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PAPER

Adoption of Internet of Things in the Higher Educational Institutions: Perspectives from South Africa

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ABSTRACT

This study investigates and identifies the determinants of Internet of Things (IoT) adoption by higher educational institutions (HEIs) within the South African setting. The study developed an empirical model to predict the determinants of IoT adoption by HEIs by utilizing the unified theory of acceptance and use of technology (UTAUT) model. Data were collected randomly through questionnaire from 250 respondents and analyzed using regression testing. The results indicated that behavioral intention to use IoT was positively influenced by performance expectancy, social influence, and effort expectancy. The findings could provide the insights into future strategies for successful IoT implementations by higher educational institutions.

KEYWORDS

unified theory of acceptance and use of technology (UTAUT), Internet of Things (IoT), IoT adoption, higher educational institutions (HEIs)

1 INTRODUCTION

Higher educational institutions (HEIs) are extensive intelligent systems since educators and learners are part of the information-complex holographic humans [1]. Technology in education has resulted in the creation of learner engagement in learning and content creation, as well as a collaborative, self-directed model [2]. The Internet of Things (IoT) is regarded as a technological trend or development that is revolutionizing the world in several ways, and business organizations, academia, and governments have to give high priority to this development [3]. Moreover, the literature has revealed that most developed countries have acquired and implemented IoT technologies in their tertiary higher educational institutions, which enhance the students learning experience and management of resources. However,

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developing countries such as South Africa are still implementing IoT technologies in their tertiary educational institutions.

The IoT is a promising philosophy of applications within the educational sector and innovative technology [4]. The IoT offers immense opportunities for HEIs to bring control that is independent and better infrastructure strength, agility, and robustness [4]. The IoT enhances teaching and learning for learners and increases processes [5]. Moreover, IoT is a cost saver and helps students learn at any time and place. Consequently, the IoT can offer solutions that will change teaching and learning activities [6]. Smart learning is the amalgamation of IoT and e-learning, and it is also referred to as IoT-based e-learning [4]. Smart learning improves the student's performance in terms of achievement, knowledge, learning, and results [7–8]. The digital era has brought about an increase in Internet usage in everyday life, and many organizations have moved online in order to gain new development opportunities [45]

Axiomatically, IoT is expected to grow in social and educational fields, and academic and research organizations are highly influencing IoT technologies, for example, the smartphone of things, the web of things, digital information systems, and using personal computers to improve learning experiences [9]. The largest platform being used in academic and research institutions is the mobility platform. The implementation of IoT at the educational level is linked to the holistic enhancement of the learning experience. Educational IoT applications are powerful tools that are revolutionizing the processes of teaching and learning. IoT has the capability to eliminate all resistance to education, such as physical location, economic development, and geography [9]. Therefore, combining education and technology has led to simpler and faster learning, thus improving the knowledge implicitly and the student's quality. Few studies have investigated the adoption of IoTs in HEIs within the South African higher education setting; therefore, this study aims to investigate the determinants that influence the adoption of IoT in HEIs within the South African higher education setting. Furthermore, this has led to the proposal of a model for IoT adoption in HEIs within developing countries.

Successful execution of any information system (IS) or information technology (IT) relies on its acceptance by users [10]. Numerous theoretical models have been developed in the fields of ISs and sociology in recent decades, and these models have been used to predict the user acceptance of technologies [11]. The model used in this study is the unified theory of acceptance and use of technology (UTAUT) to investigate the influences of technologically related factors on IoT adoption in HEIs. UTAUT was developed by Venkatesh et al. [12] by integrating eight models together to predict new technology adoption, acceptance, and usage. These theories are the technology acceptance model (TAM), the motivational model (MM), the theory of planned behavior (TPB), the combined TAM-TPB, the theory of reasoned action (TRA), the model of PC utilization (MPCU), and the social cognitive theory (SCT). The UTAUT has been extensively utilized for envisaging system utilization and making the adoption and utilization of technology decisions [11] [13–16].

