

Factors Influencing the Acceptance and Use of Internet of Things by Universities

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ABSTRACT

Internet of Things (IoT) is a new concept bringing revolution to higher educational institutions through its usage by providing smart education and better learning outcomes. It has generated new interests and complexities for researchers as well as academicians in higher educational institutions. In this paper, factors influencing the acceptance and usage of IoT in higher educational institutions were developed. Additionally, a model for consenting and using IoT in higher educational institutions was developed. This study laid a foundation for a comprehensive model based on the UTAUT framework. Regression analysis was carried out to obtain the factors that predict the acceptance and usage of IoT in higher educational institutions. All test results were reliable and valid. The study demonstrates how university administrators can use IoT technologies to improve educational operations and outcomes.

KEYWORDS

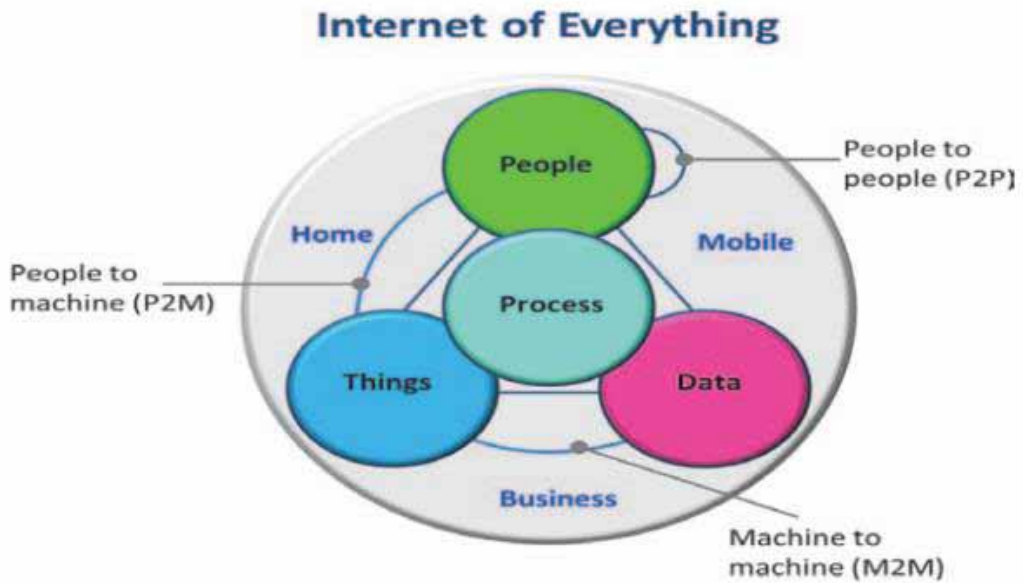
Higher Educational Institution, Internet, Internet of Things, Smart Education, UTAUT

INTRODUCTION

Educators and students have been forced to observe lockdown due to SARS-CoV-2 (COVID-19) pandemic and also to rely speedily on digital technologies such as Internet of Things (IoT) so as to ensure the successful completion of the modules within the academic year (Mourtzis et al., 2021). Moreover, due to the rapid advancement in technology, there will be connection and communication among everything in this World (Chopra et al., 2019). The Internet provides the backbone of virtual communication worldwide and it is defined as “network of networks” (Chopra et al., 2019). The Internet is used to establish connections among computers globally through servers and dedicated routers.

Many researchers define Internet of Things (IoT) at the beginning as Internet of Everything, Internet of Anything, Internet of People, Internet of Signs, Internet of Services, Internet of Data or Internet of Processes (Evans, 2011; Gul et al., 2017; Chopra et al., 2019). The futurist at Cisco, Dave Evans defines IoT as a network connecting physical objects and he also uses the term Internet of Everything for both physical and virtual objects (Evans, 2011). Figure 1 illustrates Dave Evans definition of IoT.

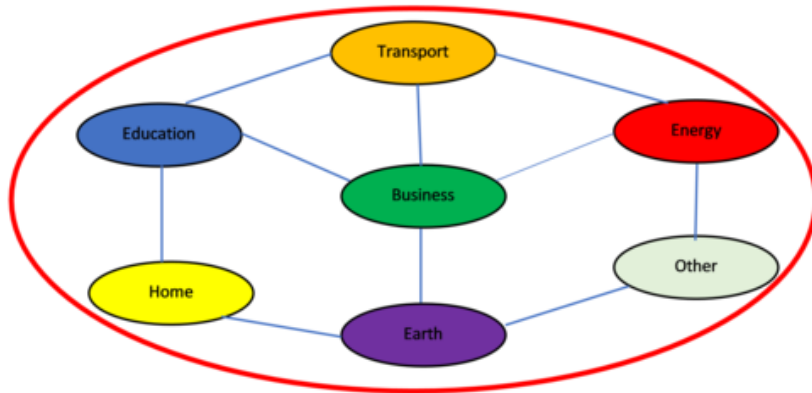
Figure 1. Internet of Everything (source: Evans, 2011)



The Internet of Things is the network of physical objects containing embedded technology for communicating and sensing or interacting with their internal states or the external environment (Gartner, 2017). The Internet of Things makes this communication and connection possible. It is one of the disruptive innovations challenging the World to be a complex interconnected infrastructure (Majeed & Ali, 2018). The Internet of Things is a rapidly growing network comprising of different 'connected things' (Gul et al., 2017).

Internet of Things has been transforming various aspects of our daily life and it is ubiquitous and encourages the development of intelligent and autonomous solutions (Aldowah et al., 2017). The Internet of Things uses the Internet as the underlying technology to enable machine-to-machine communication (M2M) (Chopra et al., 2019). Connected devices can share and communicate information that can be used for decision making (Gul et al., 2017). Technologies and concepts such as Internet of Things, cyber physical systems, were initiated from the "Industry 4.0" concept and are motivating nations for digital transformation (Akbar et al., 2018). According to Burange and Misalkar (2015), IoT is a structure in which objects, people are provided with exclusive identity and the ability to relocate data over a network without requiring two-way handshaking between human-to-human or human-to-computer interaction.

Figure 2. Internet of Things application fields (source: Abdel-Basset et al., 2018)



The IoT can be applied in all areas of our lives as shown in Figure 2 (Abdel-Basset et al., 2018). The IoT has been regarded as the latest innovation and is being employed and used in many facets of life such as higher education, thus generating new interests and complexities for researchers and university educators (Shaikh et al., 2019). There are indications pointing out that IoT will revolutionize higher education institutions especially universities (Aldowah et al., 2017). The IoT usage in academics has brought new opportunities for improving both teaching-learning process and educators' infrastructure (Gul et al., 2017). Universities can now be the forerunner in the promotion of IoT innovations and expansion as well as building IoT leadership. According to the Gartner Report (2016), IoT number of things will be escalated to 20.8 billion by 2020, with the spending on IoT reaching 3,010 billion US\$. There might be two million unfilled ICT-related jobs according to the World bank estimates, thus leading to more usage of IoT and eLearning so that more people will be trained in ICT and in other fields (Charmonman et al., 2015).

