Board 22: The Effects of Mobile Circuits on Student Learning Outcomes: Evidence from Real-time Time-stamped Interaction Data

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THE EFFECTS OF MOBILE CircuitITS ON STUDENT LEARNING OUTCOMES: EVIDENCE FROM REAL-TIME TIME-STAMPED INTERACTION DATA

Abstract- **This research paper presents a microscopic view of students' interactions with CircuitITS (CITS), a mobile learning environment-based (MLE) tutoring system that scaffolds students' circuits analysis process and Circuit Test Taker (CTT), an MLE-based test-taking tutoring system for circuit analysis that provides full-step solutions at the end of each simulated exam. The specific user behavior considered in this study was duration and frequency of use, the number of scaffolds (hints) utilized per problem and the level of difficulty of problems solved when using the MLE tutor. Scores from three examinations were recorded from all students throughout the semester. Multilevel longitudinal modeling was used to assess effects of the MLE on student exam scores over three examination periods. Results suggest that number of scaffolds utilized per problem, as well as the level of difficulty of the problems solved while using the tutors significantly increased student achievement during the semester. This research proposed that MLEs, digital assistive technology and learner analytics have the potential to increase student problem-solving performance and achievement through learning analytics and instructional strategies.** (*Abstract*)

Keywords—mobile learning environment, learning analytics, interaction data

Introduction

Engineering jobs in the field of Electrical Engineering saw a five-year wage growth of 7.61% in 2018, yet employment for electrical engineers declined by 0.6% [1]. According to the Bureau of Labor & Statistics [2], the U.S. will shed 2% of the number of electrical engineers employed over the next five years. Although there have been significant increases in students enrolled in engineering majors, a large percentage of those students will either drop out or change their major within the first year [3]. A number of factors contribute to this phenomenon, but research has suggested that students experience extreme difficulties in their first year due to Circuit Analysis (Network Theory) courses that leverages their abilities in Math to solve complex problems theoretical in nature [3-5].

There have been a number of research studies that have explored several interventional methods to increase college students' problem-solving skills in undergraduate engineering courses [6-9]. More specifically, instructional strategies embedded within digital technologies have shown to significantly increase student achievement and problem-solving performance [10-14]. An advantage of employing digital technologies, such as cognitive tutors, to increase student achievement is the ability to digitally capture students' actions when using the system or working through problems. Analysis of user interaction data or learning analytics, in digital systems, are guided by analysis of user metrics with the goal of improving some aspect of the user's interaction with the system [15-18]. Some examples include: frequency and duration using a digital system, number of visits to a web page, number of clicks on a web page etc. Research has shown that learning analytics can increase students' self-monitoring by informing them of their personal performance and progress [14, 15]. In this experimental study, a digital MLE-based tutoring system was developed and implemented to increase student achievement and collect user interaction data to determine if user behavior affected student achievement.

Background

Research has suggested that logging and analysis of user interaction data provides insight into students' academic performance and can be used to provide prescriptive remediation for students experiencing difficulties [19]. Cognitive tools such as intelligent tutoring systems (ITSs) utilize various forms of immediate feedback such as providing solutions to answers or hints to a problem based on users' input [14]. According to Greller [20], digital cognitive tools offer a wealth of unused data that could be utilized in the "evaluation of learning theories, learner feedback and support, early warning systems, learning technology, and the development of future learning applications."

Learning analytics was defined by The Society for Learning Analytics Research (SoLAR) as: "[t]he measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs" [21]. According to Ferguson [22] one of the primary objectives behind learning analytics is the push to optimize the learning process. In this study, mobile CircuitITS (CITS) was developed to assist students problem-solving abilities in a Circuit Analysis (Network Theory) course. The MLE tutor provided users with real-time feedback of their problem-solving performance in addition to providing full-text solutions to missed problems. The tutor also collected user interaction data such as duration and frequency of use as well as the level of difficulty of the problems solved when using the tutor.

