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Abstract

This study leverages data from direct assessments of learning (AoL) to build a dynamic model of student performance in competency exams related to computer technology. The analysis reveals three key predictors that strongly influence student success: performance on a practice exam, whether or not a student engaged in practice testing beforehand, and prior completion of an introductory course in computer applications. These findings offer valuable insights for enhancing technology competencies in assessment contexts. The authors suggest that future research should explore a more efficient alternative—offering brief, targeted instruction paired with a practice exam—rather than the traditional requirement of a full three-hour course. This approach could streamline the learning process while maintaining or improving performance outcomes.

Predictors of Student Technology Competencies in Assurance of Learning Assessment

Today's students are often categorized as digital natives, having grown up in a world dominated by smartphones, social media, and instant access to information (Davis, 2024). This familiarity with modern digital tools might suggest a seamless transition to using business technologies such as Microsoft Office. However, this assumption overlooks a significant gap: while these students excel in managing social media platforms, their experience with Microsoft Office—an essential suite used by 85-90% of employers in the private and public sectors—may be limited. This gap arises from the extensive use of Google Workspace in K-12 education, where over 50 million students globally have been trained primarily on Google's tools (Craig, 2024). As a result, students entering business schools often lack proficiency in Microsoft Office, which is crucial for their future careers. Addressing this discrepancy is vital for business schools to ensure that their graduates are well-prepared for the technological demands of their professional environments. This study explores how one business school has approached this issue, examining its assurance of learning (AoL) strategies for business technology skills and identifying the factors that influence the success of these initiatives. By aligning with the guidelines set forth by the Association to Advance Collegiate Schools of Business International (AACSB), the study aims to provide insights into how business schools can better prepare their graduates for the technological demands of their future careers.

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In the AACSB-accredited business school used as the focus of this study, all Bachelor of Science (BS) degrees are guided by six student learning outcomes. These outcomes address

communication skills, ethics, business knowledge, critical thinking and technology. Students are required to use technology appropriately to communicate, calculate, and present concepts and data. This study describes our assessment of this learning outcome and the conclusions we have drawn from this comprehensive data.

Literature Review

The Association to Advance Collegiate Schools of Business International (AACSB) accreditation standards require "...well-documented assurance of learning (AoL) processes that include direct and indirect measures for ensuring the quality of all degree programs that are deemed in scope for accreditation purposes." (AACSB 2020, page 44).

AoL is crucial for AACSB accreditation as it ensures that business programs meet quality standards and educational objectives (Nachouki 2017, Murray et al, 2008, Abraham 2013). The AoL system fostered by AACSB plays a critical role in validating the quality of business courses. A detailed analysis of this AoL system revealed its systemic, efficient approach to student learning, providing a double-loop process for course management. This system is based on the institutional mission, learning objectives, and strategies established by course stakeholders (Moraes et al, 2018). AoL is a globally accepted standard among colleges and universities for three reasons: 1) it influences curriculum development, 2) it signals to external stakeholders that a program is meeting and monitoring its educational objectives 3) it uses integrated processes for continuous improvement of student learning outcomes (Lawson et al., 2015).

Historically, most AACSB accredited institutions employ either direct and/or indirect AoL measures (Pringle & Michel, 2007). Direct AoL measures require students to represent, produce or demonstrate their learning. Examples include: standardized testing, portfolios, capstone semester projects, graded case studies, oral or written exams. Indirect measures use information about students' perceptions about their learning experiences and attitudes towards the learning process. Examples include: student focus groups, alumni surveys, exit interviews, and evaluation of retention rates (Minton & Lenz, 2019). Previously optional, 2020 AACSB criteria require indirect measurements. This change is largely due to the fact that schools which report their curriculum changes are often driven by indirect measures reflecting input from industry stakeholders (Fagnot 2023).