Aldowah et al. (2017) have stated that IoT will be affecting every part of the society including higher education institutions generally. They stress that universities should take a lead in advancing IoT technologies across disciplines. The use of IoT in universities is causing reflective changes in the higher education system with regards to the experimental training, teaching management, campus buildings, as well as other areas. This will be an uprising in the higher education system. It was argued that IoT can enhance the traditional higher educational system with innovative learning strategies and technologies. Additionally, Internet of Things should be regarded as complex intelligent systems by higher educational sector. This is supported by Banica, et al., (2017) and they state that the Internet of Things usage in higher education provides physical objects sensors and controllers communication for knowledge circulation by not involving human interventions.

The character of education, which spreads knowledge, turn out to be increasingly important in few years ago due to the strong criticism of knowledge development. In the meantime, the model of education procedure is going through an adaptation in which the education of different students' needs to be accomplished in numerous ways. Virtual education is used for online teaching and learning with the aid of digital services and platforms. Efficient online education depends on elements like fast and reliable internet connectivity, digital skills, learning software, affordability and technology exposure (Mourtzis et al., 2021). In this paper, the researcher provided an overview of the impact of IoT usage in universities and also developed a model for IoT usage and consent in universities.

The remainder of this paper is organized as follows. Section 2 reviews the literature as well as the conceptual framework. Next, Section 3 describes the research methodology. Then, analytical results and discussion are reported in Section 4. Finally, section 5 presents conclusions and future work of the study.

PURPOSE OF RESEARCH

The purpose of this research is to find factors that influence IoT usage and also to develop a model on IoT usage and consent in universities. Specifically, the purpose of this research are as follows:

- (a) To present the impact of IoT usage in universities.
- (b) To determine how the identified variables, influence the behavioral intention in using IoT as well as the IoT usage in universities.
- (c) To develop a model for the acceptance and usage of IoT in universities.

LITERATURE REVIEW

Teaching Factory Model

The notion of the teaching factory (TF) is based on the concept of the triangle of knowledge (Chryssolouris et al., 2006; Mavrikios et al., 2013; Mavrikios et al., 2018). The teaching factory came up as a promising paradigm for manufacturing education (Mavrikios et al., 2019). It functions as a non-geographically fixed learning space that connects remotely situated engineering and student groups working together on real-life assignments. It is originated from the medical sciences discipline and actually in the paradigm of the teaching hospitals that is the medical schools in parallel with hospitals (Mavrikios et al., 2019). Additionally, the concept of teaching factory denotes the incorporation of industries in the educational sector (Mourtzis et al., 2020).

In order to obtain bi-directional knowledge exchange using information and communication technologies (ICTs), the industry is linked with the classroom. A cloud platform used for file sharing and storage support was designed and built by the participants and this is regarded as the communications layer between the stakeholders (Mourtzis et al., 2021). There are two different modes of operations at the teaching factory namely: (a) Factory-to-classroom and (b) Laboratory-to-factory (Chryssolouris et al., 2016; Mourtzis et al., 2018a; Mourtzis et al., 2018b). The teaching factory network facilitates the connection between industrial (factories) and academic (classroom) players and enhance the launch of collaboration production training projects of joint business interest (Mavrikios et al., 2019).

TF has developed as a capable paradigm for combining the learning and working environments (Chryssolouris et al., 2006; Mavrikios et al., 2013). It is aided and accelerated by advanced ICTs and high-grade industrial educational tools and works as a bi-directional knowledge communication network that brings the real factory to the classroom and the academic lab to the factory (Mavrikios et al., 2019). According to Mourtzis (2018c), the research work under the teaching factory model explains how the introduction of cyber-physical systems and Industry 4.0 technology can improve manufacturing training while addressing the growing need for highly skilled workers.

The lab-to-factory TF process intends to shift knowledge from academia to industry. Industrial-grade of educational equipment in the academic resources are utilized as test beds and demonstrators for new technological notions that are to be certified and introduced to industrial practice. The TF paradigm has been evaluated based on real-life applications as well as with industrial organizations (Rentzos et al., 2014; Chryssolouris et al., 2014; Mavrikios et al., 2018).

Learning Factory Model

Learning factory (LF) is a subset of the teaching factory and it is a notion that relies on the university equipment, with manufacturing facilities looking like the industrial environment inside the university campus, and people from both academia and industry engaging in specified courses. This is carried out to promote new manufacturing trends, notion, and knowledge in the academic environment. Universities and training facilities need to identify future job outlines and associated competence requirements by adopting and enhancing their educational concepts (Abele et al., 2015). Industry now wants interdisciplinary training that triggers the already confirmed education and training in learning factories.

The National Science Foundation (NSF) in USA gave a grant to Penn State University to develop a learning factory in 1994 and this was the first time that the term “learning factory” was created and patented. It is regarded as the interdisciplinary hands-on senior engineering design projects that have strong connections and collaborations with industry. Learning factory also refers to hands-on senior engineering design ventures that interconnect with the industry, thus increasing industrial learning and training for young engineers while offering the requirements for small Medium Enterprises (SMEs) to investigate technology via this mode (Jimeno & Puerta, 2007). Advanced education which is otherwise known as Education 4.0 and networked environments will advance knowledge and expertise for the new manufacturing age (Mourtzis et al., 2020).

The early model of learning factories specifies the hands-on experience obtained from knowledge application learned from engineering education to decipher real problems in industry and design as well as redesign products to fulfill classified needs (Jorgensen et al., 1995; Lamancusa et al., 2008; ElMaraghy & ElMaraghy, 2014). Many different types of learning factories have been built in the last years (Wagner et al., 2012).

Learning factories offer a genuineness production environment as a learning environment that make minor abstractions possible. That is, processes and technologies inside the learning factory are constructed on real industrial sites. Trainees can perform experiments, discover and test approaches in learning factories on organizational and technological industry-related matters (Abele et al., 2010; Steffen et al., 2012; Kreimeier et al., 2014). Learning factories main goals are either technological and/or organizational innovation (for research purposes) or an active competency development (for educational and training purposes). Consequently, an educational notion specifying what and how should be learned by whom is an unquestionable part of a learning factory. Learning in the learning factory can either occur in the planning, realization and ramp-up stage or in the enhancement of existing processes and factory environments.

Academia provides new skills development and competencies for the new generation of engineers that associates with the ever-growing global market demands due to the adoption of the learning factory (Mourtzis et al., 2020).