Current Study

The purpose of this experimental research study was to examine the effects of an instructional intervention on students' learning outcomes when solving electrical circuit problems. Moreover, this study examined if user interaction data such as duration of use, frequency of use and the level of difficulty of the problems solved when using the tutor predicted student achievement or was moderated by intervention type.

This research study aimed to answer the following questions:

1) Does the duration or frequency using CircuitITS (CITS) or Circuit Test Taker (CTT) predict student exam score performance?
2) Is the effect of time spent and frequency using a system on student exam score performance moderated by the type of system used (CITS vs. CTT)?
3) Among students who use CTT or CITS, does the difficulty level of the electrical circuit problems solved in the system predict student exam score performance?
4) Among students who use CTT or CITS, is the effect of the difficulty level of the electrical circuit problems solved in the system on student exam score performance moderated by the type of intervention (CITS vs. CTT)?

Study Procedures

One section of students (n = 83) enrolled in an advanced Circuit Analysis (Network Theory) course were randomly assigned to one of three groups (Control, CITS or CTT). Students that elected not to utilize the MLE tutors were assigned to the Control group (n = 46) and were excluded from this part of the analysis. Over the course of a semester, students were encouraged to engage with the MLE tutors when studying and in their spare time over the duration of the Spring 2018 semester. Three midterm examinations were administered to all students enrolled in the course and all data were collected and processed by the researcher. This study's structure consisted of a longitudinal framework that utilized multilevel modeling to investigate the relationships among this study's implementation of an MLE tutor and students' achievement in an advanced Circuit Analysis (Network Theory) course.

Access was granted through the College of Engineering after consent was given by the department and IRB protocol obtained. Two versions of the MLE tutoring system were developed and implemented. Version one, CircuitITS (CITS), provided two-tier performance-based scaffolding with a "bottom-out" answer that presented customized text showing the step-by-step solution. In addition, CircuitITS also provided integrated testing assessments with full solutions at the end of the assessment. Version two, Circuit Test Taker (CTT), was also deployed and allowed students to engage in the same testing mechanisms as CITS with full solutions at the end of the assessment but did not provide performance-based scaffolding. Both systems provided unlimited problem variation but only CITS provided performance-based scaffolding. Both versions of the MLE tutor collected user interaction data such as: duration of use, frequency using the tutors, number of scaffolds utilized per problem (CITS) and difficulty level of the problems attempted. Once students' login credentials were confirmed, all interaction data was stored in the database and was linked to individuals' usernames and email addresses.

Study Results

Demographics

Participants utilizing the tutors were thirty-seven undergraduate students enrolled in an advanced Circuit Analysis (Network Theory) course at a Midwest research institution in Illinois. 57% of the students accessed the tutor on Windows tablets, laptops or mobile devices; 22% of the students accessed the tutor on Android tablets or mobile devices; 8% of the students accessed the tutor on iPad tablets or iPhones and 14% of the students accessed the tutor on devices other mobile technology. Fig. 1 shows the distribution of device usage by age group.

