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Evaluating Intention to Use Remote Robotics Experimentation in Programming Courses

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<u>Walden University</u>

College of Management and Technology

This is to certify that the doctoral study by

Pericles Cheng

has been found to be complete and satisfactory in all respects,
and that any and all revisions required by
the review committee have been made.

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Dr. Michael Orsega, Committee Member, Information Technology Faculty
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Walden University
2017

Abstract

Evaluating Intention to Use Remote Robotics Experimentation in Programming Courses

by

Pericles L. Cheng

MS, University of Texas at Austin, 2003

BS, University of Texas at Austin, 2001

Doctoral Study Submitted in Partial Fulfillment

of the Requirements for the Degree of

Doctor of Information Technology

Walden University

April 2017

Abstract

The Digital Agenda for Europe (2015) states that there will be 825,000 unfilled vacancies for Information and Communications Technology by 2020. This lack of IT professionals stems from the small number of students graduating in computer science. To retain more students in the field, teachers can use remote robotic experiments to explain difficult concepts. This correlational study used the unified theory of acceptance and use of technology (UTAUT) to examine if performance expectancy, effort expectancy, social influence, and facilitating conditions can predict the intention of high school computer science teachers in Cyprus, to use remote robotic experiments in their classes. Surveys, based on the UTAUT survey instrument, were collected from 90 high school computer science teachers in Cyprus, and a multiple regression analysis was used to measure the correlations between the constructs and finally the model fit of the analysis. The model was able to predict approximately 35% of the variation of the teachers' intent to use remote robotic experiments. The biggest predictor was facilitating conditions followed by effort expectancy. Performance expectancy had little impact, whereas social influence had no impact on the intention of high school teachers to use remote robotic experiments in their classes. These results can help curriculum decision makers in the Ministry of Education in Cyprus to examine what factors affect the acceptance of remote robotic experiments and develop them in ways that would increase their implementation in high schools. By incorporating remote robotic experiments in high schools, students may learn difficult concepts, leading to an increase in computer science graduates and ultimately an increase in IT professionals.

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Dedication

I would like to dedicate this study to my wife and daughter for all of their patience during the past three years that I have committed to achieve my goal.

Acknowledgments

I would like to thank Dr. Steven Case for his continuous support over the last three years and his guidance in completing this work in the best possible way. He helped me when I was beginning my journey, when I was losing focus and finally when I was charging down the last mile of my dissertation. I would also like to thank my second reviewer Dr. Michael Orsega and Dr. Reginald Taylor for their valuable feedback into making my study more complete and accurate.

I would like to thank my family for all their patience, and my friends for all of their support during the past years. Finally, I would like to thank Christos Dimopoulos for pushing me to pursue this degree, for all of his help during my studies, and for being there to push me when I was too tired to continue.

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Section 1: Foundation of the Study

In this study, I used a quantitative correlational method to examine the intention of computer science high school teachers to use remote robotics laboratories if they are provided with some conditions presented by my independent variables. The results of this study can help computer science curriculum decision makers decide whether future curricula will include remote robotic laboratories. By including more problem-based learning, students can understand difficult concepts more easily and this may decrease the attrition rates in the computer science field.

Background of the Problem

The Grand Coalition for Digital Jobs estimates that by the year 2020 there will be up to 825,000 unfilled vacancies for Information and Communications Technology (ICT) positions (Digital Agenda for Europe, 2015). This vacancy gap is mainly due to the low number of students graduating with computer science degrees. Even though the number of students entering STEM fields is high, the attrition rates for computer science majors is close to 59% (Chen, 2013). Some of the causes that lead students to leave the computer science field are the lack of problem-solving skills, analytical thinking, logical and reasoning skills, and programming and algorithmic skills (Sarpong & Arthur, 2013). This lack of skills can be attributed to students lacking practical application of concepts during a course. By providing students with problem-based learning (PBL) experiences through the use of more laboratory work, educators can tackle this lack of skills (O'Grady, 2012).

The purpose of this study was to provide curriculum decision makers with information about the relationship between performance expectancy, effort expectancy, social influence, facilitating conditions, and the intention of computer science high school teachers to use remote robotic laboratories. The unified theory of acceptance and use of technology (UTAUT) uses the performance expectancy, effort expectancy, social influence and facilitating conditions variables stated above to evaluate a person's intention to use technology (Venkatesh, Morris, Davis, & Davis, 2003). This study could provide curriculum decision makers with the necessary information that could lead to the use of remote robotic laboratories in the curriculum.

Problem Statement

Based on a data collected from a survey at Berea College in the United States, out of all the students entering a science field, only 31% complete a degree in science due to their overestimation of their ability to perform well in the field (Stinebrickner & Stinebrickner, 2014). Using laboratory practice allows a better understanding of programming concepts and improves success rates as stated by 88% percent of students (Sarpong & Arthur, 2013). The general IT problem is that there is a lack of practical experience in introductory computer programming courses in high schools in Cyprus, leading to reduced student retention in the field of computer science. The specific IT problem is that computer science curriculum decision makers often lack information about the relationships between performance expectancy, effort expectancy, social influence, facilitating conditions, and the intentions of high school computer science teachers to use remote robotic experiments.

Purpose Statement

The purpose of this quantitative correlational study was to evaluate the relationship between performance expectancy, effort expectancy, social influence, facilitating conditions, and the intentions of high school computer science teachers in Cyprus to use remote robotic experimentation technology in their classes. This evaluation could inform computer science curriculum decision makers on what factors could influence high school computer science teachers to use remote robotic experimentation. This information could lead to changes in curriculum such as the inclusion of remote robotic experimentation. This could ultimately increase student retention in the field of computer science. Using the unified theory of acceptance and use of technology (UTAUT), I examined the four independent variables: performance expectancy, effort expectancy, social influence, and facilitating conditions that the model proposes (Venkatesh et al., 2003). The dependent variable was the intention of teachers to use remote robotic experimentations in their teaching methodologies. The targeted population consisted of computer science teachers who taught programming courses in high schools in Cyprus. High school computer science teachers were all registered teachers who taught programming courses in the middle and high school levels at the time of the study. There were approximately 400 middle and high school teachers of computer science employed by the Ministry of Education in Cyprus at the time of the study. The implications for social change include the possible inclusion of remote robotic laboratories in the future computer science curriculum for a better understanding of computer science concepts by students. Including more PBL experiences could lead to an increase in student retention in the field of computer science. Higher student retention could then lead to more information technology experts entering the workforce. In addition to helping students understand programming concepts, I aimed to help high school computer science teachers deliver more laboratory-based work without impeding their in-class time.

Nature of the Study

I used a quantitative methodology approach to evaluate the relationship between performance expectancy, effort expectancy, social influence, facilitating conditions, and the intention of computer science teachers in high schools in Cyprus to use remote robotic experimentation techniques. Yilmaz (2013), stated that a quantitative study begins with a hypothesis or theory and uses formal and structured instruments to gather data in numerical indices. A qualitative study, on the other hand, uses an inductive and naturalistic methodology that is based on the observations and interpretations of peoples' perceptions (Khan, 2014). In this study, I used the four independent variables identified in the unified theory of acceptance and use of technology (UTAUT) (Venkatesh et al., 2003): (a) performance expectancy, (b) effort expectancy, (c) social influence, and (d) facilitating conditions. When variables are identifiable and measurable, then the use of a quantitative methodology is more appropriate than a qualitative methodology (Yilmaz, 2013).

I utilized a correlational quantitative design. I chose a correlational study because the study's primary purpose was to examine the relationship between the identified independent variables and the intention to use a specific technology. According to Keele's decision tree (2011), a study that has no treatment, examines relationships, and has a sample that is a single group, points to the use of a quantitative correlational research. Correlational quantitative research deals with the observation of certain concrete specifications of phenomena and the application of mathematical principles to assess the responsiveness of variables under examination (Westerman, 2011).

The use of an experimental design was not appropriate for this study because experimental design focuses on the cause and effect of variables rather than identifying that a relationship exists (Keele, 2011). In a correlational design, the relationship between variables is established first. After the relationship is established then further research can use experimental designs to validate the cause and effect of those variables. Another issue with using an experimental design in this study was a limitation in the high school teachers' available time. High school teachers in Cyprus may not want to participate in a time-consuming experiment, whereas they would be more inclined to answer a short survey. The use of an experimental design would also require the participation of high school students, and this would lead to ethical concerns that involved minors in a study. Another quantitative design type that was considered was the descriptive quantitative design. Using a descriptive design is more appropriate when knowledge of the problem area is limited. When there is a considerable amount of knowledge of the problem area then a correlational design is more suitable (Keele, 2011).

Research Question

Do (a) performance expectancy, (b) effort expectancy, (c) social influence, and (d) facilitating conditions significantly predict the intention of high school computer science teachers in Cyprus to use remote robotic experimentation in their courses?

Hypotheses

Venkatesh et al. (2003) proposed four core variables, performance expectancy, effort expectancy, social influence and facilitating conditions to predict the intention to use technology as shown in Figure 1. The proposed variables were deemed appropriate for evaluating the intention of high school computer science teachers to use remote robotic experiments.

H_o1: Performance expectancy, effort expectancy, social influence and facilitating conditions will not significantly predict the intention of high school computer science teachers to use remote robotic experiments.

H_a1: Performance expectancy, effort expectancy, social influence and facilitating conditions will significantly predict the intention of high school computer science teachers to use remote robotic experiments.

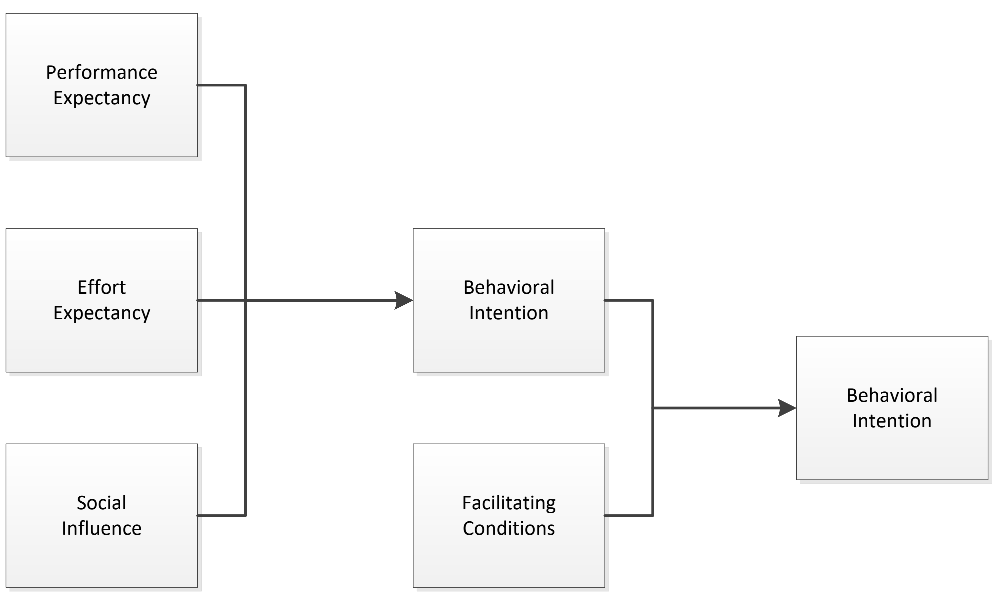

Figure 1. Diagram showing how the four constructs relate to use behavior.

Theoretical or Conceptual Framework

This quantitative study used the unified theory of acceptance and use of technology (UTAUT) (Venkatesh et al., 2003). UTAUT was introduced in 2003 by Venkatesh, Morris, Davis, and Davis (2003) and builds on the Technology acceptance model (TAM), which tries to predict and explain the use of technology (Davis, 1989). The UTAUT theoretical framework identifies four constructs that influence the use behavior (UB) for a specific system. The four constructs, as shown in Figure 1, are performance expectancy (PE), effort expectancy (EE), social influence (SI) and facilitating conditions (FC) (Venkatesh et al., 2003). Through the use of UTAUT, I evaluated the intention of high school computer science teachers in Cyprus to use remote robotic laboratories to enhance their teaching of computer-related concepts.

Definition of Terms

The following are the definitions of the terms used throughout this study.

Behavioral intention: The measure of intention that allows an understanding and prediction of the adoption of a specific behavior (P. C. Lin, Lu, & Liu, 2013).

Effort expectancy: The degree of ease that a person perceives when using the technology (Khechine, Pascot, & Bytha, 2014).

Facilitating conditions: The degree in which a person believes his organization will support his use of the technology (Venkatesh et al., 2003).

Performance expectancy: The belief of a person of how useful a technology is in performing various activities (Ain, Kaur, & Waheed, 2015).

Remote Robotic Laboratories: Web-based e-Learning resources that augment students' accessibility to experiments using autonomous robotic platforms (Chaos, Chacon, Lopez-Orozco, & Dormido, 2013).

Social influence: The belief of a person that others that are important to him believe that he should use a technology (Raman & Don, 2013).

Assumptions, Limitations, and Delimitations

Assumptions

The primary assumption in this research study was that high school teachers in Cyprus who teach introductory computer science courses understand the need for enhancing the existing curriculum with more problem-based learning methods. In its simplest form, Problem-based learning (PBL) works by introducing students to a problem and then working on solving that problem through discussion and refining the problem until it is solved (O'Grady, 2012).

High school teachers may not have been familiar with remote experimentation or the use of robotics in the classroom. In this study I assumed that high school computer science teachers in Cyprus are familiar with remote experimentation and robotics in general so that they would be able to answer the survey questions.

Self-reporting bias is another issue that had to be taken into consideration. Self-reporting bias is based on the personal experiences and the existing work environment of the participant, which may influence the answers given in a survey (Fink, 2013). Providing the participant with anonymity and requesting that they provide honest and objective answers helped mitigate this issue.

Limitations

When conducting research, practitioners and researchers must be able to identify and understand the limitations that the research method they use entails (Kirkwood & Price, 2013). A major limitation to this study was that the participants may have lacked the willingness to participate or that they were not available to complete the survey. Researchers must also be able to identify whether their findings can be generalized to other situations and contexts (Kirkwood & Price, 2013). The fact that the participants were all from Cyprus limited the validity of the results to this country only. In the future, researchers may use this study with a different set of participants and may validate the strength of the study.

Delimitations

Delimitations are the boundaries of a study (Miguel Martínez-Graña, 2013). This research study involved high school teachers that taught introductory computer science courses in Cyprus. The participant selection criteria included being a high school teacher currently employed by the Ministry of Education of Cyprus, and teaching introductory computer science courses in high schools in Cyprus. These criteria provided a specific population since there were around 400 computer science high school teachers employed by the Ministry of Education in Cyprus at the time of the study.

By providing a detailed analysis of the assumptions, limitations and delimitations of this study I am able to specify the scope and bounds of the study. The analysis of the assumptions and the provision of mitigation procedures reduces potential bias in the study.

Significance of the Study

Contribution to Information Technology Practice

Student retention rates in computer science, worldwide, are very low, and this is mostly due to the difficulties faced by students in understanding programming concepts (Burmeister, 2015; X. Chen, 2013; Freeman et al., 2014). Using remote laboratories and web services is one of the best ways to help students understand difficult concepts and continue their studies in computer science (Hosack, Lim, & Vogt, 2012; Sarpong & Arthur, 2013). In this study, I attempted to show that there is a relationship between performance expectancy, effort expectancy, social influence, and facilitating conditions and high school educators' willingness to use remote robotic experiments. By establishing such a relationship, high school teachers would realize that they can improve their teaching methods by providing students with remote laboratory work without losing time in the class. Remote robotic experiments could also free up more time for discussions in class leading to a more productive and educationally enhanced process.

Implications for Social Change

This study provides potential for social change because it may increase student retention in the field of computer science in Cyprus and the European Union. This increase would lead to an increase of IT graduates, therefore lowering the deficit of IT professionals that the European Union estimated for the year 2020 (Digital Agenda for Europe, 2015). It may also reduce overall unemployment rates in Cyprus and Europe in general.

A Review of the Professional and Academic Literature

I identified the following types of literature to address the intention of high school teachers to use remote robotic experiments in their classrooms. In the first section, I identify the purpose of study, and then explain the concepts of problem-based learning, remote experimentation, and remote robotic experimentation. Then I present the theoretical framework that I used in this study and present an analysis of the independent and dependent variables that I examined in the study. Finally, I review the measurement methodology and finally the points of view and the relationship of this study to previous studies are analyzed.

The literature review includes cited sources including research publications,and peer-reviewed scholarly articles, focusing primarily on research within the past 5 years. The primary search engines that I used in this literature review were Proquest, Google Scholar Search, and the Walden library. The following terms were used singularly or in combination: *computer science education, STEM attrition, Problem-Based Learning, remote laboratories, robot programming, technology acceptance and unified theory of acceptance,* and *use of technology*.

For this research study, I referenced 145 resources. One hundred and twenty four (85.52%) of them were published after 2013 and 127 (87.59%) were from peer-reviewed sources. Seventy-four (51.03%) of the references were included in the literature review and from those, 65 (87.84%) of them were from peer-reviewed sources. Sixty-four (86.49%) of the resources in the literature review were from sources published after 2013. The references include one doctoral dissertation and five government documents.

Application to the Applied IT Problem

Purpose of Study

In this study, I aimed to evaluate the relationship between performance expectancy, effort expectancy, social influence, facilitating conditions and the intentions of high school computer science teachers in Cyprus to use remote robotic experimentation in their classes. Several studies showed that Problem-based learning (PBL) was important in the instruction of difficult concepts to students (Lykke, Coto, Jantzen, Mora, & Vandel, 2015; O'Grady, 2012). Research has been conducted on how to use robotic experiments in the classroom (Arlegui, Pina, & Moro, 2013; Casini, Garulli, Giannitrapani, & Vicino, 2014; Jung, 2013). Research has been conducted on the use of remote experiments that allows students to perform laboratory work online rather than in the classroom (Ionescu, Fabregas, Cristescu, Dormido, & De Keyser, 2013; Jara, Candelas, Puente, & Torres, 2011; Lowe, Newcombe, & Stumpers, 2013; Marques et al., 2014; Zalewski, 2013; Zubía & Gustavo, 2012). This technology provides the instructor with more in-class time to teach difficult concepts while students experiment remotely.

In all of these research studies, the population they investigated was made up of students and very rarely focused on the instructor teaching the course. The gap in the literature was information on whether high school computer science teachers in Cyprus would actually use remote robotic experiments in their classrooms and what the variables that influence that decision were.

Problem-based Learning

Problem-based learning (PBL) is an educational approach that puts the students in the center of the learning process so they can take responsibility for how they learn (Lykke et al., 2015; O'Grady, 2012). In PBL, students are presented with a complex problem and then assigned into groups where they collaborate to identify the key issues and use self-directed learning to solve the problem (Karantzas et al., 2013). Even though PBL has been successfully used in different disciplines, it has not been widely used in computer science, even though the computer science context is highly associated with problem solving (O'Grady, 2012).

It is important in the classification of learning environments to identify all of the characteristics before an approach can be classified as problem-based (Dolmans & Gijbels, 2013). Five major characteristics differentiate PBL from other learning practices (Scott, 2014):

1. Starting the whole PBL exercise with the statement of the problem
2. Students should direct their own learning throughout the PBL experience
3. At the end of the PBL experience the students should reflect on their learning and experiences
4. Students should always work in small groups
5. The problem should be used in such a way that it would guide student learning

Dolmans and Gijbels (2013) compared PBL environments to conventional lecture-based environments, and found that the two main areas where they differed were how students examined different ideas and shared those ideas with others. In a study comparing PBL and traditional lecture-based learning (LBL), students in the PBL group learned faster than the LBL group and found many benefits in the PBL implementation, including more enjoyable learning, more participation in learning, and better interpretation of course content (Sangestani & Khatiban, 2013).

PBL has been in use for the past 30 years, encouraging students to develop problem solving skills using real life practical problems. Computing has become the second most prominent application of PBL after medical education (Tsai & Chiang, 2013). In an analysis of research studies involving PBL, O'Grady (2012) identified the most prominent computer science topics that can benefit from PBL, and programming was the most prevalent of those topics. In another study to evaluate the advantages of PBL in computer science courses, the authors came to the conclusion that using PBL enhanced the students teamwork and motivation (Martinez et al., 2014). PBL has been found to improve creative thinking, self-evaluation, and self-regulation (Allchin, 2013; Yoon, Woo, Treagust, & Chandrasegaran, 2014).

Educational robotics is hailed as a powerful and flexible teaching/learning tool that allows teachers to seek new ways of teaching (Arlegui et al., 2013). Arlegui et al. (2013) proposed a PBL approach to teach key competences at the primary school level. They used virtual and physical robots to develop a new teaching approach that uses low cost material, provides support to teachers, and allows students to participate in the learning process. The results of the study showed that the students and their families were very motivated to use robotics and teachers were able to teach the basic competences of the primary school curriculum (Arlegui et al., 2013). In another study, students provided positive feedback about using PBL, stating that some of its advantages were collaborative learning, better understanding, increased motivation to look up information independently, and greater enjoyment of classes (Kong Pak-Hin, 2014).

Remote Experimentation

One of the biggest detriments to PBL is the amount of time students must spend completing problems in class, since PBL requires student interaction and collaboration (Kong Pak-Hin, 2014). In addition to time constraints, PBL-enhanced courses are affected by requirements of equipment, space, and personnel needed to achieve the necessary tasks (Ionescu et al., 2013; Saad et al., 2013). The need for equipment means that institutions need to spend a lot of money to purchase and maintain equipment in order for several classes of students to be able to participate in the PBL-based courses. Due to these constraints, two new educational methods have emerged that allow students to perform problem-based learning activities outside of the classroom. These methods are virtual or simulated labs and remote experimentation labs (Abdulwahed & Nagy, 2013).

