Journal of Information Technology Education: Research

An Official Publication of the Informing Science Institute InformingScience.org

JITEResearch.org

**Volume 19, 2020**

# ADAPTIVE LEARNING TECHNOLOGY RELATIONSHIP WITH STUDENT LEARNING OUTCOMES

Garry White | Texas State University, San Marcos, TX, USA | gw06@txstate.edu

## ABSTRACT

| | |
|---|---|
| Aim/Purpose | The purpose of this study is to determine the effectiveness of an Adaptive Learning Technology (ALT), as compared to traditional teaching methods, in an undergraduate management information course. The effectiveness is based on Bloom's Taxonomy of Learning Competencies |
| Background | Previous studies have investigated factors involved with ALT. From one study, students enjoyed how to use new technology and believed it improves learning. However, the literature lacks studies showing gains in understanding and remembering as defined by Bloom's Taxonomy of Learning Competencies. |
| Methodology | Correlations between ALT usage and test/course grades were performed. McGraw-Hill's Connect LearnSmart® was used as the ALT. The ALT was optional for extra credit in the class. Correlations were performed between LearnSmart® scores and tests. Then, since usage was bimodal (students who took the initiative to fully complete LearnSmart® and those who did not do LearnSmart®), an independent-samples t-test was performed between these two distinct groups. |
| | Sampling was from an Information Technology course at a major university. The data collection methods composed of recording LearnSmart® scores and test scores. |
| Contribution | This study aims to provide empirical evidence of ALT outcomes in learning, to show if ALT enhance learning over traditional teaching methods. If not, the value of using ALT is provided. |
| Findings | Results showed no relationships between ALT usage and test/course grades. No differences between the two groups (those who completed ALT and those that did not do the ALT) were found with each of the four tests and final course grades. Since the ALT group did the LearnSmart® as an option, the tool appears to be a preference for learning style and provides user satisfaction. This is consistent with prior studies. |

Accepting Editor Man Fung (Kelvin) LO │Received: November 12, 2019│ Revised: January 26, February 15, February 23, 2020 │ Accepted: March 10, 2020.
Cite as: White, G. (2020). Adaptive learning technology relationship with student learning outcomes. *Journal of Information Technology Education: Research, 19,* 113-130. https://doi.org/10.28945/4526

| | |
|---|---|
| Recommendations for Practitioners | Practitioners should use ALT for convenience, preferences, and students' satisfaction. The use of both traditional teaching methods and newer technology teaching methods might be most effective because they provide flexibility for the best method that satisfies the student. Editors and developers of publishers need to consider student preferences in learning. |
| Recommendations for Researchers | Opinions and perceptions by subjects may be misleading. In future research, empirical evidence needs to be provided to validate opinions and perceptions. Research needs to focus more on students' characteristics such as learning style, learning preferences, and initiative. |
| Impact on Society | This research suggests that an ALT is efficient for the learning process rather than effective for outcomes and enhanced learning. Students can learn just as well without an ALT. Decisions to use an ALT should be based on convenience and student preferences. |
| Future Research | In this study, students had the option to do an ALT. They showed initiative. For future research, initiative needs to be removed. Random assignments to do an ALT or not need to be studied to further confirm the findings of this study. Also, a future study needs to use the same subject's outcomes for both an ALT and traditional teaching methods. |

| | |
|---|---|
| Keywords | adaptive learning technology, Bloom's Taxonomy of Learning Competencies, learning tools, LearnSmart®, SmartBook®, student grade outcomes |

# INTRODUCTION

Adaptive Learning Technology (ALT) permits students to construct their knowledge and take ownership of their learning experience (Yazon et al., 2002). ALT is a teaching software that can be accessed via an Internet connection and adjusts to the students learning style/ characteristics based on responses to questions (Jonsdottir, 2015; Truong, 2016). ALT that utilize interest may be a way to support learners in gaining fluency with abstract systems and promote the acceleration and transfer for future learning (Walkington, 2013).

This is a type of goal-oriented requirements engineering that personalizes the learning process and focuses on the needs of the learner. An ALT can provide each learner with course materials that match their learning style (Dounas et al., 2019). Studies on ALT systems that focus on cognitive learning styles reveal improved student learning (Dhakshinamoorthy & Dhakshinamoorthy, 2019).

With ALT, students work at their own pace. The teaching environment becomes "personalized" (Truong, 2016). This research is on personalized e-learning through web-based education (Drissi & Amirat, 2016) using an ALT. Personalized learning can be enhanced by considering learners' skills and intelligence. The personalized learning of ALT can modify the difficulty level or the presentation of the corresponding activity of the courseware sequencing (Hafidi & Bensebaa, 2013).

Such systems have been merged with conventional didactic lectures that embraced passive learning into an environment that is student-centered and promotes active learning via blended learning. Universities are now able to promote a learner-directed environment (Dounas et al., 2019). "Colleges and universities are turning to adaptive learning as a solution to the antiquated one-size-fits-all approach to teaching" (Cai, 2018, p.103).

## *SATISFACTION TO USE ALT*

Andrew et al.'s (2018) findings suggest that students enjoy learning how to use new technology. User satisfaction and self-efficacy lead to usage intentions of an e-learning system (Yakubu & Dasuki, 2018; Zogheib et al., 2015). In general, the results demonstrate that students will use e-learning technology if they perceive it to be useful to them, easy to use, and supportive of their educational needs (Zogheib et al., 2015).

#### Perceptions, opinions, beliefs in learning

Through ALT, individual learning styles can be addressed. Hence, students are better able to demonstrate mastery of the assigned content (Gebhardt, 2018). Students and instructors viewed adaptive learning as beneficial for the ability to focus on topics students do not understand and to motivate and engage the students (Allison & Extavour, 2017; Kakish et al., 2019; Virkler, 2017). This was shown from a 2017 Digital Study Trends Survey of over 1,000 college students by McGraw-Hill Publishers (Virkler, 2017). Two key perception findings were:

> 1. 60% of students "feel" that digital learning technology has improved their grades, with a fifth saying it "significantly" improved their grades.
>
> 2. More than 61% of students "agreed" that digital learning technology is extremely or very helpful in preparing for exams.

Andrew et al.'s (2018) findings suggest that students also "believe" ALT improves learning and prepares them for the future. Question: are these perceptions consistent with grade outcomes? An ALT was effective in providing more feedback to students. "Feedback has been identified as a key component of successful learning" (Matthews et al., 2012, p.71). But does ALT lead to successful learning? Lin et al. (2019) indicated adaptive learning resources can improve students' learning. Does it?

Miranda et al. (2017) analyzed e-learning critical success factors. One of the factors was stakeholders-students participation. However, an e-learning success factor was missing: the success of knowledge and understanding acquired by students. This is the goal of education. These systems have shown to be more effective on students' perceptions rather than their performance (Mampadi et al., 2011; Yang et al., 2013).

