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Comparing learning outcomes in physical and simulated learning environments

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ABSTRACT

The use of 2D and 3D simulated learning environments in education and training has increased significantly in the past decade. Simulated learning environments provide several advantages over physical learning environments including increased safety and accessibility. Simulated learning environments can also be utilized in an online setting, increasing the efficiency of delivery, access, and supporting greater personalization of the learning process. Despite a long history of use in workforce education, researchers have questioned whether simulations provide learners with the same quality of education as physical learning environments. This research investigated how learning to construct electrical circuits using a 2D simulation, a 3D simulation or a physical breadboard impacted learning outcomes. Additionally, this study examined the influence of learner characteristics, cognitive ability and goal orientation, on the relationship between the simulated learning environments and learning outcomes. The study utilized a pretest-posttest between subjects design and included 48 participants. Results suggest that learning to construct a circuit with physical components results in higher self-efficacy, faster construction times, and higher odds of correct construction than learning in a 2D or 3D simulation. Participants in the three conditions achieved comparable results in terms of cognitive outcomes; the differences identified were based on cognitive ability and goal orientation. There were no significant differences in outcomes achieved between participants in the 2D and 3D simulations. Implications for the design of simulated learning environments and potential impact for online technical curriculum are discussed.

Relevance to industry: This study supports the evaluation of using online educational technology to learn technical skills. This is relevant to workforce education, especially with a diverse and distributed workforce that requires technical training.

1. Introduction

Technical education has been slower than other disciplines in adopting online delivery for course and laboratory instruction (Bernard et al., 2004). This is, in part, due to the belief that laboratory education for technical skills requires hands-on, classroom-based instruction that simulated environments cannot provide (Bourne et al., 2005; Zacharia and Olympiou, 2011). This perspective is supported by concerns that the adoption of simulations has occurred more rapidly than empirical evidence supporting its effectiveness (Goode et al., 2013) and recognition that offering technical courses, specifically those requiring a lab component, in an online setting requires the development of pedagogies that support course adaptation and effective evaluation (Bernard et al., 2004). However, simulated learning environments provide several advantages over physical learning environments including a safer learner environment that allows learners to practice at their own pace, on their own schedule, and until the point of proficiency (Krueger, 1991; Zacharia, 2007). Simulations can also be delivered in an online setting, allowing increased accessed and efficiency of delivery, and greater personalization of the learning process (Henderson et al., 2015; Kim et al., 2013). Developing effective simulations for technical courses, including simulated learning environments to support laboratory-based instruction, is instrumental for increasing educational access and opportunities for students and fully exploiting the benefits of online education. This research sought to evaluate the influence of simulated learning environments, both 2D and 3D, on learning outcomes for a technical course with a corresponding laboratory-based activity.

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2. Background

2.1. Physical and simulated laboratory instruction

Laboratory instruction is a key educational feature for technical disciplines as well as science, engineering, and math. These learning environments were developed with the belief that understanding how to apply science to solve real world problems required both theory and practice (Auer et al., 2003). In laboratories, students may study proper laboratory technique, develop analytical thinking, connect theory to practice, and gain hands-on experience (Woodfield et al., 2005). Students also engage in active learning, conduct experiments, and employ problem-solving skills that facilitate the application of theory in practical situations (Feisel and Rosa, 2005). Laboratory instruction has typically occurred in a classroom environment where students work individually or in team and are guided by an instructor or teaching assistant. Using physical equipment and materials during laboratory instruction represents the highest level of fidelity. Physical learning environments allow students to experience the sensory characteristics of the equipment and experiments and gain familiarity with the environment within which they will be used (Zacharia, 2007; Zacharia and Olympiou, 2011).

Simulations are designed to model the core principles of a particular system (Jaakkola et al., 2011). Simulated learning environments include 2D, desktop 3D, and immersive virtual environments. In addition to providing increased accessibility these environments can foster the attention and engagement of students more readily than traditional methods (Adams et al., 2008; Stone, 2001). Simulations have the ability to "make the invisible visible" (e.g., showing the current flow of an electric circuit), which can help students learn complex relationships (Finkelstein et al., 2005; Jaakkola et al., 2011). Simulations also have the added benefit of helping students to learn in an ideal environment where they can focus on exploring concepts without the complications associated with equipment and device reliability (Finkelstein et al., 2005). However, simulations limit students from experiencing hands-on manipulation of real materials, may lack the necessary detail and realism to effective teach scientific techniques, and can distort reality (Scheckler, 2003; Woodfield et al., 2005). Simulations also lack physicality, which is "the actual and active touch of concrete material," which is believed to be important for learning (Zacharia and Olympiou, 2011, p. 318). Other researchers have suggested that it is the active manipulation, rather than the physicality, that is the most important element of laboratory instruction (Resnick, 1998) and physicality may only be necessary for perceptual-motor skills (Triona and Klahr, 2003).