A virtual or simulation-based lab provides students with virtual equipment that is programmed to perform in the same way that physical equipment might perform. Students use simulation software to complete their PBL tasks. The benefits of using virtual experiments is that developers of simulators can adapt reality by removing confusing details or by changing the time scale of the experiments (de Jong, Linn, & Zacharia, 2013; Merchant, Goetz, Cifuentes, Keeney-Kennicutt, & Davis, 2014).

In a review of studies regarding the learning effects of computer simulations, the authors found that computer simulations are an important addition to traditional teaching and improve student motivation and comprehension (Merchant et al., 2014). Further research shows that the use of simulation learning is beneficial to students in that it promotes context knowledge and develops process skills; however, this is only possible if the appropriate support is given to the students during their studies (Mulder, Lazonder, & de Jong, 2015).

Remote labs use physical equipment such as cameras, sensors, and controllers located in a lab in the institution and viewed through webcams over high speed networks (Lowe et al., 2013). The equipment is controlled using web interfaces and students can see real feedback from the equipment and not simulated feedback. The benefits of using remote experiments include the reduction in equipment needed, reduced maintenance costs, and constant availability (Zubía & Gustavo, 2012).

Even though research has shown that there is no major advantage between virtual and remote experiments (Abdulwahed & Nagy, 2013), the use of remote experiments is more appropriate for situations that require students to deal with imperfect data (de Jong et al., 2013). Students using remote experiments can practice and learn by observing real errors or problems that come from using a real system, but do not exist in simulations (Chaos et al., 2013; Jara et al., 2011). In a survey based on the development of a remote laboratory, 78% of the students agreed that the remote lab should be a complement to physical lab practices, with 100% rating the remote labs as quite useful and 77% as very useful and extremely useful (Barrios et al., 2013). In other studies comparing remote labs and simulations, students were more engaged when completing a remote lab because they felt that they were working on a real experiment and not a simulation (Sauter, Uttal, Rapp, Downing, & Jona, 2013; Stefanovic, 2013).

Remote Robotics Experimentation

The use of remote experiments for teaching and research has been gaining momentum over the past few years, allowing students to work with real experiments rather than using simulations (Casini et al., 2014). With the increasing deployment of learning management systems (LMS) such as Moodle and Blackboard, the use of remote experiments is becoming more widespread, which allows students to book a time slot and gain access to the remote system (Chaos et al., 2013).

Robotics research has grown exponentially during the past few years and the future of the robotics industry is predicted to have a significant increase (Kulich et al., 2013; Padir & Chernova, 2013). Robotics can also be helpful in teaching computer science and engineering concepts, and using robotics can increase teacher confidence and knowledge, allowing the integration of robotics into the curriculum (Arlegui et al., 2013). Chaos et al. (2013) identified autonomous robots as an area in which remote experiments can be applied if problems such as the use of a well-known interface, the availability of the robots, and the scheduling of the booking system are considered.

Deployment of a remote robotic experiment requires the use of a teleoperation server connected to a web server from which students are able to monitor the remote lab and observe the changes occurring in real time (Casini et al., 2014; Jara et al., 2011). Researchers have adapted LMS platforms to include scheduling systems where students can book the use of the remote robot lab at any time, which increases the number of students that can benefit from practicing on the labs (Abdulwahed & Nagy, 2013; Casini et al., 2014; Zalewski, 2013). The most prominent robotic platforms used in remote robotic experiments are based on robotic arms; however, more recently, the use of remotely controlled mobile robots such as LEGO Mindstorms NXT or EV3 is becoming more frequent (Arlegui et al., 2013; Jung, 2013; Kulich et al., 2013).

One of the issues limiting the use of remote robotic experiments is the lack of configurability on the remote robot (Verbelen, Taelman, Braeken, & Touhafi, 2013). This can be a problem when students want to work on different types of robots, requiring the lab to have one of each of the robots available for students. Verbelen et al. (2013) are working on developing reconfigurable and modular mobile robotic platforms to be used in remote experiments that will allow students to reconfigure both the hardware and software of a robot, which would allow students to work on their own individual robot designs. Another issue that is not addressed by remote robotic experiments is the collaborative nature of problem-based learning. Due to the fact that remote experiments are performed mostly individually with limited communication through forums and chat rooms, PBL is not always possible (Maiti, Maxwell, & Kist, 2014).

Using remote robotic experiments allows students from various geographic areas as well as varying educational backgrounds to have access to state-of-the-art equipment and be able to interact and learn through practice (Heradio et al., 2016). Educational institutions that have robotics courses integrated into their curriculum can benefit from using remote robotics experiments that are offered online since the institutions do not need to invest a lot of money to purchase large amounts of robotic platforms and maintain them (Lowe et al., 2013). In addition to financial benefits, the remote labs can also be offered to local schools with not access to expensive robotic setups, allowing children to experiment with robots and increasing their level of interest in robotics and consequently in computer science (Jung, 2013).

In order to facilitate competition-based learning and multi-user access to the remote robotic labs researchers developed frameworks of multiple autonomous robots that can be controlled by multiple users at the same time (Casini et al., 2014). Researchers have also developed a web interface that allows students and other researchers to program robots using the Robot Operating System (ROS) allowing seamless execution of the ROS code through a remote browser (Casan, Cervera, Moughlbay, Alemany, & Martinet, 2015).

Critical analysis and synthesis of theoretical framework

Whenever a new technology is introduced there is a concern on whether the intended users will actually use the technology. To ensure user acceptance, several theories have emerged that try to identify the key influences on acceptance of a specific technology (Williams, Rana, & Dwivedi, 2015). As a solution to this problem several models were introduced that tried to identify the factors affecting the end user acceptance of a technology such as the Theory of Reasoned Action (TRA), technology acceptance model (TAM), Motivational Model (MM), Theory of Planned Behavior (TPB), and many others (Oye, A.Iahad, & Ab.Rahim, 2014). The basic concept of user acceptance models is that each individual user of a technology has several reactions towards the technology which influense that person's intention to use it (Venkatesh et al., 2003). That intention can then be correlated to the actual use of the technology in question. All the models work in predicting the intention to use a technology so that organizations can make better decisions on whether to implement the technology (Williams et al., 2015).

Technology acceptance model. One of the earliest models is the technology acceptance model (TAM) introduced in 1985 by Fred Davis (Marangunić & Granić, 2015). TAM tries to address the reasons why users accept or reject information technology by adapting the Theory of Reasoned Action (TRA) shown in Figure 2. The theory of reasoned action states that the beliefs and evaluations of end users, along with the normative beliefs and motivations of the users have a direct influence of the users' behavioral intention to use a technology.

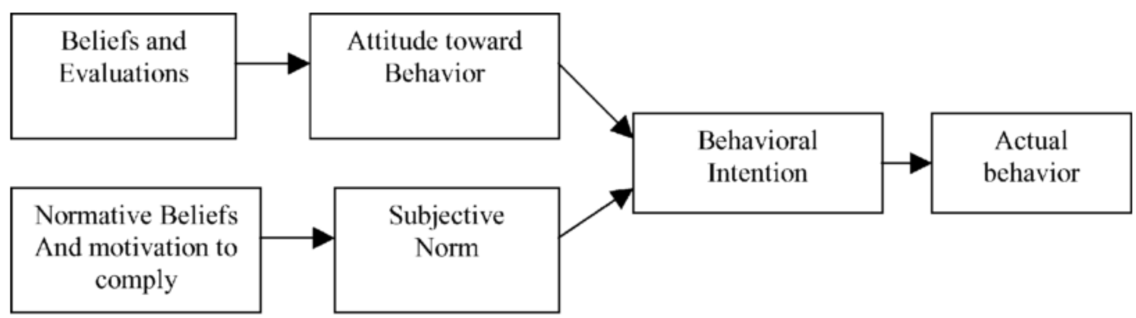

Figure 2. Theory of reasoned action. This figure shows factors affecting Behavioral intention and ultimately Actual behavior. (Reprinted from Legris et al., 2003)

The original TAM shown in Figure 3 indicates how external variables influence a user's perceived usefulness and perceived ease of use and how those two variables influence the attitude of the user towards a technology (Abdullah & Ward, 2016). In studies, both variables have been proven to be reliable with a value greater than 0.90 in Cronbach's Alpha reliability measure (Wallace & Sheetz, 2014). Cronbach's alpha is used to evaluate the internal consistency of survey instruments and a minimum of .8 is deemed an acceptable threshold for reliability (Field, 2013). This attitude is related to the behavioral intention to use a technology and finally to the actual use of the information technology. Using TAM, organizations can predict if their employees will accept a new technology and based on that information they can decide whether they should spend the time and money to implement it. If the organization still wants to implement a technology after it has identified a negative behavioral intention then the organization may need to alter the end user perception of the technology through informational meetings or training seminars that will increase the users' perception of usefulness and ease of use.

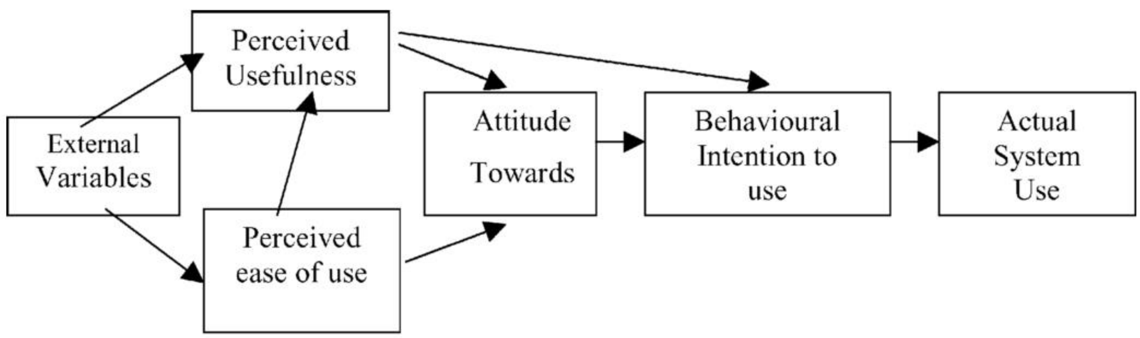

Figure 3. Original technology acceptance model (Reprinted from Legris et al., 2003)

In the original TAM, Davis made two major changes to the TRA and TRB models first by dropping the subjective norm variable and second by using two distinct constructs, namely perceived usefulness and perceived ease of use (Marangunić & Granić, 2015). But in a later study, the TAM model was extended to include additional factors that include subjective norm to help identify the factors that influence perceived usefulness (Venkatesh & Davis, 2000). Figure 4 shows the proposed TAM 2 extention with the variables that may influence perceived usefulness. The figure shows that there are several factors influencing perceived usefulness, such as subjective norm, image, and job relevance and Venkatesh and Davis (2000) examine each of these to see how they affect the perceived usefulness of a technology. In the original TAM the model was able to consistently explain approximately 40% of usage intentions and behavior but the new TAM2 model accounts for 34%-52% in usage intentions (Venkatesh & Davis, 2000). To measure the usefulness perceptions and user intentions Venkatesh and Davis (2000) evaluate four longitudinal studies using interviews and questionnaires in three points in time: after initial training, one month after implementation and three months after implementation. They then measured usage behavior at one month, three month and five month intervals leading to TAM2 explaining up to 60% of perceived usefulness.

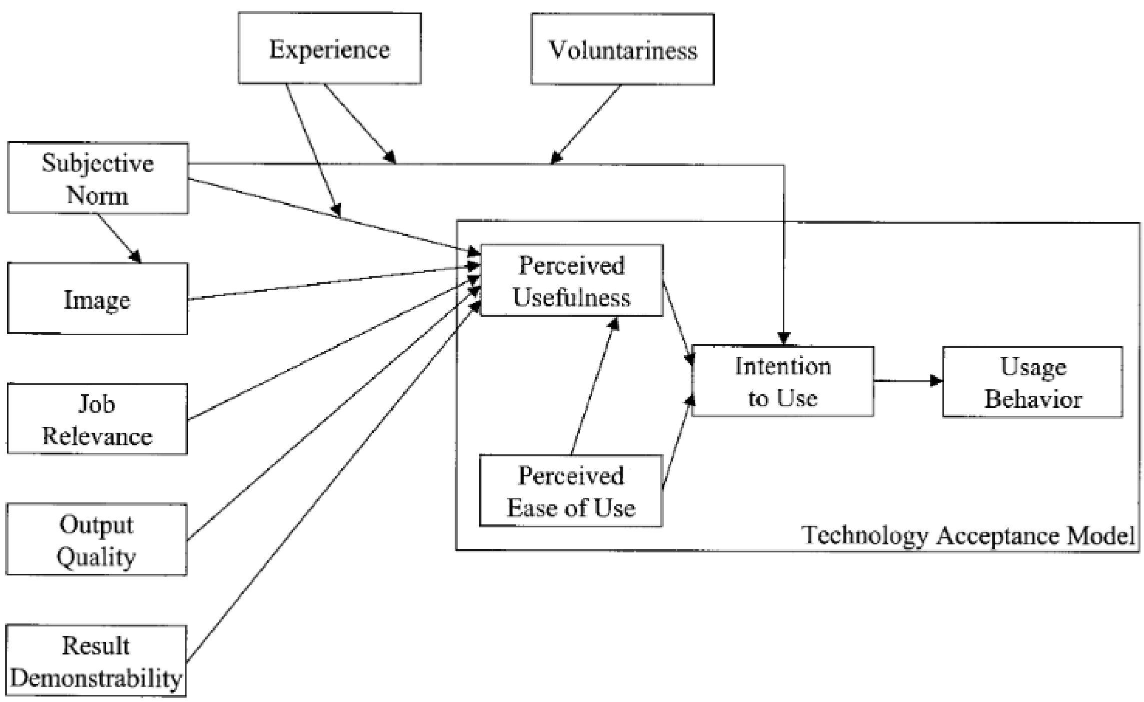

Figure 4. Proposed TAM2—Extension of the Technology Acceptance Model (Reprinted from Venkatesh & Davis, 2000)

Unified theory of acceptance and use of technology. Even with the new TAM2, the model is able to predict technology adoption success between 30-50% of the cases (Oye et al., 2014; Venkatesh & Davis, 2000). This leads researchers to try to find a model that would more accurately predict technology adoption. Venkatesh, Morris, Davis and Davis (2003) introduced the unified theory of acceptance and use of technology (UTAUT) with the ultimate goal of predicting technology adoption at a higher rate than TAM and TAM2.

In their study, Venkatesh et al. (2003) evaluated eight existing models, namely the Theory of Reasoned Action (TRA), the technology acceptance model (TAM), the Motivational Model (MM), the Theory of Planned Behavior (TPB), the Combined TAM and TPB (C-TAM-TPB), the Model of PC Utilization (MPCU), the Innovation Diffusion Theory (IDT) and finally the Social Cognitive Theory (SCT). For all of the models, Venkatesh et al. (2003a) measured the effects of all the independent variables and how they predicted behavioral intention. In the analysis of the technology acceptance models, Venkatesh et al. (2003a) found out that TRA had an R-squared value of .36, TAM .53, MM .38, TPB .36, C_TAM-TPB .39, MPCU .47, IDT .40 and SCT .36. The R-squared value represents how well the model fits the data and the higher the number the bigger the effect (Gaskin & Happell, 2014). This makes TAM the best fit for predicting intention to use a technology (Venkatesh et al., 2003).

Out of all the variables examined, four were deemed to have the most impact on accurately predicting the intention of end-users to use a technology (Figure 1). UTAUT uses performance expectancy, effort expectancy, and social influence to determine the behavioral intention and along with facilitating conditions to further determine the use behavior of an end-user. Each of these variables can be affected by secondary variables such as gender, age, experience and voluntariness of use (Venkatesh et al., 2003). Using UTAUT in the same studies as the previous models shows that UTAUT has an adjusted R-squared value of .70 that is a major improvement over the other models. UTAUT also determines use intention using four main constructs and four moderators out of the initial set of 32 constructs (Venkatesh et al., 2003).

Supporting theories. There are a number of theories available to predict technology acceptance by end-users. The Theory of Reasoned Action uses the positive or negative attitude of a person towards the technology and subjective norm. Subjective norm is the perception of the user of whether people in his environment expect him to use the technology. The technology acceptance model uses perceived usefulness, perceived ease of use and subjective norm. UTAUT evaluated several behavioral intention models to determine four main constructs that more accurately predict someone’s intention to use a technology. There are several new theories that support the use of UTAUT by extending it to predict intention in different environments and showing that the framework is applicable to different genders, cultures and IT competencies (Alaiad & Zhou, 2014; Bhatiasevi, 2015; Maillet, Mathieu, & Sicotte, 2015).

Maillet, Mathieu and Sicotte (2015) identify end-user acceptance and satisfaction as critical factors for successfully implementing a technology such as electronic patient records. The authors use an extended UTAUT to measure the acceptance and actual use of electronic patient records by nurses. The difference of the study compared to the original UTAUT model is based on the fact that UTAUT evaluates the intention to use a technology but the study wanted to measure the actual use of the technology since electronic patient records have already been implemented. The study used a questionnaire made up of 53 questions relating to compatibility of the electronic patient record, self-efficacy, performance expectancy, effort expectancy, social influence, facilitating conditions, actual use and nurse satisfaction. The results supported 13 out of the 20 hypotheses confirming many of the UTAUT variables influence on actual use and satisfaction of using electronic patient records by nurses (Maillet et al., 2015).

Venkatesh, Thong and Xu (2012) introduce UTAUT2, an extension of UTAUT that studies consumer acceptance and use of technology. By examining a specific context like consumer intention, the authors can identify new constructs that can serve as accurate predictors of intention. The authors integrated three new constructs into the original UTAUT model to adapt the model from just measuring initial acceptance to include context habit. The first construct introduced is hedonic motivation, which is the measure of fun or pleasure a consumer gets from using a technology (Raman & Don, 2013). UTAUT2 also includes price value since the cost of the technology falls to the consumer and not the organization that is implementing the technology like the original UTAUT. Finally, experience and habit is included based on how experienced a consumer is with a technology and how habitual learning influence the consumer’s intentions (Venkatesh, Thong, & Xu, 2012). Ain, Kaur and Waheed (2015) found that UTAUT did not consider student perceived value in terms of learning and associated fun and pleasure. To bridge this gap the authors used UTAUT2 and added learning value in the place of price while keeping the hedonic motivation and experience and habit constructs. The study utilized surveys given at a university that used Moodle as an LMS and from the 49.3% response rate they found that performance expectancy, social influence, and learning value were good predictors of the behavioral intention of students to use an LMS (Ain et al., 2015).

UTAUT has also been extended to provide insight on technology acceptance in educational environments (Buchanan, Sainter, & Saunders, 2013; P. C. Lin et al., 2013; Nistor, Göğüş, & Lerche, 2013). The Education behavioral intention model (EduBIM) extends the UTAUT model through the integration of cognitive individual differences that affect demographic moderators (P. C. Lin et al., 2013). Lin, Lu and Liu (2013) examined several behavioral intention models such as TRA, TAM, TAM2, TPB and UTAUT and concluded that UTAUT was a better metric for behavioral intention. EduBIM enhances UTAUT by including a measure of fit between learning styles and teaching styles. This is included in the demographic constructs providing a measure of self-reporting learning style and perceived teaching style, which can provide information on Learning-Teaching fit and ultimately on behavioral intention (P. C. Lin et al., 2013). Yeuh, Huang and Chang (2015) extended the UTAUT model to examine collaborative learning using Wikis. The authors found that the UTAUT model was more suitable than TAM due to its inclusion of social influence and facilitating conditions. In their study, the authors provided students with the actual technology and then measured the actual use of the Wiki and correlated it with the behavioral intention to continue using the Wiki in the future (Yueh, Huang, & Chang, 2015).

Contrasting Theories. One of the oldest social science theories that aims to explain adoption of a new idea or technology is the Diffusion of Innovation (DOI) theory developed by E. M. Rogers (Sahin, 2006). DOI studies the way innovation occurs and identifies four stages that innovation goes through until it is accepted. The four stages are innovation, communication channels, time and social systems (Sahin, 2006). In order for diffusion to occur there must be certain users who adopt the innovation at various stages of its lifetime. These stages follow each other and begin with the knowledge stage where an individual learns about an innovation, then move to the persuasion stage where the individual has a positive or negative view of the innovation, followed by the decision state where the individual choses to adopt the innovation or not (Sahin, 2006). After the user decides whether to adopt the innovation the implementation stage follows where the specific innovation is put into practice and then finally the confirmation stage has the adopter seek approval from others for making the decision that he made (Sahin, 2006).

Another model that is based on the Diffusion of Innovation theory is the Information Systems diffusion variance model (Agarwal & Prasad, 1998). Agarwal and Prasad (1998) define a new construct named personal innovativeness, which is a measure of end users to adopt information technology innovations faster than others. In a review of three models including personal innovativeness, the unified theory of acceptance and use of technology and a combination of all theories personal innovativeness showed no significant effect on behavioral intention but showed a strong relationship with all of the mediators (Jackson, Yi, & Park, 2013). Jackson, Yi and Park (2013) showed that the integrated model combining personal innovativeness with performance expectancy, effort expectancy, facilitating conditions and social influence provided the most complete understanding of the influence to behavioral intention.