### *Purpose of Research*

Liu et al. (2017, p.1605) indicated "research remains limited, as the field of *adaptive learning* is still evolving within higher education." For example, there is little independent empirical evidence assessing the learning effectiveness of the ALT LearnSmart by McGraw-Hill. The results of the investigations have been mixed (Dry et al., 2018). The literature lacks any research articles dealing with ALT success in learning based on Bloom's Taxonomy of learning competencies. "Further research is required to determine if ALT actually improves student understanding and active learning within a subject area" (Allison & Extavour, 2017, p.7). This is the purpose of this research study; to determine if ALT leads to students successfully acquiring knowledge based on Bloom's Taxonomy of learning competencies.

## Literature Review

### *Adaptive Learning Technology (ALT) Overview*

ALT has 4 advantages: 1) address diversity of student background and knowledge, 2) efficient use of class time by knowing the areas needing more help, 3) keeping content current, and 4) allowing for dynamic content (Kakish et al., 2019). However, ALT may not be effective in all subject areas. Liu et al.'s (2017) findings showed ALT helped address the knowledge needs for Chemistry but not for three other content areas (Biology, Math, Information Literacy). Design flaws in the ALT system could have led to a lack of more student success (Dounas et al., 2019; Liu et al. 2017).

Learners have different learning styles, learning goals, and varying progress of their learning over time. This affects the learners' performance. Dhakshinamoorthy & Dhakshinamoorthy (2019) found an adaptive learning strategy, based on learning style, can improve learning. Hence, adaptive e-learning systems need to deal with learners' characteristics and styles (Drissi & Amirat, 2016; Premlatha & Geetha, 2015).

Overall, students and instructors view adaptive learning as beneficial to focus on topics students do not understand and to provide motivation/engagement of the students. One study showed students report an overall positive experience (Liu et al. 2017). McGraw-Hill's Connect SmartBook® and LearnSmart® are such adaptive learning technology tools (Kakish et al., 2019). SmartBook® is a digital textbook linked to LearnSmart®, an ALT software.

## *McGraw-Hill's Connect SmartBook (SB) and LearnSmart (LS)*

Connect, an *adaptive learning* system, was developed by McGraw-Hill Higher Education (MHHE). It includes SmartBook® and LearnSmart®. There is little independent empirical evidence assessing the efficacy of the LearnSmart tool, and the results of investigations have been mixed (Dry et al., 2018).

> The software (LearnSmart®) can be described as follows: the instructor selects topics within the SmartBook® (digital textbook) that complement the course syllabus and is delivered online via a series of modules within the LearnSmart® feature. . . LearnSmart® features present students with content-related questions with an additional rating that ascertains the students' confidence level in answering the given question. This information, in addition to previous responses, is used in the selection of subsequent questions by the software. The *adaptive learning* system also analyzes student performance based on correctly answered questions and confidence levels. Incorrect responses result in redirection of the student to the relevant section(s) of the e-book (SmartBook®) for review of concepts. Students must review the material and answer questions correctly before they can progress further. (Allison & Extavour, 2017, p.2)

## *Past Research with McGraw-Hill's Connect LearnSmart®*

Kakish and Pollacia (2018) used McGraw-Hill's Connect SmartBook ® and found significant improvement with grades. Two groups were used. The group that used ALT had about a 10% rise in midterm and final exam grades over the one that didn't. However, of the three sections of students used, there was no indication as to how they were separated into those who used ALT and those who did not use ALT. Exam information (i.e., the source of questions) and having the same teacher across sections were not indicated.

James (2012) used the LearnSmart® tool in an introductory biology class. The tool was made available to students, but usage was not required. For those students who took the initiative to use the tool, James (2012) found a weak but statistically significant relationship between tool usage and performance on the final exam. In other words, the more the tool was used, the higher the grade. However, there was no significant difference between the final exam performances of students that chose to use the tool and those that did not (James, 2012). This suggests that those who took the initiative did as well as those who did not.

Gurung (2015) required students in a psychology course to use the LearnSmart® tool. Results showed that the number of times students used the tool was significantly related to quiz performance. Students with higher GPAs did better on the final exam and were using the tool more than other students. This finding affected the strength of the relationship between tool usage and academic performance.

Owens and Moroney (2015) reported a significant relationship between LearnSmart® usage and final exam grades in a bioscience course for nursing students. LearnSmart® was required for a small proportion of course credit. Question: will the students make the same final exam grade if LearnSmart®

was not used? The relationship may be based on initiative and applying one's abilities to their studies as indicated by the higher GPAs found in Gurung (2015).

Dry et al. (2018) also used LearnSmart® in an undergraduate Psychology course. Students who made use of the tool performed significantly better on the assessments than non-users. However, LearnSmart® was a stronger predictor of academic performance than of intellectual ability. The results of the Dry et al. (2018) study replicate the results of James (2012), Owens and Moroney (2015), and Gurung (2015). Findings suggest the use of the LearnSmart® tool is positively and significantly related to academic performance.

Griff and Matter (2013) compared the performance of undergraduate physiology students using the LearnSmart® tool as a study aid with those using a traditional, nonadaptive, online quiz. Students were randomly assigned to one of these two conditions. Group comparisons were made. Findings showed no significant difference between the two groups of students regarding academic performance. For students in the LearnSmart® group, there was no significant relationship between the number of times they used the tool and overall improvement.

Five research articles, using Connect LearnSmart® with SmartBook®, showed significant improvement while one did not. Possible intervening variables to consider are:

1) LearnSmart® performance scale was used as a part of final grade calculations,

2) it was optional (do not have to use LearnSmart®),

3) who authored (instructor or Connect authors) the assessment questions,

4) how well the LearnSmart® items and assessment questions were mapped to the subject content.

## *Bloom's Taxonomy of Cognitive Skills*

> Bloom's taxonomy is a framework which can be used to identify different levels of thinking skills. It calibrates ascending cognitive levels from the lowest, knowledge involving the recall of facts, to the highest, evaluation, which involves the comparative assessment of outcomes. . . . Bloom's taxonomy can also be used to calibrate the level of a particular assessment task retrospectively. (Oliver & Dobele, 2007, p. 347)

Cognitive skills, in information technology and other disciplines, can be assessed by using Bloom's Taxonomy of cognitive skills (Bloom et al., 1956). This taxonomy is a hierarchy of cognitive skill levels, moving from simple to complex, that can help teachers teach and students learn. "A topic may be covered at a low depth of knowledge level as part of an introductory course and in more depth (higher competency) in a subsequent course" (Gorgone et al., 2002, p. 19). The framework can be used to create assessments, evaluate the complexity of assignments, infer the level of cognitive achievement, and increase the rigor of a lesson (Athanassiou et al., 2003; Heick, 2018).

