary statistics of the variables used in our analysis. Panel A presents the full sample, panel B presents the control group, and panel C presents the test group. In the full sample, the respective means of the exams are 77.92% for E1, 74.55% for E2, and 75.08% for E3. Note that E1 has the highest mean. While the control group follows a similar pattern, the test group exhibits a different trend. The lowest grade of 74.89% was recorded in E1 for the test group, with improved performance to 80.36% and 80.30% for E2 and E3, respectively. Furthermore, the change in performance over time as measured by EC3 was -2.83% for the full sample, -8.24% for the control group, and noticeably 5.40% for the test group. Table 2 represents the correlation results of the full sample, and as shown in this table, multicollinearity is not an issue in our tests.

Tables 3 and 4 show the results from the two sample tests, within-sample tests and between-sample test, respectively. Panel A in Table 3 shows the results for the test group while Panel B shows the results for the control group. For the test group, we find a significant difference at the 0.05 level between the mean performances of E1 and E2, with higher performance in E2. There is no significant difference between the mean performances of E2 and E3. Furthermore, results show a significant difference at the 0.05 level between the mean performances of E1 and E3 with higher performance recorded in E3. We follow previous literature (Morris et al 2015) comparing performance across exams in the same semester with content differences (i.e., differences between exam 1 and 2, 2 and 3 and 1 and 3). While this could be considered a limitation, the goal is to assess the ability to perform independent of specific content knowledge. The results show that student course performance for the treatment group improved with time. Therefore, the content differences between exam 1 and exam 2 within the same group do not diminish the goal of assessing the ability to perform which is affected by many different factors, including information retention and critical thinking skills.

As for the control group, results show a trend of statistical significance but at a higher level (0.01 level) in the opposite direction, with performance lower in E2 and E3 than E1. Thus, we find a significant difference at the 0.01

[3] IDEA is an audit analytics software; students used it as a tool to analyze data for accounts receivable, accounts payable, and inventory. This project was administered between exam 1 and exam 2, and it was designed to help students prepare for chapters covered in exams 2 and 3.

level between the mean performances of E1 and E2 where E1 is higher, no significant difference between the mean performances in E2 and E3, and a significant difference at the 0.01 level between the mean performance of E1 and E3 where E1 is higher. These results suggest that performance declined with time, which could be explained by many factors, one of which is the fact that the material increased in difficulty as the semester progressed and students did not improve their learning capabilities.

Table 4 provides the between two-sample test results. In analysis 1 we find a significant difference (at the 0.01 level) in the mean changes in performance on E2 and E1 (i.e., EC1) between the control and test groups. In analysis 2, we find no significant difference in the mean changes in performance on E3 and E1 (i.e., EC2). Finally, Analysis 3 shows that for EC3 (E3 verses E1), there is a significant difference in mean changes (at the 0.01 level). Therefore, for both EC1 and EC3, the test group performed better than the control group.

As indicated previously, we also completed a multiple regression analysis as a robustness check to assess further our query of the effects of DA on performance over time. Table 5 reports the results of that analysis. First, we regressed performance over time captured by the change in exam grades between E3 and E1 (i.e. EC3) on the vector of control variables previously described; results are shown under Model 1a column. The estimated coefficient for E2 and GPA yield a positive sign for performance over time with a statistical significance at 0.01 and 0.1, respectively, where the estimated coefficient for E1 yields a negative sign for performance over time with a statistical significance at a 0.01 level. The estimated coefficients for the rest of the control variables exhibit no statistical significance.

Second, we introduced the presence of DA into the model by including the variable IDEA in Model 1; results are shown in Model 1b column. The estimated coefficient for E1 and E2 still exhibit statistical significance at the 0.01 level with negative and positive signs, respectively, with GPA no longer statistically significant. The estimated coefficient for IDEA is positive and statistically significant at the 0.01 level, indicating a positive effect of DA on performance over time. Finally, the change in R^2 from 0.42 to 0.46 when moving from Model 1a to Model 1b suggests that the predictive ability of Model 1 improves when the DA variable (i.e. IDEA) is included.

