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Abstract:

With an excess of interconnected devices, Internet of things (IoT) technologies offer an exciting area for information systems researchers; however, the inherently physical nature of IoT makes it difficult to provide hands-on laboratory exercises to remote students. Research suggests that enactive mastery provides the greatest educational improvement to individual self-efficacy, yet not all enactive experiences are the same, certainly not when individuals have no means of accessing materials physically. Through the use of a virtual laboratory and home automation IoT technology, we develop a method to teach IoT in remote settings where students can experience hands-on IoT training in remote settings. We experimentally evaluate the virtual laboratory by comparing student outcomes in a traditional setting using physical materials to those using the virtual laboratory. Results indicate that while student perceptions were lower for students using the virtual laboratory, this virtual laboratory was successful in offering students the means to perform hands-on IoT automation, with these students achieving equivalent performance metrics to those utilizing a traditional physical laboratory.

Keywords: Internet of Things, IoT, Self-Efficacy, Virtual Labs.

[Department statements, if appropriate, will be added by the editors. Teaching cases and panel reports will have a statement, which is also added by the editors.]

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1 Introduction

Internet of things (IoT) technologies are becoming increasingly ubiquitous today. From Amazon Alexa to smart watches to your refrigerator alerting you to a low supply of milk, consumers demand more devices to help easily complete tasks. In the past decade, research has looked at various areas related to IoT and information systems (Baiyere, Topi, Venkatesh, Wyatt, & Donnellan, 2020; Li, Da Xu, & Zhao, 2015; Whitmore, Agarwal, & Da Xu, 2015). These articles provide an overarching view of research as it relates to IoT, including future directions for research. One common theme is that IoT is a burgeoning area on the rise, and we as academic researchers need to more fully engage in various research paths related to IoT.

Some organizations require a working knowledge from employees for understanding these IoT technologies; however, little research within information systems has explored educational delivery regarding IoT technologies (for examples, see de Haan, 2016; Lichtenecker, Marchesan, dos Santos Sachete, & Rossi, 2020; Olagunju & Khan, 2016). One challenge regarding IoT technologies is their inherent tie to *hardware* devices. Given the increasing prevalence of online education (Dykman & Davis, 2008), the questions is whether hands-on instruction in IoT can be as effective in a remote virtual environment as it is in a traditional physical environment.

This research aims to posit an innovative method to teach IoT concepts in a practical way to students without access to the required hardware, and to demonstrate the efficacy of the virtual laboratory exercise compared to a traditional physical laboratory exercise. Using a mixed methods design we directly evaluate differences in outcomes between a traditional physical laboratory (physical) where physical IoT devices are used, and a proposed virtual laboratory (virtual) where IoT devices are represented virtually. While maintaining as much similarity between each setting as possible, we measure how each setting (virtual, physical) effects student outcomes using the virtual and physical laboratories with performance serving as the key determinant of whether the virtual laboratory is successful.

2 Background

2.1 IoT Education

IoT technologies have become commonplace for students in their homes and daily lives with many students likely to have an IoT device in the home (Brito, Dias, & Oliveira, 2018). Of these students exposed to IoT daily, few understand the devices they are using are computers capable of maintaining an internet connection. Studies have been conducted to explore not just what these students understand of IoT, but to test their ability to identify an IoT device. Research shows that children as young as six are capable of understanding IoT as a concept, many of which are capable of conceptualizing IoT as a "computer" regardless of the physical manifestation it might take (Mertala, 2020). These studies have shown that IoT is no longer relegated to upper education, hobbyists, and working professionals, but has diffused into the average household (Brito et al., 2018; Mertala, 2020).

Deployment of IoT education has been broad in disciplinary adoption, and even so, IoT education is still in a nascent state (Dobrilović, Čović, Stojanov, & Brtka, 2013; Fernández-Caramés & Fraga-Lamas, 2020; Sánchez, Mallorquí, Briones, Zaballos, & Corral, 2020; Watteyne, Tuset-Peiro, Vilajosana, Pollin, & Krishnamachari, 2017). Calls have been made by researchers that view IoT as a fruitful educational venture that should receive further focus in upper education, especially as the benefits of IoT become increasingly apparent (Burd, Barker, Divitini, Guerra, et al., 2018; Watteyne et al., 2017). Notable benefits in IoT and specific educational examples include cybersecurity (Fernández-Caramés & Fraga-Lamas, 2020; Sánchez et al., 2020), industrial process monitoring and control (Watteyne et al., 2017), wireless sensor networks (Dobrilović et al., 2013), software development, and automation (Burd, Barker, Divitini, Guerra, et al., 2018). This demonstrates the applicability of IoT in education and the generalizability of these technologies to other technology-based curricula.

Past studies have investigated the implementation of IoT curricula and how the current IoT curriculum can be improved. The motive for most of these works was the need for students going into industry to have sufficient experience with IoT technology (de Haan, 2016; Lichtenecker et al., 2020; Olagunju & Khan, 2016). Each of these studies focused on methods to implement IoT curricula, some of which used traditional IoT technology like Arduino boards as a base introduction to IoT (de Haan, 2016), then progressively increased the difficulty of the lessons throughout the semester, (de Haan, 2016;

Lichtenecker et al., 2020). Other studies used a variety of methods such as restructuring the progression of courses (Burd, Barker, Divitini, Guerra, et al., 2018; Burd, Barker, Divitini, Perez, et al., 2018; Guerra Guerra & Fermin Perez, 2017; Lichtenecker et al., 2020), integrating more interdisciplinary courses (Olagunju & Khan, 2016), or providing a more hands-on approach (Ban, Okamura, & Kaneko, 2017; de Haan, 2016). These studies each found several unique outcomes, whether that be industry companies being pleased with new hire understanding of IoT technology or students having an increased interest/motivation to learn more about IoT (de Haan, 2016). While these articles approach IoT implementation differently and have found improvements that can be made to pedagogical methods and implementation of IoT, none have considered how to deploy hands-on IoT exercises in online settings.