There are six cognitive levels of Bloom's Taxonomy (Bloom, 1984; Heick, 2018; Mull, 2011). They can be divided into two groups. The first, Lower Order Learning, deals with improvement and processing data (Mull, 2011). The second, High Order Learning, deals with innovation and is referred to as critical thinking (Anderson & Krathwohl, 2001; Bloom, 1984; Page & Mukherjee, 2007). See Figure 1.

| | |
|---|---|
| High Order of Learning Competencies | |
| 6. Create. | Design a new solution. |
| 5. Evaluate. | Make a judgment, interpret, illustrate value. |
| 4. Analyze. | Identify the parts of a concept, explain the steps of a process, explain why. |
| Lower Order of Learning Competencies | |
| 3. Apply. | Solve a problem, select a design to meet a purpose. |
| 2. Understand. | Organize content, explain differences, summarize. |
| 1. Remember. | Recall a fact |

**Figure 1.** Bloom's Taxonomy

The lower competencies process inputs from the environment. The higher competencies process knowledge from the lower competencies and create higher-level knowledge from the product of the lower competencies (Mull, 2011). If first year courses have too high a cognitive level, they may prevent students with lower ability levels from gaining a foundation from which to make upward progress (Oliver & Dobele, 2007). Hence, the use of the two Lower Order Learning Competencies were used in this study to ensure a cognitive level all students have.

### *Research Hypotheses*

H1: There is a positive relationship between ALT assignments and corresponding test grades based on Bloom's Taxonomy of Cognitive Skills.

H2: There is a positive relationship between ALT assignments and final course grade based on Bloom's Taxonomy of Cognitive Skills.

H3: Taking the initiative to use an ALT does result in higher grades based on Bloom's Taxonomy of Cognitive Skills.

## Method

McGraw-Hill Connect LearnSmart® tool and the corresponding digital textbook SmartBook® were used to study the impact of adaptive learning technology on Bloom's Taxonomy of Remember and Understand outcomes. Assessment of learning was evaluated by multiple-choice questions from the textbook author's test bank and was classified under Bloom's Taxonomy. Statistical analysis used Pearson correlation and independent-samples t-test from the IBM SPSS v25 statistical software.

### *The SmartBook and LearnSmart Tool*

LearnSmart is an online adaptive e-learning tool developed by McGraw-Hill to supplement the content presented in their textbooks (SmartBook®). Each chapter in the McGraw-Hill textbook (SmartBook®) has an associated online LearnSmart module which instructors can assign for the purpose of formative or summative assessment. LearnSmart works by presenting questions based on core content to which students are required to provide an answer and an indication of their confidence in the correctness of their answer on a four-point scale (i.e. 'I know it', 'Think so', 'Unsure', or 'No idea'). Based upon the accuracy of each response and the associated confidence rating, LearnSmart adjusts the difficulty level of subsequent questions. In this way, students who demonstrate a clear and confident understanding of the content area can be challenged with more difficult questions, and students who are struggling are given the opportunity to master the more basic concepts before being presented with more difficult material. (Dry et al., 2018, p. 24). See Figures 2 and 3.