Finally, since the DA assignment was completed between the first and second exam; we added another robustness test by regressing performance captured by the change in exam grades between E2 and E1 (i.e. EC1) on the vector of control variables and the DA variable (IDEA); and the results are shown on table 6. The estimated coefficient for IDEA is positive and statistically significant at the 0.01 level, expressing a positive effect of DA on performance, and the predictive ability of the model improves with the inclusion of the DA variable (i.e. IDEA) as shown by the increase in $R^2$from 0.40 to 0.58.

4. Conclusion and Discussion

Active learning involves five strategies (Bonwell and Eison 1991): 1) students are involved in more than just listening; 2) less emphasis is placed on transmitting information and more on developing the students' skills; 3) students are involved in higher-order thinking; 4) students are engaged in activities; and 5) greater emphasis is placed on the students' exploration of attitudes and values. Active learning can be accomplished through many different forms, particularly those that are technologically related, and both inside and/or outside of class. The inclusion of DA technology, such as IDEA, would allow students to engage in most strategies of the active learning framework. First, students go beyond just listening as they engage in related activities using IDEA. Second, students develop skills utilizing IDEA that are demanded by the audit profession. Third, students are involved in higher-order thinking as they analyze, synthesize, evaluate and comprehend data to make conclusions on the financial aspects of a business. Lastly, using IDEA in coursework requires students to learn and engage in technology related activities.

The growing use of DA has resulted in major changes in the auditing profession. DA offers the promise of added value by making processes (such as risk assessment, internal control evaluation and substantive evidence gathering) more efficient and effective through the analysis of large data sets. While the use of DA is promising in its potential, the profession has noted that there is a struggle as to how to analyze vast amounts of data, which includes having adequately trained staff to perform such analyses. It is therefore imperative that graduates entering the audit profession be exposed to DA in order to acquire higher-order thinking skills in their education to meet this new set of needs. Given that the inclusion of DA in accounting course content will continue to increase, our study focuses on determining whether benefits other than the direct increased skills in the use of DA will accrue to students as the result of such inclusion. Viewing DA as an active learning activity, there may be an indirect value-added outcome for students derived from completing DA assignments in the form of improved performance for all course content materials.

Our results suggest that for audit students exposed to DA through the completion of an IDEA assignment, student performance not only improved on the examination immediately following completion of the assignment (E2) as compared to the pre-assignment examination (E1), but also improved on the second subsequent examination (E3) when compared to the pre-assignment examination (E1). Moreover, compared to the performance of audit students not exposed to DA, the performance of those completing the assignment was substantially higher on both E2 and E3. This suggests a lasting benefit of the skills enhanced through completion of the DA assignment. This result supports the concept that the completion of an active learning DA assignment improved overall student course performance beyond the direct benefit of students developing skills in the use and application of DA.

We believe our results have important implications for both accounting education and the audit profession. The results suggest that students should be exposed to DA in their educational process because, by using this active learning technique, they not only gain experience with DA but also have improved performance for what they have learned across all course content. This should appeal to the audit profession and its desire that students learn DA during their education process so they will be better prepared for the challenges of performing DA as they begin their careers.

While we believe our results are beneficial for both accounting education and the audit profession, we do recognize certain limitations. First, the students who completed the IDEA assignment (treatment group) did complete more work and gained an overall knowledge of DA through IDEA, while the students who did not complete the DA assignment (control group) did less work and obtained the knowledge of DA only through course lecture. Therefore, other factors, along with the use of a DA assignment, may contribute to improved overall student course performance. Second, while our study provides strong internal validity by being conducted at one university with one instructor, we encourage replication of our study at other universities and with other instructors in order to potentially confirm these results.

In addition to replication, a future study could explore how student performance over specific topics covered in the DA assignment (e.g., random sampling, ratio analysis, verifying assertions) improved with use of IDEA. Further, this study focuses on students using DA in a financial statement audit course. We believe that it should be extended through studies of students completing DA assignments in other courses (e.g., financial accounting, managerial accounting, accounting information systems, tax). Determining whether this method of active learning improves student learning in other courses can lead to changes in accounting curriculum course content that can help better prepare graduates for the changing environment in accounting and business.

REFERENCES

Accounting Education Change Commission (AECC). *Objectives of Education for Accountants: Position Statement No. One*. Sarasota, Fl. American Accounting Association (1990).