Since much learning is delivered online the efficacy of digitally mediated learning must be assessed and measured. In a post-pandemic world where many business schools are expanding their reach via virtual delivery, new methodologies for AoL are now being developed (Fagnot 2023). Today as digital technologies are advancing, hybrid teaching frameworks where flexibility is highly valued by students are likely to be a growing area of research interest involving assessment methodologies (Tham et al, 2023). Several studies have compared face-to-face learning to virtual learning as well as blended learning in order to try to determine which results in the highest learning outcome, generates the most satisfied students or has the highest course completion rate. However, these studies often show that learning is swayed by more than teaching format alone. Among the manifold factors a few tend to have more effect, these include educator presence in virtual settings, interactions among students, teachers and content, and planned connections between online and offline activities (Nortvig, Petersen and Balle, 2018).

AoL relating to information systems (IS) is now of greater importance in a post-pandemic world and technological competency will likely become a learning goal of most business programs. Assessing student IS learning will become a task for many business programs (Zhou et al, 2022). Since AACSB accreditation standards mandate the AoL outcomes align with institutional missions and improve program quality, IS programs should assure that feedback from the AoL process along with input from internal and external sources are used to make curriculum adjustments (Emdad 2009). In this regard, Ducrot et al, (2008) proffer a structured framework for learning outcomes: the Learning Outcomes Management System (LOMS). It is used to integrate learning outcomes into both IS program-wide and IS course-specific curriculum development. The framework allows for ongoing monitoring and revision of the IS curriculum based on student performance and feedback.

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In addition to developing a predictive model of student performance using results from a computer skills exam, this research analyzes rich data on student behaviors (e.g. taking an optional practice exam) and background (completion of an intro IT course, GPA, etc.). Through stepwise regression and ANOVA, it identified three dominant predictors of technology competency success – performance on a practice test, completion of an introductory computer applications course, and prior practice exam participation. By quantifying which factors most strongly influence learning outcomes, this research fills a gap in AoL literature regarding what drives student achievement in tech competencies. This study offers a data-driven model that isolates key contributors to learning and deepens our understanding of how specific inputs affect AoL results. This approach of analytically mining AoL data for predictors is a framework that other programs can adopt to diagnose and enhance learning in their own AoL processes.

We propose an alternative instructional approach in response to our findings: brief, targeted training paired with a practice exam as a potentially more efficient alternative to a full three-credit course. This idea challenges the traditional curriculum design by asking if a shorter intervention could achieve similar competency levels, a question that had not been explored in earlier AoL research on skill development.

The Study

The data for this study are comprised of the results from an AoL effort at a midsouth university in the United States. The AoL effort was a direct measure for a college of business competency in technology to communicate, calculate, and present concepts and data. Students were required to take an online, hands-on exam over the Microsoft Office environment involving database development (Access), spreadsheet operations (Excel), presentation software (PowerPoint) and word processing (Word). The college deployed the Cengage online environment for the assessment exam and optional practice exam. The remaining data were developed from student records and were scrubbed of any identifying information.

The final data file contains observations on whether or not each student had taken the optional practice exam (*PractExam*, categorical) and if so, the percentage score achieved (*PE%*, ratio). Also, the file contains information on whether or not the student has taken an introductory three-hour microcomputer course (*CIS101*, categorical) focusing on Microsoft Office (*CIS101* is a disguised name for the course), the student's overall GPA (*OverallGPA*, ratio), students' GPA of any transferred hours (*TransferGPA*, ratio), overall college hours earned (*OverallHours*, ratio), hours transferred in (*HoursTrans*, ratio), year classification (senior, junior, etc., *Class*, categorical) and whether or not the student has a major in the College of Business (*COB*, categorical). Finally, the file contains each student's score on the assessment exam which is the dependent variable for the model. The cleaned data file contains results for 178 students.

We submitted the data to SPSS stepwise regression and the results are shown as *Model A* in Table 1. All nine variables enter the model that is statistically significant ($< .001$), with an R-square of .36. Three variables in the model are shown to be significant, *PE%* ($< .001$), *CIS101* (.005) and, *TransferGPA* (.019). No other variables come close to .05 significance with the exception of *HoursTrans* (.097). In examining the standardized coefficients, we see that *PE%* is largest (.510) followed by *CIS101* (.226) and finally *TransferGPA* (.177).