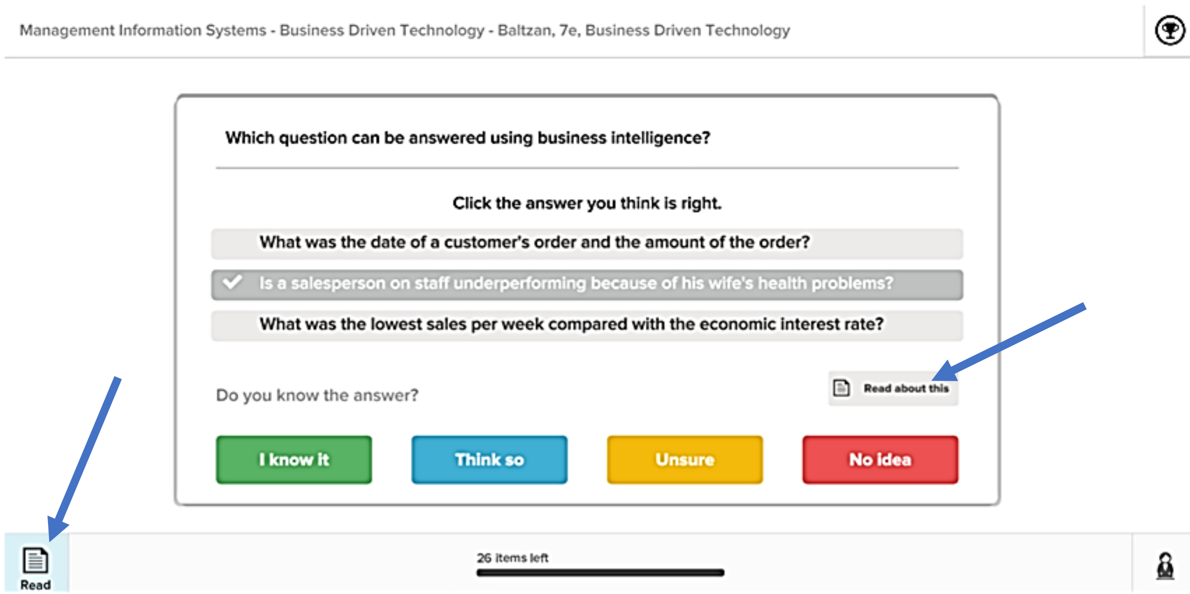


**Figure 2**. LearnSmart question.

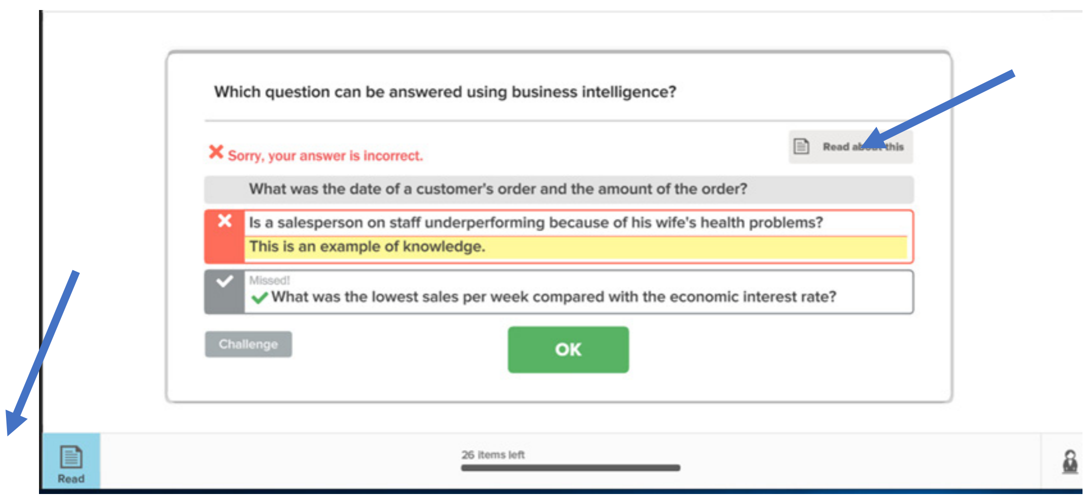


**Figure 3**. LearnSmart response to question.

LearnSmart® topic questions were mapped to the SmartBook® chapters. In each figure to the right of the screen, there is a "Read about this" button. To the far left, there is a "Read" button. These two buttons take the student directly to the SmartBook® content that provides the answer. The content is highlighted in yellow for the student to read. The student can find and record the answer easily. The LearnSmart® chapter scores were calculated by point scores of the highest level of mastery for each LearnSmart® chapter assignment. The student was able to repeat the work until total mastery of the material.

## *Test Bank of Author's Textbook and 4 Tests*

Along with the course textbook (SmartBook®), a test bank for the textbook was provided by McGraw-Hill for that specific textbook. Figure 4 is an example of a multiple-choice question from Chapter 1 of the test bank. Each chapter question was mapped to a SmartBook® Learning Objective of the same chapter and to Bloom's Taxonomy. The assessment score for learning was the total of correct answers.

| | | | | |
|---|---|---|---|---|
| 01. | Which of the following is **not** considered a core driver of the information age? | | | |
| | A. | Information | B. | Business Intelligence |
| | C. | Competitive Intelligence | D. | Data |

The core drivers of the information age include data, information, business intelligence, and knowledge.

Blooms: Understand

Difficulty: 2 Medium

Learning Objective: 01-01 Describe the information age and the differences among data, information, business intelligence, and knowledge.

Topic: Competing in the Information Age

ANS: C

**Figure 4.** Test Bank Multiple-Choice Question.

From this test bank, 4 tests were created. Only multiple-choice questions that were at Bloom's Remember and Understand levels, the two lowest competencies, were used. These questions tended to be at Easy and Medium difficulty.

## *PROCEDURE*

Subjects: 102 students in a Spring '19 Information Technology course participated. They were of different majors in the College of Business and were exposed to the same classroom lectures, textbook (BookSmart®), homework, and tests. The only difference was the degree of LearnSmart® usage. Cognitive ability was not controlled because the subjects were at the same educational level, and Bloom's Taxonomy of the lower cognitive skills were used.

Students were told that in the previous class, students who did the 31-chapter assignments in LearnSmart® tended to make higher grades (i.e., made more grades of As and Bs versus Cs). They were given the option to do LearnSmart® for 2% extra credit on their final course grade. This resulted in some not doing LearnSmart®, some partially completing the assignments, and some completing all of the assignments in LearnSmart®. This provided a wide range of usage: from a score of 0 to the maximum score. See Tables 2 to 5.

The LearnSmart® assignments were divided into 4 sets, matching the content of the 4 tests; both were mapped to the learning objectives of the e-book (SmartBook®). There were students who completed the LearnSmart® assignments for the first test, but not for the last test. All 102 students took the first test and completed the first set of LearnSmart® assignments, while only 90 took the last test and did the last set of LearnSmart® assignments. Thirteen (13) students dropped out during the semester.

Students completed 4 tests from the McGraw-Hill author's test bank containing Bloom's Remember and Understand multiple-choice questions. These are Lower Order Learning components involving improvement and processing data (Mull, 2011). Pearson's Correlations were then calculated between the 4 tests and 4 sets of LearnSmart® scores and final overall course grade.

# RESULTS

## RELIABILITY

LearnSmart® adaptive learning's 4 sets of scores had a Cronbach's Alpha of .928. Also, Pearson's Correlations among the 4 sets of LearnSmart® scores ranged from .700 to .840 ($p < .001$, 2-tailed).

The 4 tests' reliability coefficients (R) came from the Texas State University testing center (Texas State University Testing, Evaluation, and Measurement Center [TSUTEMC], n.d.). This coefficient is an estimate of a test's internal consistency. Reliability scores are between 0.00 and 1.00. Classroom tests generally have values between .60 and .80. (TSUTEMC, n.d.). The reliability (R) of the 4 tests are shown in Table 1:

**Table 1.** Tests Reliability Coefficients (R)

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Test #1 | .749 | Test #2 | .729 | Test #3 | .762 | Test #4 | .693 |

## DESCRIPTIVE STATISTICS (LEARNSMART® SCORES)

Frequency tables were created using the 4 LearnSmart® adaptive learning scores. Bimodal distributions appeared. See Figures 5 to 8. Two distinct groups can be identified: those who completely mastered the material (max scores) and those who did not use LearnSmart® (score 0).