2.2 Virtual Laboratories

Virtual laboratories are often used when real-world implementation of a specific laboratory exercise is notably arduous to deploy, or financially infeasible. A virtual laboratory is a virtual environment meant to emulate a physical environment, that evokes similar phenomenal reactions as the physical environment, and allows students to interact with this environment using virtual tools (Brinson, 2015; Reeves & Crippen, 2021). These virtual laboratories are extremely varied in design as each implementation has different motivations across many scientific disciplines and are often designed with specific outcomes in mind (Reeves & Crippen, 2021). Some are remote virtual laboratories that are accessible without requiring co-location to materials while others are virtual laboratories that require interaction with on-premise materials. This incongruence makes establishing clear differentiations between physical and virtual laboratories difficult to establish, more difficult by the lack of standard terminology for virtual laboratories (Faulconer & Gruss, 2018).

Research indicates that virtual laboratories are extremely useful in enhancing students' ability to achieve learning objectives but has found mixed results in improving student perceptions (Brinson, 2015). Some indicate that the lack of “physicality” is contributory to the lack luster improvements in student perceptions post exercise (Luse, Brown, & Rursch, 2020), while others claim that “physicality” is irrelevant so long as the laboratory is appropriately realistic and catered to the students' educational needs (Reeves & Crippen, 2021; Stahre Wästberg et al., 2019). Others posit that removal of the social aspects of co-location in remote laboratories might be impacting student perceptions due to reduced collaboration with other students and reduced feedback from educators (Shroff, Vogel, Coombes, & Lee, 2007). The varied conceptions of virtual laboratories reduce the general applicability of findings, further exemplifying the need for strong theoretical foundations in research when contexts may vary (Reeves & Crippen, 2021).

IoT can be used to enhance virtual laboratories, especially for individuals who are located remotely. We believe it is essential that research, given the value of IoT technology generally, leverage virtual laboratories to teach IoT remotely in a realistic manner as to maximize learning outcomes when actual hands-on training is untenable. We propose a solution to this issue by using a virtual laboratory which mimics real-world IoT deployment. First, we will briefly discuss salient metrics to determine whether the solution proposed here is a viable solution compared to more traditional physical laboratories.

2.3 Self-efficacy

Social Cognitive Theory (Bandura, 1986) provides a widely accepted model to explain individual behavior (Davazdahemami, Luse, Scheibe, & Townsend, 2018). Bandura identifies two cognitive components influencing behavior: outcome expectations and self-efficacy (Compeau & Higgins, 1995). Self-efficacy measures the confidence of an individual that they can successfully complete a task in the future, which has been shown to lead to success with the task (Scheibe, Mennecke, & Luse, 2007). Four sources of self-efficacy have been identified – emotional states, social persuasion, vicarious experience, and enactive mastery – with enactive mastery providing the greatest influence on individual self-efficacy (Bandura, Freeman, & Lightsey, 1999). Enactive mastery achieves this by allowing an individual to participate through hands-on interaction with a task, allowing the individual to succeed performing the task and provide affirmation they can perform the task successfully in the future (Scheibe et al., 2007). Lent (2005) extends the work of Bandura (1986) by adapting Social Cognitive Theory for education by theorizing on the relationship between self-efficacy and the decision to pursue a specific major in higher education. An adaptation of Social Cognitive Theory labelled Social Cognitive Career Theory (SCCT) has been used in the context of IT to demonstrate that students who attain a higher level of technical self-efficacy are more likely to pursue a higher education in IT, though this relationship is demonstrated indirectly through increases in interest (Luse, Rursch, & Jacobson, 2014; Rursch & Luse, 2019).

While enactive mastery provides the most potential benefit to self-efficacy through direct, hands-on experience, the type of hands-on experience can differ across contexts. Given the increase in online education, how does “hands-on” differ in this virtual context? Research has begun to explore these differences to compare traditional versus online hands-on experiences (Bautista & Boone, 2015; Luse et al., 2020). While research indicates that virtual lab experiences do not differ significantly from that of physical lab experiences regarding self-efficacy (Brinson, 2015; Luse et al., 2020; Luse & Rursch, 2021), the inherent physicality of IoT devices may lead to perceptual differences across settings.

2.4 Interest

SCCT places interest as a pivotal factor influencing a student's intention to pursue a specific area in academia and is highly influenced by perceptions of self-efficacy (Luse et al., 2014; Rursch & Luse, 2019). Interest in education is generally separated into two experiences (1) situational experiences which is a momentary interest in the task at hand and (2) individual interest which is defined as an enduring predisposition to reengage with subject matter in future endeavors (Harackiewicz, Smith, & Priniski, 2016). Situational interest improves self-regulation, task persistence, and engagement, all of which predict traditional measures of performance (Harackiewicz & Hulleman, 2010; Harackiewicz et al., 2016). Situational interest can be triggered via problem-based instruction that forces the student to seek out critical knowledge to solve a problem that is not so difficult as to foster a perception of inability (Harackiewicz et al., 2016). Individual interest is often correlative with value perceptions, incentivizing course designs that are perceived as high in utility to a student (Harackiewicz et al., 2016; Schraw & Lehman, 2001). Drawing from these recommendations, for a virtual laboratory to positively affect interest, it should capture a student's attention in such a way that it incentivizes knowledge acquisition via critical thinking scenarios (situational interest), while offering acceptable utility in their personal and professional life (individual interest) (Harackiewicz et al., 2016).

2.5 Satisfaction

There exist two widely used measures of critical success in both traditional and e-learning environments, learner outcomes and learner satisfaction. Satisfaction in education has been defined as a student's perception of the value of a course, or specific course content (Bolliger, 2004). Students subject themselves to considerable time and financial commitments to take part in higher education, which comes with a certain degree of expectation regarding quality of education. When that expectation is not met, it may have a deleterious effect on satisfaction, and as a result, their motivation to achieve in higher education (Donohue & Wong, 1997). To avoid the deleterious effects of low-quality lab design, a laboratory (virtual or otherwise) should be as similar to real-world phenomenon as possible, both perceptually and procedurally.