It is no surprise that a student's result on their practice exam is a good predictor of their results on the actual assessment exam. *PE%* bears this out as it is the most important variable in the model given its statistical significance and size of standardized coefficient. It is also a ratio variable and not in violation of the model assumption of normally distributed predictor variables. The ratio nature of *PE%* makes it richer in information than the categorical variable *PractExam* which is simply denoting whether or not a student took the exam. However, since all students do not have a score on the practice exam (*PE%*) and we are interested in the effect that taking the practice exam has on student performance, we explore *PractExam* more thoroughly.

We remove *PE%* and refit the model, the results are shown as *Model B* in Table 1. The new model is statistically significant ($< .001$) but the R-square drops to .25. The remaining eight variables enter the model with three of them being statistically significant, *PractExam* ($< .001$), *CIS101* (.004) and, *TransferGPA* (.050). *OverallGPA* comes close to the 90% confidence level but does not quite make it (.103). When we examine standardized coefficients, we see that these

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Table 1
Stepwise Multiple Regression Models

| Model | Model A | | Model B | | Model C | |
|--------------|---------------------------|--------------|---------------------------|--------------|---------------------------|--------------|
| | Standardized Coefficients | Significance | Standardized Coefficients | Significance | Standardized Coefficients | Significance |
| Constant | | .001 | | .001 | | .008 |
| PE% | .510 | < .001 | N/A | N/A | .512 | < .001 |
| PractExam | -.094 | .321 | .288 | < .001 | -.097 | .308 |
| CIS101 | .226 | .005 | .253 | .004 | .231 | .004 |
| OverallGPA | .110 | .147 | .133 | .103 | .155 | .029 |
| TransferGPA | .177 | .019 | .158 | .050 | N/A | N/A |
| OverallHours | .053 | .641 | .076 | .530 | .547 | .585 |
| HoursTrans | -.157 | .097 | -.113 | .266 | -.177 | .075 |
| Class | -.067 | .521 | -.096 | .395 | -.063 | .548 |
| COB | .042 | .542 | .084 | .255 | .038 | .580 |
| Transfer | N/A | N/A | N/A | N/A | .173 | .024 |

variables have similar patterns as the full nine variable model, *PractExam* has the largest standardized coefficient (.288) followed by *CIS101* (.253) and *TransferGPA* (.158). It is interesting that categorical variable *PractExam* is now arguably the most important variable in *Model B*, yet it was not even significant in *Model A* (.321).

CIS101 is a consistently significant predictor in both *Model A* and *B* and it merits further study for its effect on assessment outcomes. The last independent variable that is consistently significant is *TransferGPA*. We remove students that have not transferred hours from other institutions and refit the model ($N=145$, $\text{Sig} < .001$, $R\text{-Square} = .36$) interestingly *TransferGPA* is no longer a significant predictor (.724). Since non-takers are entered as zeros in the data file we feel that *TransferGPA*'s previous importance may be due to the regression process focusing on the zeros for students that did not transfer hours. We develop a new variable *Transfer*, a categorical predictor denoting whether or not a student has transferred hours from another institution. We remove *TransferGPA* and add *Transfer* then refit the model with all students; it is significant (<.001) and has an $R\text{-Squared}$ of .36, it is shown as *Model C* in Table 1. The new variable is significant (.024) with a standardized coefficient of .173. *OverallGPA* in *Model C* is also now significant (.029) with a standardized coefficient of .155.

Student performance on the assessment exam appears to be most influenced by the practice exam, the microcomputer course, whether or not the student transferred hours and potentially, a student's GPA. Since not every student in the sample took the practice exam (92 out of 178 did not take the practice exam) there is a lot of missing student data in *PE%*, however *PractExam* has data on every student and we choose to focus on it along with *CIS101* and *Transfer* for further analysis.

We run a Three-way ANOVA to check for interactions among the three variables in regard to their effect on assessment exam performance; the test is significant (.038) and results are shown in Table 2. In looking at the main effects we see that *Transfer* is not significant (.248) while *PractExam* (.003) and *CIS101* (<.001) are statistically significant. In trying to interpret the results of our Three-Way ANOVA, we choose to isolate any interaction between *PractExam* and *CIS101* across *Transfer* and run a Two-way ANOVA; our results are shown in Table 3. The new interaction between *PractExam* and *CIS101* appears to be dependent on a certain level of *Transfer*. There is no interaction when *Transfer* is equal to 0 (.279) yet when *Transfer* is at 1, there is a significant interaction (.041). We remove *Transfer* completely and run a Two-Way ANOVA with *PractExam* and *CIS101* and it shows no interaction (.295). Since *Transfer* is not significant as a main effect variable and it appears to be the culprit of the Three-Way interaction, we will focus our remaining analysis on *PractExam* and *CIS101*.