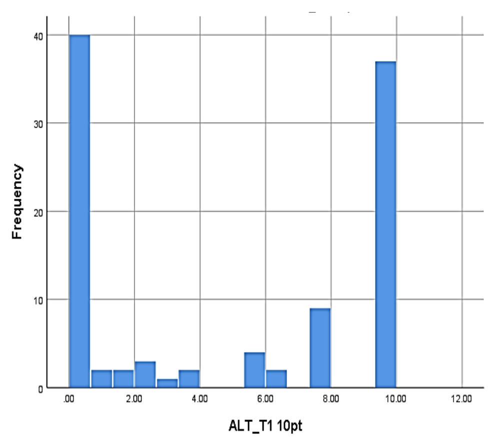


**Figure 5**. LearnSmart 01 score frequencies. N = 102 students, Mean = 4.93, Std Dev = 4.546.

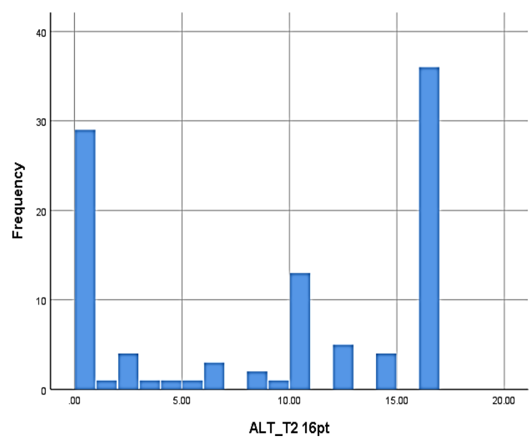


**Figure 6.** LearnSmart 02 score frequencies N = 100 students, Mean = 8.80, Std Dev = 6.786

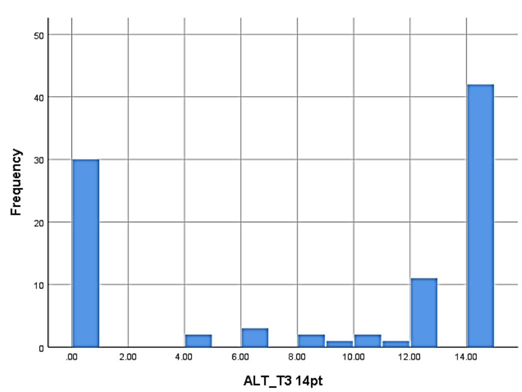


**Figure 7**. LearnSmart 03 score frequencies N = 94 students, Mean = 8.56, Std Dev = 6.234.

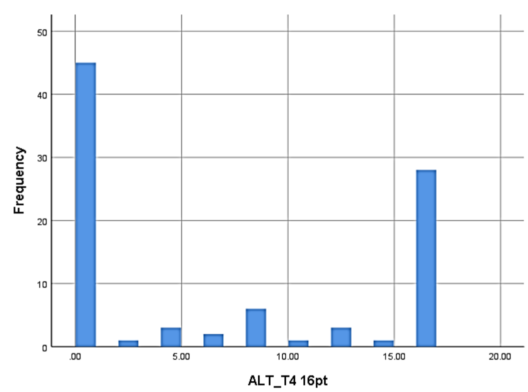


**Figure 8**. LearnSmart 04 score frequencies N = 90 students, Mean = 6.48, Std Dev = 7.228

## *DESCRIPTIVE STATISTICS (TEST SCORES AND TOTAL SCORE)*

Table 2 provides the Descriptive Statistics for Tests 1 to 4 and Total Score (final course grade without extra credit for ALT). The number after the test ID is the maximum number of points for that test, i.e., T2mc [170] means the highest grade is 170. The mean for T2mc was 138.72 with a Std. Dev. of 13.545.

**Table 2.** Descriptive Statistics for Tests 1 to 4 and Total Final Grade (final course grade)

| | N | Mini | Max | Mean | Std. Dev | Skewness | | Kurtosis | |
|---|---|---|---|---|---|---|---|---|---|
| | Stat | Stat | Stat | Stat | Statistic | Statistic | Std. Error | Statistic | Std. Error |
| T1 [200] | 102 | 86 | 192 | 155.06 | 19.193 | -.896 | .239 | 1.124 | .474 |
| T2mc [170] | 100 | 91 | 161 | 138.72 | 13.545 | -1.104 | .241 | 1.498 | .478 |
| T3mc [140] | 92 | 80 | 134 | 110.01 | 11.262 | -.441 | .251 | -.081 | .498 |
| T4mc [200] | 90 | 123 | 197 | 164.28 | 14.676 | -.489 | .254 | .249 | .503 |
| tot fin gr [1,000] | 90 | 515 | 930 | 752.56 | 85.842 | -.374 | .254 | -.449 | .503 |

The first two tests were significantly negatively skewed: few high scores and many low scores. The Skew values were greater than two Std. Errors from 0. The data were NOT symmetric, a requirement for Pearson's Correlations. Also, Kurtosis indicated a wide and flat distribution of these two test scores. The Kurtosis values were significant: greater than two Std. Errors from 0. The 3rd test, 4th test, and total score were normal distributions. What may explain Test #3, Test #4, and total score normal distributions are fewer students at the end of the course; 12 students dropped out towards the end of the semester. The students that dropped had poor academic performance. At the time of dropping, their overall grades were Ds and F's. The removal of these grades shifted the distribution to a more normal distribution: less skewed at the low-grade end and less range for Kurtosis.

## *INFERENTIAL STATISTICS (CORRELATIONS)*

Table 3 shows no relationships between the LearnSmart® Adaptive Learning assignments and the corresponding chapter tests. **Research H1: There is a relationship between ALT assignments and corresponding test scores, is not supported.** However, this may be misleading for the first two tests since the data were not symmetric.

Table 4 shows no relationships between the LearnSmart Adaptive Learning assignments and the final grade. **Research H2: There is a relationship between ALT assignments and final course grade, is not supported. Research H3: Taking the initiative to use an ALT does result in higher grades, is not supported.**

**Table 3.** Person's Correlations between LearnSmart® Adaptive Learning and Tests.

| Adaptive Learning (LearnSmart®) | Ch Test | Pearson's Correlation | N | Sig (2-tailed) |
|---|---|---|---|---|
| AL_01 | T_01 | .134 | 102 | P < .180 |
| AL_02 | T_02 | .195 | 100 | P < .052 |
| AL_03 | T_03 | -.065 | 92 | P < .537 |
| AL_04 | T_04 | -.096 | 90 | P < .369 |

**Table 4**. Person's Correlations between LearnSmart® Adaptive Learning and Total Score (Final Grade without extra credit for ALT) for those who completed the course.

| Adaptive Learning (LearnSmart®) | Pearson's Correlation | N | Sig (2-tailed) |
|---|---|---|---|
| AL_01 | .019 | 90 | P < .857 |
| AL_02 | .025 | 90 | P < .815 |
| AL_03 | .016 | 89 | P < .881 |
| AL_04 | .033 | 90 | P < .756 |
| Tot ALT score | .005 | 90 | P < .962 |

There were also no relationships between the LearnSmart® Adaptive Learning assignments and other final grade variables (two essay tests, two homework problem assignments). This was expected since content on these essay tests and homework assignments were not mapped to the Adaptive Learning assignment content.

## *Further Investigation*

Since there were no significant relationships between the variables and the LearnSmart® data are bi-modal with two distinct groups, an independent-samples t-tests were performed to confirm the findings. This also resolved the first two test scores not being symmetrical. The Levene test of homogeneity-of-variance showed there was no difference between the variances in the samples. See Tables 5 to 9. Again, for the four test grades, there was no significant difference between those who fully completed LearnSmart® and those who did not use LearnSmart®. There was also no significant difference between the two groups' Total Score (final course grade without the extra credit from doing ALT).

