ISSN: 2473-4901
v9 n6066

A Path - Analysis of Impact of Performance and Effort Expectancies on Learning Outcomes in Introductory Information System Course

Dan Liu
liu5dx@jmu.edu

Ping Wang
wangpx@jmu.edu

Shawn Lough
loughsr@jmu.edu

Department of Computer Information Systems/Business Analytics
James Madison University
Harrisonburg, VA 22807, USA

Abstract

Grounded on the Cognitive Load Theory (CLT) and the United Theory of Acceptance and Use of Technology (UTAUT), this research conducted a path analysis of the impact of performance and effort expectancies on students perceived and actual learning in an introductory information system course. The study tested the mediation effects of performance and effort expectancies on the relationships between intrinsic cognitive load and perceived learning (or germane cognitive load) and actual learning, respectively, and tested the mediation effects of performance and effort expectancies on the relationships between extraneous cognitive load and perceived learning and actual learning, respectively.

Among the findings from a sample of 294 valid responses were that intrinsic cognitive load was significantly positively associated with extraneous cognitive load and actual learning, however, not significantly associated with perceived learning. Effort expectancy partially mediated the effect of intrinsic cognitive load on actual learning. Extraneous cognitive load fully mediated the effect of intrinsic cognitive load on perceived learning and performance expectancy, respectively. Extraneous cognitive load was significantly positively associated with perceived learning, however, not significantly associated with actual learning. Performance expectancy partially mediated the effect of extraneous cognitive load on perceived learning. Each of Effort expectancy and perceived learning fully mediated the effect of extraneous cognitive load on actual learning. Perceived learning was positively associated with actual learning and fully mediated the effect of performance expectancy on actual learning. Through our integrated lens of research, these findings shed light on better learning with efforts for enhanced instructional designs which reduce students' cognitive loads and for elaborated learning motivations which increase students' learning capability and performance. The theoretical and practical implications and future research directions were discussed.

Keywords: Perceive or Actual Learning, Instructional Design, Learning Motivation, Cognitive Load, Performance Expectancy, Effort Expectancy

ISSN: 2473-4901
v9 n6066

1. INTRODUCTION

Undergraduate information system courses in business programs have proven to be challenging for both instructors and students in the post-COVID environment (Chen & Roldan, 2021; Singh et al., 2021). These courses often serve as the first exposure for students to computer-based information technology (e.g., Excel, SQL, DBMS, computer hardware and software, use of information systems, and collaboration using computers) (Singh et al., 2022). For instance, a significant number of students often begin the course with little prior experience in computer-based technology. Some students may also feel apprehensive or anxious about using new technology, given the need to adapt to various interfaces, commands, and functionalities, which can initially seem overwhelming. Pedagogical research on CLT showed promises to explain the relationships between learner's mental load due to content difficulty level and instruction design and perceived learning (Abeysekera & Dawson, 2015; Chandler & Sweller, 1991; Paas & van Merriënboer, 2020; Sweller, 2020; Sweller et al., 1998, 2019). Additional studies analyzed the relationships of attitudes toward learning, learning intention and behaviors for technology acceptance and usages (Abbad, 2021; Chao, 2019; Dwivedi et al., 2020; ultan Hammad Alshammari & Mohd Shafie Rosli, 2020). There is a clear research gap, however, for integrating CLT and UTAUT. This research fills the gap by investigating the mediation effects of performance and effort expectancies of UTAUT on the impact of intrinsic and extraneous cognitive loads on perceived learning and actual learning, respectively.

The next section constructed a theoretical framework for this study based on the extant literature of CLT and UTAUT. The methodology section described the survey instrument, data collection, and path analysis. The next section reported the testing results of the study and discussions. The conclusions and future research directions were presented.

2. DEVELOPMENT OF THEORETICAL FRAMEWORK

The theoretical framework in this study included actual learning in CLT (Sweller et al., 1998) in Figure 1 and integrated performance and effort expectancies of UTAUT in Figure 2 (Skulmowski & Xu, 2021).

CLT is composed of intrinsic, extraneous and germane cognitive loads and the relationships among them (Sweller et al., 1998). While intrinsic cognitive load is determined by the inherent complexity or amount of interactivity of the learning task to be learned and the "expertise of the learners," intrinsic cognitive load, however, "cannot be directly influenced by instructional designs" or extraneous cognitive load reduction (Sweller et al., 1998 page 262). One of the items to measure intrinsic cognitive load is "The class learning activities were very complex" (Leppink et al., 2013). A lower amount of learners' prior knowledge of a learning task (Kalyuga, 2005; Sweller et al., 1998) and the online learning delivery mode during COVID-19 increase intrinsic cognitive load (Skulmowski & Xu, 2021).