Critical analysis of studies related to the theory/conceptual models

There are several theories that are investigating technology acceptance but the most widely used models are the Theory of Reasoned Action (TRA), the Theory of Planned Behavior (TPB), the technology acceptance model (TAM) and the unified theory of acceptance and use of technology (UTAUT) (Teo, 2013). UTAUT was shown to outperform several other technology acceptance models (Venkatesh et al., 2003) but even though the model has been widely used there are still concerns on the significance of the relationships amongst the model (Taiwo & Downe, 2013). Taiwo and Downe (2013) reviewed a number of studies that used the UTAUT model where the constructs used in the model were found to significantly predict the intention to use a technology. Contrasting to the positive reviews of UTAUT there are also some studies that found some of the constructs to have little to no influence on predicting intention (Taiwo & Downe, 2013). In their study, Taiwo and Downe (2013) used a meta-analysis methodology in which they collected data from numerous articles and then analyzed them using the six variables identified in UTAUT. The variables are performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FC), behavioral intention (BI) and use behavior (UB). The results of the study showed that there was a 0.5361 correlation between PE and BI showing a medium effect size. All the other correlations, EE-BI, SI-BI, FC-BI, BI-UB, had a small effect size but the results were consistent with the original UTAUT study (Taiwo & Downe, 2013).

In a comprehensive review of UTAUT, Williams, Rana and Dwivedi (2015) identified a number of limitations that UTAUT has across several studies examined. These limitations included the fact that most research was focusing on a single subject in terms of community, culture, country, organization, agency, department, person or age group. According to the authors' research, this is a key constraint to UTAUT that limits the generalization of the results. Williams et al. (2015) also noted that this problem of generalization is also supported by the sample size of the studies. The authors also noted that even though UTAUT examined eight other intention models and showed that it outperforms those models, those models are still being used with the technology acceptance model coming second while the Theory of Planed Behavior comes third. The authors attribute the frequent use of TAM to having greater maturity over UTAUT since the number of papers using UTAUT since its inception is relatively low (Williams et al., 2015). Even though TAM has been more frequently used by researchers there is a gradual increase in the use of UTAUT in research related to predicting user intention (Bhatiasevi, 2015).

Critical analysis and synthesis of independent variables

UTAUT uses four core constructs to determine a person's intention to use a technology. These constructs are: performance expectancy, effort expectancy, social influence and facilitating conditions (Venkatesh et al., 2003). UTAUT condensed the 32 variables found in eight existing technology acceptance models to four main factors and four moderating factors increasing the efficiency of use behavior prediction to 70% (Oye et al., 2014).

Performance expectancy (PE). Every person has a measure of how a certain technology can help that person increase his job performance (Alotaibi & Wald, 2013). Several studies have shown that there are similarities in constructs such as usefulness and extrinsic motivation, usefulness and job-fit, usefulness and relative advantage, usefulness and outcome expectations and job-fit and outcome expectations (Venkatesh et al., 2003). PE has the highest effect on behavioral intention making it the most important construct in UTAUT for predicting technology use (Taiwo & Downe, 2013; Venkatesh et al., 2003). In an analysis of literature relating to UTAUT performance expectancy was the most significant predictor of behavioral intention with a weight of 0.80 (Williams et al., 2015).

Effort expectancy (EE). Effort expectancy is defined as the amount of effort a person is expecting to expend when transitioning to the new technology introduced or the degree of ease that is associated with using the technology (Alotaibi & Wald, 2013; Venkatesh et al., 2003). This variable was used in several other behavioral models such as TAM and TAM2 (Davis, 1989; Venkatesh & Davis, 2000). The critical point where EE is mostly significant is at the early stages of adoption of a technology rather than at later stages since it is more difficult to use a technology when it is experiencing transitioning issues (Venkatesh et al., 2003). In this study, EE may play a significant role because remote experimentation has not been introduced yet and the teachers may not be aware of the amount of effort they will allocate to accomplish their tasks. Williams et al. (2015) found effort expectancy to have the least significance to predicting behavioral intention with a weight of 0.58 (Williams et al., 2015).

Social influence (SI). Humans, being social beings, are influenced by the views of others and technology acceptance is also biased by others. In the case of technology acceptance a user may be influenced by people that are important to him and who believe that the person should use the system (Venkatesh et al., 2003). As Venkatesh et al. (2003) state a user's decision to use a technology is also affected by how influential the technology is to enhancing the image and status of the user within the social system. Some studies dispute the impact of SI on a user's intention to use a technology (Lin, Zimmer, & Lee, 2013; Raman et al., 2014; Wong, Teo, & Russo, 2013). On the other hand, there are studies that show that SI is one of the most important variables in behavioral intention (Chen & Chen, 2015; Tosuntas, Karadag, & Orhan, 2015) especially in STEM professions (Nistor et al., 2013). Another study reviewing the relationships between the major UTAUT variables found Social influence to have the second highest significance in predicting behavioral intention, after performance expectancy, with a weight of 0.75 (Williams et al., 2015).

Facilitating conditions (FC). Facilitating conditions deal with the degree to which the end user believes that the organizational and technical infrastructure exists to support the system (Alotaibi & Wald, 2013; Maillet et al., 2015). Facilitating conditions include technical and organizational support for the technology such as having the appropriate hardware, software, training and support (Khechine et al., 2014; Oye et al., 2014; Tarhini, Hone, & Liu, 2013). This is considered extremely important since it deals with the challenges related to integrating a technology in an organization and this may influence a person's intention to use a technology (Maillet et al., 2015). Facilitating conditions can have a relationship between the behavioral intention and the use intention of an individual to use a technology and in both cases the weights of significance were 0.69 and 0.67 respectively, putting the significance higher than effort expectancy but lower than performance expectancy and social influence (Williams et al., 2015).

Critical analysis and synthesis of dependent variables

The first dependent variable that is examined using the unified theory of acceptance and use of technology (UTAUT) is behavioral intention (BI) (Venkatesh et al., 2003). Behavioral intention is said to be influenced by performance expectancy, effort expectancy and social influence. Adding facilitating conditions to BI provides information towards the Use Behavior (UB) which is the dependent variable that this study is aiming to determine. Some studies assume that behavioral intention accurately predicts use behavior and focus more on explaining behavioral intention taking use behavior for granted (Agudo-Peregrina, Hernández-García, & Pascual-Miguel, 2014). Agudo-Peregrina et al. (2014) suggest that there is no significant relation between behavioral intention and use intention but note that this is true in the presence of habitual behaviors.

Measurement of variables

This correlational quantitative research study utilized survey questions using a Likert-type scale which would provide a numerical basis on which statistical procedures can be used to identify the correlations between the UTAUT variables (Fink, 2013). The validity of the variables were assured by using validated survey questions from previous research using UTAUT (Venkatesh et al., 2003).

Compare and contrast points of view and relationship of the study to previous research and findings

The purpose of this research study was to evaluate the relationship between performance expectancy, effort expectancy, social influence, facilitating conditions and the intention of computer science high school teachers in Cyprus that teach introductory computer science course, to use remote robotic experiments in their classrooms. Several research studies dealt with the benefits of remote experiments and even remote robotic experiments in the classroom (Ionescu et al., 2013; Lowe et al., 2013; Marques et al., 2014; Zalewski, 2013; Zubía & Gustavo, 2012). There were also research studies that evaluated the behavioral intention of teachers to use a certain technology in their classroom (Oye et al., 2014; Raman & Don, 2013; Wong et al., 2013). The gap in the literature was the evaluation of the behavioral intention of computer science high school teachers in Cyprus to use remote robotic experiments in their courses and the variables that might influence that intention.

Table 1 presents previous research that had been done in the area of remote experiments, robotics and technology acceptance. The studies presented showed that there existed research in all parts of the study but none of them tackled high school teachers and their intention to use remote robotic experiments in their introductory computer science courses. Research studies discussed the use of problem-based learning especially using robotics to enhance learning with an emphasis on student acceptance rather than teacher willingness to use the technology (Arlegui et al., 2013; Jara et al., 2011; Jung, 2013).

On the other hand, research was also done on the behavioral intention of students to use technologies in their learning process (Barnes, 2013; Cheung & Vogel, 2013; Tan, 2013). The scope of this study though was to investigate the behavioral intention of teachers to use different types of technologies in enhancing their educational environments (Buchanan et al., 2013; Schoonenboom, 2014; Teo & Noyes, 2012).

The third area that this study explored was the use of remote experiments in an educational environment. Remote experimentation has proven to be extremely beneficial to the learning process of students as well as providing educators with huge benefits like providing problem-based learning outside of the class time (Ionescu et al., 2013; Lowe et al., 2013; Marques et al., 2014; Zubía & Gustavo, 2012). By using remote experimentation, educators can allow students to perform live experiments online using web technologies and at times that do not interfere with class schedules (Jara et al., 2011).

This leads to the gap in the literature, which could be defined as a lack of research to evaluate the behavioral intention of high school teachers to use remote experiments involving robots in their introductory computer science courses. In addition to this, there was also an additional constraint where the geographical scope of the study dealt with the island of Cyprus. Extending the geographical scope of the research to other countries might not have been applicable because the educational systems differ from country to country and the views of teachers in another geographic location might have been different from the views of the teachers in Cyprus. The study can nevertheless be extended in the future to include other levels of education in Cyprus such as elementary education and tertiary education.

Table 1

Previous Research on the behavioral intention of High School Teachers in Cyprus to Use Remote Robotic Experiments in Introductory Computer Science Courses

Author/Date	BI	RE	BI to use RE with robots	Significant Findings
Arlegui, Pina, & Moro (2013)	No	No	No	Teachers and students are very motivated to use problem-based learning using either virtual or physical robots.
Lowe et al., (2013)	No	Yes	No	Students perceive remote access experiments as valid practical experience.
Jara et al., (2011)	No	Yes	No	RE improves student experimental learning through the continuous availability of the virtual equipment. Theoretical results compared with practical results.
O'Grady, (2012)	No	No	No	Adoption of PBL is based on faculty members own decision to introduce it and this can only change if key actors like students and teachers as well as key stakeholders perceive the benefits of PBL.
Oye et al., (2014)	Yes	No	No	The study validates the UTAUT model to predict the behavioral intention of academicians in the use of Information and Communication Technologies.

Note. BI = behavioral intention. RE = remote experiments. PBL = problem-based learning.

Transition and Summary

Section 1 introduced the problem tackled by this research study and presented information about the background of the problem. The section presented the problem statement, the purpose statement leading to the research question that related to an applied information technology issue and finally introduced the hypothesis that the study tried to examine. Additional information regarding the nature of the study as well as the significance of the study to information technology and how it influences social change was presented. The literature review ends the section with an in-depth description of the theoretical framework that was used and how it was applicable to the problem described.

Section 2 restates the problem and provides important information about the research methodology that was chosen for this study. The section provides information on the role of the researcher, the target population and the sample that was involved in the study followed by the data collection technique, data organization, data analysis, and a statement on reliability and validity.

Section 2: The Project

Based on data presented by the Grand Coalition for Digital Jobs, up to 825,000 vacancies for professionals in the ICT could be unfilled by 2020 (Digital Agenda for Europe, 2015). In the United States it was estimated that an extra one million science, technology, engineering and mathematics(STEM) professionals would need to enter the workforce in the next decade in order for the United States to remain competitive in the global market (Chen, 2015). Researchers found that this need for more ICT professionals lead to the need to keep more students in the field of computer science, since there was a very high attrition rate in the field (Chen, 2013). Research studies examined the reasons why students were leaving STEM to move to other fields or stopped their studies completely (Chen, 2013, 2015; Stinebrickner & Stinebrickner, 2014). Some of the reasons for STEM attrition were poor performance in STEM courses compared to non-STEM courses, weak focus on STEM courses in the first year, and poor precollege academic preparation (Chen, 2013, 2015). Based on reasons related to STEM attrition, researchers examined how educators could enhance their teaching methods to increase the number of students graduating in the field by using active learning in introductory courses, introducing laboratory exercises, and promoting group work (Graham, Mark J.; Frederick, Jennifer; Byars-Winston, Angela; Hunter, Anne-Barrie; Handelsman, 2013; Sarpong & Arthur, 2013).

In Section 2, I present the methodology that I used in my study, the purpose statement, and by my role as a researcher in this study. After that, I present my target population, the sample, and a description of the research method and design. Lastly, I will discuss the data collection methodology, including my data collection instruments, the data analysis, and a brief discussion on the reliability and validity of my research study.

Purpose Statement

The purpose of this study was to investigate the relationship between performance expectancy, effort expectancy, social influence, facilitating conditions, and the behavioral intention of high school teachers teaching introductory computer science courses to use remote robotic experiments. This study collected data from computer science high school teachers in Cyprus and analyzed the data to see whether the aforementioned independent variables could influence the teachers' intention to use remote robotic experiments in their classrooms. The implications for positive social change are that high school teachers might react more positively to the introduction of remote robotic experimentation techniques in their classrooms, leading to an increase in computer science graduates and ICT professionals.

Role of the Researcher

The role of a researcher includes networking, collaboration, the management of research, the undertaking of basic or applied research, publication, and the evaluation of research (Kyvik, 2013). My role as a researcher required me to focus on managing, implementing, and evaluating my research. Researching remote robotic laboratory use was an area of extreme importance to me. I had been teaching computer science courses for more than 10 years and had been involved with robotics in education for the past 5 years before this study. This might have resulted in problematic bias because of my own views on the subject and because individuals involved in the study knew me as an academic with a background in robotics. It is important for the researcher to identify researcher bias in data collection and try to eliminate it (Cokley & Awad, 2013). Researcher bias can be mitigated through the use of anonymous data collection techniques (Judkins-Cohn & Kielwasser-Withrow, 2014; Regan, 2013; Roberts & Allen, 2015).

The Belmont report requires a researcher to adhere to three main principles: respect for persons, beneficence, and justice (National Institutes of Health, 1979). To safeguard the principle of respect for persons as defined in the Belmont report (National Institutes of Health, 1979), a researcher needs to ensure informed consent by providing all the necessary information to the participant with respect to the study and the data collection procedure (Judkins-Cohn & Kielwasser-Withrow, 2014). Another issue that needs to be addressed to ensure informed consent it the evaluation of the risks involved due to dual roles which may influence the participants (Regan, 2013). Dual roles refer to cases where the researcher is also directly involved with the participant as a teacher for example (Regan, 2013). In addition to the anonymous collection of data, I also stated on the participant consent form that the information provided would be used as part of my doctoral study research and separate from my role as a university lecturer.

Part of my role as a researcher was to ensure the validity of the study. The instrument that I used in this research study was based on the UTAUT instrument used in previous research studies and repurposed to align with my own study. Written permission to reuse the survey instrument proposed by Venkatesh et. al. (2003) was given by both the author, Dr. Viswanath Venkatesh, and the MIS Quarterly publication (Appendix E).

After receiving IRB permission to conduct the study, I requested that the Cyprus Computer Science Teachers Association send an official email to all the participants that included a short introduction to the study, which clearly stated what the research was about and how the data provided would be used in the study. The email informed the recipients of the anonymity of the study and provided information about how data would be protected as well as the link to the online survey as required by the Belmont Report (National Institutes of Health, 1979). The use of an online survey ensures the anonymity of the respondents if it does not track or record any identifying information (Roberts & Allen, 2015). In my survey instrument (Appendix F), I did not collect any identifying information and this ensured the anonymity of the participants.

The results showing the intention of high school computer science teachers in Cyprus to use remote robotic experiments in their courses were made available to the Cyprus Ministry of Education and to the all the participants of the study in the form of a presentation. The participants in my study were high school computer science teachers and no identifying information was gathered during data collection. The Belmont report (1979) divided the respect for persons principle to two moral requirements, one of which was the protection of people with diminished autonomy. This research study involved no human subjects from vulnerable groups.

Participants

There were approximately 400 middle and high school teachers of computer science employed by the Cyprus Ministry of Education and Culture at the time of the study. These teachers made up the target population of my study. The number of eligible participants was small. Small populations require a large sample in order for the confidence level to be high enough (Cokley & Awad, 2013; Fincham & Draugalis, 2013; Schönbrodt & Perugini, 2013). To ensure that the sample of survey responses that I received was adequate for analysis, I sent the survey to all of the high school computer science teachers in Cyprus, which made my accessible population equal to my target population.

The Cyprus Computer Science Teachers Association provided access to the participants that participated in the survey. To get access to the participants I contacted the Cyprus Computer Science Teachers Association president and requested that they forward my invitation email to all their members. The association sent the survey through its own mailing list after I had the approval of the association board to conduct the research study. Distributing the survey through a sponsor can positively influence the nonresponse bias, which is the bias between respondents and nonresponders (Groves et al., 2012). Using the association to distribute the email with my survey request increased my chances to reach the required number of responses. To ensure the protection of the participants, the survey was anonymous and the email explained the research and provided a link to the survey instrument and a note that no identifiable data would be collected. Providing informed consent and anonymity protects human research participants as required by the Belmont report (Judkins-Cohn & Kielwasser-Withrow, 2014; Regan, 2013; Roberts & Allen, 2015). In this study, I provided the participants with all the required information about the study and survey and ensured their anonymity.

The eligibility criteria for participant participation were: being a high school teacher in the area of computer science and being registered at the Ministry of Education and Culture in Cyprus at the time of the study. Based on ministry regulations, a secondary education teacher must at a minimum hold a 4-year bachelor's degree in the subject of specialization (UNESCO International Bureau of Education, 2012).

Research Method and Design

The objective of this study was to evaluate if a relationship existed between the intention of high school teachers in Cyprus that teach introductory computer science courses to use remote robotic experiments and performance expectancy, effort expectancy, social influence, and facilitating conditions. In order to accomplish this goal, I used a correlational quantitative research design. Correlational research is used by researchers that are interested in discovering relationships between variables (Castillo-Page & Bunton, 2012; Turner, Balmer, & Coverdale, 2013). The theoretical framework used in this study examined four distinct independent variables and their relationship with behavioral intention as a dependent variable (Venkatesh et al., 2003). Since there was no treatment and the primary purpose of the study was to examine relationships between variables in a single group, I deemed the correlational design appropriate (Keele, 2011).

Method

When conducting research there are two main paradigms that prevail, namely qualitative and quantitative research methods (Venkatesh, Brown, & Bala, 2013). In qualitative research, researchers try to understand how and why events or behaviors occur. Qualitative research, is based on developing concepts and theories using either an inductive or a deductive content analysis approach (Elo et al., 2014; Sánchez-Algarra & Anguera, 2013; Yilmaz, 2013). Researchers using quantitative designs are more interested in how many, how often, at what level, and in what direction relationships exist between variables (Castillo-Page & Bunton, 2012). A third research design methodology is mixed methods, which combines both qualitative and quantitative methods (Venkatesh et al., 2013).

When the research question involves the identification of relationships between known independent variables and a dependent variable, a correlational quantitative methodology can be used (Castillo-Page & Bunton, 2012; Nathans, Oswald, & Nimon, 2012; Turner et al., 2013). Because this study examined the relationships between performance expectancy, effort expectancy, social influence, facilitating conditions, and the behavioral intention to use a technology the correlational quantitative methodology was deemed as appropriate. In a literature review of research done using the unified theory of acceptance and use of technology (UTAUT), the quantitative method was widely used (Williams et al., 2015). Tarhini, Hone, and Liu (2013) studied user acceptance of web-based learning systems and used a correlational quantitative method to test their proposed model that extended the TAM by adding social, institutional, and individual variables. Furthermore, Sánchez-Algarra and Anguera (2013) stated that traditionally, quantitative research methods were used to measure and verify relationships between concepts derived from a theoretical framework.

Research Design

The research method that I selected for this study was a correlational quantitative approach in which I analyzed the relationships between performance expectancy, effort expectancy, social influence, facilitating conditions, and the intention to use a technology. In this research study, I collected data using surveys given to high school computer science teachers who taught introductory programming courses in Cyprus.

An experimental or quasi-experimental research design is based on a specific treatment applied to the sample population (Keele, 2011; Wells, Kolek, Williams, & Saunders, 2015). Turner (2013) stated that quasi-experimental or experimental design studies observe cause and effect relationships, which means that a study would need to introduce the cause and then examine the effects of that introduction. In this study, no specific treatment was introduced to the participants to measure the effects of that treatment so an experimental or quasi-experimental design was not suitable for this study.

Another research method examined for use in this study was the descriptive research method. The descriptive research method is based on the concept of “what is happening” rather than “what is causing it” (Behdad, Berg, & Vance, 2013; Giorgi, 2012; Sousa, 2014). In a descriptive design study, the researcher attempts to analyze data to describe a phenomenon and then identify its characteristics (Nassaji, 2015). In this research study I already had knowledge of the independent variables that were going to be examined and therefore the use of a descriptive research method was not suitable.

A correlational quantitative design was more appropriate than experimental, quasi-experimental, and descriptive designs because I examined relationships of known variables without the introduction of a specific treatment to the participants in the study.

Population and Sampling

I collected data from high school computer science teachers who were the general population of the study. The specific geographic area of the population was the island of Cyprus in the Mediterranean Sea. There were approximately 400 computer science high school teachers employed by the Cyprus Ministry of Education at the time of the study. Since the total population that I examined was relatively small, I performed a census sampling where I distributed the survey to all the high school computer science teachers using information from the Cyprus Computer Science Teachers Association. To accomplish this, I applied for permission from the association board to conduct my research. The permission to perform the research can be found in Appendix D. Using a census sampling method did not guarantee that every single participant would fill in the survey so I had to calculate a minimum number of responses required to prove my research question (Groves et al., 2012; Tourangeau, Conrad, Couper, & Ye, 2014).