**Table 5. t-Test (Independent Samples)– LearnSmart® two groups for Test 1.**

| Test 1 [200] | Levene's Test for Equality of Variances | | t-Test for Equality of Means | | | | |
|---|---|---|---|---|---|---|---|
| | F | Sig | t | df | Sig (2-tailed) | Mean Difference | Std. Error Difference |
| Equal variances assumed | 1.526 | .221 | -.419 | 72 | .676 | -1.697 | 4.048 |
| Equal variances NOT assumed | | | -.419 | 66.762 | .676 | -1.697 | 4.048 |

**Table 6. t-Test (Independent Samples)– LearnSmart® two groups for Test 2.**

| Test 2mc [170] | Levene's Test for Equality of Variances | | t-Test for Equality of Means | | | | |
|---|---|---|---|---|---|---|---|
| | F | Sig | t | df | Sig (2-tailed) | Mean Difference | Std. Error Difference |
| Equal variances assumed | .481 | .491 | -1.074 | 61 | .287 | -3.005 | 2.797 |
| Equal variances NOT assumed | | | -1.091 | 58.986 | .280 | -3.005 | 2.753 |

**Table 7. t-Test (Independent Samples)– LearnSmart® two groups for Test 3.**

| Test 3mc [140] | Levene's Test for Equality of Variances | | t-Test for Equality of Means | | | | |
|---|---|---|---|---|---|---|---|
| | F | Sig | t | df | Sig (2-tailed) | Mean Difference | Std. Error Difference |
| Equal variances assumed | .199 | .657 | .390 | 67 | .698 | 1.052 | 2.699 |
| Equal variances NOT assumed | | | .392 | 56.632 | .697 | 1.052 | 2.684 |

**Table 8. t-Test (Independent Samples)– LearnSmart® two groups for Test 4.**

| Test 4mc [200] | Levene's Test for Equality of Variances | | t-Test for Equality of Means | | | | |
|---|---|---|---|---|---|---|---|
| | F | Sig | t | df | Sig (2-tailed) | Mean Difference | Std. Error Difference |
| Equal variances assumed | .299 | .586 | .772 | 71 | .443 | 2.741 | 3.551 |
| Equal variances NOT assumed | | | .752 | 52.704 | .455 | 2.741 | 3.643 |

**Table 9. t-Test (Independent Samples)– LearnSmart® two groups for Final Grade without extra credit**

| TotFinNo ext crd | Levene's Test for Equality of Variances | | t-Test for Equality of Means | | | | |
|---|---|---|---|---|---|---|---|
| | F | Sig | t | df | Sig (2-tailed) | Mean Difference | Std. Error Difference |
| Equal variances assumed | .011 | .917 | .675 | 41 | .503 | -17.933 | 26.560 |
| Equal variances NOT assumed | | | .663 | 32.305 | .512 | -17.933 | 27.032 |

## DISCUSSION

Students have expressed positive perceptions of the ALT SmartBook®. ALT is beneficial to the course and is valued by students (Allison & Extavour, 2017; Kakish et al., 2019). Students' perceptions from the 2017 Digital Study Trends Survey by McGraw-Hill for LearnSmart® (Virkler, 2017). suggested LearnSmart® helped with learning. Are these student perceptions correct? Kakish et al. (2019) indicated ALT has four important classroom teaching components. But do they enhance learning? The key question is "does an ALT, specifically LearnSmart®, improve student understanding as defined by Bloom's Taxonomy within a subject area?" Griff and Matter (2013) found the answer to be no in four of six schools. Also, Liu et al.'s (2017) findings showed ALT LearnSmart® helped address the knowledge needs for one content area, but not for three other content areas. This current study concurs with Griff and Matter (2013) and Liu et al. (2017) that ALT LearnSmart® does not relate to test grades.

However, the results of the Dry et al. (2018) study, along with James (2012), Owens and Moroney (2015), and Gurung (2015), suggest the use of the LearnSmart® tool is positively and significantly related to academic performance. For prior studies, where a relationship existed between using ALT and test grades, a question must be asked. "Will the students make the same grades without using ALT?"

## *Factors that may Cause Mixed Results*

What are the causes of these mixed results? Here are five possible explanations:

1. In LearnSmart®, when a question is presented, there are two buttons on the screen that send the student directly to the SmartBook® content that contains the answer. The content is highlighted in yellow. The student finds content in SmartBook® and records the answer. Hence, the right answer is given on the first try. The "do you know" part on the screen can always be "I know it." Hence, the student moves through the system faster and can make a maximum score.

2. Griff and Matter (2013) had LearnSmart® instructors select only broad categories and not specific questions, while the quiz group instructors could select specific questions that best covered the material presented in class. The quiz groups were more focused and different instructors created their final exam. There was no consistency with the outcome instruments. Group comparisons were made with final exam grades. Griff and Matter (2013) suggest that two of the six institutions showing differences may have covered material that was better matched for LearnSmart®.

3. LearnSmart® performance score was optional for extra credit. Good students may have opted out since extra credit appeared to be not needed for a higher grade, while poor students did it for the extra credit.

4. How well the LearnSmart® items and test questions were mapped to the subject content. A test question and the content may be poorly matched.

5. Source of test questions; did the instructor create the test questions or did they come from the author's test bank? Different tests/exams could have different difficulty levels. Some questions may be at the higher Bloom's Taxonomy when the content is at the lower Bloom's Taxonomy. Also, the reading level difference between question and content may also be a problem.

## *This Study*

To keep intervening variables to a minimum, all teaching and student activities were the same except for LearnSmart® usage. Time usage and student abilities were not controlled for. Since extra credit was used, students took the initiative to do more and indicated they took their education seriously. They desired to make a higher grade. Correlations were non-significant between the four LearnSmart® scores and four test grades. This may be due to test scores skewness. Also, poor students may have done more for extra credit and good students may have done less because they were making good grades.

The LearnSmart® score formed two distinct groups: those that completed LearnSmart® assignments – max score, and those that did not – score 0. Working with two distinct groups, independent t-tests showed no differences between the two groups with test scores and final course grades for three of the four LearnSmart® scores. Here are two possible explanations for these study findings of no difference with four test scores and final course grades between the two groups, those that used ALT and those that did not use ALT.

1. Poor students found and recorded answers using the LearnSmart® “Read” button to go directly to highlighted content with the answers in the textbook SmartBook®. Hence, poor students were in the LearnSmart® fully completed assignments group.

2. Good students did not see a need to do LearnSmart®. They were making good grades and did not need extra credit. Hence, good students were in the “not do” LearnSmart® group.

There was one exception with the first LearnSmart® scores. Those that completed LearnSmart®, a score of 100%, had a higher final course grade than those that did not do the LearnSmart®, a score of 0%. Since this was the beginning of the semester, speculation is that good students did the work until they saw they had good grades and poor students did the work after they saw they had poor grades, creating a need for extra credit.

### *Option to Use*

Students will use an ALT tool if they perceive it to be useful to them, is easy to use, and supports their education. Students become satisfied in using ALT (Zogheib et al., 2015). However, intervening variables are anxiety and computer self-efficacy (Saade & Kira, 2009). These can impact the use of an e-learning system. Self-efficacy will lower anxiety on perceived ease of use. (Saade & Kira, 2009).