Several studies have evaluated using simulated environments in laboratory instruction as a supplement, a substitute, or in some combination with physical instruction. Research has found both positive and negative effects of simulation based instruction on learning outcomes (Lee, 1999; Sitzmann, 2011). Simulations have been found beneficial for helping students prepare for lab (Dalgarno et al., 2009; Martinez-Jimenez et al., 2003) and students learning in simulated environments can outperform students learning in physical environments (Campbell et al., 2002; Finkelstein et al., 2005). A meta-analysis by Lee (1999) also found that simulations had a positive effect on learning but reported negative effect on students' affect for technology-based learning. Combined simulation and physical instruction was found to result in superior learning outcomes than students learning solely in a physical environment (Campbell et al., 2002; Jaakkola et al., 2011; Zacharia, 2007) and simulations were effective for learning both presentation and practice when used with other instructional methods (Lee, 1999).

Simulations, however, can also vary greatly in their level of fidelity. Instruction using 2D simulation might be less effective as 2D representations may be inherently deficient for 3D representations and translating the representation from 2D to 3D may result in additional cognitive load for learners (Regian et al., 1992; Richards and Taylor, 2015). The use of 3D representations provides more flexibility and realism, however, the increased complexity can make it difficult for inexperienced users to navigate and attend to all to all of the information being conveyed resulting in degraded performance (Gillet et al., 2013; Sampaio et al., 2010; Stuerzlinger and Wingrave, 2011). Technical issues like poor resolution and lag in a 3D virtual environment can also lead to performance deficiencies (Kenyon and Afenya, 1995). Prior research has suggested that higher levels of fidelity are not necessary, and sometimes even detrimental, to learning and transfer (Alexander et al., 2005). Additional research is needed to understand what aspects of 2D and 3D virtual representations of tasks are beneficial for learning, as well as tasks, contexts, and domains may be best suited for these types of technologies (Richards and Taylor, 2015).

2.2. Learner characteristics in simulated learning environments

Learner characteristics influence instructional effectiveness and learning outcomes (Anderson, 1982; De Raad and Schouwenburg, 1996; Noe, 1986; Snow, 1989; Shute and Towle, 2003). Personality features are believed to impact affect; overlay features influence domain knowledge; and cognitive features which influence students' information processing (Kim et al., 2013). This study focused on two learner characteristics, goal orientation and cognitive ability, previously found to influence learning outcomes. Goal orientation, commonly conceptualized as performance goal orientation (PGO) and learning (or mastery) goal orientation (LGO), describes the way an individual approaches an achievement task (Button et al., 1996; Elliott and Dweck, 1988). A PGO leads learners to focus on a narrow set of concepts impeding the learning of more involved task relationships that results in good initial performance but poor ability to apply the material in other contexts (Kozlowski et al., 2001). A LGO fosters a desire to explore relationships in greater depth and acquire the knowledge and skills required for competency while building task-specific self-efficacy (Kozlowski et al., 2001). Cognitive ability describes an individual's capacity to perform higher-order mental processes such as critical thinking and problem-solving (Clark and Voogel, 1985). Higher cognitive ability is associated with learning, retention, and application of skills and knowledge (Busato et al., 2000; Clark and Voogel, 1985). Lower cognitive ability individuals may need a more structured learning environment (Snow, 1989) suggesting that the less structured and more autonomous nature of 2D or 3D environments may be detrimental to low cognitive ability learners particularly in online settings. Currently, the authors are unaware of research investigating moderation effects of goal orientation and cognitive ability on fidelity (e.g., 2D simulation, 3D simulation, or physical labs) for learning outcomes.

2.3. Purpose of this study

Although previous research has identified value in using simulations as a supplement or in combination with laboratory education, little research outside of the workforce training has specifically investigated the differences in outcomes between 2D and 3D simulations as well as the influence of learner characteristics (Kim et al., 2013; Richards and Taylor, 2015). The current study aimed to explore the role of the fidelity of the learning environment by comparing learning outcomes associated with learning in a 2D, 3D, or physical environment. This research also aimed to investigate the roles of goal orientation and cognitive ability on learning outcomes for participants learning in those different environments.

