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Using an e-Learning Environment to Create a Baseline of Understanding of Digital Logic Knowledge

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Abstract

Our project involves the development of a novel web-based adaptive learning system to improve student mastery of digital logic concepts while considering the demographics of the individual student. Adaptive learning is a pedagogical approach that dynamically alters the difficulty of content based on an ongoing assessment of the student's capability. This technique is becoming more popular with the advancement of web-based learning solutions and increased student enrollment. Using this type of e-learning environment has the potential to address background deficiencies of students who lack the necessary prerequisite skills coming out of high school. In order to accurately assess the effectiveness of our instructional intervention, we have begun to collect detailed baseline data. The baseline data, and the data that will be collected later following the development of the adaptive learning system, are linked to course objectives and outcomes that have been developed specifically for this project. The advantage of such a detailed baseline data system is that we will be able to measure effectiveness of the instructional intervention on very specific chunks of course content. And, we will be able to attach intervention effectiveness to specific groups of students, using our demographic data (gender, grade point average, age, ethnicity, etc.). This paper will benefit those engineering educators who are developing course objectives and outcomes and designing assessment methods to measure progress toward those objectives and outcomes.

Introduction

Engineering program enrollments have been increasing steadily for nearly a decade, and instructors are investigating ways to maintain or even improve the quality of the student learning experience in this challenging environment. Adding to the complexity is the wide range of preparedness students have when beginning college. E-learning environments offer one way to supplement face-to-face instruction; designed properly, e-learning can be scalable and can personalize instruction to address background deficiencies. An adaptive e-learning system is an exciting pedagogical tool that can provide individual instruction to students by dynamically altering the difficulty of content based on an ongoing assessment of the students' capability.

In its simplest form, an adaptive learning system consists of a bank of online quiz questions on a particular subject, each with an associated difficulty level. As students answer questions, the difficulty of the next question either increases or decreases based on the students' response. In a more comprehensive form, additional targeted instruction can be provided if students answer questions incorrectly. Additionally, more thought-provoking material can be presented to students who consistently answer questions correctly, providing challenge to students when appropriate. Individualized, computer-based, adaptive learning has been shown to be nearly as effective as a live instructor guiding the student through the material when implemented carefully[1,2] . Most course management systems (i.e., Desire2Learn, Moodle, Blackboard) support question banks that are dynamically assigned based on difficulty and continual student assessment. Thus, the infrastructure to exploit adaptive learning systems for personalized instruction has greatly improved over the last decade.

One of the most promising aspects of personalized adaptive learning systems is that the material can be put into a broader context, and thus can illustrate the application of the material, which in turn has been shown to improve student understanding and increase interest in the subject. When students see how the material is relevant to their own lives, their motivation to study the material increases[3,4]. An adaptive learning system provides the opportunity to have a broad range of application-based examples that can be dynamically used depending on questions posed about student interests. Furthermore, the type of examples used can stress characteristics about the content not typically addressed by existing quiz banks. For example, highlighting how the material contributes to the overall public welfare of society, or how the field that uses this material serves others, can change the perception that a student might have about a discipline. This is especially important when trying to increase diversity in a field such as engineering as it has been shown that women and first-generation college students tend to choose careers that are more *other-oriented*[5], and engineering is commonly not perceived as such. Thus, adaptive learning has the potential to have a much broader impact on education and professional development than just technical training.

Motivation

In our work, we are developing a comprehensive, adaptive learning framework for digital logic content. Our unique contribution is that once the baseline system is created, we will augment it with learning content that provides applications of the material relevant to specific student demographics. One of the overarching goals of this work is to simultaneously increase the motivation of underrepresented minorities to persist in a STEM degree program. Increasing the number of STEM degrees has become a national priority over the past decade. Numerous reports by agencies such as the National Academy of Engineering[6] and The National Science Board[7] highlight how the U.S. is being outpaced in the production of engineering degrees relative to emerging countries. Part of the issue is retention. Indeed, only 60% of all students in the U.S. entering an engineering degree program are able to achieve graduation in 6 years[8]; at our university, only 52% of engineering students graduate in 6 years[9]. Furthermore, not all students are equally likely to pursue or persist in engineering. For example, in 2011, 83,000 engineering bachelor's degrees were awarded in the U.S.; however, only 18.4% of these degrees were awarded to women[10]. At our institution, only 14.2% of engineering degrees are awarded to women[9]. Broadening the participation of all students, especially women, will have a positive impact on the number of engineering degrees being produced in the U.S.