American Accounting Association (AAA). "Future Accounting Education: Preparing For the Expanding Profession. Issues in Accounting Education". *Issues in Accounting Education* 3 (1986): 168-195.

Anderson, R., Anderson, R., Davis, K. M., Linnell, N., Prince, C., and Razmov, V. (2007). Supporting Active Learning And Example Based Instruction With Classroom Technology. *ACM SIGCSE Bulletin, 39*(1), 69-73.

Appelbaum, D., Kogan, A., and Vasarhelyi, M. A. (2017). Big Data and Analytics in the Modern Audit Engagement: Research Needs. *Auditing: A Journal of Practice and Theory, 36*(4), 1-27.

Blankley, A. I., Kerr, D., and Wiggins, C. E. (2017). The State Of Accounting Education in Business Schools: An Examination and Analysis of Active Learning Techniques. *Advances in Accounting Education: Teaching and Curriculum Innovations, 21*, 101-124.

Blankley, A. I., Kerr, D. S., & Wiggins, C. E. (2018). An Examination And Analysis Of Technologies Employed By Accounting Educators. *The Accounting Educators' Journal, 28*, 75-98.

Bonwell, C. C., and Eison, J. A. (1991). *Active Learning: Creating Excitement in the Classroom.* The George Washington University, One Dupont Circle, Suite 630, Washington, DC 20036-1183: ERIC Clearinghouse on Higher Education.

Briggs, L. L. (2013). Closing the business analytics gap at UT Austin. *Business Intelligence Journal, 18*(4), 22-24.

Brown-Liburd, H., Issa, H., and Lombardi, D. (2015). Behavioral Implications of Big Data's Impact on Audit Judgment and Decision Making and Future Research Directions. *Accounting Horizons, 29*(2), 451-468.

Byrne, M., and Flood, B. (2008). Examining the Relationships among Background Variables and Academic Performance of First Year Accounting Students at an Irish University. *Journal of Accounting Education, 26*(4), 202-212.

Cao, M., Chychyla, R., and Stewart, T. (2015). Big Data Analytics in Financial Statement Audits. *Accounting Horizons, 29*(2), 423-429.

Carter, F. L., and Jones, R. C. (2011). Accounting for a Simulated Investment Portfolio: Active Learning Pedagogy in Intermediate Accounting. *Academy of Educational Leadership Journal, 15*(3), 105-118.

Chickering, A. W., and Gamson, Z. F. (1987). Seven principles for good practice in undergraduate education. *American Association for Higher Education Bulletin* (3), 3-7.

Chu, L., and Libby, T. (2010). Writing Mini-Cases: An Active Learning Assignment. *Issues in Accounting Education, 25*(2), 245-265.

Coffey, S. S. (2018, October 25). *The future of audit: Looking ahead in a time of rapid change.* Retrieved from accountingtoday: https://www.accountingtoday.com/opinion/the-future-of-audit-looking-ahead-in-a-time-of-rapid-change

Cottell, P. G., and Millis, B. J. (1993). Cooperative Learning Structures in the Instruction of Accounting. *Issues in Accounting Education, 8*(1), 40-59.

Diaz, M. C. (2016). Assembling the Opinion: An Active Learning Exercise for Audit Students. *Journal of Accounting Education*, *34*, 30-40.

Didia, D., and Hasnat, B. (1998). The Determinants of Performance in the University Introductory Finance Course. *Financial Practice and Education, 8*, 102-107.

Du, H. S., and Wagner, C. (2005). Learning with Weblogs: An Empirical Investigation. *Proceedings of the 38th Annual Hawaii International Conference on System Sciences* (pp. 7b-7b). IEEE.

Earley, C. E. (2015). Data Analytics in Auditing: Opportunities and Challenges. *Business Horizons*, *58*(5), 493-500.

Edmonds, C. T., and Edmonds, T. P. (2010). An Examination of the Links between SRS Technology and an Active Learning Environment in a Managerial Accounting Course. *Advances in Accounting Education, 11*, 81-100.

Eikner, E. A., and Montondon, L. (2001). Evidence on Factors Associated with Success in Intermediate Accounting I. *Accounting Educator's Journal, 13,* 1-17.