Beyond the implications of course design and instructional delivery, satisfaction in e-learning environments is also contingent on the students' attitudes, experience, and skill level using computers generally (Allen, Bourhis, Burrell, & Mabry, 2002; Piccoli, Ahmad, & Ives, 2001; Zviran & Erlich, 2003). Piccoli et al. (2001) found that students who participated in a virtual learning environment outperformed their traditional learning peers, but consistently rated themselves lower on satisfaction. Educators should understand student skills, abilities, and experience using computers so they may cater course design to their specific skill levels. For a virtual laboratory, it is essential that students have attained the necessary skills needed to interact with the environment with relative proficiency, where satisfaction will not be negatively affected.

2.6 Performance

While we make a concerted effort to justify the inclusion of student perceptions (self-efficacy, interest, satisfaction) as necessary considerations for education, our primary concern is performance. Student performance serves as an objective measure of success in performing salient actions as it relates to learning objectives. It is routinely studied in academics to establish whether students are achieving as a result of their education (Hanushek, 1997; Shachar & Neumann, 2003) and is a necessary determinant of student success. If we are to posit here that this virtual laboratory design is a suitable alternative to a physical laboratory, we must demonstrate that performance will be the same or very similar across physical and virtual settings. Now that we have introduced the primary determinants of the virtual laboratories' success, we can describe the virtual laboratory for this study.

3 Virtual Lab for IoT

3.1 Laboratory Design

The virtual lab implementing IoT utilized for this virtual laboratory consisted of a server with four 8-core processors, 512-GB RAM, and four 2-TB solid-state hard drives. VMware ESXi with vCenter was the installed operating system used to provide the virtual machine infrastructure. Students were able to access the system using a web interface, with all students provided external access to the environment from both on and off campus. The server used for the exercise is used for other courses and course content, so the overall size is significantly larger than what would be needed if only performing the IoT exercise alone.

Each student was provided with four VMs for the exercise: 1) Windows 10 client, 2) Android, 3) OpenWrt router, and 4) Home Assistant (HA).[1] The Android device utilized LineageOS, an open-source operating system based on the Android platform.[2] The device was configured to resemble a mobile phone in terms of UI and functionality. OpenWrt is an opensource router operating system providing routing and dynamic IP assignment for hosts on the network. HA is an opensource home automation system that provides the ability to control several IoT devices inside the home. HA provides a prebuilt virtual machine for VMware that can be ported to ESXi. The virtual lab environment allowed the students to display the console for each of the VMs, thereby enabling the students to interact with each of the systems as if they were physical devices. Furthermore, the three systems were each connected to an individual virtual switch for each student and configured with IP settings to allow the systems to communicate with each other on the same virtual network.

4 Study Design, Materials, and Methods

For testing purposes, we grounded the virtual laboratory as an extension of students' classwork that served as a seamless addition to their current coursework. Subjects for the field experiment included two separate sections of the same course taught by the same instructor in the same semester at a large university in the south-central United States. Both sections were taught the same content, with the only difference being that one section was taught online (virtual) while the other was a traditional (physical) environment. The course offered an introduction to networking infrastructure where students, using an array of virtual machines, design a corporate network including services (DNS, DHCP, FTP, port forwarding, etc.) alongside an array of interconnected client and server machines (Windows10 Client, Windows Server 2016, Ubuntu servers, etc.). This means the subjects in this sample were familiar with communication technology and could more easily grasp IoT communication technology. The course was a required course for all MIS majors. The online section utilized the virtual lab environment described previously, while the in-person section completed the module using physical technology including a Windows 10 client computer, their own personal phone, home assistant running on a Raspberry Pi , as well as a wireless access point and various cables to connect everything together. The physical section also included a physical smart lightbulb in addition to what was depicted on the web interface. Figure 1 shows a logical design of how the devices were hooked together for a single subject in both the virtual and physical environments, with the physical light only present in the physical section, as indicated. Both the Windows 10 client machine and home assistant running on the Raspberry Pi were configured using the same configurational settings as those in the virtual environment.

1 https://www.home-assistant.io/
2 https://lineageos.org/

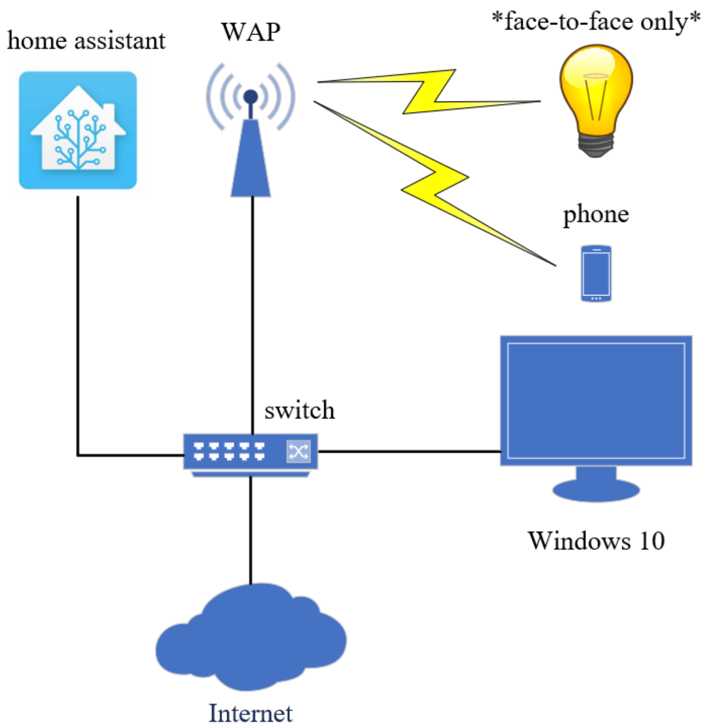

Figure 1. Logical Design of Subject Environment

A field experiment was used to test the module. While providing less control as compared to a lab experiment, the field experiment better mimicked the actual teaching environment of students in both an online section and a physical section, thereby increasing generalizability. To evaluate the module, several measures were utilized from previous studies. The primary variable of interest – self-efficacy – was developed using previous research that argues task-specific self-efficacy is needed to understand individual self-efficacy regarding a particular task (Marakas, Johnson, & Clay, 2007; Marakas, Yi, & Johnson, 1998). In addition, students were asked about their interest in IoT and home automation as well as their satisfaction with the module. Measures for this study were formulated using previously validated measures by modifying the context to IoT (Luse et al., 2014; Rursch, Luse, & Jacobson, 2009). An objective performance measure was utilized based on their performance on the module on a 0 to 4 grade of their submitted materials. The items for the study are given in the Appendix. Finally, a qualitative analysis was used to assess student perceptions of the module to address concerns in previous comparative studies that only relied on quantitative or qualitative outcomes for comparison (Brinson, 2015), providing even greater input into the efficacy of the activity.