Overall, people enjoy learning how to use new technology because they believe it improves learning and prepares them for the future (Andrew et al., 2018). Hence, students’ attitudes, opinions, and preferences with learning tools are important factors (Andrew et al., 2018).

## Conclusion

Perceptions can be misleading. ALT has shown to be more effective on students’ perceptions rather than their performance (Mampadi et al., 2011; Yang et al., 2013). In this study, an ALT was just as effective as other learning/study methods. The positive perceptions may be due to the flexibility and personalization of ALT. ALT may be a good study aid that helps students learn, pending students’ characteristics.

A student’s characteristic that needs to be considered is initiative. This may explain the mixed results from several studies. Maybe the studies were biased in that those with initiative (better performers) used the tool more and those with little/no initiative (poor performers) used the tool less. For a statistical study to be valid, the division of the two groups must be random with no other “filters” to divide the groups.

For this study, initiative was the only difference between those that used LearnSmart® and those that did not. Bloom’s Taxonomy of learning competencies of remember and understanding seem not to be a factor with ALT. Instead, student characteristics of initiative, satisfaction, convenience, etc. appear to be the pending factors of ALT usage. The findings of this study show that LearnSmart® does not enhance learning beyond traditional methods.

### *Implications*

This research suggests that an ALT is efficient for the learning process rather than effective for the outcomes or enhanced learning. Students can learn just as well without an ALT. Decisions to use an ALT should be based on convenience and student preferences. Practitioners should use ALT for convenience, preferences, and students’ satisfaction. The use of both traditional teaching methods and newer technology teaching methods might be most effective because they provide flexibility for the best method that satisfies the student.

While ALT makes teaching more convenient and flexible, there needs to be more focus on students’ characteristics such as learning/study styles and initiative. Methods, such as ALT, provide opportunities to learn, while students’ characteristics determine the outcomes from these opportunities.

Editors and developers of publishers need to consider these implications and develop a variety of learning systems other than ALT that matches students' preferences in learning.

## LIMITATIONS OF THE STUDY

This study had its limitations. Below are four limitations of this study:

1. The student sample was limited to 102 students in one upper division undergraduate business course in the U.S.A. Students' background in prior use of ALT, cognitive levels, and aptitudes were not controlled.
2. Only the lower Bloom's Taxonomy competencies were studied.
3. Different teaching styles were not compared when using ALT.
4. Students were not randomly assigned to ALT usage group and non-ALT usage group. Students were able to choose to use ALT or not.

## FUTURE RESEARCH

For future research, initiative needs to be removed. Random assignments to do an ALT or not need to be studied to further confirm the findings of this study. The study also needs to compare the subjects' grades for using an ALT and without ALT.

In future research, empirical evidence needs to be provided to show that opinions and perceptions are consistent with outcomes/grades. Research needs to focus more on students' learning outcomes along with students' characteristics such as learning style, learning preferences, and initiative.

Another needed future study is the higher Bloom's Taxonomy Order of Learning Competencies, such as Analyze and Evaluate. Can teaching Analyze and Evaluate via ALT be just as good or better as other teaching methods?

# REFERENCES


Allison, G. L., & Extavour, R. M. (2017). Pharmacy students' perceptions and usage of an adaptive learning technology (SmartBook®) in anatomy and physiology in a Caribbean School of Pharmacy. *Ubiquitous Learning: An International Journal, 10*(3). https://doi.org/10.18848/1835-9795/cgp/v10i03/1-9

Anderson, L. W., & Krathwohl, D. R. (Eds.). (2001). *A taxonomy for learning, teaching, and assessing: A revision of Bloom's Taxonomy of Educational Objectives*. New York, NY: Longman.

Andrew, M, Taylorson, J, Langille, D. J, Grange, A., & Williams, N. (2018). Student attitudes towards technology and their preferences for learning tools/devices at two universities in the UAE. *Journal of Information Technology Education: Research*, *17*, 309-344. https://doi.org/10.28945/4111

Athanassiou, N., McNett, J., & Harvey, C. (2003). Critical thinking in the management classroom: Bloom's Taxonomy as a learning tool. *Journal of Management Education, 27*, 533-555. https://doi.org/10.1177/1052562903252515

Bloom, B. (1984). *Taxonomy of educational objectives*. Boston, MA: Allyn and Bacon.

Bloom, B., Engelhart, M., Furst, E., Hill, W., & Krathwohl, D. (1956). *Taxonomy of educational objectives: The classification of educational goals*. White Plains, NY: Academic Press.

Cai, R. (2018). Adaptive learning practice for online learning and assessment. *Proceedings of the 2018 International Conference on Distance Education and Learning* (pp. 103-108). ACM. https://doi.org/10.1145/3231848.3231868

Dhakshinamoorthy, A., & Dhakshinamoorthy, K. (2019). KLSAS—An adaptive dynamic learning environment based on knowledge level and learning style. *Computer Application in Engineering Education, 27*(2), 319–331. https://doi.org/10.1002/cae.22076

Dounas, L., Salinesi, C., & El Beqqali, O. (2019). Requirements monitoring and diagnosis for improving adaptive e-learning systems design. *Journal of Information Technology Education: Research*, *18*, 161-184. https://doi.org/10.28945/4270

Drissi, S., & Amirat, A. (2016). An adaptive E-learning system based on student's learning styles: An empirical study. *International Journal of Distance Education Technologies, 14*(3), 34. https://doi.org/10.4018/ijdet.2016070103

Dry, M. J., Due, C., Powell, C., Chur-Hansen, A., & Bur, N. R. (2018). Assessing the utility of an online adaptive learning tool in a large undergraduate psychology course. *Psychology Teaching Review, 24*(2), 24-37.

Gebhardt, K. (2018). Adaptive learning courseware as a tool to build foundational content mastery: Evidence from principles of microeconomics. *Current Issues in Emerging eLearning*, *5*(1), 7-19.

Gorgone, J. T., Davis, G. B., Valacich, J. S., Topi, H., Feinstein, D. L., & Longenecker, H. E. (2002). *IS2002 model curriculum and guidelines for undergraduate degree programs in information systems*. Communications of the Association for Information Systems, 11. https://doi.org/10.17705/1cais.01101

Griff, E. R., & Matter, S. F. (2013). Evaluation of an adaptive online learning system. *British Journal of Educational Technology*, *44*(1), 170–176. https://doi.org/10.1111/j.1467-8535.2012.01300.x

Gurung, R. A. R. (2015). Three investigations of the utility of textbook technology supplements. *Psychology Learning and Teaching*, *14*(1), 26–35. https://doi.org/10.1177/1475725714565288

Hafidi, M., & Bensebaa, T. (2013). Development of an adaptive and intelligent tutoring system by expert system. *International Journal of Computer Applications in Technology,* 48(4), 353. https://doi.org/10.1504/ijcat.2013.058357

Heick, T. (2018). What is Bloom's Taxonomy? A definition for teachers. *Teach Thought.* Accessed: June 25, 2019, from https://www.teachthought.com/learning/what-is-blooms-taxonomy-a-definition-for-teachers

James, L. A. (2012). Evaluation of an adaptive learning technology as a predictor of student performance in undergraduate biology (Master of Science thesis, Appalacia State University). Accessed 6/20/2019 from https://libres.uncg.edu/ir/asu/f/James,%20Lauren_2012_Thesis.pdf

Jonsdottir, A. H. (2015). Development and use of an adaptive learning environment to research online study behavior. *Educational Technology & Society*, *18*(1), 132-144.