There are many LFs established between industry and academia but only research work offers a detailed analysis and state-of-the-art on this model (Abele et al., 2017). They include: (a) industrial application LF, (b) academic application LF (c) remote LF (d) changeability research LF (e) consultancy application LF and (f) demonstration LF.

The Hybrid Teaching Model

Mourtzis et al. (2021) propose a hybrid teaching model (HMT) framework that referred to the digitalization of laboratory operations and to the digitization of the data processes so as to facilitate continuous workflow and enhance the quality of the laboratory. The participants were the students who were based at home and the educators and the technicians were based in the laboratory since health measures considerations against the spread of COVID-19 need to be adhered to. The hybrid teaching model framework comprises of a cloud platform that serves as a server and manages the needed data and the clients who are the university supervisors, and students (Mourtzis et al., 2021).

The clients can connect to the collaborative cloud platform via devices such as tablets, personal computers and smartphones.

The team of students can work together, design, share files and communicate their assigned work in real time. The model can assist users to develop rapidly their soft skills. Students are working at home due to the lockdown caused by COVID-19 pandemic and they tend to have everything they need to use to perform their work without having to leave their chairs. The model has contributed to the enhancement of student's cooperative skills so that they can design, develop, test, redesign if necessary and deliver their work so that they can finish their academic curriculum (Mourtzis et al., 2021).

Impact of IoT on Higher Education

Higher education will affect the educated character, knowledge, skills and qualities through information transmission (Tianbo, 2012). The basic objectives of modern higher education are talents development, teaching cultural knowledge, science and technology research, strengthening international cooperation, enhancing service to the community and maintaining social harmony (Tianbo, 2012). The seven principles of effective learning are: knowledge organization, student prior knowledge, practice and feedback, motivation, course climate, mastery and self-directed learning (Ambrose et al., 2010). IoT can positively impact on all these seven principles of effective learning. Moreover, Shaikh et al. (2019) have stated that IoT is the latest innovation and it is a technology that is rapidly growing in all areas of life especially in higher education.

Improved Teaching and Learning Systems

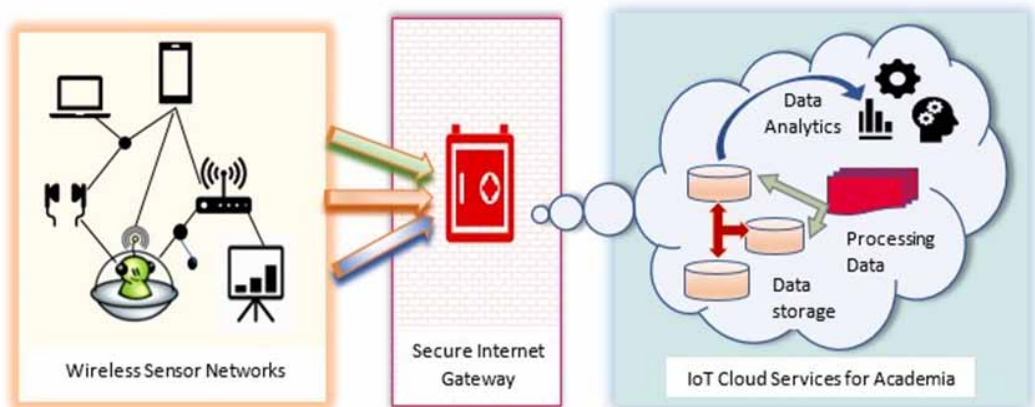
The delivery of education can be provided through three broad-based modes: face-to-face, remote and hybrid (Kassab et al., 2018). IoT has already been applied to all the three modes. Thus, IoT can actually enhance and complement teaching and learning activities to instructors, students and staff.

According to Banica et al. (2017), it is important to change the rigorous academic style of learning system from the knowledge transfer to a collaborative model in order to achieve real student-centered learning. The Internet of Things introduction into education will enhance distance learning (Kuyoro et al., 2015). Many new technologies have impacted many aspects of education e.g., learning activities such as communicating knowledge, and course presentations (Bagheri & Movahed, 2016). Akbar et al. (2018) propose a technology-based learning system developed for control lab for undergraduates and postgraduate students.

According to Johnston et al. (2015), the seven categories of technologies that steer innovation in educational environments are: Internet technologies, enabling technologies, digital technologies, consumer technologies, learning technologies, social media and visualization technologies. However, Banica et al. (2017) maintain that the most significant technology for education is the Internet of Things since it offers ways to improve learning and teaching. The use of IoT in educational environments brings the distinctive and personalized collaboration with learners since learners are able to communicate with their lecturers by sending alerts when they have learning problems and struggling academically (Majeed & Ali, 2018). Thus, IoT in universities has provided students by enhancing and improving teaching and learning.

Banica et al. (2017) provide a model of IoT for academia and this is illustrated in Figure 3.

Figure 3. A model of IoT for Academia (Source: Banica et al., 2017)



As indicated in figure 3, IoT can be implemented following three directions that is, using cloud services to provide different services such as security, infrastructure and software, Big data analytics has been used for database processing and NoSQL to indicate inclinations, concealed designs, relationships and student favorites (Banica et al., 2017).

Enhancing Smart Education

The IoT will enhance various smart learning and smart teaching activities in smart labs, classrooms, smart campus and universities (Uskov et al., 2016). IoT technology was used to build a smart classroom by Gligoric et al. (2012). They combined the IoT technology with social and behavioral analysis to transform an ordinary classroom into a smart classroom that actively listens as well as analyze voices, movements, conversations, behavior to conclude about the lecturers' presentation and listener's satisfaction.

Majeed and Ali (2018) have proposed a model to develop a university smart campus enabled through IoT technology. The current application of IoT in universities has brought smart education to the new generation of students. Students have become co-creators of knowledge due to IoT incorporation in education. The implementation of IoT in education has changed the educational system from ordinary human involvement to IoT based system (Shaikh et al., 2019).

IoT can assist in managing class attendance and instructors can manage class sessions, communicate with remote students in different places and understand students' behavior, performance, and participation (Kassab et al., 2018). IoT can assist instructors to confirm identity of students and assist students with special needs. IoT can be used to monitor students' emotional states and classroom environment. Students can be assisted by using IoT to communicate with their peers either locally or remotely, access learning materials remotely and discuss learning materials in real time. Students can integrate context and reasoning into a smart school system architecture (Kassab et al., 2018).