3. Methods

3.1. Participants

Participants were recruited using word of mouth, flyers, and email blasts. To be eligible, participants could not have been currently enrolled in or taken a circuits-based class during the previous academic year. Additionally, each participant must have been able to self-report an ACT or SAT score. This study was approved by the Clemson University IRB (# IRB 2015-001).

3.2. Experimental design and measures

This study utilized a pretest-posttest between subjects design. The fidelity of the learning environment (with three levels, physical, 2D simulation, and 3D) was the between subjects variable and primary independent variable (IV). The covariates included pretest scores, cognitive ability, and goal orientation. Pretest scores were used to control for individual differences in baseline knowledge and any exposure to electrical circuits that was not restricted due to the study design. Participants' SAT or ACT scores were used as a proxy for cognitive abilities. Past research has demonstrated that the SAT ($r = 0.82$) and the ACT ($r = 0.77$) both have a strong correlation with cognitive ability (Koenig et al., 2008; Noftle and Robins, 2007) and a strong correlation ($r = 0.87$) to one another (Dorans, 1999). For consistency, ACT composite scores were converted to total SAT scores for the analysis using the conversion chart developed by Dorans (1999). Learning and performance goal orientations were each assessed using an eight question instrument developed by Button et al. (1996). The reliability for these questionnaires, indexed by Cronbach's alpha, was 0.72 for PGO and 0.78 for LGO. These instruments also used a five-point Likert scales anchored by strongly disagree and strongly agree.

In order to facilitate a holistic evaluation of learning, the dependent measures included affective, cognitive, and skill-based outcomes (Kraiger et al., 1993). The affective measure was self-efficacy (SE), which describes a participant's belief in their ability to perform a task (Guthrie and Schwoerer, 1994). It was measured post instruction, to assess participants' confidence that they learned and can perform the instruction-related task, on a five point Likert Scale using a six question instrument with a reliability of $\alpha = .82$ (Guthrie and Schwoerer, 1994). The cognitive outcomes were gain score and circuit design score. Gain score describes the improvement from the pretest score to the posttest score. It was calculated by subtracting the pretest score from the posttest score. Circuit design score was graded on a three level scale – no errors, minor errors, and major errors. Major errors included mistakes such as designing a series circuit instead of a parallel circuit, and minor errors included using incorrect symbols. The skill-based outcomes were construction time, measured in minutes, and circuit construction score, which followed the same scale used for circuit design score. With respect to circuit construction grades, major errors included mistakes such as an inability to close the circuit properly, while minor errors included incorrect placement of the switch.

3.3. Procedures

After completing the consent form, participants completed a five question multiple choice, paper-based pretest examining their knowledge of basic electrical concepts. The pretest included questions about defining electrical concepts (e.g., voltage, resistance, and current), identifying circuit diagram symbols (e.g., switches, resistors, battery, and light emitting diodes), designing a circuit diagram, demonstrating understanding of breadboard functionality, and applying Ohm's law. Each question had four answer options. Next, participants were set-up at the study workstation which included a dual-monitor desktop, mouse, and keyboard. Participants completed the demographic survey, where they reported their SAT/ACT scores, and the goal orientation instruments. They then watched a 28 min video lecture on circuit analysis and basic circuit construction. The video lecture contained three sections and each section included learning objectives and practice exercises.

Following this instruction, students were randomly assigned to one of the experimental conditions (2D, 3D, or physical environment) and watched two videos demonstrating how to construct a series and a parallel circuit. Because students in the 2D and 3D conditions also had to learn to use the software, the instructional videos for each of the conditions varied in length. In total, each video ranged from 7 min to 17 min. These videos were designed specifically to teach participants how to construct circuits in their assigned condition. The practice circuits constructed were identical. Participants in the physical condition practiced constructing circuits using an 800-point solderless breadboard (Fig. 1). Participants in the 2D condition practiced using a 2D breadboard simulation (Fig. 2) and participants in the 3D condition practiced using a 3D breadboard) (Fig. 3). Participants in these two conditions navigated the 2D and 3D environments using a mouse and keyboard. All participants used comparable circuit components, including light emitting diodes (LEDs), switches, batteries, and resistors.