The IoT module for this study introduced IoT utilizing home automation technology. Home automation was chosen given the familiarity of most subjects with home environments (lights, fans, wireless access points, etc.). The scenario included each student being given their own instance of HA inside a virtual machine. Each of these virtual machines was connected to a separate virtual switch to prevent students from interfering with each other during the activity. While each student was provided with an instance of HA, they did not interact with the HA virtual machine directly, but instead used their Windows 10 machine to remotely configure HA using a web configuration interface. The students were given the password to their individual instance of HA so that they could log on to its configuration page.

After using their Windows 10 client to connect to their HA configuration page, students configured two separate modules. These configuration changes were made utilizing YAML (YAML Ain't Markup Language) to program HA. The first exercise was intended as a simple setup of a device by adding the ability to turn on and off a light. Students added this device, including a visual toggle to turn on and off the light. Next, students implemented a more complex task by employing presence detection. Students were instructed to utilize the Android VM as if it were a phone and implement code in HA to detect their "presence" once they had connected the phone to their network, to simulate arriving in their residence and their phone connecting to their local wireless access point. The students then programmed an automation within HA to automatically turn on the light once their Android device connected to the network and turn off when disconnected. The exercise is provided in Appendix B. Figure 2 shows an example completed module screen capture.

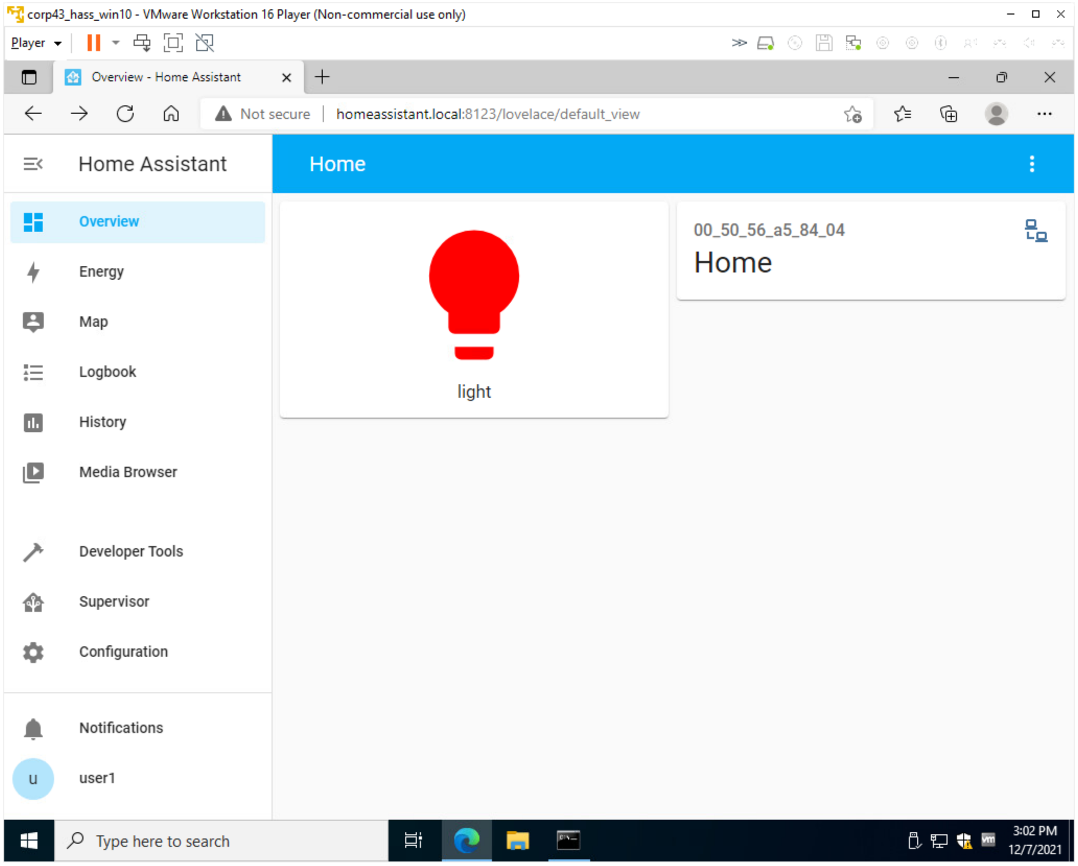

Figure 2. Logical Design of Subject Environment

The same script was followed for both sections. First, students were given a pre-survey with self-efficacy and interest measures asking about their feelings towards IoT technology. Next, the student completed the same exercise using either the physical devices or the virtual lab environment. Next, the student performed the module before completing the same survey a second time. This provided a method to subjectively measure their feelings of self-efficacy, interest, and satisfaction with the system as well as a more objective measure of the number of tasks in the module they were able to complete. The online students were limited to one hour and fifteen minutes to complete the activity to match the class period for the physical section.

5 Results

Both quantitative and qualitative data were collected to assess the effectiveness of the IOT module for student learning. Overall, 65 students completed the activity with 61 providing usable results, including 33 students in the physical section and 28 in the virtual section. The percentage of female students was 22%, which is above the 12% average of previous research in college enrollment in technology areas (Zweben, 2012). Fifty percent reported previous experience with home automation with only 9% reporting quite a bit of experience. This helps to better show the efficacy of the proposed module for those with little to moderate experience using home automation. The number of previous courses in information systems averaged 6. TSE, interest, and satisfaction were found to have high reliability with Cronbach alpha values all above 0.9. Table 1 summarizes the descriptive statistics for the measures.