Elias, T. (2011). Learning Analytics: Definitions, Processes and Potential. *Learning,* 1-22.

Ennis, C. D. (1985). Purpose Concepts in an Existing Physical Education Curriculum. *Research Quarterly for Exercise and Sport*, *56*(4), 323-333.

Ernst and Young Global Limited (EY). 2014. Ready for Takeoff? Overcoming the Practical and Legal Difficulties in Identifying and Realizing the Value of Data. London, U.K.: EY. Available at: http://www.ey.com/Publication/vwLUAssets/EY_-_Ready_for_takeoff/$FILE/EY-Ready-for-takeoff.pdf

EY Reporting. (2015, April 1). How big data and analytics are transforming the audit. London, England. Retrieved from https://www.ey.com/en_us/assurance/how-big-data-and-analytics-are-transforming-the-audit

Frakes, A. H. (1977). Introductory Accounting Objectives and Intermediate Accounting Performance. *The Accounting Review, 52*(1), 200-211.

Frederickson, J. R., and Pratt, J. (1995). A Model of the Accounting Education Process. *Issues in Accounting Education, 10*(2), 229.

Freeman, M. S. (2018). The Cpa Exam Is Changing: Are Professors Ready? *The Accounting Educators; Journal*, *28*, 1-32.

Gainor, M., Bline, D., and Zheng, X. (2014). Teaching Internal Control through Active Learning. *Journal of Accounting Education*, *32*(2), 200-221.

Gartner. (2013). IT glossary: Big data. Retrieved December 1, 2014, from http://www.gartner.com/it-glossary/big-data

Hermanson, D. R. (1994). The Effect of Self-Generated Elaboration on Students' Recall of Tax and Accounting Material: Further Evidence. *Issues in Accounting Education, 9*(2), 301-318.

Katz, D. M. (2014, April 15). Regulators fear big data threatens audit quality. CFO.com. Retrieved October 30, 2014, from http://ww2.cfo.com/auditing/2014/04/regulators-fear-big data-threatens-audit-quality/

KPMG. 2012. Leveraging Data Analytics and Continuous Auditing Processes for Improved Audit Planning, Effectiveness, and Efficiency. Available at: http://www.kpmg.com/US/en/IssuesAndInsights/ArticlesPublications/Documents/data-analytics-continuous-auditing.pdf

KPMG. (2014). Going Beyond the Data: Achieving Actionable Insights with Data and Analytics. Amstelveen, Netherlands: KPMG International Cooperative.

Liddy, J. P. (2014, August 4). The future of audit. Forbes. Retrieved October 30, 2014, from http://www.forbes.com/sites/realspin/2014/08/04/the-future-of-audit/

Lux, D. F. (2000). Accounting Educators' Concerns about the AECC Position and Issues Statements. *Journal of Education for Business, 76*(1), 24-27.

Matherly, M., and Burney, L. L. (2013). Active Learning Activities to Revitalize Managerial Accounting Principles. *Issues in Accounting Education, 28*(3), 653-680.

Monem, R. M. (2007). Does Access To Tutorial Solutions Enhance Student Performance? Evidence from an Accounting Course. *Accounting and Finance, 47*(1), 123-142.

Monsanto, J. L., Cardoso, S. M., and Joyce, J. (2004). Skills Development, Motivation and Learning in Financial Statement Analysis: An Evaluation of Alternative Types of Case Studies. *Accounting Education, 13*(2), 191-212.

Morris, M., Burnett, R. D., Skousen, C., and Author, O. (2015). Accounting Education and Reform: A Focus on Pedagogical Intervention and Its Long-Term Effects. *The Accounting Educators' Journal, 25*, 67-93.

Pelzer, J. R., & DeLaurell, R. M. (2018). Implementation Of AACSB Standard A7: A Strategy For Limited Resources. *The Accounting Educators' Joournal, 28*, 117-138.

Prensky, M. (2001). Digital natives, digital immigrants part 1. *On the horizon, 9*(5), 1-6.

Prince, M. (2004). Does Active Learning Work? A Review of the Research. *Journal of Engineering Education, 93*(3), 223-231.

PwC. (2015, February). Data Driven: What Students Need To Succeed In A Rapidly Changing Business World? London: PricewaterhouseCoopers LLC.