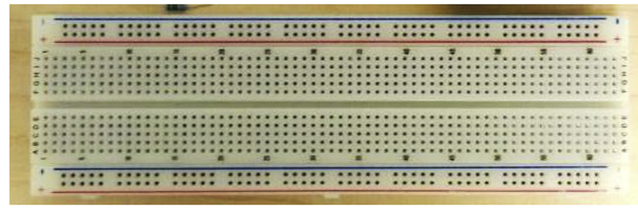

Fig. 1. 800 point solderless breadboard.

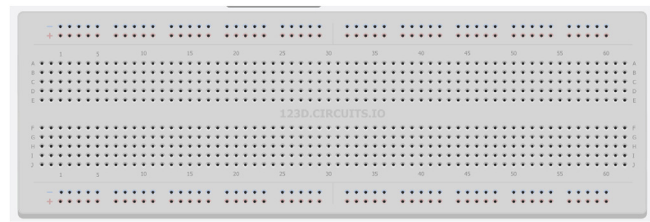

Fig. 2. Arduino 2D breadboard (123d.circuits.io).

During these videos, participants were shown how to use Ohm's law to calculate the resistance values needed for their circuit, how to design their circuit diagram and how to construct their circuit. Participants were given three practice activities to complete. One of these practice activities instructed participants to complete a series circuit using a three prong switch, the second activity had participants construct a parallel circuit, and the last activity demonstrated how to construct a circuit with parallel and series connections. During these practice sessions, they were provided with feedback concerning the accuracy of their calculations and the construction of the circuit and were referred to the appropriate video for review if they made errors. Participants were not allowed to continue the experiment until they had successfully completed the practice activities. Although this requirement led to varying practice times, it was essential that participants demonstrate a minimum level of proficiency before continuing. The study set-up included a computer workstation with two monitors so that participants could watch the video on one screen while constructing their practice circuits on the second screen. Students in all conditions had access to the instructional videos during their practice session.

Following these practice sessions, the participants completed a survey assessing their post training SE and a 5-question multiple choice,

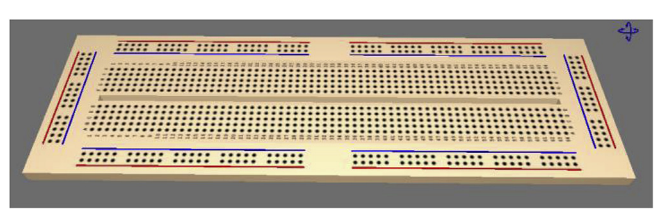

Fig. 3. National instruments multisim 3D breadboard.

paper-based post-test. The posttest was of the same structure, length, and used the same types of questions as the pretest. Finally, the participants from all conditions constructed a circuit on a physical breadboard without access to the video lectures. Participants had to first design the circuit and use Ohm's law to determine the correct amount of resistance needed based on the voltage source they selected (a 9 V battery or 1.5 V AA batteries). The circuit that needed to be designed was a simple circuit that included a switch and 3 LEDs. The circuit needed to be constructed such that the two LEDs were connected in series and powered by a switch and the third LED was connected in parallel. Construction time started once participants received the directions and ended when participants submitted their final circuit. While completing this construction task, they were video recorded using a GoPro Hero4 Black camera. The camera was positioned above the participant to record an aerial view of their work surface without being intrusive.

3.4. Analysis

The data analysis was conducted using SPSS 22. ANOVAs were used to analyze the effects of the predictor variables on self-efficacy, gain scores, and construction time. An ordered logistic regression was used to analyze the effects of the predictor variables on circuit design grade and circuit construction grade. All of the models were evaluated at the alpha = 0.05 level. Prior to the analysis, the data was evaluated to ensure it met the assumptions for an ANOVA as well as the requisite assumptions for an ordered logistic regression. For the ordered logistic regressions, the continuous variables were dichotomized into high and low values based on a median split.

4. Results

Participants for this study included 48 undergraduate and graduate students from a public mid-sized Southeastern University. Engineering students represented approximately 33% of the participants, undergraduates accounted for 50%, and females comprised 62.5%. Most participants (79%) reported that they were in the 18–27 year old category and the remaining 21% were 28 years-old or older. The majority of the participants (92%) reported having little to no prior experience working with circuits (Table 1).