In order to understand how *PractExam* and *CIS101* might affect students of different scholastic achievement, we divide the students into groups based on whether or not their *OverallGPA* score is above or below 3.0. We then examine assessment exam scores based on whether or not these students took the practice exam (*PractExam* = 1) or did not take the practice exam (*PractExam* = 0). We display the results in Table 4; *Score* is the average assessment score for that group and *OverallGPA* is the mean for that variable in the group. We run separate

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Table 2
Stepwise Multiple Regression Models

| <i>Source</i> | <i>F - Statistic</i> | <i>Significance</i> |
|-----------------------------------|----------------------|---------------------|
| <i>Corrected Model</i> | 7.717 | <.001 |
| <i>Intercept</i> | 972.158 | <.001 |
| <i>PractExam</i> | 9.168 | .003 |
| <i>Transfer</i> | 1.343 | .248 |
| <i>CIS101</i> | 22.133 | <.001 |
| <i>PractExam* Transfer</i> | .001 | .974 |
| <i>PractExam*CIS101</i> | .016 | .900 |
| <i>Transfer*CIS101</i> | .582 | .447 |
| <i>PractExam* Transfer*CIS101</i> | 4.384 | .038 |

Table 3
Three-Way ANOVA

| <i>Source</i> | <i>F - Statistic</i> | <i>Significance</i> |
|-------------------------|----------------------|---------------------|
| Corrected Model | 3.316 | .034 |
| Intercept | 223.199 | <.001 |
| <i>PractExam</i> | 2.222 | .147 |
| <i>CIS101</i> | 7.403 | .011 |
| <i>PractExam*CIS101</i> | 1.220 | .279 |
| Corrected Model | 14.290 | <.001 |
| Intercept | 1635.393 | <.001 |
| <i>PractExam</i> | 14.648 | <.001 |
| <i>CIS101</i> | 24.298 | <.001 |
| <i>PractExam*CIS101</i> | 6.060 | .041 |

four group ANOVAs and find a significant difference among the groups on *Score* (<.001) and *OverallGPA* (<.001). Post hoc *Score* Tukey tests show significant differences between Group 1 and Group 2 (.008), Group 1 and Group 3 (.024) along with Group 1 and Group 4 (<.001). There were no other statistically significant differences in *Score* between the other groups. Post hoc Tukey tests on *OverallGPA* show significant differences between all groups, all at the <.001 level; with the exceptions of Group 1 and Group 2 (.201) as well as Group 3 and Group 4 (.966).

We also examine the effect of *CIS101* and display results in a similar fashion in Table 5. We again divide the students into groups based on whether or not their *OverallGPA* score is above or below 3.0. We then examine assessment exam scores based on whether or not a student took *CIS101*, then *CIS101* is coded as 1, otherwise 0. We run separate four group ANOVAs for *Score* and *OverallGPA* and both are significant at the <.001 level. Post hoc testing on *Score* reveals significant differences between Group 1 and Group 2 (.002) and Group 1 and Group 4 (<.001); no other significant differences between the groups are found. Tukey testing on *OverallGPA* shows significant differences between all groups except Group 3 and Group 4 (.540). Group 1 and Group 2 are found to be different at .032, with all other Group combinations different at the <.001 level.