One method of calculating the sample size is based on power analysis using the G*Power software. Previous literature that uses the UTAUT model has shown that data analysis is based on a multiple regression analysis of the constructs associated with UTAUT (Attuquayefio & Addo, 2014; Oye et al., 2014). Using G*Power version 3.1.9.2, I conducted an F-test for linear multiple regression to calculate a priori the required sample size given the effect size, the error probability, the power and the number of predictors. I used a medium effect size (f = 0.15), an error probability ($\alpha = 0.05$) and a power of 0.80 with the four predictors used in UTAUT to estimate that I would need a sample size of 85 participants (Figure 5). Increasing the sample size to 129 participants would result to a power of 0.95 and further increasing the sample to 174 participants would increase the power to 0.99 as shown in Figure 6. Statistical power is a measure of the likelihood of finding a difference in some data therefore the higher the power the more accurate and true the statistical test becomes (Emerson, 2016).

Using a medium effect size (f = 0.15) was appropriate for this research study based on the analysis of previous literature based on the four constructs of UTAUT (C. Chen, Lai, & Ho, 2015; Lakens, 2013; Taiwo & Downe, 2013; Venkatesh et al., 2012). I strived to collect a minimum of 85 completed surveys from the census of the population of all high school computer science teachers registered with the Cyprus Ministry of Education at the time of the study. In the event that I collected more than 129 surveys then my data would be closer to a power of 0.95 providing a better data analysis.

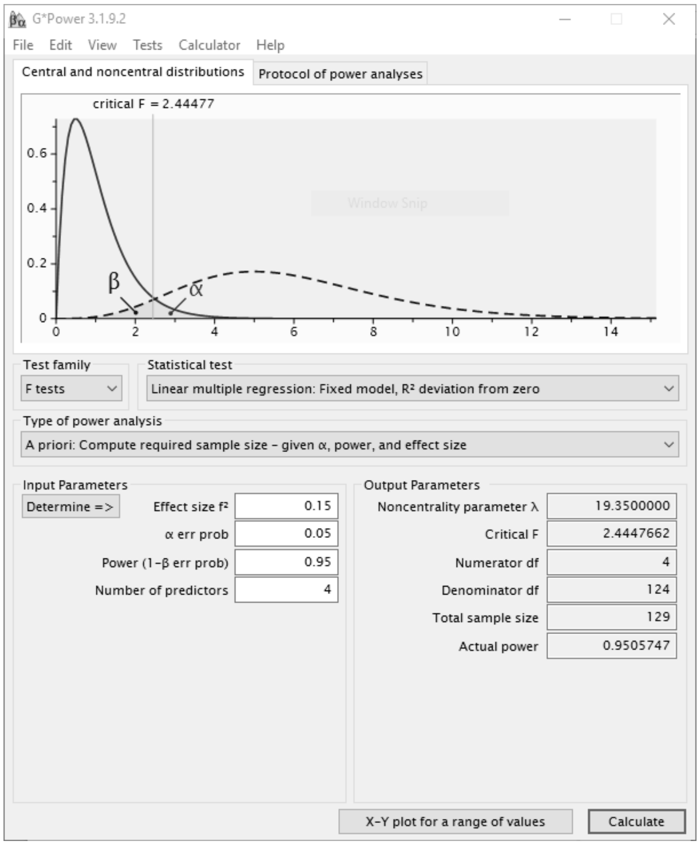

Figure 5. G*Power analysis to compute the required sample size

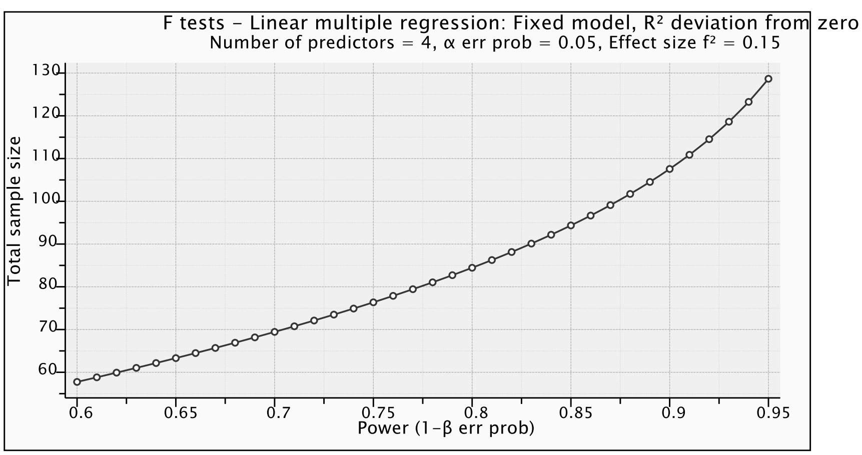

Figure 6. Power as a function of sample size

Another method of determining an appropriate sample size is using the formula 50 + 8 (m) = sample size where m is the number of independent variables examined (Carrington, Grossi, Knowles, & Scott, 2014; Lo, Chair, & Lee, 2015; Tabachnick & Fidell, 2013). Since the independent variables examined were performance expectancy, effort expectancy, social influence and facilitating conditions, that meant that m was equal to 4 and the formula 50 + 8 (4) = 82. Therefore, the sample size required for the study based on the formula by Tabchnick and Fidell (2013) would be 82 participants out of the approximately 400 computer science high school teachers.

Ethical Research

During the course of my doctoral research, I collected data from an electronic survey that was distributed to all participants in the study. All of the data collected were considered private and confidential data and needed to be protected and safeguarded from unauthorized access and disclosure. This was in line with the Respect for Persons principle of the Belmont report (National Institutes of Health, 1979). During my doctoral studies, I also completed the required certification by the National Institutes of Health (NIH) Office of Extramural Research (No. 1719416) with the title Protecting Human Research Participants (Appendix B).

To ensure the ethical collection of data in my surveys I provided participants with a consent form that was completed online by the participant. Online surveys are increasingly used in educational research with benefits including the efficient way of collecting data and the use of ethically defensible ways of conducting research (Roberts & Allen, 2015). The consent form (Appendix C) was shown to the participant before the start of the survey and the participant would need to click on the checkbox indicating that he/she have understood and agree to participate in this research. The consent form had to be easy to understand so that the participants would be able to make an informed decision to participate in the study (Holland, Browman, McDonald, & Saginur, 2013). The participants were also informed that they could leave the survey at any time simply by closing their browser window and none of the data would be stored at that time. At the end of the survey the participant was informed that after submitting the information that information could not be removed since the surveys are anonymous and there was no way of knowing which survey belonged to the specific participant. To ensure the confidentiality of the participants I stored all of the collected data in electronic form in a USB flash drive and placed it in a safe for a minimum of 5 years. I also deleted any electronic surveys from the online survey tool that was used to gather the completed surveys so that no future data breaches could allow unauthorized access to the data. The privacy policy of the online service that was used ensured that all data were encrypted using Secure Socket Layers (SSL), with two step verification and access to confidential information was restricted (Google, 2016). At the end of the five years, I will destroy the USB flash drive by burning it to ensure that no one will be able to restore the deleted data from the drive.

Data Collection

Instrumentation

I collected data using a survey instrument with closed-ended questions based on extant literature. The questions were adapted from the original UTAUT survey instrument (Venkatesh et al., 2003) as shown in **Table 2** and were reworded to apply to the specific technology that I investigated. Permission to use the survey instrument was requested and granted as presented in Appendix E. Based on the fact that English can be considered a second language in Cyprus (Baker & Avenue, 2014) all participants could answer the survey in English. The survey also had a Greek translation of each part of the survey to ensure that no one had any problems understanding the questions. The survey instrument with all the questions is provided in Appendix F.

Table 2
Data collection instrument used in UTAUT

Construct	Instrument
Performance	I would find the system useful in my job
expectancy	Using the system enables me to accomplish tasks more quickly
	Using the system increases my productivity
	If I use the system, I will increase my chances of getting a raise
Effort	My interaction with the system would be clear and understandable
expectancy	It would be easy for me to become skillful at using the system
	I would find the system easy to use
	Learning to operate the system is easy for me

Table 2 continued

Construct	Instrument
Social influence	People who influence my behavior think that I should use the system
	People who are important to me think that I should use the system
	The senior management of this business has been helpful in the use of the system
	In general, the organization has supported the use of the system
Facilitating conditions	I have the resources necessary to use the system
	I have the knowledge necessary to use the system
	The system is not compatible with other systems I use
	A specific person (or group) is available for assistance with system difficulties
Behavioral intention	I intent to use the system in the next <n> months
	I predict I would use the system in the next <n> months
	I plan to use the system in the next <n> months

As shown in **Table 2** the survey was used to measure the five constructs relating to UTAUT, namely performance expectancy, effort expectancy, social influence, facilitating conditions and behavioral intention (Venkatesh et al., 2003). The survey questions used an ordinal scale of measurement with a seven-point Likert scale ranging from 1 – Strongly disagree to 7 – Strongly agree (Boone & Boone, 2012). There were four questions relating to the measurement of each of the constructs and the values taken from the four independent constructs were evaluated along with the dependent variable that was behavioral intention.

Due to the instrument being presented in the language used in Venkatesh et al. (2003) the validity of the instrument was not affected. In addition, research showed that validity is affected by region, residence in rural area, race, and job experience (Kitagawa, 2015). Since my study was based on all high school computer science teachers in Cyprus, I limited my study to one region. The scales used in UTAUT constructs had been assessed for their psychometric properties and had been found reliable (Nistor et al., 2013; Parameswaran, Kishore, & Li, 2015; Venkatesh et al., 2012).

Participants were able to access the survey instrument through Google Forms. A prefabricated email containing a brief introduction to the survey purpose, potential benefit, encouragement to complete the survey and a link to the survey, was sent to the Cyprus Computer Science Teachers Association. The association then forwarded the email to the appropriate computer science high school teachers registered at the Ministry of Education and Culture in Cyprus. Having the survey sponsor send the email increased the chances that the survey would be completed by the recipients because it came from a reputable source (Groves et al., 2012). The survey period lasted for three weeks to allow for maximum possible participation. The responses were checked weekly and if the number reached the maximum sample size selected I would close the survey. If after the first week the minimum was not reached then a follow up email would be sent to the participants weekly to remind them of the survey and try to collect more responses. In the event that the minimum was not achieved in the three weeks then the survey would be extended and participants would be encouraged once again to fill in the survey until the minimum number of responses was met.

When a participant clicked on the link in the email he/she would be redirected to the Google Forms website where they would see a greeting page that described the purpose of the study, explained the procedures to ensure the anonymity of the respondents and the protection of the collected data as well as a checkbox that the respondent would have to select to acknowledge that they were properly informed about the survey and that they wished to proceed. Participants could exit the survey at any time simply by closing their browser window. Upon completion of the survey, the participants would see a message thanking them for their time and ensuring them that the data collected was anonymous and safe.

The data that were collected from the surveys would be downloaded from Google Forms and deleted from there so that there is no risk of data lost if the Google Forms service is hacked. The raw data were stored on a USB flash disk which in turn was stored in a safe for a period of five years. The USB flash drive will then be destroyed to avoid reconstruction of deleted data from the drive if it were to be reused. The raw data will be available upon request within the five years that they will be stored.

Data Collection Technique

In this research study I administered an online survey using Google Forms. High school computer science teachers registered in the Cyprus Ministry of Education received an invitation to participate in the survey through the Cyprus Computer Science Teachers Association’s electronic communication service. The use of online surveys in research has increased due to the many benefits it provides to the researcher, such as cheap, flexible and fast access to many types of participants from various locations around the world (Roberts & Allen, 2015). Researchers emphasize the need for informed voluntary consent by providing sufficient information to the participants before beginning the survey (Mahon, 2014; Roberts & Allen, 2015). Mahon (2014) stated that the key issues that need to be addressed when working with online surveys are informed consent, forced choice, privacy, data security and ownership of surveys and data.

Informed consent was achieved through the development of a consent form that the participants needed to read and acknowledge before starting the survey. In the consent form I provided the participant with the purpose of the study, the anonymity and safety of the data collected. The consent form also informed the participant that participation was voluntary and that there would be no negative consequences should the participant wish to decline or withdraw from the study. To avoid the issue of forced choice I did not make any of the questions required so that participants that did not want to answer a question could do so and would not be forced into answering. Forcing a participant to answer a question might lead to him quitting the survey completely (Mahon, 2014). The other option for avoiding forced choice was to make the questions required but provide one more option which will be “no response” or “NA” but that would change the survey instrument and might invalidate the survey results. Regarding privacy, security and ownership of surveys and data, I informed the participants that the data collected would be removed from the online survey service and stored on a USB flash drive for five years in a safe and afterwards destroyed to eliminate any chances of leaking data.

The instrument used for data collection was based on the survey instrument used by Venkatesh et al. (2003) as shown in **Table 2** with permission (Appendix E). The instrument used is available in Appendix F.

Data Analysis Technique

This research study tried to answer one research question about the relationship of performance expectancy, effort expectancy, social influence, facilitating conditions and the behavioral intention of high school computer science teachers to use remote robotic experimentation. The independent variables were performance expectancy, effort expectancy, social influence and facilitating conditions. The dependent variable was the behavioral intention of high school computer science teachers to use remote robotic experimentation in their courses.

RQ1. Do (a) performance expectancy, (b) effort expectancy, (c) social influence, and (d) facilitating conditions significantly predict the intention of high school computer science teachers in Cyprus to use remote robotic experimentation in their courses?

The study used multiple regression analysis to determine if the four independent variables had a significant relationship to behavioral intention. Multiple regression analysis is an extension of single linear regression which provides insight into the relationship of multiple independent variables to a single dependent variable (Nathans et al., 2012). The data was analyzed using the SPSS statistical analysis software.

The data gathered were answers to questions with a seven-point Likert-scale ranging from 1 – Strongly disagree to 7 – Strongly agree. Questions were grouped into four main groups representing the four constructs relating to UTAUT. Survey questions that are stand-alone should be analyzed as Likert-Type items using modes, medians and frequencies (Boone & Boone, 2012). Surveys using a series of questions that when combined measure a particular trait such as performance expectancy indicate that the surveys are using a Likert Scale which are analyzed using means and standard deviations (Boone & Boone, 2012). The data analysis techniques used in Likert scale data are based on descriptive statistics such as Pearson's r, t-test, ANOVA and regression procedures (Boone & Boone, 2012; Keele, 2011; Nathans et al., 2012). Using t-tests or ANOVA is appropriate for studies performing tests on multiple groups to check for significant differences between the groups (Keele, 2011; Lakens, 2013). This research study was evaluating behavioral intention within one single group of participants so t-tests and ANOVA were not deemed appropriate.

One of the most important parts of data analysis is to validate experimental data. Variance homogeneity, otherwise called homoscedasticity, is a way to guarantee the correct application of mean values comparisons (Granato, de Araújo Calado, & Jarvis, 2014). Heteroscedasticity on the other hand, is the error due to an unobserved common factor which may be observed in a scatter plot of the independent variables compared to the dependent variable (Lewbel, 2012). Normality of the experimental results is important in correlation analysis and testing normality checks if the given data follow a normal distribution (Granato et al., 2014). When examining multiple variables it is important to assess the independence of each variable from other independent variables (Yoo et al., 2014).

Multicollinearity is an effect observed when predictors in a linear regression are also linearly dependent on each other as well as the dependent variable (Dormann et al., 2013; Winship & Western, 2016). This problem can be more significant when the sample size is small, leading to spurious conclusions (Hoggarth, Innes, Dalrymple-Alford, & Jones, 2015). On the other hand, in real life there is always some kind of collinearity between predictor variables, which might stem from some underlying unmeasurable process, a latent variable, or by chance if there is a large number of variables or if the sample size is too small (Dormann et al., 2013). A researcher can assess multicollinearity issues using a correlation matrix, computing the coefficients of determination regressed on the remaining predictor variables and measuring the condition index (Yoo et al., 2014). When examining bivariate correlations a high correlation coefficient (>0.8) does not imply causation because co-variants may influence the results due to a common cause (Granato et al., 2014). In this study, I examined the bivariate correlations ensuring that they are not over 0.9 or 0.8, thus indicating that there were no influences to the correlation from other variables. Using scatter plots and normal probability plots, I examined the heteroscedasticity, normality and linearity of the data collected in this study.

Study Validity

The research study was a correlational quantitative study which focused on high school computer science teachers in Cyprus. To ensure the reliability of the data collected I distributed the survey to the high school computer science teachers registered at the Cyprus Ministry of Education. There were approximately 400 registered high school teachers at the time of the study and the survey was sent to all of them to ensure the highest possible response rate.

When conducting research, researchers try to prove or disprove a hypothesis and support that decision through evidence gathered during the study (Hales, 2016). Hales (2016) presents a model for statistical decision making while explaining how researchers can avoid Type I, II, III and IV errors. In this statistical decision model, if the requirement is to reject the null hypothesis then there are three possible outcomes. If the null hypothesis is actually true then you have a Type I error, whereas if the null hypothesis is false then if the researcher has good evidence then it is proven or else if the evidence is bad then there is a Type III error (Hales, 2016). In this research study my null hypothesis stated that performance expectancy, effort expectancy, social influence and facilitating conditions would not significantly predict the behavioral intention of high school computer science teachers' to use remote robotic experiments. I aimed to reject my null hypothesis and at the same time show that my evidence was good and support this decision. To ensure statistical conclusion validity I used a validated survey instrument that has been used in previous research studies and I aimed for a sample size of medium to high power.

Another aspect that needed to be examined to validate this study was external validity. External validity deals with the ability of the research to be extended to other particular individuals, settings, times or institutions other than those directly studied (Hales, 2016; Morse, 2015; Yilmaz, 2013). This study dealt with public high school computer science teachers in Cyprus but researchers can apply the same research design to other domains within Cyprus such as private institutions or primary and tertiary education. Due to differences in the educational system of each country this research might not be suitable to high schools in countries other than Cyprus. In the event that a researcher wants to examine a different country then they would need to adjust the study in accordance to the specific country's educational system.

In this research I used a survey instrument that had been successfully used in previous literature in various settings and on various technologies. In addition, this research study can be replicated using the same survey instrument and data analysis to ensure that anyone wishing to validate the results can do so at a later date. Due to the advancements made in technology and the fact that new high school teachers with innovative ideas will replace older high school teachers the study might present different results after a few years. The research design and analysis would remain the same but the results might be slightly different as the years go by.

Transition and Summary

Section 2 expanded the purpose statement by providing more information about the goals set for this research study. The section also included a description of the role of the researcher, an introduction to the population involved in the study, followed by the research method and design that explained the choice of using a correlational quantitative design over other experimental designs. The section then went on to describe the population and how the sample size was determined followed by information on how the study protected participants in the ethical research subsection. Section 2 then described the data collection and data analysis beginning with the choice of instrument, the data collection and data analysis techniques and finally how the study ensured study validity. The next section will present an overview of the whole study and present the findings that came out of the data analysis of the collected surveys. In addition, section 3 will present the application of the findings to professional practice, its implications for social change and recommendations for action and further study.

Section 3: Application to Professional Practice and Implications for Change

This study utilized a correlational quantitative research method that analyzed the relationships between performance expectancy, effort expectancy, social influence, facilitating conditions and the intention to use a technology. In this section I will present the results of the analysis of the data gathered through the online surveys completed by the participants of the study.

Overview of Study

The purpose of this correlational quantitative study was to evaluate the intention of high school computer science teachers to use remote robotic experimentation based on information on performance expectancy, effort expectancy, social influence and facilitating conditions. Using the G*Power tool, I calculated, *a priori*, the required sample size given the effect size, the error probability, the power, and the number of predictors. The analysis showed that a minimum of 85 responses would provide a statistical power of 0.80 while 129 responses would increase the statistical power to 0.95. I gathered data from 90 high school computer science teachers currently employed by the Ministry of Education in Cyprus and analyzed them using a multiple regression analysis. The Ministry of Education in Cyprus employs approximately 400 high school computer science teachers meaning that the 90 responses that I received would correspond to a response rate of approximately 22.5%.

The results of the data analysis showed that there is a positive correlation between the examined independent variables of performance expectancy (PI), effort expectancy (EE), social influence (SI) and facilitating conditions (FC) with regards to behavioral intention (BI) signifying the fact that these independent variables are predictors of behavioral intention. Furthermore, FC and EE were significant predictors of BI whereas PE and SI were not significant predictors.

Presentation of the Findings

In this part of the study, I will examine the reliability of the constructs, analyze the methods used to test the assumptions involved with the methodology, present the statistical results emerging from the data analysis, and provide a detailed reporting of the findings. The subsection will close with a summary of the findings.

Reliability analysis

The first part of the data analysis was to perform several reliability analysis tests to ensure that the questions relating to each independent and dependent variable correlated to the specific construct. To do this I performed a reliability analysis on the set of questions and extracted the Cronbach's Alpha. The summarized results are shown in Table 3 and the detailed analysis can be found in Appendix G. A value between 0.7 and 0.9 is considered to be a good measure of reliability for each construct and as presented in the table the values for all constructs are within the required parameters.

Table 3

Reliability Statistics

Variable	Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
Performance expectancy	.770	.807	4
Effort expectancy	.840	.847	4
Social influence	.852	.853	4
Facilitating conditions	.774	.773	4
Behavioral intention	.902	.903	3

Factor Analysis. The first part of the data analysis was to reduce the number of variables to the five constructs that were measured in the survey. There were 19 questions in the survey with four questions relating to performance expectancy, four relating to effort expectancy, four relating to social influence, four relating to facilitating conditions, and three relating to behavioral intention. The first step was to perform an exploratory factor analysis to validate the five factors that were considered. I observed four factors being identified through exploratory factor analysis using an eigenvalue of more than 1.0. The results shown in Table 4 present four constructs instead of five, and this can be further seen in

Table **5** where the facilitating conditions construct is factored with the social influence construct. In addition, Table **5** shows that one question, namely PE4, was not correctly factored with the performance expectancy construct. This can be explained by the nature of the question which asked whether the respondent would get a raise for using the technology but in Cyprus, teachers get pay raises based on teaching years and not based on performance or innovative use of technologies (Eurydice Facts &Figures, 2014).