The data for one participant, who was in the physical condition, was removed due to failure to report SAT or ACT scores as required by the study. Furthermore, three additional participants – all in the 3D environment - withdrew from the study, resulting in a different sample size for the circuit design and circuit construction activities. The total number of participants in each condition for all of the dependent measures was 15 in the physical condition, 16 in the 2D condition, and 13 in the 3D condition. A one-way ANOVA found no significant differences, F (2,44) = .123 (p = .884), in the scores from the pretest assessing knowledge of circuit theory and construction for the participants in the three conditions. This suggests that there were no detectable differences in the pre-existing knowledge of participants in the three conditions.

Table 1
Participant demographics.

Age	18–27 38 (79%)	28 + 10 (21%)
Gender	F 30 (62.5)	M 18 (37.5)
Major/Program	Engineering 16 (33.3%)	Non-engineering 42 (66.7%)
Circuit experience	Little to none 44 (92%)	More than a little 4 (8%)
Classification	Undergraduate 24 (50%)	Graduate 24 (50%)

Table 2
ANOVA for participants' self-efficacy following instruction and practice.

	Sum of Squares	DF	Mean Square	F	P-value
Fidelity	**3.16**	**2**	**1.58**	**3.81**	**0.031**
PGO	1.35	1	1.35	3.26	0.079
LGO	0.666	1	0.666	1.61	0.212
Error	16.16	39	0.414		
Total	21.2	43			

R Squared = .237 (Adjusted R Squared = .159)

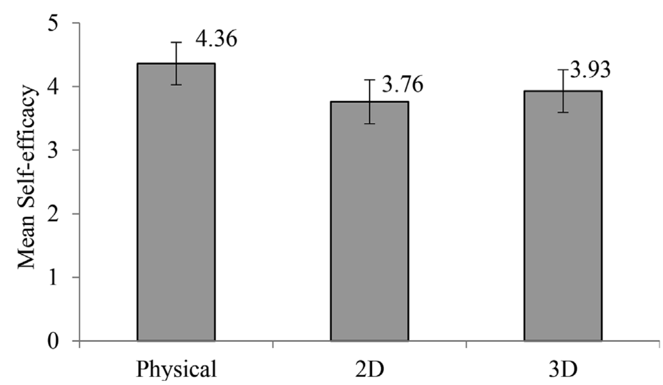

Fig. 4. Means with 95% confidence interval of self-efficacy by condition.

4.1. Main effects of fidelity and co-variates on learning outcomes

Four participants did not complete the SE survey, resulting in a total of 43 observations. The predictor variables included in the ANOVA model for SE were fidelity, LGO, and PGO. Only fidelity, F (2,39) = 3.809 (p = .031), was a significant predictor of SE (Table 2). The mean SE was 4.36 (SD = .58) for participants in the physical condition, 3.76 (SD = .67) for participants in the 2D condition, and 3.93 (SD = .75) for participants in the 3D condition (Fig. 4). Post hoc analysis completed using the least significant difference (LSD) test revealed significant differences in SE between participants in the physical condition and participants in the 2D condition (p = .014) and also between participants in physical condition and the 3D condition (p = .038). Fidelity had a unique effect size of sr^2 = .378, accounting for 37.8% of the variation in participants' self-rated SE.

The average gain score for all conditions was 0.24 (SD = .21), based on a maximum score of one. The pretest scores ranged from 0.10 to 0.80 and the posttest scores ranged from 0.45 to 1.00. The ANOVA model for gain score included the predictor variables of LGO, PGO, cognitive ability, and pretest scores. LGO, F (1,40) = 5.02 (p = .031), cognitive ability, F (1,40) = 6.49 (p = .015), and pretest scores, F (1,40) = 31.09 (p < .001), were significant predictors of gain score. Pretest scores accounted for the largest percentage in the variation in gain scores, sr^2 = .378, with cognitive ability and LGO also contributing small unique effects, sr^2 = .06 and sr^2 = .057, respectively. Fidelity and PGO were not significant predictors of gain score (Table 3).

Circuit design was graded on a scale ranging from no errors to major errors (Table 4). As one participant completed the circuit diagram prior to withdrawing from the study, there were a total of 45 observations for this model. The majority of participants (51%) were able to correctly design the circuit (Table 4). An ordered logistic regression was used to analyze the effects of the IVs – cognitive ability, LGO and PGO – on circuit design grades. The test of parallel lines for the ordered logistic model was found to be insignificant, suggesting the proportional odds assumption was met (p = .161). For circuit design, only cognitive ability was found to be a significant predictor, Wald $\chi 2$ (1, N = 45) = 5.51 (p = .019). The odds of designing the circuit correctly were 4.57 times higher [95% CI: 1.32, 17.15] for participants with high

Table 3
ANOVA for participants' gain score from the pre-test to the post-test.