Extraneous cognitive load, "is the load caused by poorly designed instructional procedures that interfere with schema acquisition." The additive nature of intrinsic and extraneous cognitive loads leads to more free working memory resources for intrinsic and germane loads with decreasing or minimizing extraneous load via optimal instructional designs. It is especially important when a complex learning task is imposed, which in the presence of successive extraneous loads would hinder effective learning to occur due to the "exceed the maximum cognitive capacity" (Paas et al., 2010). One of the items to measure extraneous cognitive load is "The instructions and/or explanations were, in terms of learning, very ineffective" (Leppink et al., 2013). Skulmowski & Xu (2021) discussed a few design principles which include the split-attention effect, the redundancy effect, staying away from seductive details, and avoiding animations.

Germane cognitive load or perceived learning "refers to the WM resources required to deal with intrinsic cognitive load" or "to deal with element interactivity that contributes to learning", which could increase with the decrease of extraneous load (Paas et al., 2010). Learners do not have control over perceived learning (Sweller, 2010, page 126). In an ideal learning environment, motivated learners would interact, engage and be active in learning activities. One of the items to measure perceived learning is "The activity really enhanced my understanding of the topic(s) covered" (Leppink et al., 2013).

A fundamental assumption of CLT is the limited working memory capacity such that reducing extraneous load by optimized instructional designs would enable more mental capacity available for active learning categorized by intrinsic load and germane load (Sweller et al., 1998, page 264). Therefore, our first research question is:

 ISSN: 2473-4901
v9 n6066

RQ1: Whether the impact of intrinsic and extraneous cognitive loads on actual learning is the same as their impact on perceived learning?

As shown in Figure 1, six hypotheses were developed to test the relationships between CLT and actual learning to answer RQ1.

H1a, H1b and H1e: intrinsic cognitive load is significantly associated with extraneous and germane cognitive load, and actual learning, respectively.

H2a and H2b: extraneous cognitive load is significantly associated with germane cognitive load and actual learning, respectively; and mediates the effect of intrinsic cognitive load on germane cognitive load.

H3: germane cognitive load is significantly associated with actual learning, and significantly medicates the effect of intrinsic and extraneous cognitive loads on actual learning.

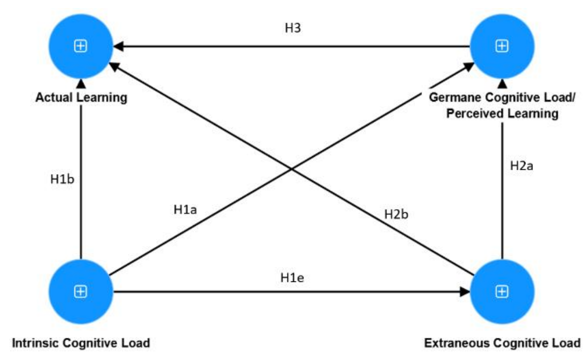

Figure 1. Cognitive Load Theory and Actual Learning

Skulmowski & Xu (2021) pointed out the limitations of CLT in explaining effective learning under certain exceptions. CLT assumed "constant levels of motivation, the learner has no control over germane cognitive load" (Sweller, 2010, page 126). This study explores the mediation effects of performance and effort expectancies on the impact of intrinsic and extraneous cognitive loads on both perceived learning and actual learning, respectively, as shown in Figure 2 below.

Effort expectancy is fundamentally defined as the level of easiness associated with using a system (Venkatesh et al., 2003). It's commonly believed that if a system is perceived as easy to use, it's more likely to lead to the perception of usefulness and the intention to use it (Jackson et al., 1997). In the educational context, effort expectancy refers to a student's assessment that their interaction with information system tools, such as DBMS, SQL, and Excel, will be relatively effortless in terms of cognitive burden. Students don't anticipate having to invest a significant amount of time and effort to operate these tools. Essentially, effort expectancy is a factor that naturally motivates students to engage with information systems to enhance their learning outcomes. One of the survey questions frequently used to measure effort expectancy is: "Learning to operate the system would be easy for me" (Davis, 1989; Davis et al., 1989).