Project First Steps and the Focus of This Paper

During 2015, our team has developed all of the baseline (i.e., traditional) content for both courses covered in this work, a sophomore-level course and an upper-division course, both of which focus on digital logic content. The sophomore-level course is taken by electrical engineering, computer engineering, and computer science students; the upper-division course is taken by electrical engineering and computer engineering students. The sophomore course is taught every semester, with around 70 students enrolling in the fall and 50 in the spring. The upper-division course is taught only in the spring, and enrollment is around 50 students.

The new content includes a textbook, associated lecture videos, new learning objectives and outcomes, and over 600 quiz questions. During the summer and fall semesters of 2015, the material was used to collect a baseline of student performance across all of the learning outcomes being measured. In 2016, the material delivery will be changed to an adaptive learning format and outcome data will be collected. This will measure how effective the adaptive learning format is in improving mastery of the topics. In 2017, demographic-specific examples will be integrated into the system.

This paper focuses on the development of the new learning objectives and outcomes and how they are assessed across specific demographic groups in the lower-level course. We give baseline data for a selected group of learning outcomes. Data are only collected on students who sign a voluntary consent form that allows their demographic information to be pulled from university records and analyzed in concert with their performance on the learning modules. All data are coded for anonymity.

New Course Learning Objectives and Outcomes

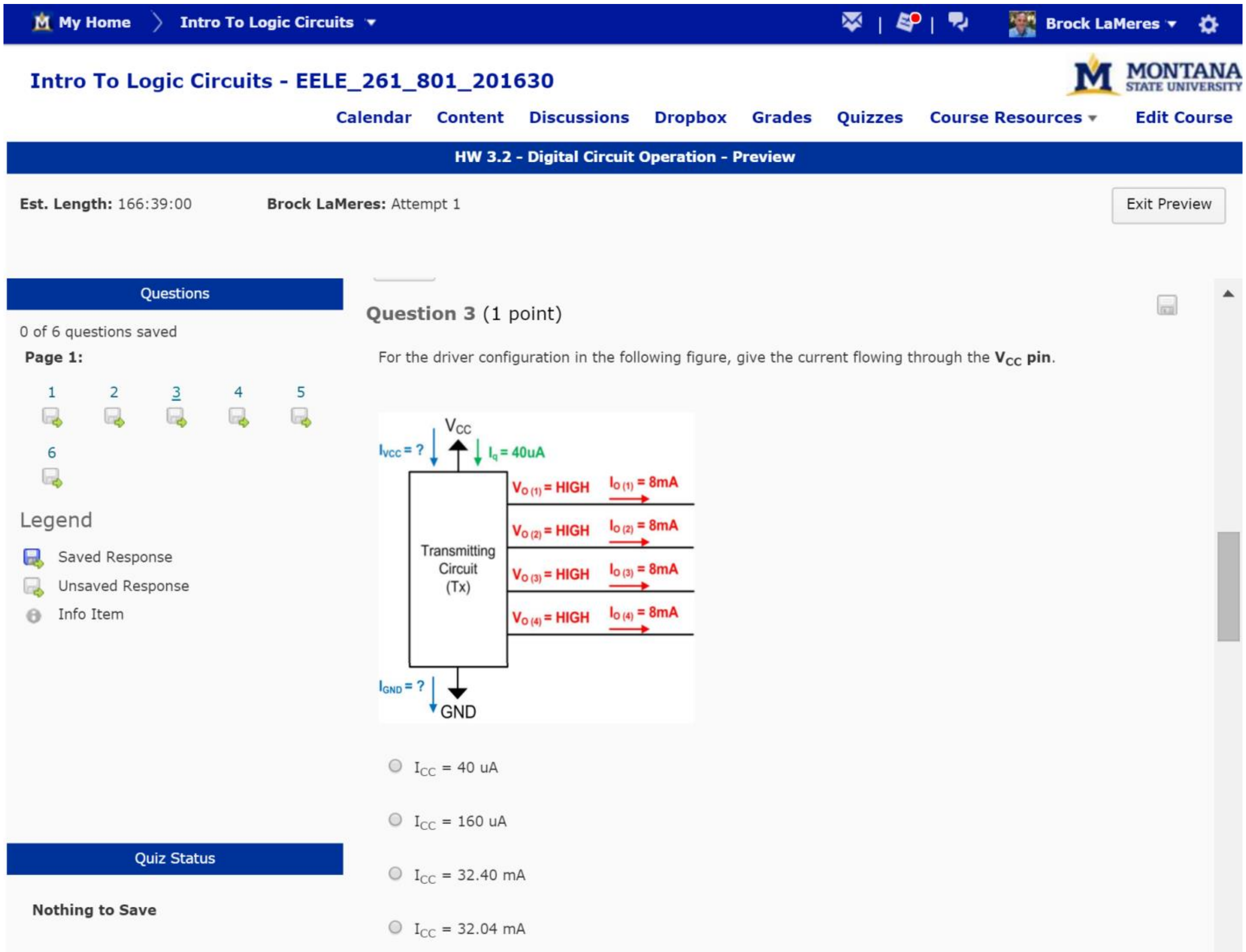
Developing new course learning objectives and outcomes was not projected to be an aspect of this project; however, while writing the new textbook associated with the course and developing the quiz questions, we discovered that the quiz questions were not always aligned with the stated learning outcomes. Thus, new objectives and outcomes were developed, and they were directly linked to quiz questions and grouped into course "modules," which could be assessed via the homework and quizzes. Below is an example of one course module with the accompanying objectives, outcomes, and a sample quiz question.