	Sum of Squares	DF	Mean Square	F	P-value
Fidelity	0.07	2	0.034	1.52	0.232
LGO	**0.11**	**1**	**0.113**	**4.86**	**0.031**
PGO	0.00	1	0.005	0.23	0.886
Cognitive ability	**0.15**	**1**	**0.118**	**5.10**	**0.015**
Pretest score	**0.70**	**1**	**0.741**	**32.0**	**< 0.001**
Error	0.90	40	0.023		
Total	1.98	46			

R Squared = 0.544 (Adjusted R Squared = 0.476)

Table 4
Frequency of errors in participants' circuit design task.

Condition	No errors	Minor Errors	Major Errors	Total
Physical	9	5	1	15
2D	7	6	3	16
3D	7	5	2	14
Total	23	16	6	45

cognitive ability compared to participants with low cognitive ability. Fidelity, PGO, and LGO were not significant predictors.

Only 44 participants attempted construction as three participants withdrew and the data for one participant was removed from the analysis. The predictor variables included in the ANOVA model for construction time were fidelity, goal orientation, and cognitive ability. Fidelity was a significant predictor of construction time, F (2,33) = 4.87 (p = .014) (see Table 5). The mean construction time differed among the three conditions, with participants in the physical condition taking 15.47 min (SD = 12.39 min), participants in the 2D simulation condition taking 29.88 min (SD = 14.76 min), and participants in the 3D condition taking 30.43 min (SD = 16.91 min). Post hoc analysis using LSD found significant differences between the physical condition and the 2D condition (p = .018) as well as between the physical condition and the 3D condition (p = .019). There were no significant differences in mean construction times between the 2D and 3D conditions (p = .620). Fidelity accounted for 19% of the variation in participants' construction time, $sr^2 = .19$. LGO, PGO, and cognitive ability did not have any main effects on construction time.

Circuit construction, like circuit design, was also scored on a scale ranging from no errors to major errors (Table 6). Of the 44 participants who attempted construction, 52% were able to correctly construct the circuit. An ordered logistic regression was used to analyze the effects of all the IVs –fidelity, cognitive ability, LGO and PGO – as well as circuit design score on circuit construction. The proportional odds assumption for this model was also met as the test of parallel lines was found to be

Table 5
ANOVA for participants' construction time on the physical breadboard.

	Sum of Squares	DF	Mean Square	F	P-value
PGO	12.35	1	12.35	0.056	0.815
LGO	1.06	1	1.06	0.005	0.945
Cognitive ability	254.46	1	254.46	1.150	0.292
Fidelity	**2161.65**	**2**	**1080.83**	**4.870**	**0.014**
Fidelity*Cognitive ability	103.67	2	51.84	0.233	0.793
Fidelity*LGO	**1513.34**	**2**	**756.67**	**3.410**	**0.045**
Fidelity*PGO	322.13	2	161.07	0.725	0.492
Error	7328.61	33	222.08		
Total	11288.31	44			

R Squared = .351 (Adjusted R Squared = .134)

Table 6
Frequency of errors in participants' circuit construction grades.

Condition	No errors	Minor errors	Major Errors	Total
Physical	11	2	2	15
2D	8	2	6	16
3D	4	2	7	13
Total	23	6	15	44

insignificant (p = .77). For circuit construction, circuit design score, Wald $\chi 2$ (1, N = 44) = 5.32, p = .024, and fidelity, Wald $\chi 2$ (2, N = 44) = 2.93, p = .021, were found to be significant predictors. The odds of constructing the circuit correctly were .04 times lower [95% CI: .003, .617] for participants who made major errors in their circuit design compared to participants who made no errors. Additionally, the odds for participants in the 3D condition were .064 times [95% CI: .003, .617] lower than the odds for participants in the physical condition.

4.2. Moderating effects of learner characteristics on outcomes

LGO was found to moderate the relationship between fidelity and construction time, F (2, 33) = 3.41 (p = .045) (Table 5). The moderation effect uniquely accounting for 13.4% of the variation in construction time, $sr^2 = .134$. In the 3D condition, participants who had a higher than average LGO constructed their circuit faster (24.11 min, SD = 9.61min) than those with a lower than average LGO (41.8 min, SD = 22.21 min). In the 2D condition, participants with a higher than average LGO took longer to construct their circuit (33.86 min, SD = 17.32 min) than participants with a lower than average LGO (26.78 min, SD = 12.61 min) (Fig. 5). In the physical condition, participants with a higher than average LGO also constructed their circuit slower (18.22 min, SD = 15.24) min than those with a lower than average LGO (11.43 min, SD = 4.89 min). Further analysis found that this pattern is consistent even after removing participants who gave up or were ultimately unsuccessful in their construction attempt.