Higher educational institutions are extensive intelligent systems since educators and learners are part of the information-complex holographic human [1]. Technology in education has resulted in the creation of learner engagement in learning and content creation, as well as a collaborative, self-directed model [2]. The IoT is regarded as a technological trend or development that is revolutionizing the world in several ways, and business organizations, academia, and governments have to give high priority to this development [3]. Moreover, the literature has revealed that most developed countries have acquired and implemented IoT technologies in their tertiary higher educational institutions, which enhance the students learning experience and management of resources. However, developing countries such as South Africa are still implementing IoT technologies in their tertiary educational institutions. According to Husein et al. [46], every IoT manufacturer supplies their own cloud and create Intranet of things by doing so.

The IoT is an evolving philosophy of applications used in the educational sector and innovative technology [4]. The IoT offers immense opportunities for HEIs to bring independent control and better infrastructure robustness, agility, and robustness [4]. The IoT enhances learning and teaching for learners and increases processes [5]. Moreover, IoT is a cost saver and assists students learn at any time and place. Consequently, the IoT can propose solutions that will change learning and teaching activities [6]. Smart learning is the amalgamation of IoT and e-learning, and it is also referred to as IoT-based e-learning [4]. Smart learning improves the performance of students in terms of learning, knowledge, achievement, and results [7] [8] [9]. Holik et al. [47] state that information and communication technology (ICT) is becoming a prominent tool that supports learning and teaching, and its use is growing gradually.

Axiomatically, IoT is expected to grow in social and educational fields, and academic and research organizations are highly influencing IoT technologies such as the web of things, smartphone of things, personal computers, and digital information systems to improve learning experiences [9]. The mobility platform is the largest platform being used in academic and research institutions. The implementation of IoT at the educational level is linked to the holistic enhancement of the learning experience. Educational IoT applications are powerful tools that are revolutionizing the process of teaching and learning. IoT has the potential to eliminate all barriers to education, such as geography, language, physical location, and economic development [9]. Therefore, combining education and technology has led to simpler and faster learning, improving implicitly and qualitatively the knowledge of students. Few studies have investigated the adoption of IoTs in HEIs within the South African higher education setting; therefore, this study aims to investigate the factors that influence IoT adoption in HEIs within the South African higher education setting. Furthermore, this has led to the proposal of an adoption model for IoT in HEIs in developing countries.

Effective implementation of any IS or IT relies on user acceptance [10]. Numerous theoretical models have been developed in the fields of information systems and sociology in recent decades, and these models have been used to predict the user acceptance of technologies [11]. The theoretical model used in this study was the unified theory of acceptance and use of technology (UTAUT) and it was used to evaluate the influences of technological related factors on IoT adoption in HEIs. UTAUT was developed by Venkatesh et al. [12] by integrating eight models together to predict new technology adoption, acceptance, and usage. These are the theory of planned behavior TPB, theory of reasoned action TRA, the combined TAM-TPB, the technology acceptance model TAM, the model of PC utilization (MPCU), the motivational modelMM, and social cognitive theory SCT. The UTAUT has been extensively utilized for predicting system utilization and making technology-adoption and technology-usage-related decisions [11] [13] [14] [15] [16].

2 THE CONCEPTUAL FRAMEWORK

The model used to develop the conceptual framework is the unified theory of acceptance and use of technology UTAUT [12] model for the adoption of IoT in HEIs, and this is illustrated in Figure 1.