Performance expectancy refers to how much an individual believes that using the system will actually boost their job performance (Venkatesh et al., 2003). It's closely related to what's known as "perceived usefulness" in the Technology Acceptance Model (TAM). Venkatesh et al. (2003) found that performance expectancy is a powerful predictor of whether someone intends to use a new technology at work. Other researchers have also found supporting evidence for the connection between performance expectancy and students' intentions to use technology to enhance their learning outcomes (Ong et al., 2004; Saadé & Bahli, 2005). One of the questions commonly used to measure performance expectancy is: "Using the system would improve my job performance" (Davis, 1989; Davis et al., 1989).

Therefore, our second research question is:

RQ2: Do effort and performance expectancies significantly mediate the relationships between intrinsic and extraneous cognitive loads and actual learning, respectively, the same as performance and effort expectancies mediate the relationships between intrinsic and extraneous cognitive loads and perceived learning?

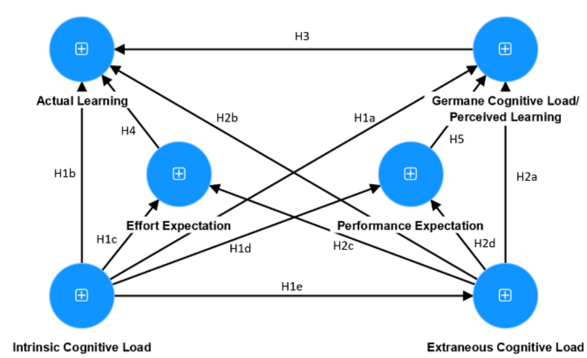

Figure 2. Integrated Theoretical Framework

As shown in Figure 2, six additional hypotheses were developed to test the mediation effects of performance and effort expectancies on the relationships between intrinsic and extraneous cognitive loads and perceived and actual learning, respectively, to answer RQ2.

ISSN: 2473-4901
v9 n6066

H1c and H1d: Intrinsic cognitive load is significantly associated with performance and effort expectancies, respectively.

H2c and H2d: Extraneous cognitive load is significantly associated with performance and effort expectancies, respectively.

H4: Effort expectancy is significantly associated with actual learning and significantly mediates the impact of intrinsic cognitive load and extraneous cognitive load on actual learning, respectively.

H5: Performance expectation is significantly associated with perceived learning and significantly mediates the impact of intrinsic and extraneous cognitive loads on perceived learning, respectively.

3. METHODOLOGY

Measurement Development

The measures of the constructs in this study were from the existing scales in the literature to test CLT with mediators of performance and effect expectancies of UTAUT in similar educational settings (Davis, 1989; Davis et al., 1989; Leppink et al., 2013). Minor modifications were made to these measures to meet the needs in this study. The institutions' review board of the university in the Southeastern region of United States approved the protocol. A pilot test of the survey instrument was conducted among the students taking the relevant courses. The survey instrument was finalized with the findings in the pilot test. The 7-point Likert scale with responses ranging from "strongly disagree" (1) to "strongly agree" (7) was used.

Data Collection and Demographic Description of the Respondents

The data in the study were collected from undergraduate students in introductory computer information systems classes in the last week of the Spring 2022 semester. Out of the 410 responses collected, 294 (71.7%) were valid responses with matching test and final exam scores. The other 116 responses were discarded because of the missing items, speedy responses and other issues. Only the students who indicated they were at least 18 years old and agreed to the informed consent could access the survey via Qualtrics.com.

The respondents' demographic statistics included respondents' gender, age, ethnicity, and major. Among the 294 valid respondents, 153 (52%) were males and 141 (48%) were females; 243 (82.7%) were 18 to 19 years old; 238 (81%) were Whites and the others 56 (19%) were Asians and other ethnicity. The top four majors were finance or quantitative finance with 63 (21.4%), marketing with 63 (21.4%), management with 64 (21.8%), and computer information systems with 35 (11.9%).

Assessment of multivariate normality

The SEM PLS via SmartPLS is used to estimate both the measurement and structural models due to the non-normal distribution of data as measured by Mardia's normalized multivariate kurtosis (cutoff value of 3) with a value of 77 (Cain et al., 2017; Finney & DiStefano, 2013).