Table 4

Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
Comp	Total	% of Var.	Cum. %	Total	% of Var.	Cum. %	Total	% of Var.	Cum %
1	7.641	40.217	40.217	7.641	40.217	40.217	4.084	21.496	21.496
2	2.267	11.932	52.149	2.267	11.932	52.149	3.336	17.555	39.051
3	1.894	9.970	62.118	1.894	9.970	62.118	3.008	15.832	54.883
4	1.369	7.205	69.324	1.369	7.205	69.324	2.744	14.441	69.324
5	.954	5.020	74.343						
6	.749	3.944	78.287						
7	.690	3.629	81.917						
8	.619	3.257	85.174						
9	.558	2.938	88.112						
10	.439	2.308	90.420						
11	.322	1.693	92.113						
12	.288	1.515	93.628						
13	.280	1.476	95.103						
14	.208	1.097	96.200						
15	.190	.999	97.199						
16	.158	.833	98.032						
17	.144	.760	98.793						
18	.129	.679	99.471						
19	.100	.529	100.000						

Extraction Method: Principal Component Analysis.

Table 5

Pattern Matrix

	Factor				
	1	2	3	4	5
PE1: I would find remote robotic experimentation useful in my teaching				.868	
PE2: Using remote robotic experimentation will enable me to teach programming concepts more quickly				.746	
PE3: Using remote robotic experimentation increases my teaching efficiency				.758	
PE4: If I use remote robotic experimentation, I will increase my chances of getting a raise	.629				
EE1: My interaction with remote robotic experimentation would be clear and understandable		.464			
EE2: It would be easy for me to become skillful at using remote robotic experiments		.747			
EE3: I would find remote robotic experiments easy to use		1.011			
EE4: Learning to work with remote robotic experiments will be easy for me		.923			
SI1:People who influence my behavior think that I should use remote robotic experimentation	.591				.562
SI2: People who are important to me think that I should use remote robotic experimentation	.828				.477
SI3: The Ministry of Education in Cyprus will be helpful in the use of remote robotic experimentation	.648				
SI4: In general, the Ministry of Education in Cyprus is supporting the use of remote robotic experimentation	.791				
FC1: I will have the resources necessary to use remote robotic experimentation	.590				
FC2: I will have the knowledge necessary to use remote robotic experimentation	.477				
FC3: Remote robotic experimentation is not compatible with other educational tools I use					
FC4: A specific person (or group) is available for assistance with remote robotic experimentation difficulties	.623				

Table 5 continued

	Factor				
	1	2	3	4	5
BI1: I intent to use remote robotic experimentation when it will become available			.747		
BI2: I predict I would use remote robotic experimentation when it becomes available			.919		
BI3: I plan to use remote robotic experimentation when it becomes available			1.003		

Extraction Method: Maximum Likelihood.
Rotation Method: Promax with Kaiser Normalization.
a. Rotation converged in 7 iterations.

Assumptions

In Section 2 I presented several tests of assumptions that were considered important to validate the findings of this study. These tests included multicollinearity, normality, linearity, homoscedasticity, outliers and independence of residuals. I will examine each of these tests and present the findings, which support the assumptions.

Multicollinearity. Since my sample was closer to the minimum number of responses needed, I had to check for multicollinearity within my data. Inspecting a scatterplot matrix assessed multicollinearity. Table 6 depicts the bivariate correlation matrix showing that all bivariate correlations were < .7. Therefore, multicollinearity was not a concern.

Table 6

Predictor Bivariate Correlation Scatterplot Matrix

		BI	PE	EE	SI	FC
Pearson Correlation	BI	1.000	.355	.511	.339	.508
	PE	.355	1.000	.412	.584	.365
	EE	.511	.412	1.000	.400	.558
	SI	.339	.584	.400	1.000	.639
	FC	.508	.365	.558	.639	1.000

Note: *N* = 90

In order to further test for multicollinearity, I considered the tolerance of the independent variables. Independent variable tolerance clarifies how much of the variability is not explained by other predictor variables (Dormann et al., 2013). A value less than 0.1 may indicate multicollinearity.

Table 7 shows a tolerance of .610 for PE, .634 for EE, .447 for SI and .473 for FC. This is a good indicator that that there is no multicollinearity. In addition to tolerance, we can use the Variance Inflation Factor (VIF) where values above 10 indicate multicollinearity (Dormann et al., 2013). The VIF values for PE, EE, SI and FC are 1.640, 1.577, 2.238 and 2.112 respectively which is much lower than the 10 threshold of multicollinearity.

Table 7

Coefficients

		Unstandardized Coefficients		Standardized Coefficients			95.0% Confidence Interval for B		Collinearity Statistics	
Model		B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	1.762	.656		2.686	.009	.458	3.066		
	PE	.191	.130	.164	1.467	.146	-.068	.449	.610	1.640
	EE	.343	.131	.287	2.614	.011	.082	.604	.634	1.577
	SI	-.085	.118	-.094	-.721	.473	-.320	.150	.447	2.238
	FC	.357	.131	.347	2.733	.008	.097	.617	.473	2.112

a. Dependent Variable: BI

Outliers, normality, linearity, homoscedasticity, and independence of residuals. Outliers, normality, linearity, homoscedasticity, and independence of residuals were by examining a normal probability plot (P-P) of regression standardized residual (Figure 7) and observe if the data plotted follows a linear distribution. The points do not lie on a reasonable straight diagonal line from bottom left to top right. More so, the evidence of a clear cone pattern (right to left) in the scatterplot (Figure 8) of the residuals is further evidence of assumption violation. Therefore, bootstrapping, using 2,000 samples were computed and reported where appropriate.

In order for me to test for outliers I calculated the Mahalanobis Distance which measures the distance of a point from the distribution (Todeschini, Ballabio, Consonni, Sahigara, & Filzmoser, 2013). Using the Chi-squared critical value for four predictor variables (18.467) I checked the Mahalanobis value from the Residuals table (Table 8) and found a value of 16.969 which is below the critical value.

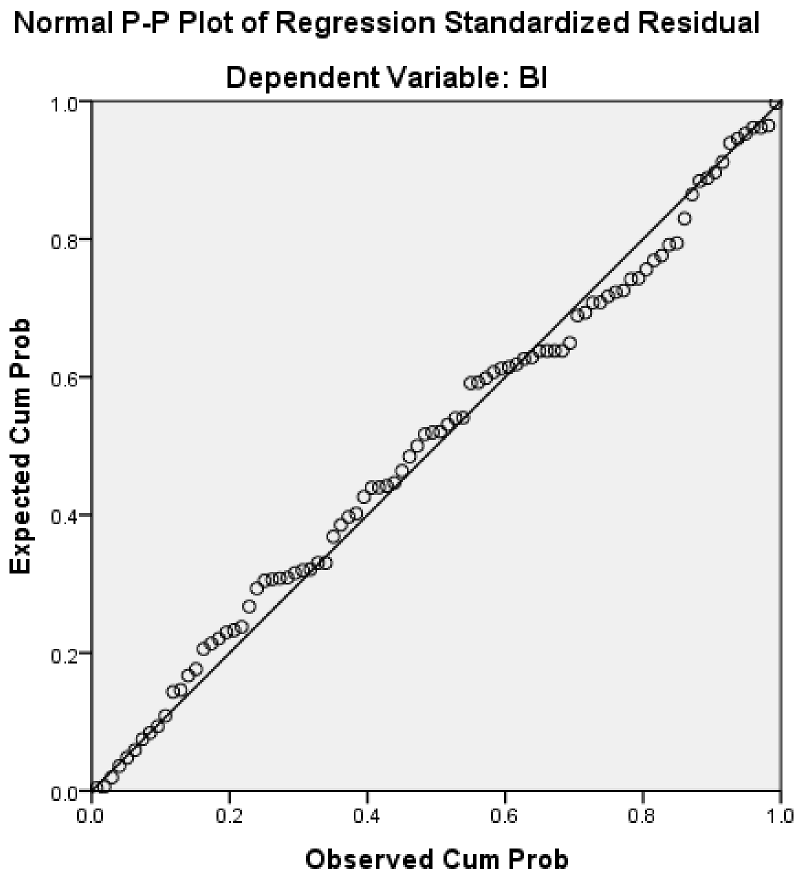

Figure 7. Normal P-P Plot of regression standardized residual.

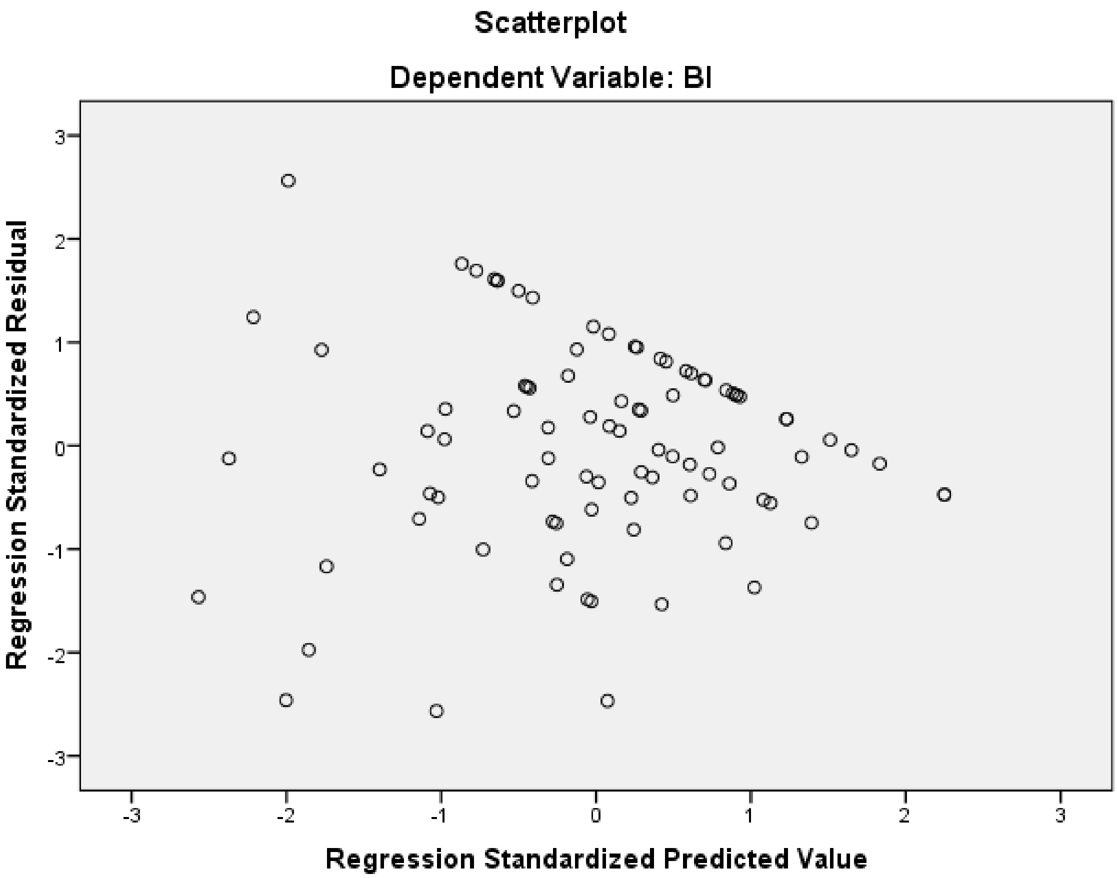

Figure 8 Scatterplot of standardized residuals and predicted values

Table 8

Residuals Statistics

			Bootstrap[b]			
					95% CI	
		Statistic	Bias	Std. Error	Lower	Upper
Predicted Value	Minimum	3.65				
	Maximum	7.53				
	Mean	5.72	0.00	0.14	5.42	5.99
	Std. Deviation	0.81	0.03	0.15	0.54	1.13
Residual	Minimum	-2.89				
	Maximum	2.88				
	Mean	0.00	0.00	0.00	0.00	0.00
	Std. Deviation	1.10	-0.05	0.09	0.87	1.24
Std. Predicted Value	Minimum	-2.57				
	Maximum	2.25				
	Mean	0.00	0.00	0.00	0.00	0.00
	Std. Deviation	1.00	0.00	0.00	1.00	1.00
Std. Residual	Minimum	-2.57				
	Maximum	2.56				
	Mean	0.00	0.00	0.00	0.00	0.00
	Std. Deviation	0.98	0.00	0.00	0.98	0.98

a. Dependent Variable: BI
b. Unless otherwise noted, bootstrap results are based on 2000 bootstrap samples
Note: N = 90

Homoscedasticity assumes that the error variance is consistent across all observations in the data set (Aslam, Riaz, & Altaf, 2013). A test for homoscedasticity is the Durbin Watson test, which is a formal method of testing if correlations between independent variables negatively affect the confidence of the predictability of the dependent variable (G. Jacob et al., 2014). A Durbin Watson value ranges from 0 to 4 where the number 2 means that there is no correlation between the independent variables (G. Jacob et al., 2014). In Table 9 we can see that the Durbin Watson value is 1.91, which is close to 2 showing that the homoscedasticity assumption was met.

Table 9

Model Summary

Model	R	R^2	Adjusted R^2	Std. Error	Durbin-Watson
1	.591[a]	.349	.319	1.12554	1.906

a. Predictors: (Constant), FC, PE, EE, SI
b. Dependent Variable: BI

Descriptive Statistics

The total number of surveys completed by my participants was 90 and none of the surveys was removed due to missing or incorrect data. Each survey was fully completed and no errors were identified during the data analysis. Table 10 contains the descriptive statistics for all the survey questions.

Table 10
Means and Standard Deviations for Quantitative Study Variables

Variable	*M*	*SD*	Bootstrapped 95% CI (*M*)
Behavioral intention	5.72	1.36	[5.42, 5.99]
Performance Expectancy	5.08	1.18	[4.85, 5.31]
Effort expectancy	5.28	1.14	[5.00, 5.51]
Social influence	3.93	1.51	[3.63, 4.25]
Facilitating conditions	4.23	1.33	[3.96, 4.51]

Note: $N = 90$.

Inferential Results

This study used a standard multiple linear regression, $\alpha = .05$ (two-tailed), to examine the effectiveness of performance expectancy, effort expectancy, social influence, facilitating conditions in predicting the behavioral intention of high school computer science teachers to use remote robotic experiments. The independent variables were performance expectancy, effort expectancy, social influence and facilitating conditions.

The dependent variable was behavioral intention. The null hypothesis and alternative hypothesis were:

H1_0: Performance expectancy, effort expectancy, social influence and facilitating conditions will not significantly predict the intention of high school computer science teachers to use remote robotic experiments.

H1_a: Performance expectancy, effort expectancy, social influence and facilitating conditions will significantly predict the intention of high school computer science teachers to use remote robotic experiments.

The model as a whole was able to significantly predict behavioral intention, $F(4, 85) = 11.417, p = .000, R^2 = .34$ (Table 9). The R^2 value indicated that the model could explain 34.9% of the total variability in behavioral intention. The final model (Table 11) shows that effort expectancy and facilitating conditions were statistically significant with facilitating conditions ($t = 2.733, p < .008$) being the biggest contributor to the prediction, higher than the other contributor which was effort expectancy ($t = 2.614, p < .011$).

Table 11

Regression Analysis Summary for Predictor Variables

Variable	*B*	*SE B*	*β*	*t*	*p*	*B 95% Bootstrap CI*
PE	.191	.130	.164	1.467	.146	[4.85, 5.31]
EE	.343	.131	.287	2.614	.011	[5.00, 5.51]
SI	-.085	.118	-.094	-.721	.473	[3.63, 4.25]
FC	.357	.131	.347	2.733	.008	[3.96, 4.51]

Note. *N* = 90

The final predictive equation based on the predictor variables was:

Behavioral intention = 1.762 + .191(PE) + .343(EE) - .085(SI) + .357(FC)

Facilitating conditions. FC has a positive slope (.357) which indicates that for every point of increase in FC there is a .357 increase in behavioral intention. The squared semi-partial coefficient (sr^2) was .239. This means that 23.9% of the variance in behavioral intention is based on facilitating conditions, if performance expectancy, effort expectancy and social influence are controlled.

Effort expectancy. EE also has a positive slope (.343) which in turn indicates that every point of increase in EE there is a .343 increase in behavioral intention. The squared semi-partial coefficient (sr^2) for effort expectancy was .229, which indicates that 22.9% of the variance of behavioral intention is based on effort expectancy.

Performance expectancy. Even though PE has a positive slope (.191) it is not a significant predictor of BI due to the fact that $p > .05$. This means that even though one can assume that a point increase in PE will predict almost two points of increase in BI it cannot be said that it significantly predicts that increase.

Social influence. SI on the other hand has a negative slope (-.085), which means that an increase in SI would decrease BI. But due to the fact that p is significantly greater than .05 it cannot be used to predict Behavioral intention.

Analysis summary. The purpose of this study was to examine how efficiently performance expectancy, effort expectancy, social influence and facilitating conditions could predict the behavioral intention of high school computer science teachers to use remote robotic experiments. In order for me to examine the effectiveness of the predictor variables I used standard multiple linear regression. The assumptions surrounding multiple regression were evaluated and no serious violations were found to exist. The model was able to significantly predict behavioral intention, $F(4, 85) = 11.417, p = .000$, $R^2 = .349$. Out of the four predictor variables, facilitating conditions and effort expectancy were able to provide useful predictive information about behavioral intention. The findings in this study reject the null hypothesis showing that performance expectancy, effort expectancy, social influence and facilitating conditions can predict the behavioral intention of high school computer science teachers in Cyprus to use remote robotic experimentation in their classes. More specifically, facilitating conditions and effort expectancy are associated with behavioral intention whereas performance expectancy and social influence do not significantly predict behavioral intention.

Theoretical conversation on findings. After analyzing the data collected by the high school computer science teachers in Cyprus I was able to show that the model could significantly predict the behavioral intention (BI) to use remote robotic experimentation. More specifically, the model showed that the facilitating conditions (FC) construct was the more significant predictor of BI, with effort expectancy (EE) being the second most significant predictor. performance expectancy (PE) and social influence (SI) were not significant predictors of BI.

In studies performed to examine the use of interactive whiteboards by teachers the results showed that FC significantly predicted BI while PE and SI had partial significance in predicting BI and EE had no significance in predicting BI (Raman et al., 2014; Sumak & Sorgo, 2016). In several other studies based on the use of interactive whiteboards, Wong et al. (2013) showed that PE and EE significantly predicted BI, while Tosunta, Karada and Orhan (2015) found that all four constructs were able to predict BI. This study supports the literature that behavioral intention can be predicted using certain predictor variables.

The most significant predictor of BI in this study was FC. In most studies FC is examined post-implementation of the technology since in the original UTAUT model FC is said to predict Use Behavior along with BI (Figure 1). Even though FC is not directly associated with BI, there are studies that examine that relationship like it was done in this study and the results show that there is a significant positive correlation between FC and BI (Bhatiasevi, 2015; Raman & Don, 2013). As in this study, the predictability of FC is considered the most significant predictor of BI (Bhatiasevi, 2015; Raman & Don, 2013).

In this study, I identified EE as the second most significant predictor supporting the literature. Oye, et al. (2014) also measured the predictability of BI with regards to EE and found EE to also be a significant predictor in cases of academics adopting ICT in their teaching. Several other studies support the fact that EE is a significant predictor of BI (Chen, 2013; Tosuntas et al., 2015; Wong et al., 2013). Bhatiasevi (2015) also found EE to be a significant factor alongside FC.

Even though PE is considered in several studies to significantly predict BI (Dečman, 2015; Raman et al., 2014; Tosuntas et al., 2015; Wong et al., 2013), studies that involve teachers rather than students also show that PE might not be a significant predictor similar to this study (Chen, 2013; Chen & Chen, 2015). In this study PE did not significantly predict the behavioral intention of high school computer science teachers.

Social influence was also not significant in predicting behavioral intention in this study. This result is again supported by literature that ranks social influence as the least significant predictor of behavioral intention (Escobar-Rodriguez, T., Carvajal-Trujillo, E., & Monge-Lozano, 2014; Oye et al., 2014).

The differences in the results of this survey from other surveys could be attributed to the fact that the participants did not know about remote robotic experimentation before this survey. This was examined before in surveys given to pre-adopters and post-adopters and identifying the existence of a variance between the two types of participants (Sumak, Pusnik, Hericko, & Sorgo, 2016; Sumak & Sorgo, 2016). Another aspect that may affect participants reactions to technology is the experience of the participant with regards to the technology, which was something not measured in this study (Govender & Dhurup, 2014; P. C. Lin et al., 2013).

Applications to Professional Practice

This study aimed at examining the correlation between performance expectancy, effort expectancy, social influence, facilitating conditions and the behavioral intention of high school computer science teachers to use remote robotic experimentation in their classes. The results of this study will allow curriculum decision makers at the Ministry of Education in Cyprus to take specific actions that may positively influence the decision of high school computer science teachers to adopt remote robotic experimentation in their classes.

It is apparent from the data collected that high school computer science teachers are influenced by facilitating conditions when deciding to use remote robotic experiments. This means that teachers value the presence of a good infrastructure both in the availability of the hardware as well as in the availability of support channels that they can use to reduce the amount of effort and frustration that may stem from using a new technology.