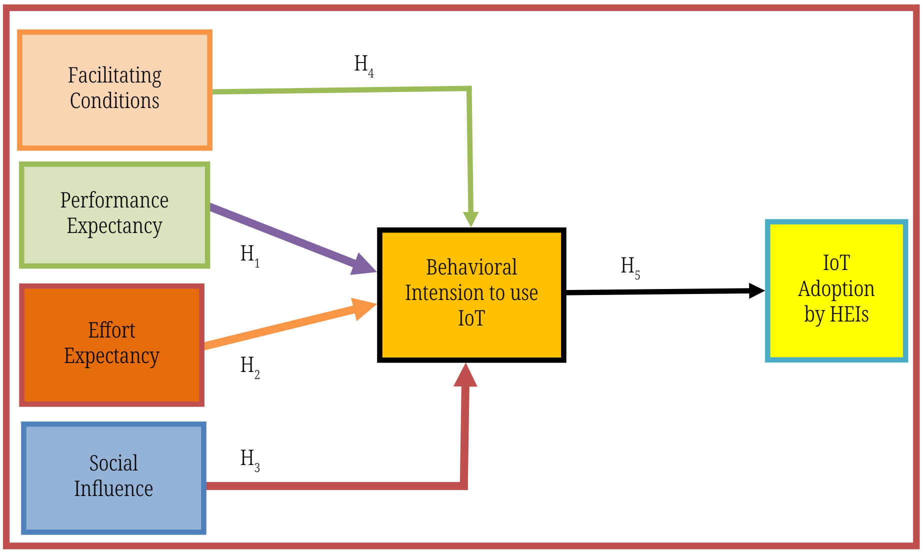

Fig. 1. The conceptual framework

2.1 Performance expectancy

Performance expectancy is referred to as "the extent to which a person has articulated determined plans regarding whether to execute a specified future behavior" [12]. PE represents university staff and students' beliefs regarding whether using IoT will improve their performance. According to Venkatesh et al. [12], PE is the strongest determinant of a user's behavioral intention to adopt technology. Furthermore, PE was found to be a determining factor influencing teachers in Africa to use ICT in their classrooms [17]. Based on this background, it is proposed that:

H_1: Performance expectancy is positively influenced by the behavioral intension to use IoT in higher educational institutions.

2.2 Social influence

Social influence is defined as "the extent to which an individual observes those important others believe he or she should use the new system" [12]. A previous study showed that SI is categorized by friends, family, coworkers, and students and found that SI influences BIs [17–19]. Thus, the following hypothesis is postulated:

H_2: Social influence is positively influenced by the behavioral intension to use IoT in higher educational institutions.

2.3 Effort expectancy

Effort expectancy is "the extent of ease related with the use of a system" [12]. EE represents university staff and students' beliefs towards the ease of use of IoT. According to previous studies, EE has a positive influence effect on the use of technology to teach [20–22]. Based on this background, the third proposed hypothesis was:

H_3: Effort expectancy is positively influenced by the behavioral intension to use IoT in higher educational institutions.

2.4 Facilitating conditions

Facilitating conditions are defined as "the extent to which an individual believes that an organizational and technical infrastructure exists to support use of the system" [12]. Some authors have found that FC positively influences BI [23–25] and has a significant effect of FC. Thus, the fourth hypothesis was:

H_4: Facilitating conditions is positively influenced by the behavioral intension to use IoT in higher educational institutions.

2.5 Behavioral intention

Behavioral intention is defined as "a measure of the power of one's ability to conduct a specific behavior" [26]. According to Dwivedi et al. [27], people having confidence on IoT usage are motivated to execute and implement IoT projects more frequently than those that have negative views concerning the technology implementation. Consequently, IoT implementations become more common than those with a negative view of technology [27]. This is the most significant factor influencing the adoption of IoT by HEIs. Thus, it is proposed that:

H_5: Behavioral intention is positively influenced by the use of IoT in higher educational institutions.

3 METHODOLOGY

The research method used in this study is the quantitative (empirical) method. A field study was conducted followed by a sampling process to identify the respondents. The SPSS statistical software was used to analyze the collected data and provide insights into the research problem.

3.1 Data collection and sampling techniques

An in-depth literature review on the utilization of IoT in HEIs was performed in order to generate the questionnaire (see Appendix, Table A1). The questionnaire comprised of 33 questions based on six variables that are associated with the UTAUT model. The questionnaire was made up of a five-point Likert scale format as follows: 1 represents– "strongly disagree"; 2 represents– "disagree"; 3 represents– "neutral"; 4 represents– "agree"; and 5 represents– "strongly agree." The following variables were used in the questionnaire: performance expectancy, effort expectancy, social influence, facilitating conditions, behavioral intention to use IoT, and use of IoT in higher educational institutions.