Roehl, A., Reddy, S. L., and Shannon, G. J. (2013). The Flipped Classroom: An Opportunity to Engage Millennial Students through Active Learning Strategies. *Journal of Family and Consumer Sciences, 105*(2), 44-49.

Setty, K., and Bakhshi, R. (2013). What Is Big Data And What Does It Have To Do With IT Audit. *ISACA Journal, 3*, 23-25.

Springer, C. W., and Borthick, A. F. (2007). Improving Performance in Accounting: Evidence for Insisting On Cognitive Conflict Tasks. *Issues in Accounting Education, 22*(1), 1-19.

Titera, W. R. (2013). Updating Audit Standard—Enabling Audit Data Analysis. *Journal of Information Systems, 27*(1), 325-331.

Togo, D. F., and McNamee, A. H. (1995). Computer Integration into the Accounting Curriculum: Learning Benefits, Problems, and Guidelines. *Journal of Accounting Education, 13*(2), 149-158.

Turner, J. L., Holmes, S. A., and Wiggins, C. E. (1997). Factors Associated With Grades In Intermediate Accounting. *Journal of Accounting Education, 15*(2), 269-288.

Wang, T., and Cuthbertson, R. (2015). Eight Issues On Audit Data Analytics We Would Like Researched. *Journal of Information Systems, 29*(1), 155-162.

Warren Jr, D. J., Moffitt, K. C., and Byrnes, P. (2015). How Big Data Will Change Accounting. *Accounting Horizons, 29*(2), 397-407.

Weidenmier, M. L., & Herron, T. L. (2004). Selecting an Audit Software Package for Classroom Use. *Journal of Information Systems, 18*(1), 95-110.

Whittington, O. R., & Pany, K. (2019). *Principles of Auditing & Other Assurance Services 21st edition.* New York: McGraw-Hill Education.

Yoder, J. D., and Hochevar, C. M. (2005). Encouraging Active Learning Can Improve Students' Performance On Examinations. *Teaching of Psychology, 32*(2), 91-95.