5. Discussion

Self-efficacy (SE) is an important learning outcome as it influences effort, persistence, and emotional response (Zimmerman, 2000). Participants in the physical condition had a higher mean SE than the participants in both the 2D and 3D conditions. This result was contradictory to the findings of the meta-analysis conducted by Sitzmann (2011) which found participants in simulated environments SE was 20% higher than those in traditional instructional environments. However, the studies in the meta-analysis replaced traditional classroom methods, lectures and discussion, with simulated learning and this study focused on the technical task, circuit construction, and only varied the practice portion. In this regard, participants in the physical condition had the advantage of fidelity for the circuit construction task as it was completed on a physical breadboard although they were unaware of this fact beforehand as the SE instrument was completed before the construction task. Potentially, participants in the simulated environments recognized that constructing a circuit is a hands-on and that what they learned would inherently be different from how the task would be performed in the real world and, as a result, had a lower self-efficacy. Prior research has found that participants learning in simulated environment may doubt the real-world application of the phenomena experienced in the simulation (Couture, 2004).

Fidelity did not significantly predict the cognitive outcomes, gain scores or circuit design grades. This finding is in line with prior research that has found that are no differences in cognitive outcomes between physical and simulated environments when the instructional method is controlled, as it was in the study (Clark, 1994; Jaakkola and Nurmi,

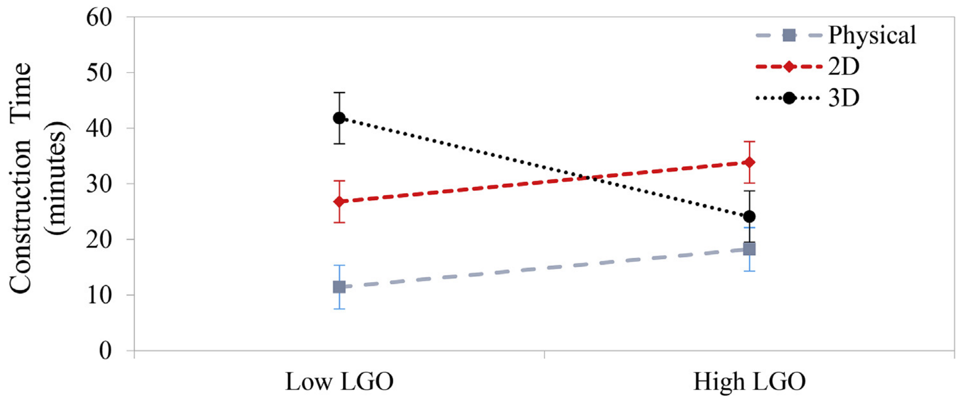

Fig. 5. LGO and physical fidelity interaction on construction time.

2008; Triona and Klahr, 2003; Zacharia and Olympiou, 2011). Participants in all of the conditions watched the same video lecture and completed the same practice exercises and activities, therefore it was not anticipated that fidelity would impact the cognitive outcomes. LGO was a significant predictor of gain score and cognitive ability was a significant predictor of both gain score and circuit design. Both of these characteristics are associated with better educational performance (Button et al., 1996; Clark and Voogel, 1985). Specifically for circuit design, while most participants knew how to construct a diagram, those with a higher cognitive ability were likely better able to design a circuit that was different than what had been designed during practice.

Fidelity was a significant predictor of the skill-based outcomes, construction time and circuit construction. Participants in the physical condition were able to construct the circuit twice as fast as participants in either the 2D or 3D condition and were more likely to construct the circuit correctly. The identical elements theory may explain this difference in construction time between participants in the three conditions as it posits that there will be a higher positive transfer when the instruction environment is identical to the performance environment (Goldstein and Ford, 2002). Participants who practiced in the physical condition had the benefit of a higher level of fidelity, a situation which likely contributed to their ability to construct the circuit much faster than participants in the other two conditions. Participants in the 2D and 3D conditions likely exerted additional effort (and thus time) to acclimate to working with physical components. Furthermore, there were characteristics of the software design, rather than an innate characteristic of 2D simulations and 3D learning environments, that may have been detrimental to participants' performance when they transitioned from the simulated environment to the physical environment. Various abstractions such as keying resistance value versus reading it from a resistance color code sheet and feedback mechanisms, such as displaying blown LEDs or incorrect connections, simplified circuit construction and provided a level of support unavailable to participants when they transitioned to working with the physical breadboard. These findings provide insights regarding how the design of simulated environments can be improved to support learning and transfer. Certain abstractions may need to be removed to facilitate transfer or may need to be introduced only after learners have established proficiency. Similarly, feedback should be reduced as learners gain proficiency so they do not become too dependent on it, which can hinder performance (Goodman and Wood, 2004).