In addition to FC, the teachers value the effort required to implement these experiments in their classes. If the use of remote robotic experiments causes an increase in effort just to implement the technology, then that would negatively influence the decision to use it. In my data analysis the teachers showed that if they would not have to expend a lot of effort to use remote robotic experiments in their classes they would be more prone to use it if it was available. EE was the second biggest contributor to predicting BI indicating that the less effort needed to use remote robotic experiments teachers will be more positive in using the experiments in their classes.

PE was not statistically significant on predicting BI and this may be due to teachers not knowing how beneficial remote robotic experiments can be to their teaching since it has not been used yet. At the time of the study, the subject of remote experiments is novel in Cyprus and robotics was still a new idea that had not been used in schools yet.

Social influence was not a statistically significant predictor of behavioral intention. This means that high school teachers are not affected by others in deciding whether to use the technology. The decision is purely their own choice and even if the Ministry of Education would tell them that using remote robotics experiments would be beneficial to them, they would only use the technology if they think that it is beneficial.

Overall, based this study, the implementation of remote robotic experiments in high schools and its adoption by high school computer science teachers depends on how the Ministry of Education can inform end-users of the benefits of the technology, provide training to reduce effort expended on using the technology and providing the required infrastructure to support the technology. Social influence would not make a big difference and the study showed that SI had a negative impact on the intention to use behavioral intention.

Implications for Social Change

This study was done to identify if four constructs, namely performance expectancy, effort expectancy, social influence and facilitating conditions, where able to predict the behavioral intention of high school computer science teachers to use remote robotics experiments. The results of the study showed that EE and FC could predict the intention to use the technology. Knowing this information, the Ministry of Education in Cyprus can take steps to increase the knowledge of high school teachers and reduce the effort required to use the technology by building more user friendly and accessible interfaces as well as by providing seminars to familiarize teachers with the platform. Making it effortless for the teacher can increase the chance that the teacher will use remote robotic experiments.

In using remote robotics experiments, teachers might be more understandable in explaining difficult computer science concepts to students thus making students more inclined to follow a computer science field. A shift in teaching with more practical experience would enhance the problem solving skills of students and allow them to perform better in several courses including computer science courses. Eventually, this shift in computer science graduates could help reduce the need for IT professionals that is projected to increase dramatically in the following years.

Recommendations for Action

In this doctoral study I used the UTAUT model to determine if four constructs, namely performance expectancy, effort expectancy, social influence and facilitating conditions, were able to predict the intention of high school computer science teachers to use remote robotic experimentation in their classes. This study has a number of benefits for both the Ministry of Education in Cyprus, the high school computer science teachers and ultimately high school students. The study will be sent to the Ministry of Education with recommendations on what are the best actions to take if they want to implement remote robotic experiments in high schools in Cyprus. My recommendations included the thorough development of a remote robotics laboratory with all the necessary equipment both in hardware and software and the training of specialized personnel to support that infrastructure. In addition, the Ministry should provide training to all high school computer science teachers to familiarize them with the technology and how to use it and show them that there will always be someone available to help them if they are stuck. This will increase the chances of remote robotic experiments being adopted by teachers.

Through this study, high school computer science teachers also have the ability to learn more about remote robotic experiments and also how these will help them in their teaching. The study will be sent to the Cyprus Computer Science Teachers Association who helped me distribute the surveys and hopefully they will distribute the results to all their members. Seeing a completed study would hopefully intrigue teachers to look more deeply into remote experiments and robotics and spur a movement towards implementing the technology in schools.

Finally, the study can help students gain more understanding of difficult computer science concepts leading to more of them choosing to follow a computer science degree at the university and eventually increasing the amount of IT professionals in the market.

Recommendations for Further Study

This study had a few limitations. The first one was the fact that the study was held in Cyprus and it was aimed at high school computer science teachers. Another limitation was that the sample used was fairly small partly because the number of high school computer science teachers registered with the Ministry of Education in Cyprus was small.

Future studies could expand the sample population by including teachers from technical fields and also from the vocational field. In addition to this, studies could be directed to higher levels of education such as universities to evaluate the intention to use remote robotic experiments to keep students from dropping out of the computer science field due to not understanding difficult concepts.

Future researchers can also use this study as a source that would allow them to research technologies other than remote robotic experimentation and maybe include other independent variables that could help in predicting the intention to use a specific technology.

Reflections

After teaching at a local university for ten years I decided that if I wanted to advance in academia I had to obtain my doctoral degree. I researched various options and Walden provided me with an option that I could work with while working at the university. All of the courses taken at the university were intensive but I was able to handle the coursework and do well on all of them. At times it was difficult to manage the time to complete the work but it always worked out and I was able to finish all of my coursework and doctoral study within the predicted three and a half years.

This doctoral study allowed me to learn how to do research in academia and how this research can influence the society around me. One of the biggest advantages from the whole process was the information that I was able to get from working with teachers and being able to give back to the Ministry, the teachers and the students some tools that might help them become better in the future.

Summary and Study Conclusions

Even though the analysis showed that performance expectancy and social influence did not contribute in predicting the intent to use remote robotic experiments, the model as a whole was able to confirm that there were predictors that influenced the decision. Those predictors are the ones that curriculum decision makers should focus on if they want the introduction of remote robotic experiments to succeed in Cyprus.

Introducing remote robotic experimentation in high schools can lead to better understanding of computer science concepts and eventually to more students choosing an

IT career reducing the estimated 825,000 unfilled vacancies for Information and Communications Technology (ICT) in the year 2020 (Digital Agenda for Europe, 2015).

References

Abdullah, F., & Ward, R. (2016). Developing a General Extended Technology Acceptance Model for E-Learning (GETAMEL) by analysing commonly used external factors. *Computers in Human Behavior*, *56*, 238–256. http://doi.org/10.1016/j.chb.2015.11.036

Abdulwahed, M., & Nagy, Z. K. (2013). Developing the TriLab, a triple access mode (hands-on, virtual, remote) laboratory, of a process control rig using LabVIEW and Joomla. *Computer Applications in Engineering Education*, *21*(4), 614–626. http://doi.org/10.1002/cae.20506

Agarwal, R., & Prasad, J. (1998). A Conceptual and Operational Definition of Personal Innovativeness in the Domain of Information Technology. *Information Systems Research*, *9*(2), 204–215. http://doi.org/10.1287/isre.9.2.204

Agudo-Peregrina, Á. F., Hernández-García, Á., & Pascual-Miguel, F. J. (2014). Behavioral intention, use behavior and the acceptance of electronic learning systems: Differences between higher education and lifelong learning. *Computers in Human Behavior*, *34*, 301–314. http://doi.org/10.1016/j.chb.2013.10.035

Ain, N., Kaur, K., & Waheed, M. (2015). The influence of learning value on learning management system use: An extension of UTAUT2. *Information Development*, 0266666915597546-. http://doi.org/10.1177/0266666915597546

Alaiad, A., & Zhou, L. (2014). The determinants of home healthcare robots adoption: An empirical investigation. *International Journal of Medical Informatics*, *83*(11), 825–840. http://doi.org/10.1016/j.ijmedinf.2014.07.003

Allchin, D. (2013). Problem- and case-based learning in science: An introduction to distinctions, values, and outcomes. *CBE Life Sciences Education*, *12*(3), 364–372. http://doi.org/10.1187/cbe.12-11-0190

Alotaibi, S. J., & Wald, M. (2013). Acceptance Theories and Models for Studying the Integrating Physical and Virtual Identity Access Management Systems. *International Journal for E-Learning Security (IJeLS)*, *4*(1–2), 1–10.

Arlegui, J., Pina, A., & Moro, M. (2013). A PBL approach using virtual and real robots (with BYOB and LEGO NXT) to teaching learning key competences and standard curricula in primary level. *Proceedings of the First International Conference on Technological Ecosystem for Enhancing Multiculturality - TEEM '13*, 323–328. http://doi.org/10.1145/2536536.2536585

Aslam, M., Riaz, T., & Altaf, S. (2013). Efficient Estimation and Robust Inference of Linear Regression Models in the Presence of Heteroscedastic Errors and High Leverage Points. *Communications in Statistics - Simulation and Computation*, *42*(10), 2223–2238. http://doi.org/10.1080/03610918.2012.695847

Attuquayefio, S., & Addo, H. (2014). Review of Studies With Utaut As Conceptual Framework. *European Scientific Journal*, *10*(8), 249–258.

Baker, A., & Avenue, S. (2014). English in Cyprus or Cyprus English: An empirical investigation of variety status . *World Englishes*, *33*(3), 413–415.

Barnes, B. C. (2013). Use and Acceptance of Information and Communication Technology Among Laboratory Science Students. Retrieved from http://adsabs.harvard.edu/abs/2013PhDT........14B

Barrios, A., Panche, S., Duque, M., Grisales, V. H., Prieto, F., Villa, J. L., … Canu, M. (2013). A multi-user remote academic laboratory system. *Computers and Education*, *62*, 111–122. http://doi.org/10.1016/j.compedu.2012.10.011

Behdad, S., Berg, L. P., & Vance, J. M. (2013). Synergy Between Normative and Descriptive Design Theory and Methodology. *ASME 2013 International Design Engineering Technical ConferencesInternational Design Engineering Technical Conferences*, DETC2013-13035. http://doi.org/10.1115/DETC2013-13035

Bhatiasevi, V. (2015). An extended UTAUT model to explain the adoption of mobile banking. *Information Development*. http://doi.org/10.1177/0266666915570764

Boone, H. N. J., & Boone, D. a. (2012). Analyzing Likert Data. *Journal of Extension*, *50*(2), 30. http://doi.org/10.1111/j.1365-2929.2004.02012.x

Buchanan, T., Sainter, P., & Saunders, G. (2013). Factors affecting faculty use of learning technologies: implications for models of technology adoption. *Journal of Computing in Higher Education*, *25*(1), 1–11. Retrieved from http://link.springer.com/article/10.1007/s12528-013-9066-6

Burmeister, O. K. (2015). Improving professional IT doctorate completion rates. *Australasian Journal of Information Systems*, *19*, 55–70. http://doi.org/10.3127/ajis.v19i0.1073

Carrington, E. V., Grossi, U., Knowles, C. H., & Scott, S. M. (2014). Normal values for high-resolution anorectal manometry: A time for consensus and collaboration. *Neurogastroenterology and Motility*, *26*(9), 1356–1357. http://doi.org/10.1111/nmo.12364

Casan, G. A., Cervera, E., Moughlbay, A. A., Alemany, J., & Martinet, P. (2015). ROS-based online robot programming for remote education and training. *Proceedings - IEEE International Conference on Robotics and Automation*, *2015–June*(June), 6101–6106. http://doi.org/10.1109/ICRA.2015.7140055

Casini, M., Garulli, A., Giannitrapani, A., & Vicino, A. (2014). A remote lab for experiments with a team of mobile robots. *Sensors (Switzerland)*, *14*(9), 16486–16507. http://doi.org/10.3390/s140916486

Castillo-Page, L., & Bunton, S. A. (2012). AM last page: Understanding qualitative and quantitative research paradigms in academic medicine. *Academic Medicine*, *87*(3), 386.

Chaos, D., Chacon, J., Lopez-Orozco, J. A., & Dormido, S. (2013). Virtual and remote robotic laboratory using EJS, MATLAB and LabVIEW. *Sensors (Switzerland)*, *13*(2), 2595–2612. http://doi.org/10.3390/s130202595

Chen, C., Lai, H., & Ho, C. (2015). Why do teachers continue to use teaching blogs? The roles of perceived voluntariness and habit. *Computers & Education*, *82*(1), 236–249. http://doi.org/10.1016/j.compedu.2014.11.017

Chen, X. (2013). STEM Attrition: College Students' Paths Into and Out of STEM Fields. *National Center for Education Statistics.*, (Statistical Analysis Report. NCES 2014-001), 102. Retrieved from http://necs.ed.gov

Chen, X. (2015). STEM Attrition Among HIgh-Performing College Students in the United States: Scope and Potential Causes. *Journal of Technology and Science Education*, *5*(1), 41–59.

Chen, Y.-F., & Chen, H.-J. (2015). The Influence on Behaviors of Teachers Using the Interactive Electronic Whiteboard for Teaching at Primary Schools. *International Journal of Humanities Social Sciences and Education*, *2*(7), 105–111.

Cheung, R., & Vogel, D. (2013). Predicting user acceptance of collaborative technologies: An extension of the technology acceptance model for e-learning. *Computers & Education*, *63*, 160–175. http://doi.org/10.1016/j.compedu.2012.12.003

Cokley, K., & Awad, G. (2013). In defense of quantitative methods: Using the "master's tools" to promote social justice. *Journal for Social Action in Counseling and Psychology*, *5*(2), 26–41. Retrieved from http://www.psysr.org/jsacp/Cokley-V5N2-13_26-41.pdf

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

de Jong, T., Linn, M. C., & Zacharia, Z. C. (2013). Physical and Virtual Laboratories in Science and Engineering Education. *Science*, *340*(6130), 305–308. http://doi.org/10.1126/science.1230579

Dečman, M. (2015). Modeling the acceptance of e-learning in mandatory environments of higher education: The influence of previous education and gender. *Computers in Human Behavior*, *49*, 272–281. http://doi.org/10.1016/j.chb.2015.03.022

Digital Agenda for Europe. (2015). *Grand Coalition for Digital Jobs*. *Digital Agenda for Europe - A Europe 2020 Initiative*. Retrieved from https://ec.europa.eu/digital-agenda/en/grand-coalition-digital-jobs-0

Dolmans, D., & Gijbels, D. (2013). Research on problem-based learning: Future challenges. *Medical Education*, *47*(2), 214–218. http://doi.org/10.1111/medu.12105

Dormann, C. F., Elith, J., Bacher, S., Buchmann, C., Carl, G., Carré, G., … Lautenbach, S. (2013). Collinearity: A review of methods to deal with it and a simulation study evaluating their performance. *Ecography*, *36*(1), 027–046. http://doi.org/10.1111/j.1600-0587.2012.07348.x

Elo, S., Kääriäinen, M., Kanste, O., Pölkki, T., Polkki, T., Utriainen, K., & Kyngas, H. (2014). Qualitative Content Analysis: A Focus on Trustworthiness. *SAGE Open*, *4*(1), 1–10. http://doi.org/10.1177/2158244014522633

Emerson, R. W. (2016). Statistical Power : A Reflection of Reality. *Journal of Visual Impairment & Blindness*, *110*(2), 142.

Escobar-Rodriguez, T., Carvajal-Trujillo, E., & Monge-Lozano, P. (2014). Factors that influence the perceived advantages and relevance of Facebook a...: EBSCOhost, *30*(2), 136–151. http://doi.org/10.14742/ajet.v30i2.585

Eurydice Facts &Figures. (2014). *Teachers' and School Heads' Salaries and Allowances in Europe, 2013/14*.

Field, A. (2013). Discovering Statistics using IBM SPSS Statistics. *Discovering Statistics Using IBM SPSS Statistics*, 297–321. http://doi.org/10.1016/B978-012691360-6/50012-4

Fincham, J. E., & Draugalis, J. R. (2013). The importance of survey research standards. *American Journal of Pharmaceutical Education*, *77*(1), 4. http://doi.org/10.5688/ajpe7714

Fink, A. (2013). *How to conduct surveys: A Step-by-step guide* (5th ed.). SAGE Publications, Inc.

Freeman, S., Eddy, S. L., McDonough, M., Smith, M. K., Okoroafor, N., Jordt, H., & Wenderoth, M. P. (2014). Active learning increases student performance in science, engineering, and mathematics. *Proceedings of the National Academy of Sciences, 111*(23), 8410–8415. http://doi.org/10.1073/pnas.1319030111

G. Jacob, B., Mendoza, D., Ponce, M., Caliskan, S., Moradi, A., Gotuzzo, E., … J. Novak, R. (2014). Pseudo R² Probablity Measures, Durbin Watson Diagnostic Statistics and Einstein Summations for Deriving Unbiased Frequentistic Inferences and Geoparameterizing Non-Zero First-Order Lag Autocorvariate Error in Regressed Multi-Drug Resistant Tube. *American Journal of Applied Mathematics and Statistics*, *2*(5), 252–301. http://doi.org/10.12691/ajams-2-5-1

Gaskin, C. J., & Happell, B. (2014). International Journal of Nursing Studies On exploratory factor analysis : A review of recent evidence , an assessment of current practice , and recommendations for future use. *International Journal of Nursing Studies*, *51*(3), 511–521. http://doi.org/10.1016/j.ijnurstu.2013.10.005

Giorgi, A. (2012). The Descriptive Phenomenological Psychological Method. *Journal of Phenomenological Psychology*, *43*(1), 3–12. http://doi.org/10.1163/156916212X632934

Google. (2016). Privacy Policy, *2016*. Retrieved from http://www.google.com/policies/privacy/#nosharing%5Cr%5Cn

Govender, D. W., & Dhurup, M. (2014). An exploratory factorial analysis of teachers ' perceptions of perceived pedagogical benefits of adoption of information and communication technology in teaching and learning. *Mediterranean Journal of Social Sciences*, *5*(20), 1214–1224. http://doi.org/10.5901/mjss.2014.v5n20p1214

Graham, Mark J.; Frederick, Jennifer; Byars-Winston, Angela; Hunter, Anne-Barrie; Handelsman, J. (2013). Increasing Persistence of College Students in STEM. *Science*, *341*(September), 1455–1456. http://doi.org/10.1126/science.1240487

Granato, D., de Araújo Calado, V. M., & Jarvis, B. (2014). Observations on the use of statistical methods in Food Science and Technology. *Food Research International*, *55*, 137–149. http://doi.org/10.1016/j.foodres.2013.10.024

Groves, R. M., Presser, S., Tourangeau, R., West, B. T., Couper, M. P., Singer, E., … Couper, M. P. (2012). Support for the survey sponsor and nonresponse bias. *Public Opinion Quarterly*, *76*(3), 512–524. http://doi.org/10.1093/poq/nfs034

Hales, A. H. (2016). Does the conclusion follow from the evidence? Recommendations for improving research. *Journal of Experimental Social Psychology*. http://doi.org/10.1016/j.jesp.2015.09.011

Heradio, R., De La Torre, L., Galan, D., Cabrerizo, F. J., Herrera-Viedma, E., & Dormido, S. (2016). Virtual and remote labs in education: A bibliometric analysis. *Computers and Education*, *98*, 14–38. http://doi.org/10.1016/j.compedu.2016.03.010

Hoggarth, P. A., Innes, C. R. H., Dalrymple-Alford, J. C., & Jones, R. D. (2015). Prediction of driving ability: Are we building valid models? *Accident Analysis and Prevention*, *77*, 29–34. http://doi.org/10.1016/j.aap.2015.01.013

Holland, J., Browman, G., McDonald, M., & Saginur, R. (2013). Protecting human research participants: Reading vs understanding the consent form. *Journal of the National Cancer Institute*, *105*(13), 927–928. http://doi.org/10.1093/jnci/djt152

Hosack, B., Lim, B., & Vogt, W. P. (2012). Increasing Student Performance Through the Use of Web Services in Introductory Programming Classrooms: Results from a Series of Quasi-Experiments. *Journal of Information Systems Education, 23*(4), 373–383.

Ionescu, C. M., Fabregas, E., Cristescu, S. M., Dormido, S., & De Keyser, R. (2013). A Remote Laboratory as an Innovative Educational Tool for Practicing Control Engineering Concepts. *IEEE Transactions on Education*, *56*(4), 436–442. http://doi.org/10.1109/TE.2013.2249516

Jackson, J. D., Yi, M. Y., & Park, J. S. (2013). An empirical test of three mediation models for the relationship between personal innovativeness and user acceptance of technology. *Information and Management*, *50*(4), 154–161. http://doi.org/10.1016/j.im.2013.02.006

Jara, C. A., Candelas, F. A., Puente, S. T., & Torres, F. (2011). Hands-on experiences of undergraduate students in Automatics and Robotics using a virtual and remote laboratory. *Computers and Education*, *57*(4), 2451–2461. http://doi.org/10.1016/j.compedu.2011.07.003

Judkins-Cohn, T. M., & Kielwasser-Withrow, K. (2014). Ethical Principles of Informed Consent: Exploring Nurses' Dual Role of Care Provider and Researcher. *The Journal of Continuing Education in Nursing · J Contin Educ Nurs, 4545*(11), 35–42. http://doi.org/10.3928/00220124-20131223-03

Jung, S. (2013). Experiences in Developing an Experimental Robotics Course Program for Undergraduate Education. *IEEE Transactions on Education*, *56*(1), 129–136. http://doi.org/10.1109/TE.2012.2213601

Karantzas, G. C., Avery, M. R., MacFarlane, S., Mussap, A., Tooley, G., Hazelwood, Z., & Fitness, J. (2013). Enhancing critical analysis and problem-solving skills in undergraduate psychology: An evaluation of a collaborative learning and problem-based learning approach. *Australian Journal of Psychology*, *65*(1), 38–45. http://doi.org/10.1111/ajpy.12009

Keele, R. (2011). Nursing Research and Evidence-Based Practice, *18*(1), 35–52. http://doi.org/10.1111/j.1552-6909.1989.tb01609.x

Khan, S. N. (2014). Qualitative Research Method: Grounded Theory. *International Journal of Business and Management*, *9*(11), 224–233. http://doi.org/10.5539/ijbm.v9n11p224

Khechine, H., Pascot, D., & Bytha, A. (2014). UTAUT Model for Blended Learning: The Role of Gender and Age in the Intention to Use Webinars. *Interdisciplinary Journal of E-Learning and Learning Objects*, *10*, 33–52. Retrieved from http://www.ijello.org/Volume10/IJELLOv10p033-052Khechine0876.pdf

Kirkwood, A., & Price, L. (2013). Examining some assumptions and limitations of research on the effects of emerging technologies for teaching and learning in higher education. *British Journal of Educational Technology*, *44*(4), 536–543. http://doi.org/10.1111/bjet.12049

Kitagawa, T. (2015). A Test for Instrument Validity. *Econometrica*, *83*(5), 2043–2063.

http://doi.org/10.3982/ECTA11974

Kong Pak-Hin, A. (2014). Students' perceptions of using Problem-Based Learning (PBL) in teaching cognitive communicative disorders. *Clinical Linguistics & Phonetics*, *28*(1/2), 41–53. http://doi.org/10.3109/02699206.2013.808703

Kulich, M., Chudoba, J., Kosnar, K., Krajnik, T., Faigl, J., & Preucil, L. (2013). SyRoTek-Distance teaching of mobile robotics. *IEEE Transactions on Education*, *56*(1), 18–23. http://doi.org/10.1109/TE.2012.2224867

Kyvik, S. (2013). The academic researcher role: Enhancing expectations and improved performance. *Higher Education*, *65*(4), 525–538. http://doi.org/10.1007/s10734-012-9561-0

Lakens, D. (2013). Calculating and Reporting Effect Sizes to Facilitate Cumulative Science : A Practical Primer for t-tests and ANOVAs. *Frontiers in Psychology*, *4*, 863. http://doi.org/10.3389/fpsyg.2013.00863

Lewbel, A. (2012). Using heteroscedasticity to identify and estimate mismeasured and endogenous regressor models. *Journal of Business & Economic Statistics*, *30*(1), 67–80. http://doi.org/10.1080/07350015.2012.643126

Lin, P. C., Lu, H. K., & Liu, S. C. (2013). Towards an education behavioral intention model for e-learning systems: An extension of UTAUT. *Journal of Theoretical and Applied Information Technology*, *47*(3), 1200–1207.