Learning Objective for Module 3: Understand the basic operation of combinational logic circuits.

Learning Outcomes for Module 3:

- Describe the functional operation of a basic logic gate using truth tables, logic expressions, and logic waveforms.
- Describe the DC and AC operation of a digital circuit.
- Describe the meaning of a logic family and the operation of the most common technologies used (CMOS, TTL).
- Determine the operation conditions of a logic circuit when driving various types of loads.

An example of a Quiz question associated with Module 3 is on the next page.



Data Analysis and Assessment of Student Learning

For our baseline data from Fall 2015, we were interested in student performance on all learning outcomes and modules. We had the following demographic data about each student enrolled in the sophomore-level digital logic course:

- Gender
- Ethnicity
- Age
- Major
- Whether the student started his/her college career at our institution or at another school
- Number of transfer credits
- Number of credits completed at our institution
- Grade Point Average from credits completed at our institution
- SAT and ACT scores (for students who started at our institution only)

Out of 55 students who signed the informed consent forms, only 3 were female, and 7 were non-Caucasian, so we could not use these groupings in tests of statistical significance. However, we did compare quiz and module averages for gender and ethnicity. For Module 3 overall, which included both the related homework and the module quiz, the female student average was higher than the male average (91 vs. 80); there was little standard deviation among the female scores. The female students also out-performed the male students on the Module 3 quiz: 96 average score vs. 83.

In regard to the comparison between the Caucasian (n=48) and non-Caucasian students (n=7), the former had a higher average score on the quiz for Module 3: 84 vs. 79, as well as a higher average score on Module 3 as a whole: 81 vs. 79. In both comparisons, the standard deviation was higher for the non-Caucasian students.