Impact of Machine Learning and Artificial Intelligence on IoT Adoption in Universities

The introduction, proliferation and evolution of technology, more specifically artificial intelligence (AI) has made the dispensation of instructors' duties easier in an efficient and effective manner (Chen et al., 2020). This innovation has also penetrated other division of the academia thus promoting efficiency and effectiveness. There has been expansion in AI application within the educational

sector, starting from the perception of AI as a supercomputer to include embedded computer systems. Artificial intelligence (AI) and machine learning (ML) are tools that developed from data management and developing processes (Kuleto et al., 2021). AI is defined as “computing systems that are able to engage in human-like processes such as learning, adapting, synthesizing, self-correction and use of data for complex processing tasks (Popenic & Kerr, 2017). ML is a field under AI and is defined as an AI subfield comprising software that can distinguish patterns, make predictions and use the newly found patterns to circumstances that were not part of their initial design. The future of higher education is basically connected with developments on new technologies and computing functions of new intelligent machines and advances in AI has opened new opportunities and challenges for teaching and learning in higher education, thus creating the probable fundamental change in governance and internal architecture of universities (Popenic & Kerr, 2017).

The development of AI and ML technologies has changed the educational world by providing students new skills as well as collaborative learning environment in universities (Asthna & Hazela, 2020; Liu et al., 2018). Most universities have the knowledge that AI and ML signifies the present and future in educational development. AI and ML are enhancing the efficiency and security of universities by providing accessible computing place for research and making students to obtain the required skills (Kumar, 2021).

AI technologies are regarded to be powerful and well-suited to the improvement of educational objectives and there has been considerable AI expansion in education for the past two decades (Taneri, 2020). AI in education has been integrated into instruction, administration, teaching and learning (Chassignol et al., 2018). The progress of AI in education has improved teaching and learning efficiency and effectiveness while students are being prepared for the AI world of work (Jahanian, 2020). AI also improves teacher, faculty and staff support while reforming administration in schools and colleges.

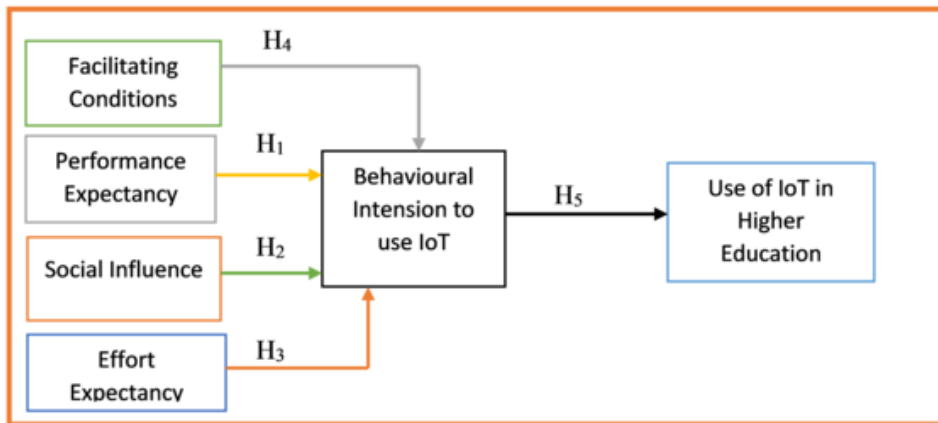
ML and AI are making tremendous impact on educational sectors as well as on the quality of people’s lives. ML is used to detect cyber attacks on the Internet of things and AI is used in IoT data, fast connectivity and high-performance computers. New approaches to problems faced by lecturers, researchers and students are being resolved by using AI and ML (Ilic et al., 2020). Algorithms are being used in universities to allocate resources, market prospective students, plan curriculum, estimate class size and career paths. Many university leaders are using AI to perform tedious and repetitive tasks and automation of their daily work.

AI is being used in the educational sector to build smart campus, and obtain intelligent teaching, learning and management (Huang et al., 2021). Some AI technologies such as image recognition technology, face recognition technology and adaptive learning have been used in the educational sector to enhance teachers’ work efficiency (Kuo, 2020) and student’s learning experience (Cui et al., 2019). AI advances the virtual learning development which includes the application of learning analytics, data mining, real time analysis and intelligent teaching systems in adaptive learning (Huang et al., 2021). Examination questions can be generated by AI technology (Rahim et al., 2018) and AI can also correct the assignments and test papers automatically (Li et al., 2018). The development of technologies such as virtual reality (VR) and augmented reality (AR), hearing and sensing technologies have all contributed to teaching environment reforms (Huang et al., 2021).

The Conceptual Framework

The unified theory of acceptance and use of technology (UTAUT) model was used in this study as the theoretical framework to evaluate the IoT usage in universities as illustrated in Figure 4.

Figure 4. The conceptual framework



Performance Expectancy

Performance expectation (PE) is defined as the extent where perception of performance excels by the usage of IoT in universities, i.e., an individual believes that by using IoT, it will enhance benefits in performing universities' operations. Performance expectancy is also defined as the extent to which emerging technologies (e.g., IoT) might help improve job performance (Lewis et al., 2013). In other models, performance expectancy is referred to as outcome expectancy, perceived usefulness, or relative advantage (Rahi et al., 2018). According to Dwivedi et al. (2017), performance expectancy is an indication of the extent of an individual trust in using an IoT technology will encourage the person in question to accomplish job performance gains.

Performance expectancy is the most important factor used in explaining behavioural intention (Venkatesh et al., 2003). Thus, in this study, the relationship between performance expectancy and behavioural intention was proposed and extended to IoT usage in universities. From previous studies, performance expectancy has helpful power in relation to the intention to use a technology in an educational institution (Bandyopadhyay & Fraceastoro, 2007). Thus, it is hypothesized that:

H₁: Performance expectancy positively influences on the behavioral intension to use IoT in universities.

Social Influence

Social influence is regarded as the extent that an individual recognizes that other persons trust in him or her using the system (Kripanont, 2007). According to Rahi et al. (2018), social influence is regarded as the influence of environmental factors. Social influence (SI) is the extent to which users perceive that important persons are of the opinion that an IS should be used. It is a way that other people affect a person's beliefs, values and feeling (Foon et al., 2011; Jaganathan et al., 2014). Social influence is defined as the extent to which students and lecturers perceive that some individuals expect them to use the technology (Lewis et al., 2013). It is also the extent to which important people to the user perceive the crucial nature of technology to the user (Diaz & Loraas, 2010). It was expected that IoT technologies will affect both its users as well as students in institutions, and it was anticipated that potential IoT users will understand the opinions about IoT (Aldossari & Sidorova, 2018). Thus, it is hypothesized that:

H₂: Social influence positively influences on the behavioral intension to use IoT in universities.

Effort Expectancy

Effort expectancy (EE) details how a system is used easily (Chandio, et al., 2017). Effort expectancy is regarded as the extent of ease of use related with the use of IoT in universities (Rahi et al., 2018). Effort expectancy is defined as the extent of educational institutions perceiving technology such as IoT to be effort free during its usage (Lewis et al., 2013). Venkatesh et al. (2003) have stated that the more effort the technology use is perceived, then the less likely that that technology will be used by individuals. Effort expectancy is effective in predicting the use of personal technologies (Venkatesh & Bala, 2008). Thus, it is hypothesized that:

H₃: Effort expectancy positively influences on the behavioral intension to use IoT in universities.