Internal consistency reliability and validity

McDonald Omega (ω) and the corresponding 95% confidence intervals were used to assess the internal consistency reliability of the constructs (McDonald, 2013, 1999). The calculations were carried out by JASP. The values of McDonald Omega (ω) ranged from 0.763 for actual learning to 0.939 for perceived learning. The lower confidence limits of McDonald Omega (ω) ranged from 0.711 for actual learning to 0.928 for perceived learning among all six constructs. These results, therefore, indicated that the data in this study possessed acceptable internal consistency reliability.

Convergent and Discriminant Validity, and Model Fit

To assess the convergent and discriminant validity, consistent PLS-SEM bootstrapping algorithm was conducted with 5000 replications with acceptable results of measures. Model fit indices showed that the absolute fit index SRMR of a value of 0.043 was within the suggested value of 0.08 or less (Hu & Bentler, 1999). The values of the composite reliability (rho-c) of constructs ranged from 0.851 for actual performance to 0.942 for perceived learning, exceeding the suggested cutoff value of 0.7 (Fornell and Larcker, 1981). The values of Average Variance Extracted (AVE) for constructs ranged from 0.616 for effort expectancy to 0.803 for perceived learning, higher than the suggested cutoff value of 0.50 (Fornell & Larcker, 1981). These results suggested the satisfactory convergent validity of the constructs in this study. The square root of the AVE values for each construct was larger than the correlations between a construct and all other constructs. These results indicated the adequate discriminant validity of the constructs according to Fornell and Larcker (1981). All HTMT values were well within 0.90 that showed discriminant validity between two reflective constructs. The f-square values supported the results shown in Figure 4.

ISSN: 2473-4901
v9 n6066

4. RESULTS AND DISCUSSIONS

Figure 3 and Figure 4 showed the testing results from 5000 replications of the consistent SEM - PLS bootstrapping algorithm. The path-coefficient values and their corresponding p-values were labeled for each hypothesis.

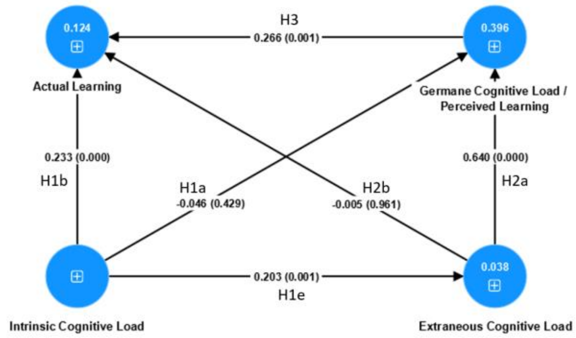

Figure 3. The testing results for CLT with actual learning.

Remarks: The values on the links were the path coefficients and the values within the parentheses were their p-values.

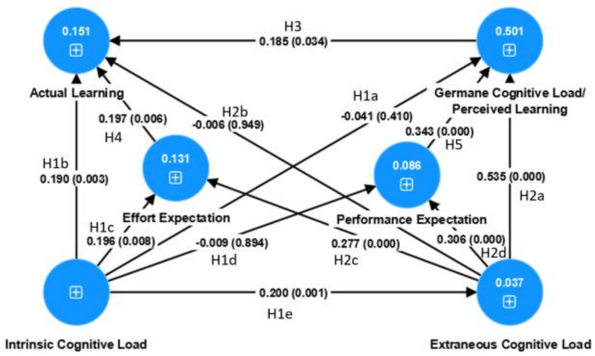

Figure 4 Testing results of mediation effects of effort and performance expectancies on impact of intrinsic and extraneous cognitive loads on perceived learning and actual learning, respectively.

Remarks: The values on the links were the path coefficients and the values within the parentheses were their p-values.

As shown in Figure 3 and Figure 4, the hypothesis H1a for the association between intrinsic cognitive load and perceived learning was not supported. The hypothesis H1b for the association between intrinsic cognitive load and actual learning was supported with a moderate positive path coefficient (0.190, p-value of 0.003). This confirmed the findings in our initial model in Figure 3. We found that intrinsic cognitive load had a significant impact on actual learning, however, it did not have a significant effect on perceived learning. This suggested that the difficulties students perceived in the course materials did not significantly impact how they perceived their learning outcomes. However, it did significantly influence their actual learning outcomes. This could be because students tended to overestimate their own abilities to succeed when they encountered challenging course materials.