Lin, S., Zimmer, J. C., & Lee, V. (2013). Podcasting acceptance on campus: The differing perspectives of teachers and students. *Computers and Education*, *68*, 416–428. http://doi.org/10.1016/j.compedu.2013.06.003

Lo, S. W. S., Chair, S. Y., & Lee, F. K. (2015). Factors associated with health-promoting behavior of people with or at high risk of metabolic syndrome: Based on the health belief model. *Applied Nursing Research*, *28*(2), 197–201. http://doi.org/10.1016/j.apnr.2014.11.001

Lowe, D., Newcombe, P., & Stumpers, B. (2013). Evaluation of the Use of Remote Laboratories for Secondary School Science Education. *Research in Science Education*, *43*(3), 1197–1219. http://doi.org/10.1007/s11165-012-9304-3

Lykke, M., Coto, M., Jantzen, C., Mora, S., & Vandel, N. (2015). Motivating Students Through Positive Learning Experiences : A Comparison of Three Learning Designs for Computer Programming Courses. *Journal of Problem Based Learning in Higher Education*, *3*(2), 80–108.

Mahon, P. Y. (2014). Internet research and ethics: Transformative issues in nursing education research. *Journal of Professional Nursing*, *30*(2), 124–129. http://doi.org/10.1016/j.profnurs.2013.06.007

Maillet, E., Mathieu, L., & Sicotte, C. (2015). Modeling factors explaining the acceptance, actual use and satisfaction of nurses using an Electronic Patient Record in acute care settings: An extension of the UTAUT. *International Journal of Medical Informatics*, *84*(1), 36–47. http://doi.org/10.1016/j.ijmedinf.2014.09.004

Maiti, A., Maxwell, A. D., & Kist, A. A. (2014). Features, Trends and Characteristics of Remote Access Laboratory Management Systems. *International Journal of Online Engineering*, *10*(2), 30–37.

Marangunić, N., & Granić, A. (2015). Technology acceptance model: a literature review from 1986 to 2013. *Universal Access in the Information Society*, *14*(1), 81–95. http://doi.org/10.1007/s10209-014-0348-1

Marques, M. A., Viegas, M. C., Costa-Lobo, M. C., Fidalgo, A. V, Alves, G. R., Rocha, J. S., & Gustavsson, I. (2014). How remote labs impact on course outcomes: Various practices using VISIR. *IEEE Transactions on Education*, *57*(3), 151–159. http://doi.org/10.1109/TE.2013.2284156

Martinez, J. E. P., Garcia Martin, J., Alonso, A. S., P??rez Mart??nez, J. E., Garc??a Mart??n, J., & Sierra Alonso, A. (2014). Teamwork competence and academic motivation in computer science engineering studies. In *IEEE Global Engineering Education Conference, EDUCON* (pp. 778–783). http://doi.org/10.1109/EDUCON.2014.6826182

Merchant, Z., Goetz, E. T., Cifuentes, L., Keeney-Kennicutt, W., & Davis, T. J. (2014). Effectiveness of virtual reality-based instruction on students' learning outcomes in K-12 and higher education: A meta-analysis. *Computers and Education*, *70*, 29–40. http://doi.org/10.1016/j.compedu.2013.07.033

Miguel Martínez-Graña, A. (2013). Cartographic-Environmental Analysis of the Landscape in Natural Protected Parks for His Management Using GIS. Application to the Natural Parks of the "Las Batuecas-Sierra de Francia" and "Quilamas" (Central System, Spain). *Journal of Geographic Information System*, *5*(1), 54–68. http://doi.org/10.4236/jgis.2013.51006

Morse, J. M. (2015). Critical Analysis of Strategies for Determining Rigor in Qualitative Inquiry. *Qualitative Health Research*, *25*(9), 1212–1222.

http://doi.org/10.1177/1049732315588501

Mulder, Y. G., Lazonder, A. W., & de Jong, T. (2015). Simulation-Based Inquiry Learning and Computer Modeling: Pitfalls and Potentials . *Simulation & Gaming* . http://doi.org/10.1177/1046878115577159

Nassaji, H. (2015). Qualitative and descriptive research: Data type versus data analysis. *Language Teaching Research*, *19*(2), 129–132. http://doi.org/10.1177/1362168815572747

Nathans, L., Oswald, F. L., & Nimon, K. (2012). Interpreting Multiple Linear Regression: A Guidebook of Variable Importance. *Practical Assesment Research & Evaluation*, *17*(9), 19. http://doi.org/10.3102/00346543074004525

National Institutes of Health. (1979). The Belmont Report. *The Belmont Report Ethical Principles and Guidelines for the Protection of Human Subjects of Research*, 4–6. http://doi.org/10.1002/9780471462422.eoct093

Nistor, N., Göğüş, A., & Lerche, T. (2013). Educational technology acceptance across national and professional cultures: A European study. *Educational Technology Research and Development*, *61*(4), 733–749. http://doi.org/10.1007/s11423-013-9292-7

O'Grady, M. (2012). Practical Problem-Based Learning in Computing Education. *ACM Transactions on Computing Education*, *12*(3).

Oye, N. D., A.Iahad, N., & Ab.Rahim, N. (2014). The history of UTAUT model and its impact on ICT acceptance and usage by academicians. *Education and Information Technologies*, *19*(1), 251–270. http://doi.org/10.1007/s10639-012-9189-9

Padir, T., & Chernova, S. (2013). Guest Editorial Special Issue on Robotics Education. *IEEE Transactions on Education*, *56*(1), 1–2. http://doi.org/10.1109/TE.2012.2235631

Parameswaran, S., Kishore, R., & Li, P. (2015). Within-study measurement invariance of the UTAUT instrument: An assessment with user technology engagement variables. *Information and Management*, *52*(3), 317–336. http://doi.org/10.1016/j.im.2014.12.007

Raman, A., & Don, Y. (2013). Preservice teachers' acceptance of learning management software: An application of the UTAUT2 model. *International Education Studies*, *6*(7), 157–164. http://doi.org/10.5539/ies.v6n7p157

Raman, A., Don, Y., Khalid, R., Hussin, F., Omar, M. S., & Ghani, M. (2014). Technology acceptance on smart board among teachers in terengganu using UTAUT model. *Asian Social Science*, *10*(11), 84–91. http://doi.org/10.5539/ass.v10n11p84

Regan, J.-A. (2013). Risks to informed consent in pedagogic research. *Journal of Perspectives in Applied Academic Practice*, *1*(1), 25–29. http://doi.org/10.14297/jpaap.v1i1.36

Roberts, L. D., & Allen, P. J. (2015). Exploring ethical issues associated with using online surveys in educational research. *Educational Research and Evaluation*, *21*(2), 95–108. http://doi.org/10.1080/13803611.2015.1024421

Saad, M., Mhiri, R., Amadou, M. D., Sahli, S., Ouertani, S., Brady, G., & Nerguizian, V. (2013). Enhanced remote laboratory work for engineering training. *Proceedings of the Canadian Engineering Education Association*, 1–4.

Sahin, I. (2006). Detailed Review of Rogers' Diffusion of Innovations Theory and Educational Technology: Related Studies Based on Rogers' Theory. *The Turkish Online Journal of Educational Technology*, *5*(April 2006), 14–23.

Sánchez-Algarra, P., & Anguera, M. T. (2013). Qualitative/quantitative integration in the inductive observational study of interactive behaviour: impact of recording and coding among predominating perspectives. *Quality & Quantity*, *47*(2), 1237–1257. http://doi.org/10.1007/s11135-012-9764-6

Sangestani, G., & Khatiban, M. (2013). Comparison of problem-based learning and lecture-based learning in midwifery. *Nurse Education Today*, *33*(8), 791–795. http://doi.org/10.1016/j.nedt.2012.03.010

Sarpong, K. A., & Arthur, J. K. (2013). Causes of Failure of Students in Computer Programming Courses : The Teacher – Learner Perspective. *International Journal of Computer Applications*, *77*(12), 27–32. http://doi.org/10.5120/13448-1311

Sauter, M., Uttal, D. H., Rapp, D. N., Downing, M., & Jona, K. (2013). Getting real: the authenticity of remote labs and simulations for science learning. *Distance Education*, *34*(1), 37–47. http://doi.org/10.1080/01587919.2013.770431

Schönbrodt, F. D., & Perugini, M. (2013). At what sample size do correlations stabilize? *Journal of Research in Personality*, *47*(5), 609–612. http://doi.org/10.1016/j.jrp.2013.05.009

Schoonenboom, J. (2014). Using an adapted, task-level technology acceptance model to explain why instructors in higher education intend to use some learning management system tools more than others. *Computers and Education*, *71*, 247–256.

http://doi.org/10.1016/j.compedu.2013.09.016

Scott, K. S. (2014). A Multilevel Analysis of Problem-Based Learning Design Characteristics, *8*(2), 4–9.

Sousa, D. (2014). Validation in qualitative research: General aspects and specificities of the descriptive phenomenological method. *Qualitative Research in Psychology*, *11*(December), 211–227. http://doi.org/10.1080/14780887.2013.853855

Stefanovic, M. (2013). The objectives, architectures and effects of distance learning laboratories for industrial engineering education. *Computers and Education*, *69*, 250–262. http://doi.org/10.1016/j.compedu.2013.07.011

Stinebrickner, R., & Stinebrickner, T. R. (2014). A major in science? Initial beliefs and final outcomes for college major and dropout. *Review of Economic Studies*, *81*(1), 426–472. http://doi.org/10.1093/restud/rdt025

Sumak, B., Pusnik, M., Hericko, M., & Sorgo, A. (2016). Differences between prospective, existing, and former users of interactive whiteboards on external factors affecting their adoption, usage and abandonment. *Computers in Human Behavior*. http://doi.org/10.1016/j.chb.2016.09.006

Sumak, B., & Sorgo, A. (2016). The acceptance and use of interactive whiteboards among teachers: Differences in UTAUT determinants between pre- and post-adopters. *Computers in Human Behavior*, *64*, 602–620. http://doi.org/10.1016/j.chb.2016.07.037

Tabachnick, B. G., & Fidell, L. S. (2013). *Using multivariate statistics*. *Pearson Education 6th ed*. http://doi.org/10.1037/022267

Taiwo, A. A., & Downe, A. G. (2013). The Theory of User Acceptance and Use of Technology (Utaut): a Meta-Analytic Review of Empirical Findings. *Journal of Theoretical & Applied Information Technology*, *49*(1).

Tan, P. J. B. (2013). Applying the UTAUT to Understand Factors Affecting the Use of English E-Learning Websites in Taiwan. *SAGE Open*, *3*(4). http://doi.org/10.1177/2158244013503837

Tarhini, A., Hone, K., & Liu, X. (2013). User Acceptance Towards Web-based Learning Systems: Investigating the Role of Social, Organizational and Individual Factors in European Higher Education. *Procedia Computer Science*, *17*, 189–197. http://doi.org/10.1016/j.procs.2013.05.026

Teo, T. (2013). A comparison of non-nested models in explaining teachers' intention to use technology. *British Journal of Educational Technology*, *44*(3), 81–85. http://doi.org/10.1111/j.1467-8535.2012.01350.x

Teo, T., & Noyes, J. (2012). Explaining the intention to use technology among pre-service teachers: a multi-group analysis of the Unified Theory of Acceptance and Use of Technology. *Interactive Learning Environments*, *22*(1), 1–16. http://doi.org/10.1080/10494820.2011.641674

Todeschini, R., Ballabio, D., Consonni, V., Sahigara, F., & Filzmoser, P. (2013). Locally centred Mahalanobis distance: A new distance measure with salient features towards outlier detection. *Analytica Chimica Acta*, *787*, 1–9. http://doi.org/10.1016/j.aca.2013.04.034

Tosuntas, B., Karadag, E., & Orhan, S. (2015). The factors affecting acceptance and use of interactive whiteboard within the scope of FATIH project: A structural equation model based on the Unified Theory of acceptance and use of technology. *Computers & Education*, *81*, 169–178. http://doi.org/10.1016/j.compedu.2014.10.009

Tourangeau, R., Conrad, F. G., Couper, M. P., & Ye, C. (2014). The effects of providing examples in survey questions. *Public Opinion Quarterly*, *78*(1), 100–125. http://doi.org/10.1093/poq/nft083

Tsai, C. W., & Chiang, Y. C. (2013). Research trends in problem-based learning (PBL) research in e-learning and online education environments: A review of publications in SSCI-indexed journals from 2004 to 2012. *British Journal of Educational Technology*, *44*(6), 185–191. http://doi.org/10.1111/bjet.12038

Turner, T. L., Balmer, D. F., & Coverdale, J. H. (2013). Methodologies and study designs relevant to medical education research. *International Review of Psychiatry*, *25*(3), 301–10. http://doi.org/10.3109/09540261.2013.790310

UNESCO International Bureau of Education. (2012). Cyprus. *World Data on Education*, (VII 2010-2011). Retrieved from http://www.ibe.unesco.org/fileadmin/user_upload/Publications/WDE/2010/pdf-versions/Cyprus.pdf

Venkatesh, V., Brown, S. a, & Bala, H. (2013). Bridging the qualitative-quantitative divide: Guidelines for conducting mixed methods research in information systems. *MIS Quarterly*, *37*(1), 21–54. Retrieved from http://misq.org/bridging-the-qualitative-quantitative-divide-guidelines-for-conducting-mixed-methods-research-in-information-systems.html?SID=hoiroittfvokfvihphk189ndu2

Venkatesh, V., & Davis, F. D. (2000). A Theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies. *Management Science*, *46*(2), 186–204. http://doi.org/10.1287/mnsc.46.2.186.11926

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

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology. *MIS Quarterly*, *36*(1), 157–178. Retrieved from http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2002388

Verbelen, Y., Taelman, P., Braeken, A., & Touhafi, A. (2013). Reconfigurable and modular mobile robotics platform for remote experiments. *International Journal of Online Engineering*, *9*(3), 19–26. http://doi.org/10.3991/ijoe.v9i3.2554

Wallace, L. G., & Sheetz, S. D. (2014). The adoption of software measures: A technology acceptance model (TAM) perspective. *Information and Management*, *51*(2), 249–259. http://doi.org/10.1016/j.im.2013.12.003

Wells, R. S., Kolek, E. A., Williams, E. A., & Saunders, D. B. (2015). “How We Know What We Know”: A Systematic Comparison of Research Methods Employed in Higher Education Journals, 1996-2000 v. 2006-2010. *Journal of Higher Education*, *86*(2), 171–195. http://doi.org/10.1353/jhe.2015.0006

Westerman, M. a. (2011). Conversation analysis and interpretive quantitative research on psychotherapy process and problematic interpersonal behavior. *Theory &*

Psychology, *21*(2), 155–178. http://doi.org/10.1177/0959354310394719

Williams, M. D., Rana, N. P., & Dwivedi, Y. K. (2015). The unified theory of acceptance and use of technology (UTAUT): a literature review. *Enterprise Information Management*, *28*(3), 443–488.

Winship, C., & Western, B. (2016). Multicollinearity and Model Misspecification. *Sociological Science*, *3*, 627–649. http://doi.org/10.15195/v3.a27

Wong, K. T., Teo, T., & Russo, S. (2013). Interactive Whiteboard Acceptance: Applicability of the UTAUT Model to Student Teachers. *Asia-Pacific Education Researcher*, *22*(1), 1–10. http://doi.org/10.1007/s40299-012-0001-9

Yilmaz, K. (2013). Comparison of Quantitative and Qualitative Research Traditions : epistemological , theoretical. *European Journal of Education*, *48*(2), 311–325.

Yoo, W., Mayberry, R., Bae, S., Singh, K., (Peter) He, Q., & Lillard, J. W. (2014). A study of effects of multicollinearity in the multivariable analysis. *International Journal of Applied Science and Technology*, *4*(5), 9–19. http://doi.org/10.3851/IMP2701.Changes

Yoon, H., Woo, A. J., Treagust, D., & Chandrasegaran, A. (2014). The Efficacy of Problem-based Learning in an Analytical Laboratory Course for Pre-service Chemistry Teachers. *International Journal of Science Education*, *693*(January 2015), 1–24. http://doi.org/10.1080/09500693.2012.727041

Yueh, H., Huang, J., & Chang, C. (2015). Exploring factors affecting students ’ continued Wiki use for individual and collaborative learning : An extended UTAUT perspective. *Australasian Journal of Educational Technology*, *31*(1), 16–31.

Zalewski, J. (2013). Cyberlab for Cyberphysical Systems : Remote Lab Stations in Software Engineering Curriculum. *The Fourth International Conference on E-Learning (ICEL2013). The Society of Digital Information and Wireless Communication*, 1–7.

Zubía, J. G., & Gustavo, R. A. (2012). *Using Remote Labs in Education: Two Little Ducks in Remote Experimentation*. Retrieved from http://books.google.com/books?id=PQsXw6q5arIC&pgis=1

Appendix A: Researcher's NIH Certificate

Certificate of Completion

The National Institutes of Health (NIH) Office of Extramural Research certifies that **Pericles Cheng** successfully completed the NIH Web-based training course "Protecting Human Research Participants".

Date of completion: 03/14/2015

Certification Number: 1719416

Appendix B: Confidentiality Agreement

Name of Signer: Pericles Cheng

During the course of my activity in collecting data for this research: "Evaluating Intention to Use Remote Robotics Experimentation in Programming Courses", I will have access to information, which is confidential and should not be disclosed. I acknowledge that the information must remain confidential and that improper disclosure of confidential information can be damaging to the participant.

By signing this Confidentiality Agreement, I acknowledge and agree that:

1. I will not disclose or discuss any confidential information with others, including friends or family.
2. I will not in any way divulge, copy, release, sell, loan, alter or destroy any confidential information except as properly authorized.
3. I will not discuss confidential information where others can overhear the conversation. I understand that it is not acceptable to discuss confidential information even if the participant's name is not used.
4. I will not make any unauthorized transmissions, inquiries, modification or purging of confidential information.
5. I agree that my obligations under this agreement will continue after termination of the research that I will perform.
6. I understand that a violation of this agreement will have legal implications.

Signing this document, I acknowledge that I have read the agreement, and I agree to comply with all terms and conditions stated above.

Signature: <Insert Signature Here> Date: xx/xx/2016

Appendix C: Permission to use survey instrument

A request was sent to Dr. Venkatesh to request permission to use his instrument in my research study. Dr. Venkatesh informed me that permissions are given through his website http://www.vvenkatesh.com/paper/ and consequently I went to the website and requested permission to use the instrument for the paper "User Acceptance of Information Technology: Toward a Unified View" published at MIS Quarterly in 2003. A screenshot of the permission request procedure is shown in Figure 9.