Kakish, K., & Pollacia, L. (2018). Adaptive learning to improve student success and instructor efficiency in introductory computing course. *Proceedings of the Information Systems Education Conference* (ISECON). San Antonio, Texas. v34, 72-78.

Kakish, K., Robertson, C., & Jonassen, L. (2019). Understanding perceptions of conceptual information technology adaptive learning. *Proceedings of Information system Education Conference* (ISECON), Galveston, TX, USA, v35, 47-54.

Lin, H., Xie, S., Xiao, Z., & Deng, X. (2019). Adaptive recommender system for an intelligent classroom teaching model. *International Journal of Emerging Technology in Learning*, *14*(5), 51-63. https://doi.org/10.3991/ijet.v14i05.10251

Liu, M., McKelroy, E., Corliss, S. B., & Carrigan, J. (2017). Investigating the effect of an adaptive learning intervention on students' learning. *Education Tech Research Dev*, *65*,1605–1625. https://doi.org/10.1007/s11423-017-9542-1

Mampadi, F., Chen, S. Y., Ghinea, G., & Chen, M. P. (2011). Design of adaptive hypermedia learning systems: A cognitive style approach. *Computers and Education, 56*(4), 1003–1011. https://doi.org/10.1016/j.compedu.2010.11.018

Matthews, K., Janicki, T., He, L., & Patterson, L. (2012). Implementation of an automated grading system with an adaptive learning component to affect student feedback and response time. *Journal of Information Systems Education, 23*(1), 71-84.

Miranda, P., Isaias, P., Costa, C., & Pifano, S. (2017). Validation of an e-learning 3.0 critical success factors framework: A qualitative research. *Journal of Information Technology Education: Research, 16*, 339-363. https://doi.org/10.28945/3865

Mull, C. W., II. (2011). *Higher-order thinking competencies: A cognitive approach to managing innovation and value creation* (Doctoral Dissertation, University of Maryland University College). https://search.proquest.com/openview/4363bc032c863fca1d925e3cf0067562/1?pq-origsite=gscholar&cbl=18750&diss=y

Oliver, D., & Dobele, T. (2007). First year courses in IT: A Bloom rating. *Journal of Information Technology Education, 6*, 347-360. https://doi.org/10.28945/220

Owens, A., & Moroney, T. (2015). Shifting the load: Improving bioscience performance in undergraduate nurses through student focused learning. *Collegian*, *24*(1), 37-43. https://doi.org/10.1016/j.colegn.2015.09.006

Page, D., & Mukherjee, A. (2007). Promoting critical thinking skills by using negotiation exercises. *Journal of Education for Business*, *82*(5), 251-257. https://doi.org/10.3200/joeb.82.5.251-257

Premlatha, K. R., & Geetha, T. V. (2015). Learning content design and learner adaptation for adaptive e-learning environment: A survey. *The Artificial Intelligence Review, 44*(4), 443-465. https://doi.org/10.1007/s10462-015-9432-z

Saade, R. & Kira, D. (2009). Computer anxiety in e-learning: The effect of computer self-efficacy. *Journal of Information Technology in Education*, *8*, 177-191. https://doi.org/10.28945/166

Texas State University Testing, Evaluation, and Measurement Center (TSUTEMC). (n.d.). *How to read faculty exam output.* Faculty Exam Output, TEMC 1. Accessed 6/29/2019 from https://gato-docs.its.txstate.edu/jcr:7257c349-2713-4f96-b75d-9f43e4e4f1f6/How%20to%20read%20faculty%20exam%20output_2019.pdf

Truong, H. M. (2016). Integrating learning styles and adaptive e-learning system: Current developments, problems and opportunities. *Computers in Human Behavior, 55*(Part B), 1185–1193. https://doi.org/10.1016/j.chb.2015.02.014

Virkler, S. (2017). *2017 digital study trends survey*. McGraw-Hill. Accessed 6/24/2019 from https://www.mheducation.com/highered/explore/studytrends.html

Walkington, C. A. (2013). Using adaptive learning technologies to personalize instruction to student interests: The impact of relevant contexts on performance and learning outcomes. *Journal of Educational Psychology*, *105*(4), 932-945. https://doi.org/10.1037/a0031882

Yang, T. C., Hwang, G. H., & Yang, S. J. (2013). Development of an adaptive learning system with multiple perspectives based on students' learning styles and cognitive styles. *Journal of Educational Technology, 16*(4), 185–200.

Yakubu, M. N., & Dasuki, S. (2018). Assessing eLearning systems success in Nigeria: An application of the DeLone and McLean Information Systems Success Model. *Journal of Information Technology Education: Research*, *17*, 183-203. https://doi.org/10.28945/4077

Yazon, J. M., Mayer-Smith, J., & Redfield, R. R. (2002). Does the medium change the message? The impact of web-based genetics course on university students' perspectives on learning and teaching. *Computers and Education, 38* (1–3), 267-285. https://doi.org/10.1016/s0360-1315(01)00081-1

Zogheib, B., Rabaa'i, A., Zogheib, S., & Elsaheli, A. (2015). University student perceptions of technology use in mathematics learning. *Journal of Information Technology Education: Research*, *14*, 417-438. https://doi.org/10.28945/2315

## BIOGRAPHY

**Garry L. White** is an Associate Professor in the Computer Information Systems department at Texas State University in San Marcos, Texas. He holds a MS in Computer Sciences from Texas A & M University – Corpus Christi and a PhD in Information Systems Education, from The University of Texas at Austin. Professional Certifications from the Institute of Certified Computer Professionals (ICCP) include C.D.P, C.C.P., C.S.P. and Expert Certified in Security Systems. His research interests and work are in the areas of human factors with computer technology, infrastructure security, Internet security, privacy, and global assurance. He has published papers in journals such as the Journal of Computer Information Systems and Journal of Information Systems Education. He was a guest editor for a special issue of the Journal of Information Systems Education; Global Information Security and Assurance in IS Education.