Facilitating Conditions

Facilitating condition (FC) is regarded as the influence of both organizational and technical infrastructures to support IoT usage in universities. It is also regarded as the extent to which students and lecturers trust the institution and technical infrastructure in sustaining the usage of the system (Lewis et al., 2013). This is akin to people seeking assistance when they use the technology. Venkatesh et al. (2011) have pointed out that if such facilitating conditions are available, then the people are more likely to form positive attitudes to use the technology. Venkatesh et al. (2012) point out that facilitating condition refers to how the consumers comprehend the resources and support when executing a behavior. According to Baabdullah (2018), facilitating conditions indicate the resources that can be used to make possible IoT usage in the consumer setting. Consequently, users with increased access to FC will be more willing to use specific technology.

Thus, it is hypothesized that:

H₄: Facilitating conditions positively influence on the behavioral intension to use IoT in universities.

Behavioral Intention

Behavioral intention (BI) is defined as the individual's plan to use a specific technology for different tasks (Ain et al., 2016). Behavioral intention is defined as a purpose that combines both views and general patterns about the target behavior so as to forecast the actual behavior (Pickett et al., 2012). Thus, the behavior intention can be used to assess the relative depth of a person's dedication to engage in a unique behavior (Lewis et al., 2013).

There is a relationship between attitude and conduct (Shaikh et al., 2019). Dwivedi et al. (2017) have stated that people having confidence on IoT usage are inclined to execute IoT projects more frequently than those with a negative view of technology. As people tend to realize IoT benefits and ease of use or risks is exposed to people, this leads to gradual changes in overall positive effect on IoT. Consequently, IoT implementations become more frequent than those with a negative view of technology (Dwivedi et al., 2017).

Behavioral intension can be used to evaluate the depth of individuals' dedication to engage in a specific behavior (Ngai et al., 2007). Some authors (Raman & Don, 2013; Motaghian et al., 2013; Wang & Wang, 2009) have stated that behavioral intention to use a technology significantly influences the actual system use.

Behavioral intention is hypothesized as:

H₅: Behavioral intention positively influences on the use of IoT in higher educational institutions.

RESEARCH METHODOLOGY

A quantitative research method is followed in this study. This begins with a field study and sampling process to identify the respondents. The collected data was then analyzed using SPSS statistical package. A field study was conducted to provide intuitions into the research problem by using a survey questionnaire.

Data Collection and Sampling Technique

The conceptual framework was formulated from in-depth literature review on IoT usage in universities. The primary data collection approach was the questionnaire. Questionnaires were designed with the primary focus on resolving the research questions. The questionnaire contains thirty-three (33) questions on six (6) factors that are associated with the UTAUT model (see Appendix A). The questions were on a five-point Likert scale format as follows: 1 – “strongly disagree”; 2 – “disagree”; 3 – “neutral”; 4 – “agree”; 5 – “strongly agree”. The questionnaire consists of the following variables: performance expectancy, effort expectancy, social influence, facilitating conditions, behavioral intention to use IoT and use of IoT in higher education. A pilot test was conducted involving fifty lecturers and students of a university to guarantee the reliability and validity of the constructs. The outcome of the pilot test revealed that the reliability of the constructs of the questionnaire was good. Therefore, there was no need to modify the questionnaire.

After the pilot test, six hundred and fifty questionnaires were distributed to lecturers and students of universities. Some of the questionnaires were given to the respondents by hand while others were sent through email. Gatekeepers were used to facilitate the distribution of the questionnaire in universities. Three hundred and fifty-five respondents completed the questionnaires and five of them were partially completed and therefore rejected, thus, a response rate of 53.8% was achieved. The respondents were from research universities, technical & vocational education and training (TVET) colleges, Technological universities, private institutions and other universities and they were drawn upon by using random sampling.

DATA ANALYSIS METHOD

The IBM SPSSv25.0 statistical package was used as the tool for data analysis. Factor analysis was used to perform the data analysis. Exploratory factor analysis (EFA) and regression analysis were used to predict the UTAUT factors.

RESULTS AND DISCUSSION

Respondent’s Demographics

Table 1. illustrates the demographics of the research participants.

Table 1. Descriptive statistics – Survey respondents

Institutions		
Research Universities	52	14.5%
TVET Colleges	27	7.5%
University of Technology	214	59.6%
Private Institutions	51	14.2%
Others	6	1.7%
Respondent Levels		

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Table 1 continued

Institutions		
Lecturer/Facilitator	44	12.3%
Student	286	79.7%
Other	20	5.6%
Sex		
Female	214	59.6%
Male	136	37.9%
Race		
Black	261	72.7%
Asian	13	3.6%
Colored	36	10%
White	24	6.7%
Foreign	16	4.5%
Age		
< 25 years	92	25.6%
26 – 35 years	205	57.1%
36 – 45 years	50	13.9%
³ 55 years	3	0.8%
Basis of Employment		
Permanent	142	39.6%
Temporary	26	7.2%
Fixed Term Contract	141	39.3%
Other	41	11.4%
Department		
ICT	217	60.4%
Humanities	17	4.7%
Engineering	23	6.4%
Tourism	17	4.7%
Science	16	4.5%
Other	60	16.7%
Employment Years		
2 or Less	232	64.6%
3 – 5 years	96	26.7%
6 – 10 years	22	6.1%

Many responses were received from the universities of technology (59.6%) and this was followed by research universities (14.5%) and private institutions (14.2%). Many students (79.7%) participated in the study while only 12.3% were lecturers. More female participants (59.6%) participated while 37.9% were males. Furthermore, participants were relatively young (less than 35 years) and most of them were from the ICT department of their higher institutions.

DATA ANALYSIS

Validity and Reliability Analysis

Internal consistency assesses the reliability of results across the factors within a test and the Cronbach alpha (Cronbach, 1951) is the mostly used item to calculate internal reliability measurement (Taan & Hajjar, 2018). Validity is the most important measure for assessing test quality and it leads to the derivation of ideas, deduction or measurement while relating accurately to the real world (Brains et al., 2011).

The internal reliability of the constructs was investigated and the validity of the various sub-constructs was further explored by examining relationships between the items (Nielsen et al., 2017). Table 3 shows the validity and reliability analysis of the questionnaire used in the study.

In order to assess the validity and reliability of the constructs, the loading factors (LF) of all the items, the average variance entreated (AVE), the composite reliability (CR) and the maximum shared variance (MSV) of each construct were all estimated and the results shown in Table 2.