Interestingly, we observed opposite results for extraneous cognitive load which could be reduced by effective instructional designs. The results indicated that extraneous cognitive load significantly positively affected students' perceived learning outcomes, however, did not significantly impact their actual learning outcomes. This shed light on the ongoing debate regarding the impact of instructors' course design procedures (how they presented course materials) on students' perceived or actual learning outcomes. In other words, students may believe they learned a lot from an instructor who delivered the content effectively, however, in reality, they may not learn as much as they believed.

Subsequently, we analyzed how performance and effort expectancies mediated the associations between intrinsic cognitive load and both perceived learning and actual learning. We also investigated the mediation effects of performance and effort expectancies on the relationships between extraneous cognitive load and both perceived learning and actual learning, respectively.

Based on our findings, we discovered that effort expectancy partially mediated the impact of intrinsic cognitive load on actual learning and fully mediated the influence of extraneous cognitive load on actual learning. This suggested that the perceived ease of using technology tools could significantly affect students' actual learning outcomes, especially when the course materials were challenging. Additionally, the perceived ease of using technology tools could also play a significant role in determining students' actual learning outcomes, even in cases where the instructor's design was not optimal. This underscored the importance of students mastering computer-based technology for success in undergraduate information system courses.

Regarding the mediation effect of performance expectancy, our findings were quite intriguing. We discovered that performance expectancy partially mediated the relationship between extraneous cognitive load and perceived learning, however, it did not significantly impact the association between intrinsic cognitive load and perceived

 ISSN: 2473-4901
v9 n6066

learning. This suggested that emphasizing the practicality or usefulness of information systems could improve students' perception of their learning (or their evaluation of a course), even when the instructor's delivery of course material was less than ideal. This underscored the significance of highlighting the utility of computer-based technology in motivating student learning.

5. CONCLUSIONS AND FUTURE RESEARCH DIRECTIONS

As one of the first studies to test the integration of performance and effort expectancies of UTAUT and CLT, this study answered two research questions. In answering RQ1 and RQ2 as shown in Figure 3 and Figure 4, we concluded that the inherent complexity as measured by intrinsic cognitive load was not significantly associated with perceived learning and performance expectancy. However, the association between intrinsic cognitive load and perceived learning was fully mediated by extraneous cognitive load. Extraneous cognitive load was significantly positively associated with both performance expectancy and perceived learning. This result signified the importance of both improved instructional designs to reduce the extraneous cognitive load and motivating learners which had a significant positive association with perceived learning. The results in this study also concluded that the inherent complexity as measured by intrinsic cognitive load had a significant positive impact on actual learning and effort expectation, which had a significant positive association with actual learning. Therefore, it is beneficial for learners to have easy access to technical elements of the materials.

6. REFERENCES

Abbad, M. M. M. (2021). Using the UTAUT model to understand students' usage of e-learning systems in developing countries. Education and Information Technologies, 26(6), 7205–7224. https://doi.org/10.1007/s10639-021-10573-5

Abeysekera, L., & Dawson, P. (2015). Motivation and cognitive load in the flipped classroom: Definition, rationale and a call for research. Higher Education Research & Development, 34(1), 1–14. https://doi.org/10.1080/07294360.2014.934336

Chandler, P., & Sweller, J. (1991). Cognitive Load Theory and the Format of Instruction. Cognition and Instruction, 8(4), 293–332. https://doi.org/10.1207/s1532690xci0804_2

Chao, C.-M. (2019). Factors Determining the Behavioral Intention to Use Mobile Learning: An Application and Extension of the UTAUT Model. Frontiers in Psychology, 10. https://www.frontiersin.org/articles/10.3389/fpsyg.2019.01652

Chen, Y., & Roldan, M. (2021). Digital innovation during COVID-19: Transforming challenges to opportunities. Communications of the Association for Information Systems, 48(1), 3.

Davis, F. D. (1989). Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. MIS Quarterly, 13(3), 319–340. https://doi.org/10.2307/249008

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User Acceptance of Computer Technology: A Comparison of Two Theoretical Models. Management Science, 35(8), 982–1003. https://doi.org/10.1287/mnsc.35.8.982

Dwivedi, Y. K., Rana, N. P., Tamilmani, K., & Raman, R. (2020). A meta-analysis based modified unified theory of acceptance and use of technology (meta-UTAUT): A review of emerging literature. Current Opinion in Psychology, 36, 13–18. https://doi.org/10.1016/j.copsyc.2020.03.008