Discussion of Results

To better understand what drives student performance on our technology assessment exam we built three different multiple regression models and focused on the explanatory aspects of these models rather than their predictive capabilities. The best predictor of a student's

Table 4
Analysis of *PractExam*

| Group 1 Above 3.0 <i>PractExam</i> = 1 | | Group 2 Above 3.0 <i>PractExam</i> = 0 | | Group 3 Below 3.0 <i>PractExam</i> = 1 | | Group 4 Below 3.0 <i>PractExam</i> = 0 | |
|--|------------|--|------------|--|------------|--|------------|
| Score | OverallGPA | Score | OverallGPA | Score | OverallGPA | Score | OverallGPA |
| 72.07 | 3.54 | 62.13 | 3.44 | 58.53 | 2.58 | 51.53 | 2.54 |
| N=57 | | N=62 | | N=29 | | N=30 | |

Table 5
Analysis of *CIS101*

| Group 1 Above 3.0 <i>CIS101</i> = 1 | | Group 2 Above 3.0 <i>CIS101</i> = 0 | | Group 3 Below 3.0 <i>CIS101</i> = 1 | | Group 4 Below 3.0 <i>CIS101</i> = 0 | |
|---|------------|---|------------|---|------------|---|------------|
| Score | OverallGPA | Score | OverallGPA | Score | OverallGPA | Score | OverallGPA |
| 71.51 | 3.54 | 58.04 | 3.40 | 61.67 | 2.63 | 52.24 | 2.53 |
| N=69 | | N=50 | | N=18 | | N=41 | |

score on the assessment exam was their score on the practice exam (*PE%*). However, in *Model B* we dropped that variable (*PE%*) since we did not have information on all students and found that a categorical variable involving the practice exam, *PractExam*, became very important in explaining student performance. In *Model C* we used a categorical variable, *Transfer*, in the place of *TransferGPA*, and it performed well and contained information on all students in the study. A third categorical variable *CIS101* always proved to be an important predictor of student scores across all models. By focusing our further study on the three best performing categorical variables, we could put our students in various groups to study the effects of the variables on student scores. Our Three-Way ANOVA testing and subsequent examination of main effects and two-way effects resulted in us removing *Transfer* due to its interaction with *PractExam* and *CIS101*.

Whether or not students took the practice exam has some interesting effects on their assessment scores. We see that students in Group 1, who have high GPAs and take the practice exam, clearly outperform all other groups of students. Their average score of 72.07 is higher than any other group's score and those differences are statistically significant. This result is not particularly surprising. However, when we examine Group 2 and Group 3, we see that students in Group 3, with significantly different and lower average GPAs (2.58) compared to Group 2 (3.44) score almost as well on the assessment exam to the point of no significant difference in the scores. It is also interesting to observe that although the difference in average GPAs for Groups 1 and 2 was not shown to be statistically significant, their respective scores on the assessment exam were. The results involving *PractExam* give evidence that the mere taking of the practice exam, a relatively inexpensive investment of time for a student could yield marked improvement in their assessment scoring. While other groups display some interesting trends, potential differences in performance do not have statistical significance, likely due to the smaller *N*s of the students below 3.0.

Whether or not a student took the introductory microcomputer course, *CIS101*, proves interesting in the study as well. High scholastic achieving students with above a 3.0 GPA that take *CIS101* appear to outperform all other groups, although the difference with Group 3 is not statistically significant, potentially due to Group 3's small *N*. Similar to the results of *PractExam*, when we compare Groups 2 and 3, we have significantly different GPAs of 3.40 and 2.63, respectively, yet there is no significant difference in scores. We can conclude that lower scholastically achieving students that take *CIS101* can perform as well as higher achieving students that do not take the course.

Conclusion

This study involves assurance of learning data regarding a business school's student competencies in technology. The results provide evidence that interventions may substantially affect final results and assist student technology achievement.

Lower scholastically achieving students that take CIS101 can perform as well as higher achieving students that do not take the course.

In today's digitally charged environment business faculty may wonder if a three-hour course in something as fundamental as Microsoft Office is still appropriate for student learning. Given the understandable "googlification" of K-12 education due to cost, (Craig 2024) and the gap this creates to the ubiquitous use of Microsoft Office tools in business, clearly one of the key strategies of the business school is to bridge this gap and ready graduates for professional careers. These results show that indeed, the requirement of a three-hour course in basic Microsoft Office skills is needed. Lower scholastically achieving students do benefit from taking such a course; our group of students with a 2.63 GPA that took the course performed at the same level as the group of students with a 3.40 GPA that did not take the course. Also, even higher scholastically achieving students will likely have better technology competencies from taking such a course; our group with a 3.40 GPA that did not take the course scored well below the group with a 3.54 GPA that did take the course.