Table 2. Estimation of LF, AVE, CR and MSV

Constructs / Items	LF	AVE	CR	MSV
Performance Expectancy (B)		0.747	0.922	0.661
B1.1	0.883			
B1.2	0.906			
B1.3	0.908			
B1.4	0.751			
Social Influence (C)		0.605	0.860	0.304
C1.1	0.758			
C1.2	0.804			
C1.3	0.776			
C1.4	0.772			
Effort Expectancy (D)		0.529	0.812	0.367
D1.1	0.851			
D1.2	0.782			
D1.3	0.740			
D1.4	0.483			
Facilitating Conditions (E)		0.594	0.851	0.373
E1.1	0.576			
E1.2	0.788			
E1.3	0.830			

Table 2 continued on next page

Table 2 continued

Constructs / Items	LF	AVE	CR	MSV
E1.4	0.857			
Behavioral Intention (F)		0.703	0.904	0.548
F1.1	0.797			
F1.2	0.850			
F1.3	0.810			
F1.4	0.893			
IoT Usage in Universities (G)		0.594	0.879	0.480
G1.1	0.874			
G1.2	0.814			
G1.3	0.717			
G1.4	0.665			
G1.5	0.765			

The lowest permissible value of LF is 0.707 (Borroso et al., 2010) while the lowest permissible value of composite reliability (CR) of each construct is 0.5 (Hair et al., 2011). The lowest permissible value of AVE is 0.7 (Urbach & Ahlemann, 2011). The value of each MSV should be less than its corresponding value of AVE. Considering the estimated values in Table 2, almost all the estimated values are within the acceptable range. Therefore, this confirms that the items are reliable and the constructs are valid and reliable.

Construct Reliability, Multicollinearity and Discriminant Validity Test

Table 3 illustrates the estimation of the Cronbach’s Alpha (σ), variance inflation factor (VIF) and AV.

Table 3. Estimation of Cronbach’s Alpha, VIF and AV (Discriminant Validity Test)

	TransB	TransC	TransD	TransE	TransF	AV	σ	VIF	No. of Items
TransB	0.385					0.864	0.940	1.482	4
TransC	0.454	0.422				0.778	0.781	1.640	4
TransD	0.567	0.342	0.414			0.727	0.759	2.361	4
TransE	0.542	0.325	0.350	0.520		0.771	0.856	1.958	4
TransF	0.624	0.373	0.475	0.542	0.381	0.838	0.827	1.000	4

TransB: Performance Expectancy; **TransC:** Social Influence; **TransD:** Effort Expectancy; **TransE:** Facilitating Conditions; **TransF:** Behavioral Intention;

The Cronbach’s Alpha (σ) of each construct was estimated in order to confirm that the constructs are reliable and consistent as shown in Table 3. The lowest acceptable value of Cronbach’s Alpha

for a construct is 0.6 (Hair Jr. et al., 2010). The Cronbach Alpha values of all the constructs range from 0.759 and 0.940 that is, they are all above 0.6. Consequently, all the constructs are all highly reliable and consistent.

Multicollinearity defect results when the inner meanings of the constructs become very close to each other. Because of this, the variance inflation factor (VIF) of each construct needs to be estimated. The maximum acceptable value of VIF is 5 (Ringle et al., 2015), although Hair et al. (1995) put the maximum acceptable value of VIF to be 10.

Discriminant validity is said to be established when each item is found to be strongly related with its own construct and weakly related with other constructs. In order to test for discriminant validity, the average variance (AV) of each construct must be computed. The AV is computed from calculating the square root of the corresponding AVE. Then, the discriminant validity is established if the AV of each construct is more than the correlation coefficients of that construct with other constructs (Gefen & Straub, 2005). From Table 3, the value of all the AVs of the constructs in the ninth column is greater than the corresponding correlation coefficients shown in off-diagonal places. Therefore, discriminant validity is confirmed for all the constructs (Fornell & Larcker, 1981). The values of VIF for all constructs lie between 1.474 to 2.739, thus confirming that the data is free from multicollinearity defect.

Inferential Statistics – Bivariate Correlations of the Variables

Inferential statistics is used to draw conclusions from a sample to a population (Guetterman, 2019). It is also used to examine differences among groups and the relationships among variables. Examples include t-test, analysis of variance (ANOVA), correlation and regression.

By using data from two constructs, bivariate correlation coefficients test is used to test if there is a linear relationship between them (Akoglu, 2018). By using a scatterplot to check for linearity, it was found that there is a linear relationship between the variables. The Pearson correlation coefficient (r) needs normally distributed continuous variables (Schober et al., 2018) and parametric test is used to calculate Pearson correlation coefficient among variables. According to Akoglu (2018), in case of non-normal distributions, correlation coefficients should be calculated from the types of the data and not from their actual values. Such data can use either the Spearman's rho (ρ or r_s) or Kendall's Tau (τ). An extension to Spearman's rho is the Kendall's Tau and it is used when the same type is repeated too many times in a small dataset. According to Kutner et al. (2005), a spearman coefficient is a Pearson correlation coefficient that is calculated with the types of the values of each of the two variables rather than their actual values.

In this study, it was found that there is a linear relationship between the variables from the scatterplot and the Pearson correlation coefficient test was carried out. Table 4 shows the Pearson correlations of the variables used in this study.

Table 4. Pearson Correlations of the Variables

	IoT Usage in HE Institutions 1	Performance Expectancy 2	Social Influence 3	Effort Expectancy 4	Facilitating Conditions 5	Behavioural Intention 6
1	1					
2	0.551**	1				
3	0.597**	0.505**	1			
4	0.730**	0.500**	0.564**	1		
5	0.674**	0.404**	0.463**	0.693**	1	
6	0.800**	0.500**	0.664**	0.704**	0.537**	1
**. Correlation is significant at the 0.01 level (2-tailed).						

It should be noted that a statistically significant correlation does not necessarily result in a strong correlation. The *P*-value indicates that the probability that this strength may occur by chance. A *P*-value is the probability that a statistical summary of the data (e.g. the sample mean difference between two compared groups, would be equal to or more extreme than the observed value under a specified statistical model (Wasserstein & Lazar, 2016). Thus, the strength of the Pearson correlation can be determined by using Table 5.

Table 5. Interpretation of Pearson Correlation Coefficients (Source: Dancey and Reddy, 2007)

Correlation Coefficients		Interpretation
+1	-1	Perfect
+0.9	-0.9	Strong
+0.8	-0.8	Strong
+0.7	-0.7	Strong
+0.6	-0.6	Moderate
+0.5	-0.5	Moderate
+0.4	-0.4	Moderate
+0.3	-0.3	Weak
+0.2	-0.2	Weak
+0.1	-0.1	Weak
0	0	Zero

The Pearson correlation coefficients of the variables ranges from 0.404 to 0.800. The strongest correlation relationship is 0.800 which is between IoT usage in HE institutions and behavioral intention. The lowest correlation relationship is 0.404 which is between Facilitating conditions and performance expectancy. The correlation relationship between IoT usage in HE institutions and effort expectancy can be said to be strong. The correlation relationship between effort expectancy and behavioral intention is also strong.