A simple random sampling process was used to sample the population and 250 respondents completed the questionnaire accurately. The use of gatekeepers facilitated the questionnaire distribution at the universities and colleges. The respondents were selected randomly from some tertiary institutions such as research universities, technical and vocational education, and training (TVET) colleges, technological universities, private institutions, and other universities.

3.2 Data analysis method

A statistical package, IBM SPSSv25.0, was used as the tool for data analysis. Item analysis was conducted to access the reliability of the constructs. Construct and discriminant analysis were used to perform the validity of the constructs. Exploratory factor analysis (EFA) and regression analysis were used to predict the UTAUT factors.

4 RESULTS AND DISCUSSION

4.1 Respondent's demographics

The majority of responses came from the universities of technology (61.6%), followed by research universities (14.8%), and private institutions (14.4%). A significant number of participants were students (82.0%), while only 12.4% were lecturers. Regarding gender distribution, more female participants (61.6%) took part in the research, while 38.4% were males. Furthermore, most of the young participants were from the ICT department, and they were less than 35 years old.

4.2 Reliability analysis

The need to evaluate the questionnaire and the individual questions included in it is crucial based on the consistency of each question group supporting the individual variable, as well as pertinence of question selection [28]. The Cronbach's Alpha (σ) was used to evaluate data reliability. The Cronbach's Alpha values for all the variables were between 0.672 and 0.884 (see Table 1), which is within the acceptable threshold of 0.6 [28–30]. In two cases (PE and BI), the Cronbach's Alpha values were beyond 0.8, implying good reliability. Thus, the reliability of the constructs has been satisfied since their Cronbach's Alpha values are all greater than 0.7.

Table 1. Data reliability

Variable	Cronbach's Alpha (σ)
PE(B)	0.884
SI (C)	0.774
EE (D)	0.672
FC (E)	0.759
BI (F)	0.858
IoT Adoption by HEIs	0.796

4.3 Composite reliability and convergent validity analysis

Convergent validity analysis criteria have been proposed by Anderson and Gerbin [29] and also by Bagozzi and Yi [30], where they explain how confirmatory factor analysis evaluation criteria can be applied. In addition, Gefen et al. [31] propose goodness-of-fit indicators to assessment. The assessment standard comprises of the following criteria:

(a) The composite reliability of determinants should be greater than 0.7.
(b) The factor loadings of the variables in their respective fields should be significant.
(c) The average variance extracted (AVE) should be greater than 0.5.

However, Fornell and Larker [32] argue that if AVE is less than 0.5, but the composite reliability (CR) is higher than 0.6 [33], then the convergent validity of the construct is satisfied and still considered adequate. This implies that, for example, Social Influence has an AVE of 0.445 which is less than 0.5, but its CR is equal to 0.757, which is greater than 0.6. Therefore, convergent validity is satisfied for this construct. The same process applies to Effort Expectancy, Facilitating Conditions, and IoT adoption by higher educational institutions.

Furthermore, the study calculated the maximum shared variance (MSV) of each construct, the CR, the AVE, and the loading factors (LF) of all the items to evaluate and assess the convergent validity of the constructs. The results of these calculations are presented in Table 2.

The CR of all the determinants is above 0.6, and while some determinants have values of AVE that is less than 0.5, the convergent validity of the constructs have been satisfied. Each determinant's composite reliability CR falls between 0.719 and 0.843, exceeding the standard value of 0.7. The lowest permissible value of composite reliability CR of each construct is 0.5 [34], while the lowest permissible value of LF is 0.707 [35], and the lowest permissible value for AVE is 0.7 [36]. According to Fornell and Larker [32], the convergent validity of the construct is considered satisfied and adequate if the composite reliability CR is higher than 0.6, even if AVE is less than 0.5 [33]. The value of each MSV should be less than its corresponding value of AVE. By checking the estimated values in Table 2, it is evident that almost all the estimated values fall within the acceptable range. Therefore, this indicates that the constructs have convergent validity, and the items are reliable.