Table 1. Descriptive Statistics

	Pre					**Post**			
	TSE	Interest	exp IoT	exp auto	exp hass	TSE	Interest	Satisfaction	Performance
Mean	3.19	3.23	2.49	2.43	1.72	4.26	3.97	3.89	3.65
SD	1.19	0.88	0.83	0.81	0.86	0.99	0.90	1.17	0.82
Items	5	3	1	1	1	5	3	3	5
Range	1-5	1-5	1-4	1-4	1-4	1-5	1-5	1-5	0-4
α	0.97	0.90	NA	NA	NA	0.94	0.94	0.95	NA

TSE: task-specific self-efficacy, exp IoT: previous experience with Internet of Things, exp auto: previous experience with home automation, exp hass: previous experience with homeassistant, Interest: interest in IoT, satisfaction: Satisfaction: satisfaction with their solution, Performance: number correct for the module

5.1 Quantitative Analysis

A generalized linear model was chosen for several reasons. First, only two levels of endogenous and exogenous variables were included in the analysis, negating the need for a path analysis. Second, each IV and DV were combined using an average of each observed item to construct a single variable, negating the need for a full structural model (Hair, Black, Babin, Anderson, & Tatham, 2006). Third, given the nominal nature of the experimental condition along with the continuous nature of both the covariate IVs and DV, a generalized linear model provides a method to account for all these (McCullagh & Nelder, 1989). Altogether, these reasons point to the use of a generalized linear model. Each dependent variable was tested using a separate model. The models included regressing each DV on the grouping variable (operationalized as a 0/1 value for virtual vs. physical). Additional covariates of previous experience in IoT, previous experience in home automation, and previous experience with home assistant were also added to further account for any variance in previous user experience that may bias the results. TSE and Interest were measured both before and after the exercise, to account for any preexisting TSE or Interest in the area of home automation that may bias these results. Accordingly, a residualized GLM (often referred to as a residualized regression) was utilized. Residualized regression involves also including the pre score as an added IV in the analysis, providing a method to find differences in groups on a specific variable while also covarying out pre levels of that same variable.

Table 2 provides the estimate (β), t-value, p-value, mean, and standard deviation for each of the analyses. While four separate GLM models were run for each of the DVs – including the grouping variable, pre-test scores (if applicable), and covariates – for brevity, only the statistics for the grouping variable were included for each of the four analyses.

5.2 Self-assessed Items

Table 2 shows that, after accounting for previous experience and pre-TSE, there is a significant difference between the subjects' feelings about their self-efficacy pertaining to home automation depending on whether they performed the activity in the virtual laboratory or in the physical laboratory ($\beta = 0.67$, $p = 0.009$). Specifically, students in the physical laboratory felt a greater feeling of self-efficacy after finishing the activity (mean=4.49) as compared to those completing the activity in the virtual laboratory (mean=3.99). Similarly, there is a significant difference in interest in home automation ($\beta = 0.53$, $p = 0.016$) whereby students in the physical laboratory felt greater feelings of interest after finishing the activity (mean=4.14) as compared to students using the virtual laboratory (mean=3.77). In addition, there is a significant difference in satisfaction with their solution to the activity ($\beta = 0.79$, $p = 0.007$) with students in the physical laboratory feeling greater satisfaction (mean=4.26) as compared to students using the virtual laboratory (mean=3.44). Overall, student feelings on self-assessed items show a more positive impact for students in the physical laboratory as compared to students using the virtual laboratory.

Table 2. Virtual versus Physical Post-Test Comparison

				post	
	β	t	p-value	virtual	physical
TSE	0.67	2.43	0.009	3.99 (1.23)	4.49 (0.67)
Interest	0.53	2.21	0.016	3.77 (0.99)	4.14 (0.79)
Satisfaction	0.79	2.52	0.007	3.44 (1.21)	4.26 (1.01)
Performance	0.19	0.92	0.18	3.56 (1.02)	3.74 (0.57)
Performance (With EC)	0.41	1.45	0.15	4.00 (1.32)	4.41 (0.96)

5.3 Performance

Performance was measured on a 5-point scale whereby the student received 0, 1, 2, 3, or 4 points. These performance measures were graded by the instructor by evaluating the materials turned in by the student based on the deliverable. Results show that there is no significant difference in performance on the activity between students in the physical laboratory and students using the virtual laboratory ($\beta = 0.19$, $p = 0.18$), with the average score being 3.65. It should be noted that, given the one-sided nature of the test, this provides a very stringent test as a two-sided test would be even less significant at $p = 0.36$. Given the non-significant results, a power analysis was run to provide credence to the experimental results. Given the 5-points (0 through 4) of the performance measure, a 1-point difference was deemed qualitatively important. Using the variance of performance (0.67) as the planning value, results show that a sample size of 22 per group is needed to find a 1-point confidence interval mean difference, which is met given the group sizes of 33 and 28 (Bonett, 2022).

To provide even more thoroughness to the results, an extra credit item was included as a more stringent test of the non-significant result of performance. The extra credit item was given to both groups whereby the students were required to search online for a solution. This extra credit item was done within the same time constraints as the primary exercise for those who still had time left. The extra credit item involved not only turning on a light when the phone was connected through presence detection, but also turning the light the color red, adding an extra point to the total score whereby a possible six points could be obtained by the student (0-5). While the students in the physical laboratory were not helped during the primary activity, some small help was given for those who reached the extra credit activity, while those using the virtual lab were not provided with any additional assistance. Even with this extra help, results show there is still no significant difference in performance between the students using the virtual lab and those in the physical laboratory ($\beta = 0.41$, $p = 0.15$), with the average score being 4.21. This provides even greater credence to the ability of the module to effectively teach IoT concepts using home automation to students with statistically similar performance to those receiving instruction in the physical laboratory.