Figure 1: Exam Measurements and IDEA Intervention

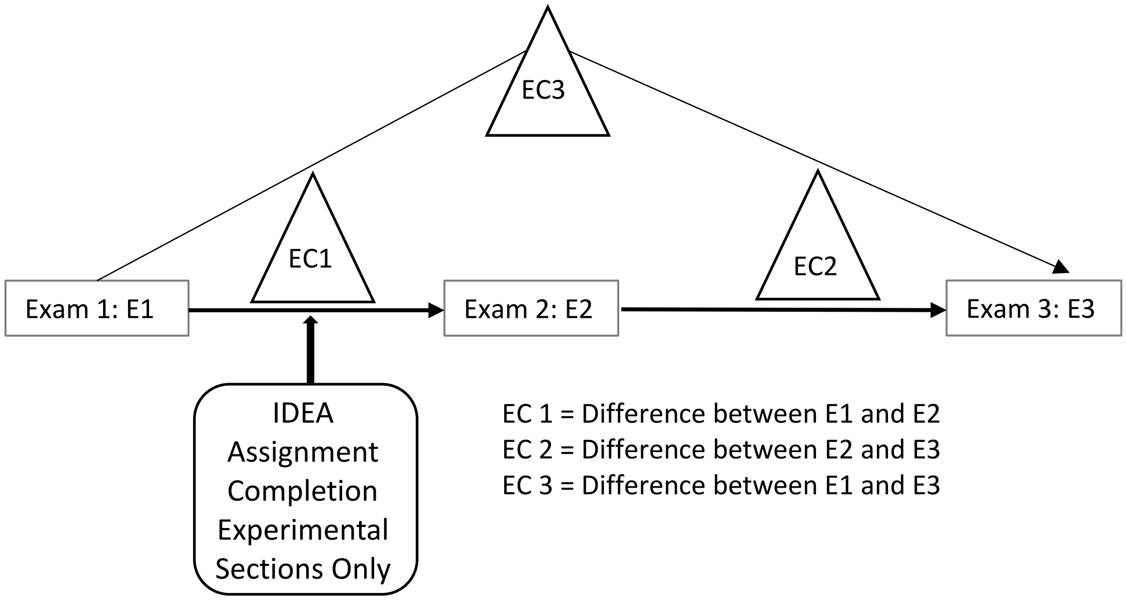

Table 1
Descriptive Statistics

Variable	N	Mean	Std Dev	Minimum	Maximum
Panel A: Full Sample					
E1	154	77.9253	11.5503	52.0000	100.0000
E2	154	74.5551	10.9500	25.0000	97.0000
E3	154	75.0876	13.3804	24.0000	98.5000
EC1	154	-3.3701	12.5095	-40.0000	33.5000
EC2	154	0.5324	10.5301	-43.0000	27.0000
EC3	154	-2.8376	12.4674	-37.0000	33.0000
GPA	154	3.2058	0.4522	2.2393	4.0000
AGE	154	25.1623	6.3744	19.0000	55.0000
LOAD	154	12.1233	3.1917	3.0000	19.0000
GENDER	154	0.5974	0.4920	0.0000	1.0000
RACE	154	0.5324	0.5005	0.0000	1.0000
IDEA	154	0.3961	0.4906	0.0000	1.0000
Panel B: Control Group					
E1	93	79.9139	11.4214	54.0000	100.0000
E2	93	70.7419	10.2849	25.0000	88.0000
E3	93	71.6666	13.7858	24.0000	96.0000
EC1	93	-9.1720	9.7407	-40.0000	21.0000
EC2	93	0.9247	11.5835	-43.0000	27.0000
EC3	93	-8.2473	10.3699	-37.0000	22.0000
GPA	93	3.2009	0.4661	2.2393	4.0000
AGE	93	25.1505	5.8420	19.0000	44.0000
LOAD	93	12.1612	2.9351	6.0000	19.0000
GENDER	93	0.6236	0.4870	0.0000	1.0000
RACE	93	0.5376	0.5012	0.0000	1.0000
Panel C: Test Group					
E1	61	74.8934	11.1669	52.0000	99.5000
E2	61	80.3688	9.3090	53.0000	97.0000
E3	61	80.3032	10.9240	43.5000	98.5000
EC1	61	5.4754	11.0379	-24.5000	33.5000
EC2	61	-0.0655	8.7414	-17.5000	26.0000
EC3	61	5.4098	10.8149	-17.5000	33.0000
GPA	61	3.2134	0.4340	2.2900	4.0000
AGE	61	25.1803	7.1612	19.0000	55.0000
LOAD	61	12.0655	3.5724	3.0000	18.0000
GENDER	61	0.5573	0.5008	0.0000	1.0000
RACE	61	0.5245	0.5035	0.0000	1.0000

This table reports the descriptive statistics for the key study variables. E1 = The grade (percentage of correct answers) posted for Exam 1; E2 = The grade (percentage of correct answers) posted for Exam 2; E3 = The grade (percentage of correct answers) posted for Exam 3; EC1 = The difference in exam results posted between the second exam of the course and the first exam of the course; EC2 = The difference in exam results posted between the third exam of the course and the second exam of the course; EC3 = The difference in exam results posted between the third exam of the course and the first exam of the course; GPA = Cumulative grade point average at the start of the semester in which the audit course was taken (4.0 basis); AGE = Age of student; LOAD = Current semester course load; GENDER = Dichotomous variable equals 1 if student is a male and 0 otherwise; RACE = Dichotomous variable equals 1 if African American and 0 otherwise; IDEA = Dichotomous variable equal to 1 if student was exposed to analytics and 0 otherwise.

Table 2
Pearson Correlation Analysis
N= 154

	E1	E2	E3	EC1	EC2	EC3	GPA	AGE	LOAD	GENDER	RACE	IDEA
E1	1	0.38*	0.50*	-0.58*	0.24*	-0.38*	0.58*	0.06	-0.00	0.15	0.07	-0.21*
E2		1	0.64*	0.52*	-0.22*	0.33*	0.40*	0.17*	-0.13	0.11	0.12	0.43*
E3			1	0.09	0.60*	0.60*	0.47*	0.19*	-0.11	0.17*	0.13	0.31*
EC1				1	-0.42*	0.64*	-0.18*	0.08	-0.11	-0.04	0.04	0.57*
EC2					1	0.41*	0.18*	0.07	-0.01	0.09	0.03	-0.04
EC3						1	-0.02	0.15	-0.11	0.03	0.07	0.53*
GPA							1	-0.02	0.12	0.18*	0.11	0.01
AGE								1	-0.43*	0.18*	0.17*	0.00
LOAD									1	-0.01	-0.14*	-0.01
GENDER										1	0.00	-0.06
RACE											1	-0.01
IDEA												1