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

Items/Constructs	LF	AVE	CR	MSV
Performance Expectancy (B)		0.578	0.843	0.660
B1	0.748			
B2	0.855			
B3	0.808			
B4	0.606			
Social Influence (C)		0.445	0.757	0.299
C1	0.837			
C2	0.549			
C3	0.615			
C4	0.632			

(*Continued*)

Table 2. Estimation of AVE, LF, MSV, and CR (*Continued*)

Items/Constructs	LF	AVE	CR	MSV
Effort Expectancy (D)		0.392	0.719	0.360
D1	0.635			
D2	0.714			
D3	0.606			
D4	0.537			
Facilitating Conditions (E)		0.494	0.796	0.376
E1	0.695			
E2	0.695			
E3	0.685			
E4	0.736			
Behavioral Intention (F)		0.537	0.821	0.548
F1				
F2				
F3				
F4				
IoT Adoption by HEIs (G)		0.432	0.752	0.480
G1	0.648			
G2	0.682			
G3	0.691			
G4	0.604			

4.4 Multicollinearity and discriminant validity test

According to Gaski and Nevin [33], discriminant validity is considered satisfied if two criteria are met:

(1) The correlation coefficient between any two determinants is lower than 1.
(2) The correlation coefficient of the two determinants is lower than the individual Cronbach's Alpha reliability coefficient (σ). Additionally, Fornell and Larcker [32] proposse another criterion for discriminant validity:
(3) The correlation coefficient between any two determinants is less than the average variance (AV).

In Table 3 the estimation of the average variance AV, the Cronbach's Alpha (σ), and variance inflation factor (VIF) were computed.

As illustrated in Table 3, the correlation coefficient of the two determinants is less than the individual Cronbach's Alpha reliability coefficient. Additionally, the correlation coefficient between the two determinants is less than 1. Finally, the correlation coefficient of the two determinants is less than the AV. As a result, discriminant validity is confirmed for all the determinants. Moreover, when each item is strongly related to its own construct and weakly related to other constructs, discriminant validity is considered confirmed. The average variance AV of each construct must be calculated to test discriminant validity. The AV is calculated from computing the square root of the corresponding AVE. Then, the discriminant validity is determined if the AV of each construct is greater than the correlation coefficients of that construct with other constructs [37]. According to Table 4, the value of all the AVs of the constructs in the ninth column exceeds the corresponding correlation coefficients shown in off-diagonal places. Consequently, discriminant validity is established for all the constructs [32].

When the inner meanings of the constructs become very close to each other, it may lead to a multicollinearity defect. Therefore, the VIF needs to be calculated for each construct. The maximum acceptable value of VIF is 5 [38], although Hair et al. [39] suggest that the maximum acceptable value of VIF is 10. In this case, the values of VIF for all constructs are in the range of 1.506 to 2.826, indicating that the data is free from multicollinearity defect.

Table 3. Assessment of cronbach's alpha, AV and VIF (discriminant validity test)

	TransB	TransC	TransD	TransE	TransF	AV	σ	VIF
TransB	0.489					0.760	0.884	1.506
TransC	0.548	0.532				0.667	0.778	1.976
TransD	0.702	0.440	0.537			0.626	0.672	2.826
TransE	0.578	0.383	0.430	0.632		0.703	0.759	1.949
TransF	0.739	0.469	0.611	0.675	0.465	0.732	0.858	2.516

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

4.5 Factor analysis

The Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy and Bartlett's Test of Sphericity were conducted to assess the suitability of the respondent data for factor analysis. A KMO value of 0.5 is suitable for factor analysis [39] [40]. Additionally, for factor analysis to be appropriate, there is a need for Bartlett's Test of Sphericity to be significant ($p < 0.05$) [39] [40]. In Table 4, the KMO and Bartlett's test of sphericity values for this study are presented. From Table 5, the KMO value is 0.788 (i.e., KMO > 0.50), thus indicating that the data is suitable for factor analysis. Moreover, the Bartlett's test of sphericity χ^2 (276) = 4642.394, $\rho < 0.05$ [$\rho = 0.000$] shows that the items did not exhibit patterned relationships between them.