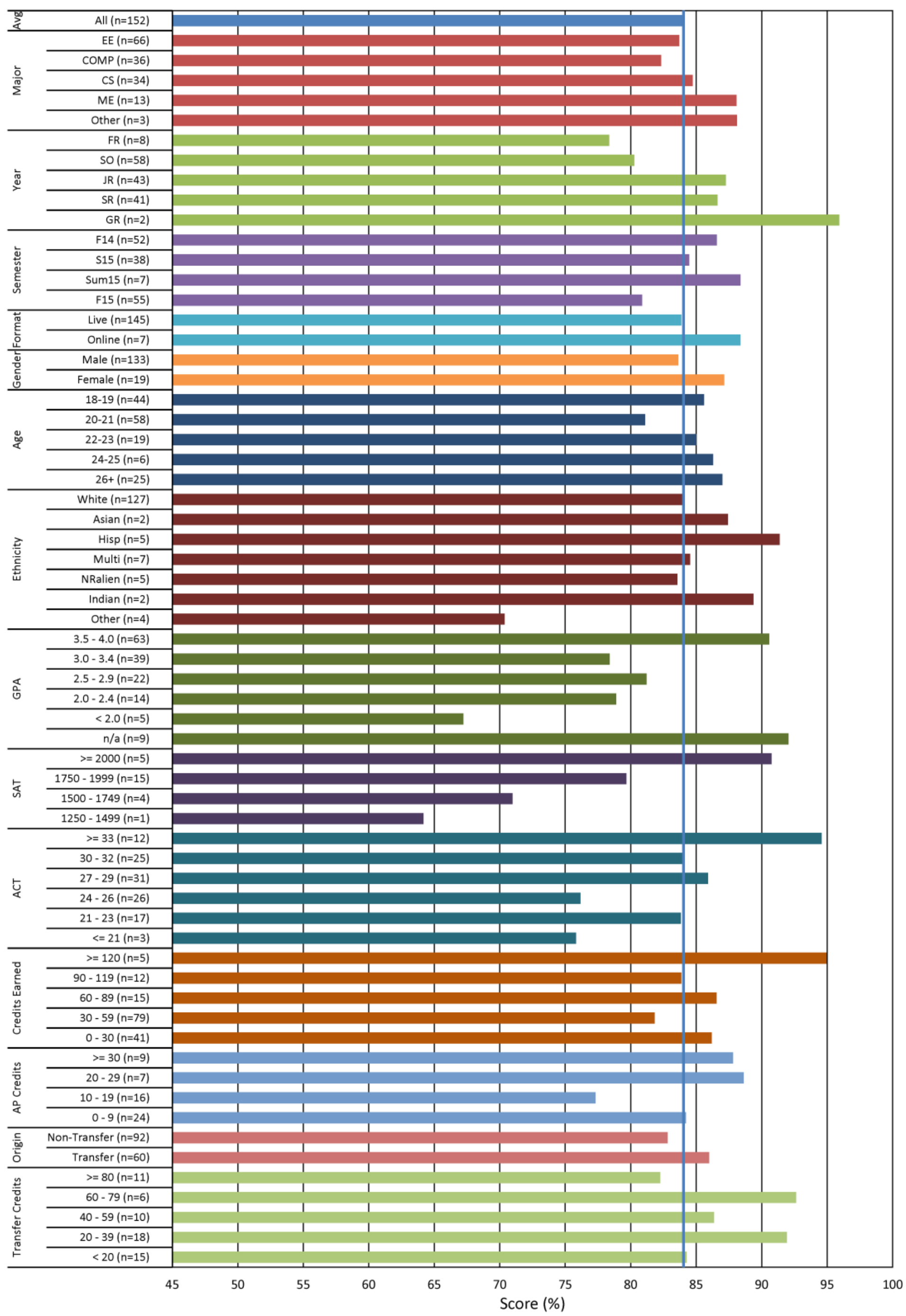
No differences were found for any of the seven modules when major was used as the grouping variable. In addition, an analysis of the Pearson correlation of the performance on the modules and the age variable showed no significant results.

We expected that student grade point average at our institution would be correlated with performance on the course outcomes. For Module 3, that correlation was, indeed, a positive correlation, but it was not significant. A Pearson correlation of ACT and SAT scores with Module 3 overall scores showed an insignificant positive correlation, with the SAT correlation showing more strength. The correlation was stronger for Quiz 3 by itself: Pearson correlation between the SAT and Quiz 3 was .357 (p = .087).