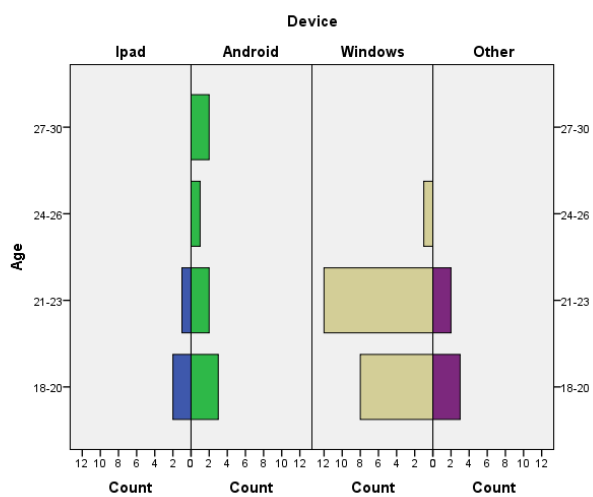

Fig. 1: Distribution of device type by users' age

Associated Research

In research connected to this study, it was shown that the effects of the performance-based scaffolding predictor, *Hints*, was a statistically significant predictor of student exam scores ($p < .05$). Results from multilevel modeling showed a significant positive effect of the scaffolding predictor (β_{20} = 1.54; $p < .05$) on student exam scores across time (where β_{20} is the effect of the scaffolding predictor on student exam scores) with the a medium to large effect size. In addition, each digital tutor type produced a positive significant effect of the use of both the CTT intervention (β_{01} = 4.67; $p < .01$) and CITS intervention (β_{02} = 4.17; $p < .01$) on exam scores (where β_{01} and β_{02} are the effects of the CTT and CITS interventions on student exam scores, respectively) with a medium to large effect size.

RQ 1 & 2

The first research question examined if the midterm exam scores of students who utilized either version of the intervention were related to the duration and frequency of intervention usage. The control group cases were not used in this analysis. Results from multilevel random effects ANCOVA linear growth models showed no statistically significant effects of the *Duration* (β_{20} and $p > .05$) and *Frequency* (β_{30} and $p > .05$) predictors on student exam scores (where β_{20} and β_{30} are the effects of the *Duration* and *Frequency* predictors on student exam scores, respectively). In addition, the type of intervention (CITS or CTT) did not moderate the effects of the *Duration* and *Frequency* predictors ($p > .05$).

RQ 3 & 4

The next research question examined if the midterm exam scores of students who utilized either version of the intervention were related to the difficulty level of the problems solved when using the intervention. Results from a multilevel random effects ANCOVA model showed a significant positive effect of the difficulty predictor (β_{20} = 1.23; $p < .05$) on student exam scores across time (where β_{20} is the effect of the *Difficulty* predictor on student exam scores) with the proportion of the variance explained by the difficulty predictor (R^2 = .134) and medium effect size. In addition, the type of intervention (CITS or CTT) did not moderate the effect of the *Difficulty* predictor ($p > .05$).

Discussion and Conclusion

Research related to this study examined the effects of MLE-based tutors on student achievement and problem-solving performance in an advanced Circuit Analysis (Network Theory) course. Results of multilevel modeling indicated positive significant differences between the control group and the intervention groups with mean student achievement increasing in a range of 13% to 19% over the course of a semester.

In this part of the research study, user interaction data were collected to determine if any of the predictors (hints used, duration and frequency of MLE tutor usage or difficulty of the problems solved in the tutor) had a significant effect on student achievement. Results of multilevel modeling indicated that the difficulty level of the problems solved when utilizing the MLE tutor had a significant positive effect with mean student achievement increasing by 4% over the course of the semester as measured by three semester exams.

A number of research articles cite the importance of the collection and analysis of user interaction data and its significance to learning analytics [23-25]. Picciano [23] states that collection of this data could assists instructors and researchers "study patterns of student performance over time." He also states that for learning analytics to be effective, "especially time-sensitive learning analytics" the process should occur in "real-time or near real-time". Furthermore, analysis of specific user interaction data could be prescriptive in the development of personalized instructional strategies, analysis of problem-solving performance or adaptive measures to iterate scaffolding processes. Many universities employ learning management systems (LMSs) so that students can proactively interact with course materials, view grades or participate with discussions. Most incorporate instructor dashboards that deliver course statistics in real-time [23]. Learning analytics can inform students of their progress in courses as well as inform instructors, through monitored statistics, of warning signs exhibited by students with difficulties [24].

This research study examined the effects of user interaction data, collected by an MLE-based tutor, on student achievement in an advanced Circuit Analysis (Network Theory) course. This research posits that the analysis of user interaction data for learning analytics could be critical for students utilizing learning technologies. Learning technologies equipped with embedded capacities to capture user interaction data may be used to predict students learning outcomes as well as iterate the learning process [26-28]. Providing students with the ability to "see" their learning trajectory could enable them to become more effective learners such as becoming more adept at video games. As such, results from this study could be used to inform developers and instructors how to capture, analyze and predict learning outcomes as well as provide information relevant to each students' level of ability when using digital tutors.

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