Fornell, C., & Larcker, D. F. (1981). Structural Equation Models with Unobservable Variables and Measurement Error: Algebra and Statistics. Journal of Marketing Research, 18(3), 382–388. https://doi.org/10.1177/002224378101800313

Hu, L., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. Structural Equation Modeling: A Multidisciplinary Journal, 6(1), 1–55. https://doi.org/10.1080/10705519909540118

Jackson, C. M., Chow, S., & Leitch, R. A. (1997). Toward an Understanding of the Behavioral Intention to Use an Information System. Decision Sciences, 28(2), 357–389.

https://doi.org/10.1111/j.1540-5915.1997.tb01315.x

Kalyuga, S. (2005). Prior Knowledge Principle in Multimedia Learning. In The Cambridge handbook of multimedia learning. (pp. 325–337). Cambridge University Press. https://doi.org/10.1017/CBO9780511816819.022

Leppink, J., Paas, F., Van der Vleuten, C. P. M., Van Gog, T., & Van Merriënboer, J. J. G. (2013). Development of an instrument for measuring different types of cognitive load. Behavior Research Methods, 45(4), 1058–1072. https://doi.org/10.3758/s13428-013-0334-1

McDonald, R. P. (2013). Test theory: A unified treatment. psychology press.

Ong, C.-S., Lai, J.-Y., & Wang, Y.-S. (2004). Factors affecting engineers' acceptance of asynchronous e-learning systems in high-tech companies. Information & Management, 41(6), 795–804. https://doi.org/10.1016/j.im.2003.08.012

Paas, F., van Gog, T., & Sweller, J. (2010). Cognitive Load Theory: New Conceptualizations, Specifications, and Integrated Research Perspectives. Educational Psychology Review, 22(2), 115–121. https://doi.org/10.1007/s10648-010-9133-8

Paas, F., & van Merriënboer, J. J. G. (2020). Cognitive-Load Theory: Methods to Manage Working Memory Load in the Learning of Complex Tasks. Current Directions in Psychological Science, 29(4), 394–398. https://doi.org/10.1177/0963721420922183

Saadé, R., & Bahli, B. (2005). The impact of cognitive absorption on perceived usefulness and perceived ease of use in on-line learning: An extension of the technology acceptance model. Information & Management, 42(2), 317–327. https://doi.org/10.1016/j.im.2003.12.013

Singh, J., Evans, E., Reed, A., Karch, L., Qualey, K., Singh, L., & Wiersma, H. (2022). Online, Hybrid, and Face-to-Face Learning Through the Eyes of Faculty, Students, Administrators, and Instructional Designers: Lessons Learned and Directions for the Post-Vaccine and Post-Pandemic/COVID-19 World. Journal of Educational Technology Systems, 50(3), 301–326. https://doi.org/10.1177/00472395211063754

Singh, J., Steele, K., & Singh, L. (2021). Combining the Best of Online and Face-to-Face Learning: Hybrid and Blended Learning Approach for COVID-19, Post Vaccine, & Post-Pandemic World. Journal of Educational Technology Systems, 50(2), 140–171. https://doi.org/10.1177/00472395211047865

Skulmowski, A., & Xu, K. M. (2021). Understanding cognitive load in digital and online learning: A new perspective on extraneous cognitive load. Educational Psychology Review, 1–26.

Sweller, J. (2010). Element Interactivity and Intrinsic, Extraneous, and Germane Cognitive Load. Educational Psychology Review, 22(2), 123–138. https://doi.org/10.1007/s10648-010-9128-5

Sweller, J. (2020). Cognitive load theory and educational technology. Educational Technology Research and Development, 68(1), 1–16. https://doi.org/10.1007/s11423-019-09701-3

Sweller, J., van Merriënboer, J. J. G., & Paas, F. (2019). Cognitive Architecture and Instructional Design: 20 Years Later. Educational Psychology Review, 31(2), 261–292. https://doi.org/10.1007/s10648-019-09465-5

Sweller, J., van Merrienboer, J. J. G., & Paas, F. G. W. C. (1998). Cognitive Architecture and Instructional Design. Educational Psychology Review, 10(3), 251–296. https://doi.org/10.1023/A:1022193728205

ultan Hammad Alshammari, & Mohd Shafie Rosli. (2020). A Review of Technology Acceptance Models and Theories. Innovative Teaching and Learning Journal.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User Acceptance of Information Technology: Toward a Unified View. MIS Quarterly, 27(3), 425–478. JSTOR. https://doi.org/10.2307/30036540