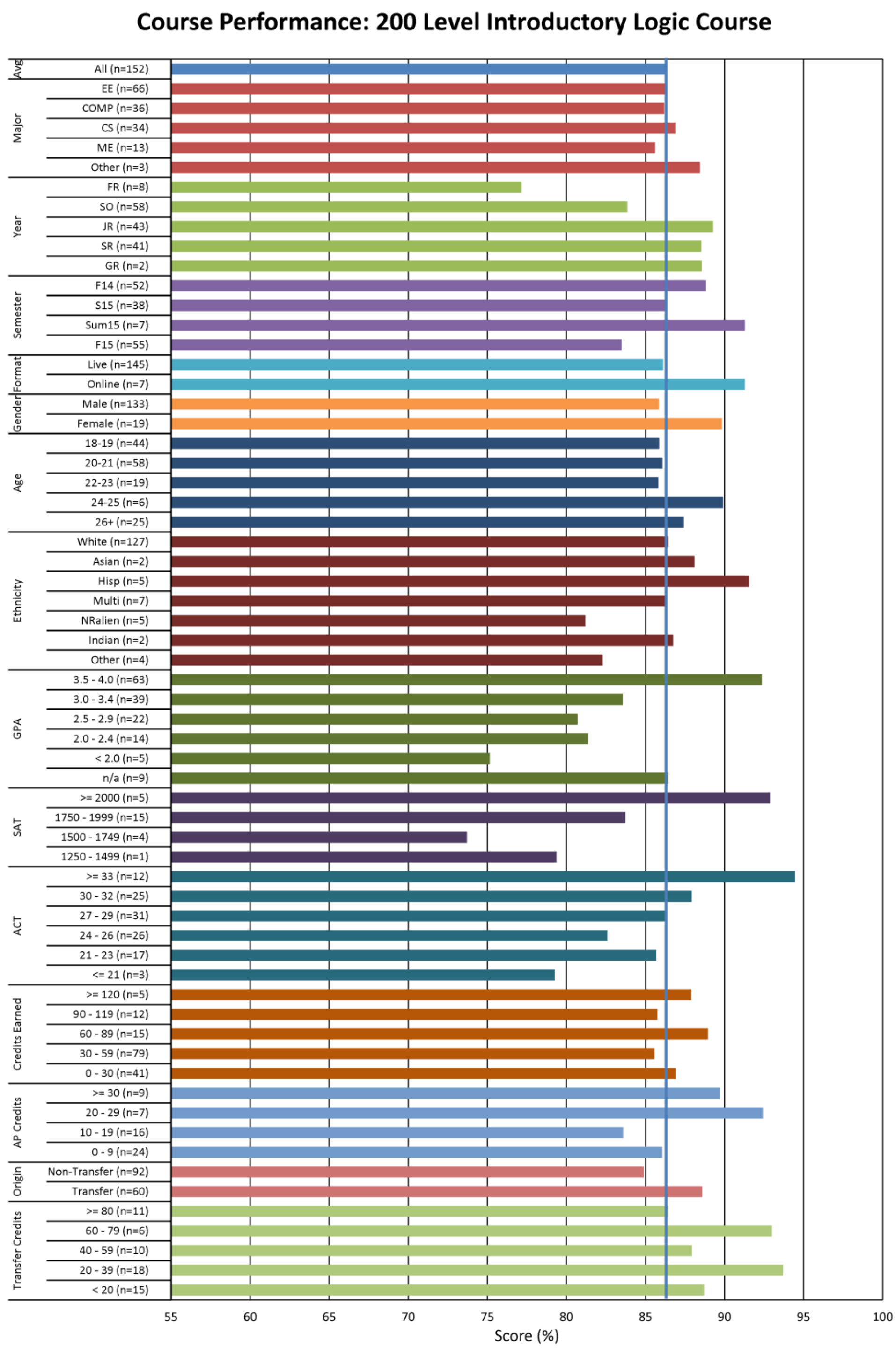
The largest differences in student performance surfaced in the variable regarding whether the student was a non-transfer student or a transfer student. In the Fall 2015 semester, 37 of our sample were non-transfer students and 18 were transfer students. The latter group consistently performed better on all modules, and that difference was significant when compared via an Analysis of Variance on the quiz for Module 3 (p = .035). The standard deviation for the non-transfer group was quite a bit higher (26.60) than for the transfer group (8.64). The average on the quiz for the non-transfer students was 79.28, and the average for the transfer students 93.21. The comparison of the two groups on the module as a whole (quiz plus homework) was not significant (p = .104).

The plot on the following page shows the comparison of student performance on Module 3 in the sophomore-level course for all of our variables for all semesters for which we have student data (Fall 2014 through Fall 2015). Across all semesters, 152 students signed consent forms. These data include performance on Module 3 both before and after the learning outcomes revised to more closely align to the homework and quiz questions; therefore, we did not do any of the statistical analyses on these combined data from several semesters. When we have data from spring 2016, we will be able to combine Summer 2015, Fall 2015, and Spring 2016 data for a baseline across semesters with the new learning outcomes. The two plots on the next two pages (one for Module 3 and one for course performance overall) are provided as an example of how future data will be displayed.