Inference Statistics – Regression Analysis of the Variables

Multiple Linear Regression

Table 6 shows the summary of the first regression model. The R square value of the regression model in this study is 0.606. The adjusted R square value is 0.601, which implies that the following variables: performance expectancy, social influence, effort expectancy and facilitating conditions collectively predict 60.1% for the behavioral intention.

Table 6. Summary of the First Regression Model

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	Sig. F Change
1	.778	.606	.601	.53681	.606	.000

Table 7 shows the summary of the second regression model for the study.

Table 7. Summary of the Second Regression Model

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	Sig. F Change
1	.800	.641	.640	.46630	.641	.000

The R square value of the second regression model in this study is 0.641. The adjusted R square value is 0.640, which implies that the variable: behavioral intention predicts 64.0% for the IoT usage in HE institutions.

The *P*-value (or the calculated probability) is used to calculate the probability of the event occurring by chance provided that the null hypothesis is true (Anaesth, 2016). The *P*-value is a numerical between 0 and 1 and is used by researchers to conclude the acceptance or rejection of the null hypothesis. The *P*-value is an approach to review the inconsistency between a particular data set and a proposed model for the data (Wasserstein& Lazar, 2016).

In the first regression table (Table 8), the *P*-values of all the variables are as follows: performance expectancy is 0.032, social influence is 0.000, effort expectancy is 0.000 and facilitating conditions is 0.441. These results indicate only three out of the four variables meaningful contributes to the prediction of behavioral intention to use IoT. These variables are: performance expectancy, social influence and effort expectancy. Their *P*-values are less than the maximum threshold of 0.05.

From the unstandardized coefficients of the variable effort expectancy, the beta value of effort expectancy is 43.2% which is the variable contributing to the highest prediction of behavioral intention. Thus, the variable with the highest contribution towards the prediction of behavioral intention to use IoT is effort expectancy.

Table 8. Contribution of Individual Constructs (First Regression Table)Coefficients^a

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta (β)		
1	(Constant)	-.116	.174		-.663	.508
	Performance Expectancy	.082	.038	.089	2.158	.032
	Social Influence	.374	.045	.358	8.268	.000
	Effort Expectancy	.538	.065	.432	8.325	.000
	Facilitating Conditions	.040	.052	.036	.772	.441

a. Dependent Variable: Behavioral Intention (TransF)

In the second regression table (Table 9), the *P*-values of the only variable is as follows: behavioral intention to use IoT is 0.000. These results indicate that this only variable, that is, behavioral intention to use IoT meaningful contribute to the prediction of IoT usage in HE institutions. The *P*-value is 0.000 for behavioral intention to use IoT which is less than the maximum threshold of 0.05.

From the unstandardized coefficients of the only variable: behavioral intention to use IoT, the beta value of behavioral intention to use IoT is 80.0%. Thus, the only variable contributing towards the prediction of IoT usage in HE institutions is behavioral intention to use IoT.

Table 9. Contribution of Individual Constructs (Second Regression Table)Coefficients^a

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta(β)		
1	(Constant)	.950	.111		8.533	.000
	Behavioral Intention	.731	.029	.800	24.912	.000

a. Dependent Variable: IoT Usage in HE Institutions (TransG).

Hypothesis Evaluation

Table 10 illustrates the hypothesis testing outline from the two regression models.

Table 10. Hypothesis Testing Outline

Hypothesis Symbols	Hypothesis	Beta(β)	<i>P</i> -Values	Is <i>P</i> < 0.05?	Remarks
H ₁	PE BI	0.089	0.032	Yes	Supported
H ₂	SI BI	0.358	0.000	Yes	Supported
H ₃	EE BI	0.432	0.000	Yes	Supported

Table 10 continued on next page

Table 10 continued

Hypothesis Symbols	Hypothesis	Beta(β)	<i>P</i> -Values	Is <i>P</i> < 0.05?	Remarks
H ₄	FC BI	0.036	0.441	No	Not Supported
H ₅	BI IoT in HE	0.800	0.000	Yes	Supported

PE: Performance Expectancy; SI: Social Influence; EE: Effort Expectancy; FC: Facilitating Conditions; BI: Behavioral Intension

According to Anaesth (2016), if *P* value < 0.01, then the result is highly significant and the null hypothesis should be rejected. If *P* value ³ 0.01 but *P* value < 0.05, then the result is significant and the null hypothesis should be rejected. If *P* value ³ 0.05, then the result is not significant and the null hypothesis should not be rejected. In Table 10 based on Anaesth (2016) interpretation of the *P* value, only four out of the five hypotheses (namely: H₁, H₂, H₃ and H₅) are supported.

The Resulting Model

The resulting model is shown in Figure 5 and it is based on the five hypotheses.

H₁: Performance expectancy positively influences on the behavioral intension to use IoT in universities.

The first hypothesis (H₁) of the study predicted a positive relationship between the performance expectancy and behavioral intension to use IoT in universities. It is significant ($\beta = 0.089$, *P*-value < 0.05) with a *P*-value of 0.032 which is below the threshold of 0.05 and is therefore supported.

H₂: Social influence positively influences on the behavioral intension to use IoT in universities.

The second hypothesis (H₂) of the study predicted a positive relationship between the social influence and behavioral intension to use IoT in universities. It is significant ($\beta = 0.358$, *P*-value < 0.05) with a *P*-value of 0.000 which is below the threshold of 0.05 and is therefore supported.

H₃: Effort expectancy positively influences on the behavioral intension to use IoT in universities.

The third hypothesis (H₃) of the study predicted a positive relationship between the effort expectancy and behavioral intension to use IoT in universities. It is significant ($\beta = 0.432$, *P*-value < 0.05) with a *P*-value of 0.000 which is below the threshold of 0.05 and is therefore supported.

H₅: Behavioral intention positively influences on the use of IoT in higher educational institutions.