5.4 Qualitative Analysis

Students were asked the following open-ended questions (Warren, 2002): (Q1) “If we were to use this module in the future, what things did you find useful/beneficial?”, (Q2) “If we were to use this module in the future, what things would you change?”, and (Q3) “Which step did you find the most straightforward? The most difficult?” These responses allowed us to gain deeper insights about student perceptions of the IOT module, understand how the module might be improved, and make pedagogical recommendations for future research. Coding was performed to analyze the data, 52 complete responses on Q1-Q3. First, each response was open coded. Second, discussions around the open codes led to the identification of broader categories under each question (Q1-Q3). To assess inter-rater reliability, two researchers analyzed the same subset of responses (around 20 percent of the total responses or 12 of the 52 overall responses) independently and placed them into one of the broader categories. The percentage of total agreement showed a very high inter-rater agreement of 92%. Furthermore, a Cohen’s Kappa coefficient of 88%, which is considered “almost perfect” (Landis & Koch, 1977), showed a very high degree of inter-rater reliability. Any disagreements were discussed and resolved by the researchers. Once a high degree of inter-rater reliability was established, one researcher analyzed the remaining data. The research team reviewed and discussed the analysis and its findings.

Regarding Q1, the vast majority of students using both the virtual and physical labs found the use of home automation “interesting” and relevant for learning about IOT. They also found the “step-by-step instructions” useful for completing the module. However, while some students appreciated that each step of instruction involved some independent problem solving (e.g., “good balance between guidance and pushing for [independent] student exploration"), other students said they prefer that the instructions at each step contain more details. These students attributed their desire for more explicit instructions to their lack of experience with programming IOT devices. For Q2, approximately 21% of students stated that adding more home automation features to the module could improve student learning. As one student explained,

> *I would recommend that in the future you add more things to this [module] as learning how to add a plethora of different items or customizing them in different ways would greatly increase the ability of those learning to experiment and do their own automation.*

For Q3, the vast majority of students reported that configuring the light to turn on and off was straightforward. In a similar proportion, students found that changing the color of the light to be the most difficult task due to having to search the internet for a solution. This step was said to require more “patience” and “trial and error" rather than copying and pasting from the instructions.

Overall, we did not find significant differences between students using the physical laboratory and students using the virtual laboratory with respect to the aspects of the module that participants found useful/beneficial. However, we did find differences across these environments regarding aspects of the module that they would change and found most straightforward or most difficult. The VM in the virtual environment introduced additional steps for completing the module versus the those using the physical environment, such as having to type code directly into the VM (rather than copying and pasting code) and VM authentication. Students using the virtual lab stated their desire for more direct methods of connection to improve copying and pasting and other functions. Students in both environments agreed about the steps that they found most straightforward (e.g., “adding a device/light”, “turning the light on/off”) and most difficult (e.g., “changing the color of the light”). However, a significantly larger percentage of students in the physical environment (62%) found that changing the color of the light was the most difficult task compared to students in the virtual environment (22%). Lastly, 35% of students in the physical laboratory versus 4% of students in the virtual laboratory said that the module could be improved by asking students to implement additional features, such as adding more “devices”, “colors”, and “automations”.

5.5 Post-hoc Quantitative Analysis

To add some control for course modality, a third control group was run using students in a separate section who received face-to-face (F2F) instruction on-premises but instead completed the activity using the developed virtual IoT lab. While the original field experiment provides credence to the developed virtual IoT lab for similar performance as compared to a physical IoT lab environment, the differences in results could be due to the modality of the course (F2F versus online) as opposed to the lab type (virtual versus physical). Results between all three experimental manipulations (F2F/physical, online/virtual, F2F/virtual) are given in Table 3. Results show that while the self-assessed measures differ between the online/virtual and F2F/physical manipulations, these self-assessed measures do not differ between online/virtual and F2F/virtual or F2F/physical and F2F/virtual, providing credence that the modality of the course is not the distinguishing factor. The one outlier is satisfaction, where the modality cannot be ruled out. The key finding is that both performance measures are not significantly different across both course modalities and regardless of whether the physical or the developed virtual IoT lab was utilized, providing even greater credibility to the developed virtual IoT lab.

Table 3. Post-hoc Analysis Results Showing Mean Difference and Significance

	online/virtual vs. F2F/physical	online/virtual vs. F2F/virtual	F2F/physical vs. F2F/virtual
TSE	-0.72*	-0.41	0.30
Interest	-0.58*	-0.18	0.40
Satisfaction	-0.94**	-0.85*	0.09
Performance	-0.19	-0.05	0.14
Performance (With EC)	-0.41	-0.19	0.22

5.6 Post-hoc Qualitative Analysis

In parallel with the post-hoc quantitative analysis previously described; we performed a qualitative analysis on the third control group --- students in a separate section of F2F instruction who completed the activity using the developed virtual IoT lab. Results largely support the findings of our quantitative post-hoc analysis and provide additional details about participant perceptions of the module. Overall, the F2F/virtual group provided similar answers to the F2F/physical group on questions Q1 and Q3. We noted several dissimilarities between the F2F/virtual group and the other two groups. Regarding Q2, a higher percentage of the F2F/virtual group (28% vs. 9% in the F2F/physical and 17% in the online/virtual group) expressed the desire for more detailed instructions, primarily regarding how to change the light color (n=7), and secondarily, regarding other parts of the module (n=2). Yet, a relatively large number of participants in the F2F/virtual group said that they would not change anything (n=9, 28%), indicating some level of satisfaction with the module. Fewer students in the F2F/virtual (n=2, 6%) and online/virtual groups (n=1, 4%) versus face-to-face/physical (n=12, 35%) felt that configuring additional features beyond automating lights could improve the module. Interestingly, regarding Q3, no one in the F2F/virtual group complained about difficulties copying and pasting, time limits, or the virtual machine as did the online/virtual group. In fact, two students in the F2F/virtual group said that copying and pasting was the step they found most straightforward. This was likely due to the live narration that the instructor provided during the activity.

Taken together, the instructor's presence and the focus of effort on the activity in the F2F environment seemed to influence participant expectations and overall satisfaction. Although the F2F/virtual group performed similar to the other groups, the presence of the instructor was somewhat of a “crutch” in that participants looked to the instructor for immediate answers rather than troubleshooting issues independently. Compared to the F2F groups, the online/virtual participants expressed less desire for more instruction and less difficulty with the bonus question. Thus, F2F/virtual and online/virtual participants formed different expectations of instructor engagement, which influenced their feelings of satisfaction with the module. However, the challenges that students experienced with the online module were not impactful enough to significantly reduce their performance. These findings support both the efficacy of the virtual IoT lab and explain differences in satisfaction across course modalities, highlighting areas of potential improvement.