Performance on Learning Objective "M3: Digital Circuits"



The plot on the following page shows the comparison of student performance across all semesters in the course as a whole for all of our variables.


Course Performance: 200 Level Introductory Logic Course
Avg
All (n=152)
Major
EE (n=66)
COMP (n=36)
CS (n=34)
ME (n=13)
Other (n=3)
Year
FR (n=8)
SO (n=58)
JR (n=43)
SR (n=41)
GR (n=2)
Semester
F14 (n=52)
S15 (n=38)
Sum15 (n=7)
F15 (n=55)
Format
Live (n=145)
Online (n=7)
Gender
Male (n=133)
Female (n=19)
Age
18-19 (n=44)
20-21 (n=58)
22-23 (n=19)
24-25 (n=6)
26+ (n=25)
Ethnicity
White (n=127)
Asian (n=2)
Hisp (n=5)
Multi (n=7)
NRalien (n=5)
Indian (n=2)
Other (n=4)
GPA
3.5 - 4.0 (n=63)
3.0 - 3.4 (n=39)
2.5 - 2.9 (n=22)
2.0 - 2.4 (n=14)
< 2.0 (n=5)
n/a (n=9)
SAT
>= 2000 (n=5)
1750 - 1999 (n=15)
1500 - 1749 (n=4)
1250 - 1499 (n=1)
ACT
>= 33 (n=12)
30 - 32 (n=25)
27 - 29 (n=31)
24 - 26 (n=26)
21 - 23 (n=17)
<= 21 (n=3)
Credits Earned
>= 120 (n=5)
90 - 119 (n=12)
60 - 89 (n=15)
30 - 59 (n=79)
0 - 30 (n=41)
AP Credits
>= 30 (n=9)
20 - 29 (n=7)
10 - 19 (n=16)
0 - 9 (n=24)
Origin
Non-Transfer (n=92)
Transfer (n=60)
Transfer Credits
>= 80 (n=11)
60 - 79 (n=6)
40 - 59 (n=10)
20 - 39 (n=18)
< 20 (n=15)
55
60
65
70
75
80
85
90
95
100
Score (%)

Discussion of Results

One of the major goals of this project is to determine whether adaptive learning modules can positively affect various demographic groups. The small numbers of female and under-represented minority students in the course Fall 2015 hampered our ability to determine if there were any significant statistical differences; however, we were able to compare actual performance of the women students vs. the men students, and this comparison showed that the women students out-performed the men students on most of the assessment measures. The three women students showed little variation in their scores. This result is not surprising, in that women students who enter electrical engineering, computer engineering, and computer science disciplines tend to be high-achieving students. If adaptive learning modules affect the male students in a positive way, bringing their performance up to the level of the female students, that would be a positive result. Although the numbers of non-white students did not allow statistical comparisons, it is clear, at least in the case of Module 3, that we have an opportunity to improve the performance of those students with the adaptive learning modules.

We expected a difference in regard to major for some of the course content, with computer science students performing at a higher level on some content and electrical/computer engineering students performing at a higher level on other course content. The Fall 2015 student group did not show any differences in regard to performance of the different major groups. This result will be monitored in future semesters, particularly Spring 2016 semester (before the adaptive learning modules are developed), as it would be relatively easy to tailor adaptive learning module content to match students in the various majors.

The fact that transfer students outperform students who begin college at our institution is somewhat surprising, and we will track that result in future semesters to see if it is consistent. If we knew more about the preparation of transfer students at their specific community colleges, it might be possible to take that preparation into account when designing adaptive learning modules for our non-transfer students; however, research into the experience of transfer students prior to their entrance into our institution is beyond the scope of our work.

Conclusion

Our project is in its early stages; however, the foundational work we have done so far has been crucial to understanding the effect of our future instructional intervention (the adaptive learning modules) on different groups of students in the two digital logic courses. Developing the new learning objectives and outcomes for the sophomore-level course, and linking those directly to a bank of quiz questions, has allowed us to assess student learning in a fine-grained manner, and we will be able to track the performance of students on each of the learning outcomes and objectives as they begin to use the adaptive learning modules. Our hope is that the instructional intervention will improve student performance across the board, but especially for students who traditionally struggle with the content or are unmotivated to learn it—or both.

Acknowledgements

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