The fifth hypothesis (H₅) of the study predicted a positive relationship between the behavioral intention and the use of IoT in universities. It is significant ($\beta = 0.800$, *P*-value < 0.05) with a *P*-value of 0.000 which is below the threshold of 0.05 and is therefore supported. [Figure 5 insert here]

Figure 5. The model for the acceptance and usage of IoT in higher educational institutions

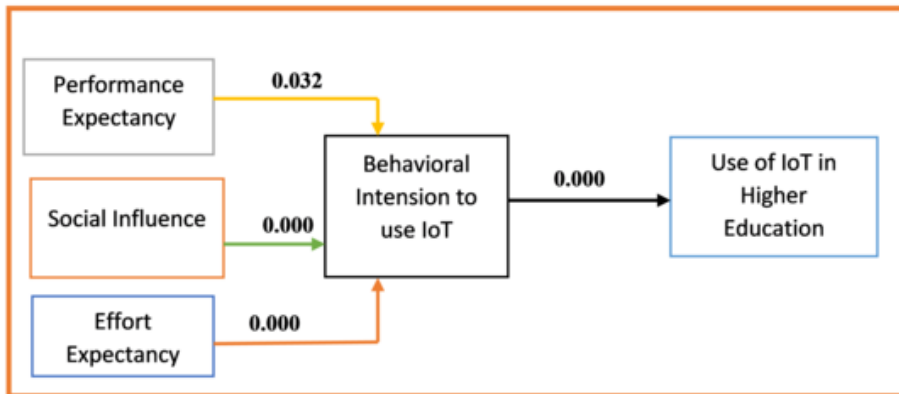


Figure 5. The model for the acceptance and usage of IoT in higher educational institutions

CONCLUSION

This study investigates empirically the factors influencing the acceptance and usage of Internet of Things (IoT) in universities. Knowing the factors will give rise to a positive significance on utilization of IoT in universities. The IoT usage in academics has brought new opportunities for improving both teaching-learning process and educations' infrastructure (Gul et al., 2017). In this study, the results obtained were in agreement with most of the results of previous studies that were insinuated to in this research.

To this end, a model based on the unified theory of acceptance and use of technology (UTAUT) was developed by using five factors namely performance expectancy, social influence, effort expectancy, behavioral intention and IoT usage in universities. The proposed model was validated using an instrument developed specifically for this research. The questionnaire was given to six hundred and fifty respondents by hand, email and gatekeepers in various universities in order to ensure the generalization of the model. Three hundred and fifty respondents completed the questionnaires while five were partially completed and rejected, therefore contributing to a response rate of 53.8%. The three hundred and fifty responses were considered valid and were further analyzed by using the SPSSv25.0 software.

All test results met reliability and validity requirements. The discriminant validity was assessed among the factors and the result demonstrated the sufficiency of the model. The *P*-value was utilized to establish the significance of the factors during the hypotheses testing. The results indicated that performance expectancy, social influence and effort expectancy were the predictors of behavioral intention to use IoT while behavioral intention predicts the IoT usage in universities. However, facilitating conditions did not have any effect on behavioral intention directly or indirectly.

LIMITATIONS AND FUTURE WORK

Although the research findings stated here investigate and unearth some new insights to researchers, however there are some limitations which can be addressed in future studies. Firstly, owing to the focus of this research which is finding the factors that influence IoT usage and also to develop a model on IoT usage and consent in universities, other determinants such as hedonic motivation, price,

technology anxiety and attitude were not evaluated and they could have contributed to the model development. Therefore, future research might expand this study by incorporating these determinants for evaluation. Finally, the use of random sampling technique may have limited the representativeness of the participants that are part of the intended population. Consequently, the research result may not be as generalizable as could be expected. Therefore, it is suggested that probability sampling technique should be used to assess IoT adoption in universities in future research so that the result can be more representative of the population of the participants.

This research offers the groundwork to explore the process of the actual adoption of IoT services for universities. For future research considerations, more factors should be identified and included to the model, in order to gain more intuition and ensure greater success of such service. Moreover, the current findings can be extended by examining the moderating effects of age, cultural background and other factors. The findings of this study could be utilized by university administrators and decision makers in universities.

CONFLICT OF INTEREST

The author of this publication declares there is no conflict of interest.

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APPENDIX A:

QUESTIONNAIRE ITEMS

Factors/ Authors	Question Identifiers	Questions
Performance Expectancy (Lewis et al. (2013); Dwivedi et al. (2017); Venkatesh et al. (2003))	B1.1	Do you think employing the Internet of Things (IoT) applications will lead the change and reform the higher education institutions in South Africa?
	B1.2	Will the IoT applications operating over the platform system support the professional of the higher institutions, enable teaching, and learning activities, and enhance student's performance?
	B1.3	Will the employment of IoT tools and technologies assist instructors and professors to improve the quality of research and address ethical issues within the higher institution?
	B1.4	Do you think it will be possible to eliminate human biasness and aforementioned flaws for accessing student capabilities by employing IoT?
Social Influence (Rahi et al. (2018); Jaganathan et al. (2014); Aldossari and Sidorova (2018))	C1.1	The information that you have regarding IoT, is enough to employ or start using the IoT technology?
	C1.2	Do you think the consumer's social network has a positive influence on trust towards IoT technology adoption?
	C1.3	Is the user's intention to use the IoT technology influenced by their beliefs about it?
	C1.4	Through social image, do you believe that using the IoT technology will improve the student's performance within the institution?
Effort Expectancy (Chandio et al. (2017); Venkatesh et al. (2003); Venkatesh and Bala (2008))	D1.1	Do you think it will be easier for lecturers/facilitators to capture learner's attendance and marks by using IoT technologies?
	D1.2	Do you think educational policy change can easily be performed by IoT?
	D1.3	Do you think the implementation of IoT technologies can easily help with and be the powerful mechanism for learning foreign languages in institutions?
	D1.4	Do you think that IoT can eliminate the struggle of understanding lessons during lectures?
Facilitating conditions (Lewis et al. (2013); Venkatesh et al. (2011, 2012); Baabdullah (2018))	E1.1	Users with increased facilitating conditions will be more willing to use specific technology.
	E1.2	IoT has the ability to optimise the classroom learning environment
	E1.3	Many students and administrators are already carrying, every day, very powerful IoT devices in a form of mobile devices
	E1.4	By employing some elements of gamification, the institution can reward students digitally for engaging and for completing tasks on time
Behavioural Intention (Ain et al. (2016); Raman and Don (2013); Motaghian et al. (2013); Wang and Wang (2009))	F1.1	Consumer trust of IoT technologies and services providers is believed to play a vital role in behavioural intentions.
	F1.2	When the use of IoT technologies can bring fun and pleasure, will the students and lecturers be intrinsically motivated to adopt them
	F1.3	For IoT users to adopt IoT, they need to feel that IoT is easy to use
	F1.4	IoT technologies are supposed to achieve better adoption rates if they could facilitate the student's and lecturer's daily life
IoT Usage in Higher Education (Ambrose et al. (2010); Shaikh et al. (2019); Kassab et al. (2018); Kuyoro et al. (2015); Banica et al. (2017); Majeed and Ali (2018))	G1.1	IoT technologies are used in my university.
	G1.2	IoT technologies are better utilized in universities
	G1.3	Universities will derive competitive advantage by using IoT technologies.
	G1.4	IoT technologies have made universities to become efficient in bringing good quality to education.
	G1.5	IoT technologies are very vitally important for the success of universities.