This table reports the correlation analysis for the key study variables. E1 = The grade (percentage of correct answers) posted for Exam 1; E2 = The grade (percentage of correct answers) posted for Exam 2; E3 = The grade (percentage of correct answers) posted for Exam 3; EC1 = The difference in exam results posted between the second exam of the course and the first exam of the course; EC2 = The difference in exam results posted between the third exam of the course and the second exam of the course; EC3 = The difference in exam results posted between the third exam of the course and the first exam of the course; GPA = Cumulative grade point average at the start of the semester in which the audit course was taken (4.0 basis); AGE = Age of student; LOAD = Current semester course load; GENDER = Dichotomous variable equals 1 if student is a male and 0 otherwise; RACE = Dichotomous variable equals 1 if African American and 0 otherwise; IDEA = Dichotomous variable equal to 1 if student was exposed to analytics and 0 otherwise.

Table 3
Within T-Test
Single Test Performance

E2	E1	t-stat on diff	E3	E2	t-stat on diff	E3	E1	t-stat on diff
Panel A: Test Group Performance (N=61)								
80.36 (1.19)	74.89 (1.41)	5.47**						
			80.30 (1.39)	80.36 (1.19)	-0.06			
						80.30 (1.39)	74.89 (1.42)	5.40**
Panel B: Control Group Performance (N=93)								
70.74 (1.06)	79.91 (1.18)	-9.17***						
			71.67 (1.42)	70.74 (1.06)	0.92			
						71.67 (1.42)	79.91 (1.18)	-8.24***

This table reports the difference in exam performance within the same group. . *, **, and *** denote statistical significance at the 0.1, 0.05 and 0.01 levels. E1 = the grade (percentage of correct answers) posted for Exam 1; E2 = the grade (percentage of correct answers) posted for Exam 2; E3 = the grade (percentage of correct answers) posted for Exam 3.

Table 4
Between T-Test
Single Test Performance

Analysis 1		Analysis 2		Analysis 3		T-Test Results		
Control EC1	Test EC1	Control EC2	Test EC2	Control EC3	Test EC3	t-stat EC1vsEC1	t-stat EC2vsEC2	t-stat EC3vsEC3
-9.17	5.48							
(1.01)	(1.41)					-14.64***		
		0.92	-0.07					
		(1.20)	(1.11)				0.99	
				-8.25	5.41			
				(1.07)	(1.38)			-13.66***

This table reports the difference in performance between groups. *, **, and *** denote statistical significance at the 0.1, 0.05 and 0.01 levels. E1 = The grade (percentage of correct answers) posted for Exam 1; E2 = The grade (percentage of correct answers) posted for Exam 2; E3 = The grade (percentage of correct answers) posted for Exam 3; EC1 = The difference in exam results posted between the second exam of the course and the first exam of the course; EC2 = The difference in exam results posted between the third exam of the course and the second exam of the course; EC3 = The difference in exam results posted between the third exam of the course and the first exam of the course.

Table 5
Ordinary Least Squares Regression Estimates of Model 1
Model: $EC3 = \alpha + \beta_1 E1 + \beta_2 E2 + \beta_3 GPA + \beta_4 AGE + \beta_5 LOAD + \beta_6 GENDER + \beta_7 RACE + \beta_8 IDEA + \epsilon$

Independent Variables	Model 1a	Model 1b
Intercept	-6.31	-4.71
	(8.50)	(8.16)
E1	-0.74	-0.60
	(0.08)***	(0.09)***
E2	0.57	0.38
	(0.08)***	(0.09)***
GPA	4.53	4.18
	(2.24)*	(2.15)
AGE	0.18	0.20
	(0.14)	(0.13)
LOAD	-0.12	-0.16
	(0.27)	(0.26)
GENDER	1.00	1.47
	(1.63)	(1.57)
RACE	0.45	0.80
	(1.59)	(1.52)
IDEA		7.03
		(1.90)***
N	154	154
Adjusted R-Squares	0.42	0.46