Table 4. Kaiser-Meyer-Olkin and Bartlett's test of Sphericity

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		.788
Bartlett's Test of Sphericity	Approx. Chi-Square	4642.394
	df	276
	Sig.	.000

4.6 Multiple linear regression

The summary of the first regression model is presented in Table 5. The adjusted R-square value is 0.561, which indicates that the following variables: performance expectancy, social influence, and effort expectancy collectively predict 56.1% in behavioral intention. In Table 5, the R-square value of the regression model in this study is 0.567.

Table 5. Summary of the first regression model

Model Summary[b]									
Model	R	R-Square	Adjusted R-Square	Std. Error of the Estimate	Change Statistics				
					R-Square Change	F Change	df1	df2	Sig. F Change
1	.753[a]	.567	.561	.53200	.567	96.698	4	295	.000

Notes: [a]Predictors: (Constant), TransE, TransC, TransB, TransD; [b]Dependent Variable: TransF.

Table 6 depicts the summary of the second regression model for the study.

Table 6. 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	.792	.628	.626	.495	.628	.000

To estimate the probability of the event occurring by chance, the P-value (or the calculated probability) is used under the assumption that the null hypothesis is true [41]. The P-value is a numerical between 0 and 1 and is used to either accept or reject the null hypothesis. It is a method to assess the variation between a particular dataset and a proposed model for the data [42].

From Table 6, the variable "behavioral intention" predicts 62.8% for the IoT usage in HEIs because the R-square value of the second regression model in this study is 0.628, and the adjusted R-square value is 0.626.

In Table 7, which represents the first regression table, the P-values of all the variables are as follows: performance expectance is 0.003, social influence is 0.000, effort expectancy is 0.000, and facilitating conditions is 0.456. These results show that only three out of the four variables contribute meaningfully to the prediction of behavioral intention to use IoT. These variables are social influence, performance expectancy, and effort expectancy. Their P-values are less than the maximum threshold of 0.05.

The variable with the highest contribution towards the prediction of behavioral intention to use IoT is effort expectancy. The unstandardized coefficients of the variable (beta value) of effort expectancy is 49.9%, indicating that it has the highest impact among the variables considered in the regression model. Therefore, effort expectancy plays a crucial role in predicting behavioral intention to use IoT in this study.

Table 7. Contribution of individual constructs (first regression table)

Model		Unstandardized Coefficients[a]		Standardized Coefficients[a]	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.142	.184		.771	.441
	TransB	.159	.053	.160	2.978	.003
	TransC	.248	.059	.226	4.165	.000
	TransD	.499	.072	.431	6.907	.000
	TransE	.045	.060	.044	.747	.456

Note: [a]Dependent Variable: Behavioral Intention (TransF).

Table 8. Contribution of individual constructs (second regression table)

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

Note: [a]Dependent Variable: IoT Adoption by HEIs (TransG).

Table 8 reveals that Behavioral intension contributes to IoT adoption by HEIs.

4.7 The evaluation of the hypotheses

The hypothesis testing outline from the two regression models is shown in Table 9. Anaesth [41] states that if the P value is < 0.01, then the result is highly significant and the null hypothesis should be rejected. Furthermore, if the P value is ≥ 0.01 but the P value is < 0.05, then the result is said to be significant, and the null hypothesis should be rejected. Also, if the P value is ≥ 0.05, then the result is said to be not significant and the null hypothesis should not be rejected. In Table 9, based on Anaesth's clarification of the P value [41], only 4 out of the 5 hypotheses (namely, H_1, H_2, H_3, and H_5) are supported. H_4 is not supported, as indicated in Table 9.