6 Discussion

This study provides an introductory module for education in IoT technologies. As a relatively novel technology, IoT technology is still in its infancy with regard to establishing effective methods for instruction in the topic. While several studies have begun to look at education and IoT including improvements found for varying pedagogical approaches (de Haan, 2016; Lichtenecker et al., 2020; Olagunju & Khan, 2016), one area lacking is the ability to educate IoT concepts within an online setting. IoT technologies are inherently physical in nature, yet given the increasing prevalence of online education, greater understanding is needed on how to effectively instruct on IoT concepts in this non-F2F setting.

Results from this field study show very interesting findings. First subjects utilizing the physical environment show significantly higher feelings of self-efficacy, interest, and satisfaction as compared to those in the virtual environment, which is in line with previous research (Boix, Gomis, Montesinos, Galceran, & Sudrià, 2008; Chen & Gao, 2012; Luse & Rursch, 2021; Pellas, 2014; Reeves & Crippen, 2021). Conversely, performance does not differ significantly between those performing the activity physically and those performing the activity virtually.

Our qualitative data largely supported this finding and provided additional pedagogical insights. One interesting finding is in the student’s attitude towards the online activity whereby they claimed the VM in the online environment introduced additional steps for completing the module versus the F2F environment by not allowing copying and pasting like in the physical section. Given this, the performance of the virtual section would be expected to suffer, but results show it did not. This interesting finding further demonstrates the efficacy of the proposed virtual lab for providing similar performance as physically co-located students, even in the face of perceived disadvantages of the system.

7 Implications and Future Research

While concerted efforts were taken to account for any possible combination of F2F and online learning environments with regards to the virtual laboratory, it would be impractical to have online students travel on-premises to use the physical laboratory. Given this, we are limited on how thorough discussions regarding modality can be. We suggest here that the post-hoc analysis provided some control for modality as an influence in our statistical findings, but future research may investigate how online students' perceptions, when given an on-premises experience, are affected by the sudden change into a higher fidelity representation of their coursework.

Another pertinent consideration is that of the samples used in this study, and whether the results here are applicable generally. The samples used in this study were comprised of undergraduates in MIS where some had previous experience using automation and rated themselves relatively high in TSE. This draws into question whether samples external to academia would exhibit similar results, or whether they would have substantively different outcomes. As stated earlier, this population is somewhat familiar with IoT due to exposure outside of academia, but this may not be applicable to an older population. It is possible that an older population is not as familiar with IoT and may have a lower sense of interest and satisfaction in learning how to use IoT. Future research should extend the sample space beyond academia to provide rigor to these findings. Given what we have learned from our qualitative study and the feedback we received, we provide some recommendations for education in IoT going forward. Students specifically asked for the inclusion of other types of automation in IoT. We recommend including these extended uses so students may receive a more broadened understanding of the breadth of uses in IoT, but also as a means of increasing student interest and satisfaction. We found that while step-by-step instruction was necessary for completion of the more complicated aspects of this module, students performed well when given the chance to solve problems independently. This forces them to take a more trial and error approach to solving problems which better replicates the type of problem solving they would do in real world application of such services, though concerted effort should be made to cater the challenge level to the student so as not to negatively influence perceptions due to overwhelming difficulty.

While each setting was comparable in terms of activities performed and processes to do so, there were many differences that could have influenced our results. For instance, one major aspect of recommended virtual laboratory design is in relation to communication and collaboration (Brinson, 2015; Reeves & Crippen, 2021; Stahre Wästberg et al., 2019). As a consequence of the research design, the virtual laboratory was not meant to be social in nature as it was meant to control key differences. That said, students in the traditional setting were co-located with other students, as well as the professor, providing a sense of community that was not afforded to the remote group. Additionally, the traditional group were provided physical hardware devices, one of which was a functioning IoT lightbulb. The lightbulb, once programmed to do so, would light up and could be seen by all students. Therefore, the physical representation of the outcomes could have influenced student perceptions where the remote section had only the user interface and no indication of others performance. Future research should investigate if and to what degree the co-location of others affects student outcomes when they do not directly interact but are aware of their presence.

8 Lessons Learned

In this section we would like to highlight lessons learned (McKeen & Smith, 2010) from the qualitative analysis and observations made during the experiment.

- **Educators should make an effort to create coursework that is salient to their students.** Students reported a desire for extended application of IoT in this virtual laboratory design. While we consider this virtual laboratory a success given the performance outcomes, the recommendations of the student sample provided valuable insight on how to improve the laboratory for further deployment. Educators should not assume knowledge of what is important to students. Giving them a chance to enunciate their perceptions and opinions on coursework can help to improve course design, even beyond a laboratory setting.
- **Educators should consider how teaching style affects students in the classroom compared to online students.** We found that students in the F2F sections were far more reliant on the professor to assist them when they perceived a task as difficult or ambiguous. The restrictive nature of this experiment was necessary to make it analogous to the online setting, which means

these students were not assisted as freely as they are used to. As explained earlier, we believe this served as a “crutch” where students did not feel confidence in themselves to problem solve issues without clearly defined solutions.

- **Virtual laboratories, when designed appropriately, allow students access to resources they may have limited or no access to otherwise.** While this study is concerned with IoT specifically, it bears implications for academia broadly. There are many areas where students must forgo skill attainment at the expense of limited resources. Virtual laboratories enable educators by allowing for inexpensive approximations that serve as viable replacements for the real thing.

9 Conclusion

This research provides an evaluation of education in IoT technologies. Specifically, the study evaluates the ability to use virtual labs to educate students in a technology that is inherently physical. Results show that, while students *feel* better about these technologies in a physical hands-on environment, the *performance* in a virtual hands-on environment is equivalent to that in the physical environment. This is indicative that the virtual laboratory is acceptably similar to the real-world phenomena and is beneficial to students who would otherwise have no access to such training. With the continued increase in online education, this research provides both a usable module for online IoT education and demonstrates the efficacy of this educational method.