The economics of merely taking a practice exam cannot go unnoticed. High achieving students that took the practice assessment exam outperformed all others which is not unexpected. However, lower scholastically achieving students that took the practice exam (Group 3) performed at the same level of other groups that did not take the exam, including Group 2 with a 3.44 GPA. However, statistically there is no difference between Group 3 and Group 4 on assessment scores so it remains to be seen how much the exam helps.

An important component of an assurance of learning or assessment process is "closing the loop" to improve student learning and that this improvement be measurable in assessment data. The results of this study offer some very low effort and potentially high impact learning interventions. Given that we found higher technology competency in students who had completed CS101, we noted that 54 percent of the students had not taken CS101. This was surprising as CS101 is a freshman level required core course in the business school and this technology skill assessment was conducted in a junior level core business course. Investigation revealed that CS101 was offered infrequently in our online program and that students were progressing in the curriculum without it. Quickly and simply corrected, more online sections of CS101 were added and advisors notified to stress prerequisites and appropriate progression through the curriculum.

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Other educational settings can benefit from these results as well. In STEM fields educators could apply the business AoL findings by incorporating optional practice tests to bolster student competencies. Research in engineering education shows that structured practice exam programs can improve student outcomes. For example, an engineering school that held guided practice exam sessions before each test saw participants achieve higher exam scores and reported more positive learning experiences than non-participants (Shew et al, 2019). These practice sessions function as brief, focused interventions – analogous to the optional practice exam in this study.

Many institutions are now integrating IS into humanities, having history and literature students learn text analysis software, GIS mapping, or media production tools as part of their coursework (e.g., University of North Carolina's Digital Humanities program). Direct AoL measures might include digital projects or portfolios, which require demonstrating competency with specific IS tools. To prepare students, brief targeted training sessions can be offered, much like this study's idea of a short module in lieu of a full course.

Rapid advances in AI mean that students across disciplines need to develop proficiencies that didn't even exist in curricula a few years ago. The AoL approach from the study of practice exams and targeted skill training can be directly applied to teaching these emerging technologies. For example, an instructor might create a brief tutorial on how to use a given AI platform, followed by a practice exercise where students must accomplish a task with it (such as training a simple machine learning model or prompting an AI to generate a desired output). This practice task serves as a formative assessment, revealing which students have grasped the tool and which may need more help. A subsequent performance-based AoL assessment of having students actually use the AI tool to solve a problem provides direct evidence of competency.

Despite the significant findings in this study, limitations exist that future assessments and research will address. While the overall sample size is robust (n=178), increasing the

number of assessments could result in larger sub-groups within the data. Furthermore, the assessment was implemented in a required core business course that does not specifically address technology within the curriculum. It is possible that changing the assessment venue will change student engagement and performance. Additionally, data on course modality, student program, and student demographics may provide insights, e.g. online/face-to-face course/program, traditional/non-traditional students. This assessment was implemented in multiple sections of one course within one university. Collaboration with another institution could provide greater generalizability.

In future assessments of our technology outcome, we will configure the exam to require the practice exam as these results support this as a tool to improve assessment scores. While the goal of learning intervention is to obviously improve learning, perhaps the practice exam provides practice in these concepts and does indeed improve learning as well as assessment scores. Further research includes repeating this assessment to understand the effect of offering CS101 more frequently and accessibly, advisor effectiveness, and slight modification of assessment methodology to require the practice exam.

As a model of assessment and learning, this study provides a description and a baseline for evaluating both the methodology of assessment implementation and student learning. The aim of this study is to describe our process of measuring student learning in an effective and efficient methodology consistent with assessment best practices to improve such methods as needed, make data-driven changes to both curriculum and support services and to complete the cycle with longitudinal data. Through this cycle of continuous improvement, the aim of future research and assessment is to understand the long term impact of curricular changes on student learning.

The AoL approach from the study of practice exams and targeted skill training can be directly applied to teaching these emerging technologies.

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