This table reports the results of regressing the change in performance over the duration of the course on a vector of independent variables and the variable of interest. Standard errors are in parenthesis. *, **, and *** denote statistical significance at the 0.1, 0.05 and 0.01 levels for a two tailed test. E1 = The grade (percentage of correct answers) posted for Exam 1; E2 = The grade (percentage of correct answers) posted for Exam 2; E3 = The grade (percentage of correct answers) posted for Exam 3; EC1 = The difference in exam results posted between the second exam of the course and the first exam of the course; EC2 = The difference in exam results posted between the third exam of the course and the second exam of the course; EC3 = The difference in exam results posted between the third exam of the course and the first exam of the course; GPA = Cumulative grade point average at the start of the semester in which the audit course was taken (4.0 basis); AGE = Age of student; LOAD = Current semester course load; GENDER = Dichotomous variable equals 1 if student is a male and 0 otherwise; RACE = Dichotomous variable equals 1 if African American and 0 otherwise; IDEA = Dichotomous variable equal to 1 if student was exposed to analytics and 0 otherwise.

Table 6
Ordinary Least Squares Regression Estimates of Models 1
Model 2: $EC1 = \alpha + \beta_1 E1 + \beta_2 GPA + \beta_3 AGE + \beta_4 LOAD + \beta_5 GENDER + \beta_6 RACE + \beta_7 IDEA + \epsilon$

Independent Variables	Model 2a	Model 2b
Intercept	-37.97	28.31
	(8.25)***	(7.02)
E1	-0.82	-0.65
	(0.08)***	(0.07)***
GPA	7.50	4.74
	(2.18)**	(1.86)**
AGE	0.17	0.16
	(0.14)	(0.11)
LOAD	-0.37	-0.33
	(0.28)	(0.23)
GENDER	0.14	0.81
	(1.66)	(1.39)
RACE	-0.93	-0.40
	(0.66)	(0.55)
IDEA		11.20
		(1.40)***
N	154	154
Adjusted R-Squares	0.40	0.58

This table reports the results of regressing the change in performance over the duration of the course on a vector of independent variables and the variable of interest. Standard errors are in parenthesis. *, **, and *** denote statistical significance at the 0.1, 0.05 and 0.01 levels for a two tailed test. E1 = The grade (percentage of correct answers) posted for Exam 1; E2 = The grade (percentage of correct answers) posted for Exam 2; E3 = The grade (percentage of correct answers) posted for Exam 3; EC1 = The difference in exam results posted between the second exam of the course and the first exam of the course; EC2 = The difference in exam results posted between the third exam of the course and the second exam of the course; EC3 = The difference in exam results posted between the third exam of the course and the first exam of the course; GPA = Cumulative grade point average at the start of the semester in which the audit course was taken (4.0 basis); AGE = Age of student; LOAD = Current semester course load; GENDER = Dichotomous variable equals 1 if student is a male and 0 otherwise; RACE = Dichotomous variable equals 1 if African American and 0 otherwise; IDEA = Dichotomous variable equal to 1 if student was exposed to analytics and 0 otherwise.

Appendix 1
Variable Definitions

Variable	**Definition**
EC3	The difference in exam results posted between the third exam of the course and the first exam of the course
EC1	The difference in exam results posted between the second exam of the course and the first exam of the course
EC2	The difference in exam results posted between the third exam of the course and the second exam of the course
E3	The grade (percentage of correct answers) posted for exam 3
E1	The grade (percentage of correct answers) posted for exam 1
E2	The grade (percentage of correct answers) posted for exam 2
GPA	Cumulative grade point average at the start of the semester in which the audit course was taken (4.0 basis)
AGE	Age of student
LOAD	Current semester course load
GENDER	Dichotomous variable equal to 1 if student is male and 0 otherwise
RACE	Dichotomous variable equal to 1 African American and 0 otherwise
IDEA	Dichotomous variable equal to 1 if student was exposed to analytics and 0 otherwise
ε	Error term