Table 9. Hypothesis testing outline

Hypothesis Symbols	Hypothesis	Beta(β)	*P* –Values	Is *P* < 0.05?	Remarks
H_1	PE → BI	0.090	0.003	Yes	Supported
H_2	SI → BI	0.350	0.000	Yes	Supported
H_3	EE → BI	0.435	0.000	Yes	Supported
H_4	FC → BI	0.036	0.456	No	Not Supported
H_5	BI → IoT Adoption by HEIs	0.792	0.000	Yes	Supported

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

4.8 The final resulting model

The final resulting model is shown in Figure 2 and it is based on the four hypotheses.

H_1: Performance expectancy is positively influenced by the behavioral intension to use IoT in universities.

As indicated in Figure 2, 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 (β = 0.090, P-value < 0.05) with a P-value of 0.003 which is less than the ceiling of 0.05 and thus hypothesis H1is therefore supported.

H_2: Social influence is positively influenced by the behavioral intension to use IoT in universities.

As shown in Figure 2, the second hypothesis (H_2) of the study predicted a positive relationship between the social influence and behavioral intension to use IoT in universities. It is significant (β = 0.350, P-value < 0.05) with a P-value of 0.000 which is below the ceiling of 0.05 and thus hypothesis H_2 is therefore supported.

H_3: Effort expectancy is positively influenced on the behavioral intension to use IoT in universities.

As illustrated in Figure 2, the third hypothesis (H_3) of the study predicted a positive relationship between the effort expectancy and behavioral intension to use IoT in universities. It is significant (β = 0.435, P-value < 0.05) with a P-value of 0.000 which is below the ceiling of 0.05 and thus hypothesis H_3 is therefore supported.

H_5: Behavioral intention is positively influenced by the use of IoT in higher educational institutions.

As shown in Figure 2, the fifth hypothesis (H_5) of the study predicted a positive relationship between the behavioral intention and the use of IoT in universities. It is significant (β = 0.792, P-value < 0.05) with a P-value of 0.000 which is below the ceiling of 0.05 and thus hypothesis H_5 is therefore supported.

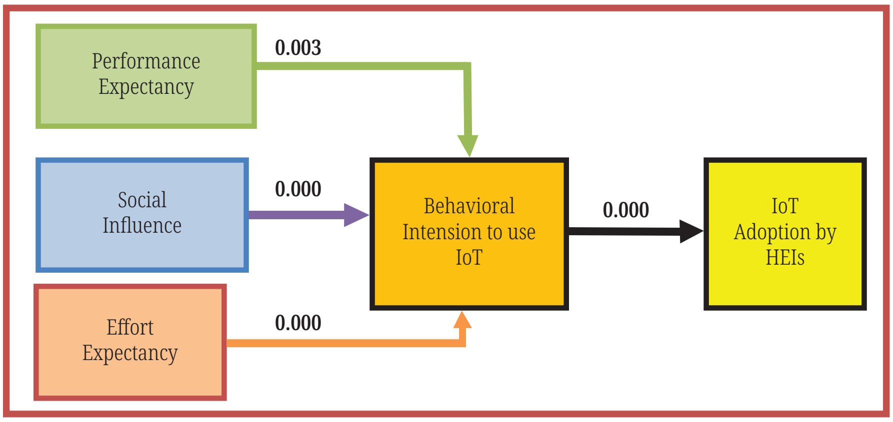

Fig. 2. The model for the acceptance and usage of IoT in higher educational institutions

4.9 Effects of removing facilitating conditions (TransE) variable

Table 10 shows the effect of removing facilitating conditions (TransE) variable.

Table 10. Effects of removing facilitating conditions (TransE) on contributions of individual constructs

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.157	.183		.857	.392
	TransB	.166	.052	.168	3.178	.002
	TransC	.253	.059	.231	4.286	.000
	TransD	.528	.062	.456	8.576	.000

If the Facilitating Conditions (TransE) is removed, then this results in performance expectancy (TransB), social influence (TransC), and effort expectancy (TransD) to be significant and predict behavioral intension and all these variables will all be part of the model since their *P*-value is less than 0.5.

Table 11 shows the effects of the model summary when Trans E is removed.