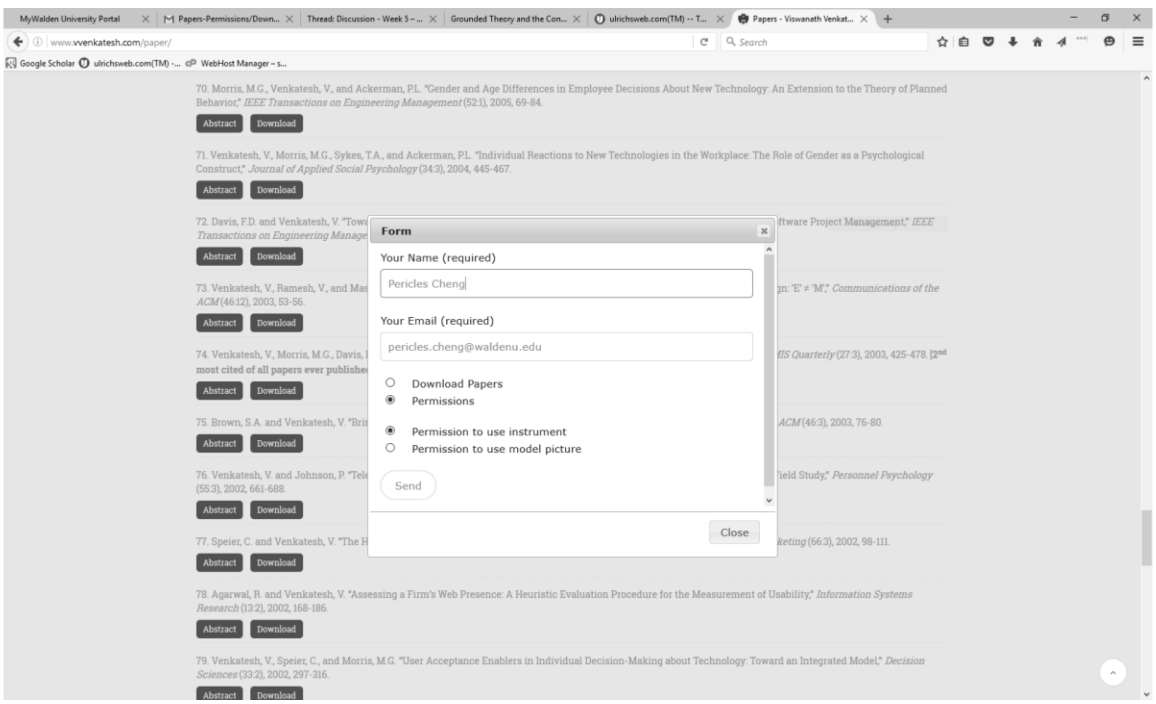

Figure 9. Procedure to request permission to use survey instrument

After the request was submitted I received an email granting me permission to use the survey instrument. The permission is shown in Figure 10.

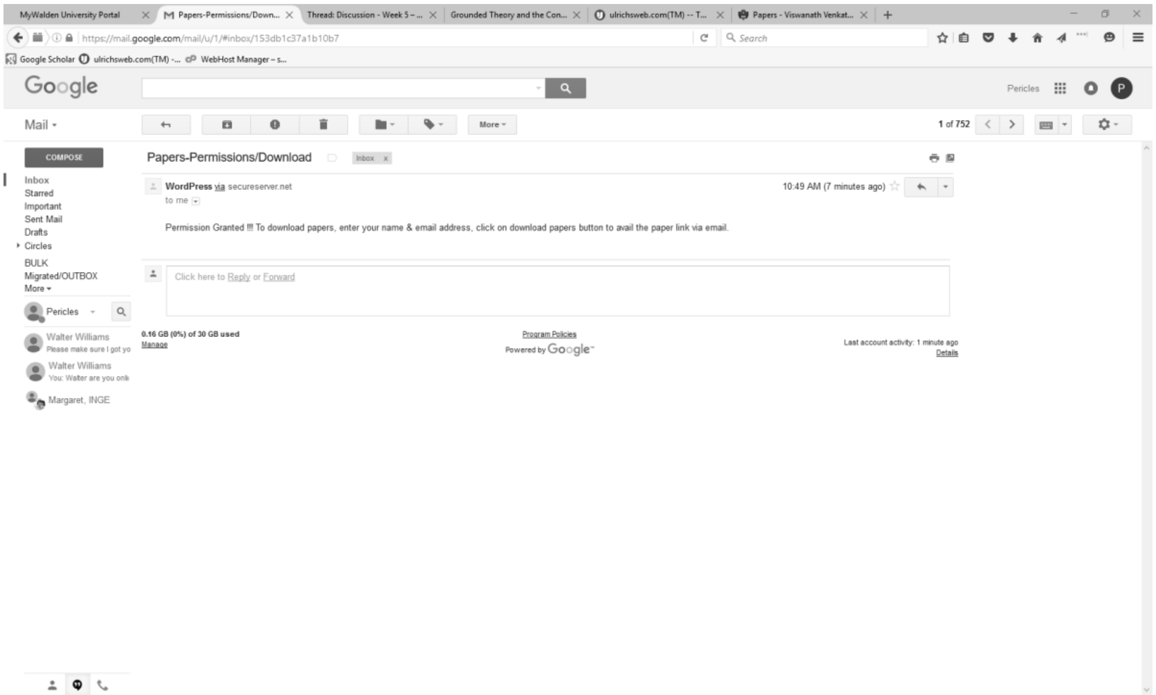

Figure 10. Email containing permission to use survey instrument

MIS Quarterly

MIS Quarterly
Carlson School of Management
University of Minnesota
Suite 4-339 CSOM
321 19th Avenue South
Minneapolis, MN 55455

May 24, 2016

Pericles Cheng
School of Information Systems and Technology
Walden University

Permission to use material from
MIS Quarterly in doctoral dissertation

Permission is hereby granted for Pericles Cheng to use the material from "User Acceptance of Information Technology: Toward a Unified View," V. Venkatesh, M. G. Morris, G. B. Davis, and F. D. Davis, *MIS Quarterly* (27:3), September 2003, pp. 424-478, specifically Figure 3 (or an adaptation of Figure 3), the survey instrument in the appendix (or an adaptation thereof), and supporting material as necessary, in his dissertation titled *Evaluating Intention to Use Remote Robotics Experimentation in Programming Courses*, being completed at Walden University.

In addition to the citation information for the work, the legend should include

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DN: cn=Janice DeGross, o=MIS Quarterly, ou,
Date: 2016.05.25 08:20:37 -05'00'

Janice I. DeGross
Manager

Figure 11. Letter of permission to use material from Venkatesh et al. (2003) from the publisher

Appendix D: Data Collection Instrument

Evaluating Intention to Use Remote Robotics Experimentation in Programming Courses

The Grand Coalition for Digital Jobs estimates that by the year 2020 there will be up to 825,000 unfilled vacancies for Information and Communications Technology (ICT) (Digital Agenda for Europe, 2015). This vacancy gap is mainly due to the low number of students graduating with computer science degrees. Even though the number of students entering STEM fields is high, the attrition rates for computer science majors is close to 59 percent (Chen, 2013). Some of the causes that lead students to leave the computer science field are the lack of problem-solving skills, analytical thinking, logical and reasoning, programming and algorithmic skills (Sarpong & Arthur, 2013). This lack of skills can be attributed to students lacking practical application of concepts during a course. By providing students with problem-based learning (PBL) experience through the use of more laboratory work, educators can tackle this lack of skills (O’Grady, 2012).

The purpose of this study is to provide curriculum decision makers with information about the relationship between performance expectancy, effort expectancy, social influence, facilitating conditions, and the intention of computer science high school teachers to use remote robotic laboratories. The unified theory of acceptance and use of technology (UTAUT) uses the variables above to evaluate a person’s behavioral intention to use technology (Venkatesh, Morris, Davis, & Davis, 2003). This study can then provide curriculum decision makers with the necessary information that can lead to the inclusion of remote robotic laboratories in the curriculum.

Survey (Ερευνητικό εργαλείο)

I would find remote robotic experimentation useful in my teaching *

Θα θεωρούσα τον εξ’ αποστάσεως ρομποτικό πειραματισμό βοηθητικό στην διδασκαλία *

Mark only one oval.

	1	2	3	4	5	6	7	
Strongly Disagree	◯	◯	◯	◯	◯	◯	◯	Strongly Agree

Using remote robotic experimentation will enable me to teach programming concepts more quickly *

Η χρήση εξ’ αποστάσεως ρομποτικού πειραματισμού θα με βοηθήσει να διδάξω προγραμματιστικές έννοιες πιο γρήγορα *

Mark only one oval.

	1	2	3	4	5	6	7	
Strongly Disagree	◯	◯	◯	◯	◯	◯	◯	Strongly Agree

Using remote robotic experimentation increases my teaching efficiency *

Η χρήση εξ’ αποστάσεως ρομποτικού προγραμματισμού αυξάνει την αποτελεσματικότητα της διδασκαλίας μου *

Mark only one oval.

	1	2	3	4	5	6	7	
Strongly Disagree	◯	◯	◯	◯	◯	◯	◯	Strongly Agree

If I use remote robotic experimentation, I will increase my chances of getting a raise *

Αν χρησιμοποιήσω εξ’ αποστάσεως ρομποτικό πειραματισμό, θα αυξήσει τις πιθανότητές μου να πάρω αύξηση *

Mark only one oval.

	1	2	3	4	5	6	7	
Strongly Disagree								Strongly Agree

My interaction with remote robotic experimentation would be clear and understandable *

Η αλληλεπίδραση μου με τον εξ’ αποστάσεως ρομποτικό πειραματισμό θα είναι σαφής και κατανοητή *

Mark only one oval.

	1	2	3	4	5	6	7	
Strongly Disagree								Strongly Agree

It would be easy for me to become skillful at using remote robotic experiments *

Θα ήταν εύκολο για μένα να γίνω ικανός χρήστης εξ’ αποστάσεως ρομποτικού πειραματισμού *

Mark only one oval.

	1	2	3	4	5	6	7	
Strongly Disagree								Strongly Agree

I would find remote robotic experiments easy to use *

Θα έβρισκα τον εξ’ αποστάσεως ρομποτικό πειραματισμό εύκολο στη χρήση *

Mark only one oval.

	1	2	3	4	5	6	7	
Strongly Disagree								Strongly Agree

Learning to work with remote robotic experiments will be easy for me *

Μαθαίνοντας να εργάζομαι με εξ’ αποστάσεως ρομποτικά πειράματα θα είναι εύκολο για μένα *

Mark only one oval.

	1	2	3	4	5	6	7	
Strongly Disagree								Strongly Agree

People who influence my behavior think that I should use remote robotic experimentation *

Άνθρωποι που επηρεάζουν τη συμπεριφορά μου, νομίζουν ότι θα πρέπει να χρησιμοποιήσω τον εξ’ αποστάσεως ρομποτικό πειραματισμό *

Mark only one oval.

	1	2	3	4	5	6	7	
Strongly Disagree								Strongly Agree

People who are important to me think that I should use remote robotic experimentation *

Άνθρωποι που είναι σημαντικοί για μένα πιστεύουν ότι θα πρέπει να χρησιμοποιήσω τον εξ' αποστάσεως ρομποτικό πειραματισμό *

Mark only one oval.

	1	2	3	4	5	6	7	
Strongly Disagree	⬭	⬭	⬭	⬭	⬭	⬭	⬭	Strongly Agree

The Ministry of Education in Cyprus will be helpful in the use of remote robotic experimentation *

Το Υπουργείο Παιδείας της Κύπρου θα είναι βοηθητικό για τη χρήση του εξ' αποστάσεως ρομποτικού πειραματισμού *

Mark only one oval.

	1	2	3	4	5	6	7	
Strongly Disagree	⬭	⬭	⬭	⬭	⬭	⬭	⬭	Strongly Agree

In general, the Ministry of Education in Cyprus is supporting the use of remote robotic experimentation *

Σε γενικές γραμμές, το Υπουργείο Παιδείας της Κύπρου υποστηρίζει τη χρήση του εξ' αποστάσεως ρομποτικού πειραματισμού *

Mark only one oval.

	1	2	3	4	5	6	7	
Strongly Disagree	⬭	⬭	⬭	⬭	⬭	⬭	⬭	Strongly Agree

I will have the resources necessary to use remote robotic experimentation *

Θα διαθέτω τους απαραίτητους πόρους για να χρησιμοποιήσω τον εξ' αποστάσεως ρομποτικό πειραματισμό *

Mark only one oval.

	1	2	3	4	5	6	7	
Strongly Disagree	◯	◯	◯	◯	◯	◯	◯	Strongly Agree

Remote robotic experimentation is not compatible with other educational tools I use *

Ο εξ' αποστάσεως ρομποτικός πειραματισμός δεν είναι συμβατός με άλλα εκπαιδευτικά εργαλεία τα οποία χρησιμοποιώ *

Mark only one oval.

	1	2	3	4	5	6	7	
Strongly Disagree	◯	◯	◯	◯	◯	◯	◯	Strongly Agree

A specific person (or group) is available for assistance with remote robotic experimentation difficulties *

Ένα συγκεκριμένο άτομο (ή ομάδα) είναι διαθέσιμη για βοήθεια με δυσκολίες στον εξ' αποστάσεως ρομποτικό πειραματισμό *

Mark only one oval.

	1	2	3	4	5	6	7	
Strongly Disagree	◯	◯	◯	◯	◯	◯	◯	Strongly Agree

Debriefing

Thank you for participating in this survey. Your responses have been documented and will be kept safe and anonymous. Your participation will help in providing information to curriculum makers involved with the computer science curriculum to decide whether remote robotics experimentation will be beneficial in the future.

Please note that due to the anonymity of the survey your response cannot be removed from the system since it will be impossible to identify it.

Thank you for your participation in this study,

Pericles Cheng

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Appendix F: Reliability Analysis

Performance Expectancy

Table 12

Performance Expectancy Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.770	.807	4

Table 13

Performance Expectancy Item Statistics

	Mean	Std. Deviation	N
PE1: I would find remote robotic experimentation useful in my teaching	5.77	1.391	90
PE2: Using remote robotic experimentation will enable me to teach programming concepts more quickly	5.58	1.461	90
PE3: Using remote robotic experimentation increases my teaching efficiency	5.64	1.266	90
PE4: If I use remote robotic experimentation, I will increase my chances of getting a raise	3.31	1.912	90

Table 14

Performance Expectancy Inter-Item Correlation Matrix

	PE1: I would find remote robotic experimentation useful in my teaching	PE2: Using remote robotic experimentation will enable me to teach programming concepts more quickly	PE3: Using remote robotic experimentation increases my teaching efficiency	PE4: If I use remote robotic experimentation, I will increase my chances of getting a raise
PE1: I would find remote robotic experimentation useful in my teaching	1.000	.786	.763	.214
PE2: Using remote robotic experimentation will enable me to teach programming concepts more quickly	.786	1.000	.696	.297
PE3: Using remote robotic experimentation increases my teaching efficiency	.763	.696	1.000	.311
PE4: If I use remote robotic experimentation, I will increase my chances of getting a raise	.214	.297	.311	1.000

Table 15

Performance Expectancy Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
PE1: I would find remote robotic experimentation useful in my teaching	14.53	13.128	.696	.713	.655
PE2: Using remote robotic experimentation will enable me to teach programming concepts more quickly	14.72	12.517	.718	.650	.638
PE3: Using remote robotic experimentation increases my teaching efficiency	14.66	13.711	.721	.621	.655
PE4: If I use remote robotic experimentation, I will increase my chances of getting a raise	16.99	14.123	.299	.123	.898

Table 16

Performance Expectancy Scale Statistics

Mean	Variance	Std. Deviation	N of Items
20.30	22.078	4.699	4

Effort expectancy

Table 17

Effort expectancy Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.840	.847	4

Table 18

Effort expectancy Item Statistics

	Mean	Std. Deviation	N
EE1: My interaction with remote robotic experimentation would be clear and understandable	5.39	1.459	90
EE2: It would be easy for me to become skillful at using remote robotic experiments	5.31	1.519	90
EE3: I would find remote robotic experiments easy to use	5.04	1.226	90
EE4: Learning to work with remote robotic experiments will be easy for me	5.37	1.328	90

Table 19

Effort expectancy Inter-Item Correlation Matrix

	EE1: My interaction with remote robotic experimentation would be clear and understandable	EE2: It would be easy for me to become skillful at using remote robotic experiments	EE3: I would find remote robotic experiments easy to use	EE4: Learning to work with remote robotic experiments will be easy for me
EE1: My interaction with remote robotic experimentation would be clear and understandable	1.000	.447	.455	.390
EE2: It would be easy for me to become skillful at using remote robotic experiments	.447	1.000	.692	.695
EE3: I would find remote robotic experiments easy to use	.455	.692	1.000	.804
EE4: Learning to work with remote robotic experiments will be easy for me	.390	.695	.804	1.000

Table 20

Effort expectancy Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
EE1: My interaction with remote robotic experimentation would be clear and understandable	15.72	13.574	.476	.241	.884
EE2: It would be easy for me to become skillful at using remote robotic experiments	15.80	11.151	.726	.552	.774
EE3: I would find remote robotic experiments easy to use	16.07	12.490	.788	.693	.756
EE4: Learning to work with remote robotic experiments will be easy for me	15.74	12.125	.750	.684	.765

Table 21

Effort expectancy Scale Statistics

Mean	Variance	Std. Deviation	N of Items
21.11	20.819	4.563	4

Social influence

Table 22

Social influence Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.852	.853	4

Table 23

Social influence Item Statistics

	Mean	Std. Deviation	N
SI1:People who influence my behavior think that I should use remote robotic experimentation	4.07	1.835	90
SI2: People who are important to me think that I should use remote robotic experimentation	4.06	1.770	90
SI3: The Ministry of Education in Cyprus will be helpful in the use of remote robotic experimentation	4.06	1.862	90
SI4: In general, the Ministry of Education in Cyprus is supporting the use of remote robotic experimentation	3.54	1.800	90

Table 24

Social influence Inter-Item Correlation Matrix

	SI1:People who influence my behavior think that I should use remote robotic experimentation	SI2: People who are important to me think that I should use remote robotic experimentation	SI3: The Ministry of Education in Cyprus will be helpful in the use of remote robotic experimentation	SI4: In general, the Ministry of Education in Cyprus is supporting the use of remote robotic experimentation
SI1:People who influence my behavior think that I should use remote robotic experimentation	1.000	.833	.492	.496
SI2: People who are important to me think that I should use remote robotic experimentation	.833	1.000	.531	.611
SI3: The Ministry of Education in Cyprus will be helpful in the use of remote robotic experimentation	.492	.531	1.000	.591
SI4: In general, the Ministry of Education in Cyprus is supporting the use of remote robotic experimentation	.496	.611	.591	1.000

Table 25

Social influence Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
SI1:People who influence my behavior think that I should use remote robotic experimentation	11.66	21.195	.713	.699	.804
SI2: People who are important to me think that I should use remote robotic experimentation	11.67	20.674	.795	.747	.769
SI3: The Ministry of Education in Cyprus will be helpful in the use of remote robotic experimentation	11.67	22.315	.615	.405	.845
SI4: In general, the Ministry of Education in Cyprus is supporting the use of remote robotic experimentation	12.18	22.238	.656	.476	.828

Table 26

Social influence Scale Statistics

Mean	Variance	Std. Deviation	N of Items
15.72	36.607	6.050	4

Facilitating conditions

Table 27

Facilitating conditions Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.774	.773	4

Table 28

Facilitating conditions Item Statistics

	Mean	Std. Deviation	N
FC1: I will have the resources necessary to use remote robotic experimentation	4.21	1.771	90
FC2: I will have the knowledge necessary to use remote robotic experimentation	4.58	1.662	90
FC3: Remote robotic experimentation is not compatible with other educational tools I use	3.90	1.710	90
FC4: A specific person (or group) is available for assistance with remote robotic experimentation difficulties	4.23	1.736	90

Table 29

Facilitating conditions Inter-Item Correlation Matrix

	FC1: I will have the resources necessary to use remote robotic experimentation	FC2: I will have the knowledge necessary to use remote robotic experimentation	FC3: Remote robotic experimentation is not compatible with other educational tools I use	FC4: A specific person (or group) is available for assistance with remote robotic experimentation difficulties
FC1: I will have the resources necessary to use remote robotic experimentation	1.000	.725	.330	.536
FC2: I will have the knowledge necessary to use remote robotic experimentation	.725	1.000	.214	.514
FC3: Remote robotic experimentation is not compatible with other educational tools I use	.330	.214	1.000	.440
FC4: A specific person (or group) is available for assistance with remote robotic experimentation difficulties	.536	.514	.440	1.000

Table 30

Facilitating conditions Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
FC1: I will have the resources necessary to use remote robotic experimentation	12.71	15.489	.686	.575	.658
FC2: I will have the knowledge necessary to use remote robotic experimentation	12.34	16.970	.617	.554	.698
FC3: Remote robotic experimentation is not compatible with other educational tools I use	13.02	19.438	.386	.217	.812
FC4: A specific person (or group) is available for assistance with remote robotic experimentation difficulties	12.69	16.307	.632	.402	.689

Table 31

Facilitating conditions Scale Statistics

Mean	Variance	Std. Deviation	N of Items
16.92	28.185	5.309	4

Behavioral intention

Table 32

Behavioral intention Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.902	.903	3

Table 33

Behavioral intention Item Statistics

	Mean	Std. Deviation	N
BI1: I intent to use remote robotic experimentation when it will become available	5.76	1.368	90
BI2: I predict I would use remote robotic experimentation when it becomes available	5.69	1.511	90
BI3: I plan to use remote robotic experimentation when it becomes available	5.71	1.588	90

Table 34

Behavioral intention Inter-Item Correlation Matrix

	BI1: I intent to use remote robotic experimentation when it will become available	BI2: I predict I would use remote robotic experimentation when it becomes available	BI3: I plan to use remote robotic experimentation when it becomes available
BI1: I intent to use remote robotic experimentation when it will become available	1.000	.740	.748
BI2: I predict I would use remote robotic experimentation when it becomes available	.740	1.000	.781
BI3: I plan to use remote robotic experimentation when it becomes available	.748	.781	1.000

Table 35

Behavioral intention Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
BI1: I intent to use remote robotic experimentation when it will become available	11.40	8.557	.788	.621	.877
BI2: I predict I would use remote robotic experimentation when it becomes available	11.47	7.645	.815	.665	.850
BI3: I plan to use remote robotic experimentation when it becomes available	11.44	7.216	.821	.674	.848

Table 36

Behavioral intention Scale Statistics

Mean	Variance	Std. Deviation	N of Items
17.16	16.740	4.091	3