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Appendix A: Survey Items

Task-Specific Home Automation Self-Efficacy (Strongly Disagree – 1 to Strongly Agree – 5)

Please answer the following questions based on your feelings about your current skills/assessments with home automation.

I can configure home automation to allow a user to turn on a light.

I can implement presence detection to track my mobile phone to show when I arrive home.

I can create an automation to automatically turn on a light when I arrive home.

I can create an automation to automatically turn off a light when I leave home.

I can modify an automation to automatically make a light shine a specific color when I arrive home.

Interest (Strongly Dislike – 1 to Strongly Like – 5)

Rate how much you like or dislike the following items...

Setting up home automation

Configuring IoT devices

Setting up presence detection.

Satisfaction (Strongly Disagree – 1 to Strongly Agree – 5)

Please answer the following questions based on your feelings about your final product for this module.

I am satisfied with my final product on this module.

I am satisfied with the quality of my work on this module.

I am satisfied with my outcome on this module.

Appendix B: Technical Excercise

In this module we are going to implement IoT by setting up an open-source home automation system called home assistant or hass.

Open a Word document to save the information indicated where points are specified throughout this module. This should be a separate word document from this one. Save file as your name.

The activity today will take place in an environment separate from your project. Go to esx04.bus.okstate.edu > MSIS4523 > hass > corp*x*.

<u>Log into HASS</u>

- From within your win10 VM, use a web browser on your network and open your hass supervisor page at http://homeassistant.local:8123.
- Log in user1 and ******** if prompted

<u>Add a light</u>

First, you want to add a light to allow the user to turn it on/off from the dashboard. Let's do that.

- Click on Overview. This is the primary dashboard where the user is presented with the IoT devices for the home.
- In the upper right click the three vertical dots and Edit Dashboard
- Add a Card
- Select the button card
- There will be a dropdown showing various entities in the system. Make sure the entity is set to your light entity. Save.
- Turn on the light

(pts) add a screencap to your Word document <u>showing your VM</u> with the light turned on

<u>Track someone</u>

Now we are going to track when someone gets home by detecting their mobile phone. We will do this by editing the hass configuration file to enable device tracking using a router. For example, when you come home and your phone connects to your home wireless access point, this will notify hass you are home.

- Go to Supervisor > File Editor
- Click on Open Web UI. This allows you to configure the files associated with hass.
- In the upper left, click the folder icon to edit the configuration.yaml file. This is the primary file where you add various IoT devices you would like to use for home automation.
- Open a command prompt on your machine to find the default gateway (router) that is doing the presence detection. Insert this below where *x.x.x.x* is this DG IP.
- Add the following to enable device tracking, where host is the default gateway of your router. Add **below** the default_config: heading (spaces, not tabs – exactly as shown, even between colon and text after).

```
device_tracker:
 - platform: luci
   host: x.x.x.x
   username: root
   password: ********
```

```
    consider_home: 40
```

- Save the file
- Click on Configuration > Server Controls and select Check Configuration to make sure the file is formatted correctly. If not, go back and see what you missed.
- Once correct, under Server management, click Restart > OK (~30 seconds to fully restart)

- Now we will track a phone.
- Connect the Android phone VM to the network switch assigned to you.
- Inside the Android phone VM, click on the six dots to open all apps
- Open Terminal Emulator
- Run ifconfig
- Find the MAC address (HWaddr) of your eth0 device interface (this is what you want to track)

- Back on hass, on the Overview page, edit your dashboard by clicking Add Card and select the Entity Card.
- For the entity, select the device tracker for your Android phone VM and then click Save. The device tracker will append the MAC address of your Android phone VM to the end of the name. You should now have a card with the MAC of your phone that says “Home”.

(pts) add a screencap to your Word document showing your VM and your phone as home

- Go to your Android phone VM and disconnect it from the switch (i.e., you are not home).
- The phone will take a minute to show as “Away.” This is because you do not want the phone to disconnect all the time when you don’t actually leave your house (e.g., go out to the garage, turn your phone off Wi-Fi for a second, etc.)

Automations - I’m home

Home assistant allows you to program several different types of powerful automations. Let’s make one for when we get home (i.e., our phone connects) to automatically turn on the light.

- Go back to the file editor (Supervisor > File editor > Open Web UI) and use the folder icon to open the **automations**.yaml file. Remove everything in the file and type the following.

```
- alias: I’m home
  trigger:
    platform: state
    entity_id: device_tracker.yourDevice
    from: not_home
    to: home
  action:
  - service: light.turn_on
    entity_id: light.yourLight
```

- Fill in the appropriate device tracker where the x’s correspond to your MAC address (Can use the Entities dropdown to find it along the left)
- Fill in the appropriate light where light1 corresponds to the name of your light
- Let’s break this down a little.
    - Make a new automation with the alias I’m home.

- The trigger to signify you are home is when the state of your device tracker changes from not_home to home.
- The action taken when you get home is to turn on your light.

- Save the file, check your configuration (Configuration > Server Controls), and restart hass
- Connect your Android phone VM back to your switch (i.e., you are home).
- On the Overview page, did your light come on?

(pts) add a screencap to your Word document showing your VM and “I’m home” automation code

- Disconnect your Android phone VM from the switch to simulate leaving your house.

Automations - I’m away

- Now, **create a new** automation by copying and pasting and then modifying the code above to turn off the light when you leave the house.
- Check your syntax and restart hass.
- Connect your Android phone VM back to your switch and wait for it to show you as home and turn on the light.
- Disconnect your Android phone VM from the switch to simulate leaving your house.
- Wait one minute. On the Overview page, did your light go off when your device went “Away”?

(pts) add a screencap to your Word document showing your VM and “I’m away” automation code

Automations - I’m home and feeling red

- Now, **modify** your “I’m home” automation code.
- Add to this automation by adding to the **action**, **data** that tells your light to be the **hs_color** of red, or **[360,100]** (feel free to use Google if needed)
- Check your syntax and restart hass.
- Connect your Android phone VM back to the switch (i.e., you are home).
- On the Overview page, did your light come on? Is it red?

(pts) add a screencap to your Word document showing your VM with light on and red

(pts) add a screencap to your Word document showing your VM with new “I’m home” automation code

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