Table 11. Effects of the model summary when Trans E is removed

Model Summary[b]									
Model	R	R-Square	Adjusted R-Square	Std. Error of the Estimate	Change Statistics				
					R-Square Change	F Change	df1	df2	Sig. F Change
1	.753[a]	.566	.562	.53160	.566	128.938	3	296	.000

Notes: [a]Predictors: (Constant), TransD, TransB, TransC; [b]Dependent Variable: TransF.

In Table 11, the adjusted R-square is 0.562 which implies that the variables performance expectancy (TransB), social influence (TransC), and effort expectancy (TransD) collectively predict 56.2% for the behavioral intention. Their R-square is 56.6%. This implies that the variables predicted 56.2% (0.562) which is more than when Trans E was not removed with the prediction of 56.1% (0.561) by 0.1%.

5 CONCLUSION

This study developed a model by investigating empirically the determinants positively influencing the behavioral intention to adopt IoT and the usage and acceptance of IoT in HEIs. The results obtained in this study were in strong accord with other previous studies in the literature.

To this end, data was collected from 250 respondents from universities and colleges of higher education. The results indicated that the model had reliability and internal consistency, an indication that the proposed model possessed explanatory power. The findings of this study revealed that performance expectancy, social influence, and effort expectancy had a positive influence on behavioral intention to adopt IoT, with effort expectancy indicating the strongest significant impact. However, facilitating conditions do not have any significant effect.

The study further revealed that social influence has a positive influence on behavioral intentions, thus indicating that individuals tend to use new technologies due to finding out that other people around them are also using the same technologies. Prior studies [43] [44] had identified social influence as an important determinant during technology adoption and utilization.

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7 APPENDIX A: QUESTIONNAIRE ITEMS

Table A1. Questionnaire with authors

Factors/Authors	Question Identifiers	Questions
Performance Expectancy ([22]; [33])	B1	Do you think employing the Internet of Things (IoT) applications will lead the change and reform the higher education institutions in South Africa?
	B2	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?
	B3	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?
	B4	Do you think it will be possible to eliminate human biasness and aforementioned flaws for accessing student capabilities by employing IoT?

(*Continued*)

Table A1. Questionnaire with authors (*Continued*)

Factors/Authors	Question Identifiers	Questions
Social Influence ([22]; [33–35])	C1	The information that you have regarding IoT, is enough to employ or start using the IoT technology?
	C2	Do you think the consumer's social network has a positive influence on trust towards IoT technology adoption?
	C3	Is the user's intention to use the IoT technology influenced by their beliefs about it?
	C4	Through social image, do you believe that using the IoT technology will improve the student's performance within the institution?
Effort Expectancy ([22]; [36–38])	D1	Do you think it will be easier for lecturers/facilitators to capture learner's attendance and marks by using IoT technologies?
	D2	Do you think educational policy change can easily be performed by IoT?
	D3	Do you think the implementation of IoT technologies can easily help with and be the powerful mechanism for learning foreign languages in institutions?
	D4	Do you think that IoT can eliminate the struggle of understanding lessons during lectures?
Facilitating conditions ([22]; [39–41])	E1	Users with increased facilitating conditions will be more willing to use specific technology.
	E2	IoT has the ability to optimize the classroom learning environment.
	E3	Many students and administrators are already carrying, every day, very powerful IoT devices in a form of mobile devices.
	E4	By employing some elements of gamification, the institution can reward students digitally for engaging and for completing tasks on time.
Behavioural Intention ([32]; [42])	F1	Consumer trust of IoT technologies and services providers is believed to play a vital role in behavioural intentions.
	F2	When the use of IoT technologies can bring fun and pleasure, will the students and lecturers be intrinsically motivated to adopt them.
	F3	For IoT users to adopt IoT, they need to feel that IoT is easy to use.
	F4	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 ([43–45])	G1	IoT technologies are used in my university.
	G2	IoT technologies are better utilized in universities.
	G3	Universities will derive competitive advantage by using IoT technologies.
	G4	IoT technologies have made universities to become efficient in bringing good quality to education.
	G5	IoT technologies are very vitally important for the success of universities.

8 AUTHOR

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