These differences in the 2D and 3D environments potentially influences interaction found between LGO and fidelity on construction time. For participants in the 3D condition, having a high LGO resulted in a lower construction time but in the 2D and physical condition, having a higher LGO resulted in a higher mean construction time. The 3D software provided immediate feedback about circuit connectivity and thus participants with a low LGO may have depended more heavily on this feedback than those with a high LGO and it was detrimental to their performance when they transitioned to the physical environment (Goodman and Wood, 2004). Interestingly, this moderation effect was the only significant difference detected in the outcomes achieved between participants in the 2D and the 3D simulations, although participants in the 3D demonstrated lower SE, higher construction time, and lower odds of correctly constructing their circuit. Existing literature has suggested that increasing the level of fidelity does not necessarily improve learning outcomes as higher levels of fidelity are more difficult to navigate and may increase the cognitive load of participants and (Alexander et al., 2005; Gillet et al., 2013; Paas and Sweller, 2014; Stuerzlinger and Wingrave, 2011). The poor results for 3D participants may have been exacerbated by the fact that majority of the participants (n = 30) were female and prior research has identified gender differences in the spatial ability (Feng et al., 2007). The value of 3D environments over 2D is likely dependent on the task being studied (Richards and Taylor, 2015).

5.1. Limitations

Although both undergraduate and graduate students were used to create a more diverse group of participants, a more representative sample would have included non-traditional students as they are more likely to enroll in online courses and technical curriculum than traditional students (Allen and Seaman, 2007). Participants without any prior experience working on circuits would have been preferable; however, the majority of the participants in the study reported having little to no prior experience. The exclusion criteria for participation, could not have taken a circuits course in the past year, is supported by prior research which has found that the unused skills and knowledge decay quickly following instruction and then more slowly until it reaches the pre-instruction levels in several months (Arthur et al., 1998; O'Hara, 1990). The engineering students in the study may have only completed a survey circuits course for non-electrical engineers or may not have taken a circuits course at all, depending on their year.

The sample size for the study was relatively low (16 per condition) and was reduced further due to the withdrawal of several participants. As a result, the power of the analysis was not ideal. Despite the low power, significant differences were identified between the fidelity of the environment or learner characteristics on all of the measured DVs. Dichotomizing continuous variables for the logistic regression facilitated interpretation of the results but also reduced the sensitivity of the analysis. Since both the 2D and 3D software were purchased off the shelf, there were differences in these environments, besides fidelity, such as level of feedback provided, that potentially contributed to the results. Lastly, while circuit construction may be compared to other cognitive procedural tasks, additional research should evaluate the extent to which the results from this study are generalizable across tasks and other types of laboratory-based instruction.

6. Conclusions

Identifying how technical and hands-on tasks can be effectively learned in simulated environments is an important question for expanding course offerings in online education and subsequently increasing access and educational equity. While these findings suggest that instruction using physical components was superior, there was evidence of transfer for participants who learned to construct a circuit in a simulated environment. Improvements in the design of both the 2D and 3D software and better incorporation of instructional design principles could help address issues participants faced when they transitioned and reduce the time needed to acclimate to the physical environment. The 3D condition appeared to offer no significant advantages over a 2D simulation for helping participants learn to construct a circuit on a breadboard. Therefore, it may not be necessary to devote the time and resources to develop and maintain 3D environments and for learners using 2D environments likely reduces the technological requirements to run the simulation. This finding may be specific to the task as prior research has identified value in using 3D representation for other tasks, such as navigation (Regian et al., 1992). This research also highlighted the importance of identifying and evaluating learner characteristics when selecting the learning environment as characteristics, such as cognitive ability and goal orientation, can influence performance. Future research should continue to identify which learner characteristics are most important and how they impact various learning outcomes in simulated environments.

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