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Developing and Validating a Model for the Adoption of Internet of Things Based Smart Building

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***Abstract*— Buildings are key contributors to climate warning that is very detrimental to the health of the fragile earth that we live in. The climate change needs to be curbed through reduced global warming and since buildings are key contributors of green gas emissions, that's the right place to start as it is cost effective. The arrival of M2M (Machine to Machine), IoT (Internet of Things), AEP (Application Enablement Platform) technologies that are able to interconnect sensors attached to devices in a building and intelligently, monitor the building is a solution to energy efficient smart buildings. The goal of this study is to develop a model for successful Adoption of Internet of Things Based Smart Energy Building. The study contributes to the widening debate about how the transformation of energy efficient buildings in cities responds to the changing smart technologies and climate change.The developed model was validated through partial least squares Structural Equation Modeling (SEM). The quality of both levels defined in -SEM analysis, i.e., the measurement model and the structural model, were assessed on performance measures defined in literature using data collected from national Construction Authority. According to the findings, the study recommends that Internet of Things smart building technologies area necessity for energy efficiency which, if adopted en-mass by an enforceable legal framework, could lead to significant improvement in the adoption rate of Smart Building in Kenya resulting in reduced global warming.**

***Index Terms*— Climate Change, Energy efficiency, Global Warming, Internet of Things, Smart Buildings, Model, Validation.**

I. Introduction

Climate change is real, and it is already happening. ICTs are becoming ubiquitous throughout the society. Given the momentous gains that ICT and Internet have achieved in the few decades it has been in existence, it's only imperative that ICT professionals urgently search for a concrete solution to counter global warming disaster that is waiting to wipe out the entire face of the earth. Most of the global changes on earth have been analyzed and a number of indirect measures of climate such as ice cores, tree rings, glacier lengths, heat waves, pollen remains and ocean sediments and by studying changes in Earth's orbit around the sun indicate that all is not well worldwide. One of the applications of ICT is in smart technologies associated with smart buildings. Buildings offer the most cost-effective mitigation potential, and the reason why the sector has become a focus for climate change policy-makers.

Smart buildings are a bleeding edge technology integration movement in the built environment. Based on the growing development of cloud computing and data management, a smart building links together multiple data sources, inputs, and user types into a cloud of useful information to create a more efficient, effective and engaging workplace [1].

A fully integrated smart building connects this data to allow previously disparate systems and users to engage with the built environment in new and more effective ways. Appropriately deployed, a 'smart' building should become more efficient over time, continuously engaging the workforce and ultimately helping to reduce operational costs and increase occupant wellbeing and productivity [1].

The construction industry has been there from time immemorial and yet the technologies to help the industry to automate most of their operations has not been forthcoming until just few years ago, thanks to the arrival of M2M (Machine to Machine), IoT (Internet of Things), AEP (Application Enablement Platform) technologies that are able to interconnect sensors attached to devices in a building and intelligently, monitor the building operations with ability to generate renewable power and conserve any unused power thus yield energy efficient smart buildings. The construction industry is a pillar and a fundamental enabler of Kenya's vision 2030. There is a serious need for developing an optimized solution of sustainability and intelligence in buildings that will help the agenda of living in a healthy, comfortable and technologically advanced world. Energy security is one of the main concerns of the future in the world today. The rapidly growing world energy use has already raised concerns over supply difficulties, exhaustion of energy resources and heavy negative environmental impacts (ozone layer depletion, global warming, climate change, etc.). Today, climate changes real-time effects are vivid in every corner of the world and now it's absolute for everyone to have a conversation about it. To most people, climate change doesn't matter to them. The global contribution from buildings towards energy consumption, both residential and commercial, has steadily increased reaching figures between 20% and 40% in developed countries, and has exceeded the other major sectors such as industrial and transportation, creating immense energy and climatic change crisis [2].

National government and County legislations are laws that govern the country at large. If you consider all these laws, very little is mentioned on Smart energy efficient building technologies. The government of Kenya is striving to put in place appropriate legislation, policies and strategies to increase the resilience and safety of the built environment. Well-designed and locally specific building regulations are central to this effort: building regulations translate safe practices for design and construction into a set of rules and

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laws which govern and specify minimum agreed levels of safety and resilience for buildings.

In this study it is envisaged that Perceived value will be affected by both perceived benefit and perceived sacrifice. In particular, perceived benefit and perceived fee is expected to have a strong positive effect on perceived value. The objective of this study was to develop an acceptance model using VAM (Value-based Adoption Model) tailored to the goals of this research by utilizing the peripheral cues of TAM (Technology Adoption Model) and ELM (Elaboration Likelihood Model) in order to identify the factors that affect the adoption of smart building technologies. The study is significant to the researchers who will reference it in their research work and also to the government and built industry agencies that will get to know how well to design and develop energy efficient smart buildings.The other significance is to the built industry as it needs a way of streamlining the Industry so as to deliver value to the millions of clients who need buildings every year.

A. *Study Objective*

The objective of the study was to develop and validate a model for adoption of internet of things based smart energy building

B. ***Research Question***

What is the Validity of the Model for Adoption of Internet of Things Based Smart Energy Building?

II. LITERATURE REVIEW

The study considers four theories to help formulate the adoption model; Theory of Reasoned Action, Technology Acceptance Theory, Value-Based Adoption Model and Elaboration Likelihood Model (ELM) [3],extended the conception of earlier customer value by not only considering functional value (quality and monetary) but five aspects including: functional value, social value, emotional value, epistemic value and conditional value.[4]omitted attitude in his final TAM. Empirical studies have found that attitude did not influence intention directly. [4]has posited that perceived usefulness and perceived ease of use together determined an individual's attitude towards using a technology.In measuring the mobile internet adoption, [5] adopts the benefits and costs conceptualisation and proposed value-based model of mobile internet adoption. However, [5] criticized that the adoption behavior in TAM was only represented by two factors: usefulness and ease of use (without attitude). Attitude is important for adoption of Smart Building today.The Theory or Reasoned Action is developed for explaining a situation specific in adoption of technology introduced TAM as an adaptation of TRA. Technology Adoption Model (TAM) is considered as one of the most widely applied technology adoption models in the information technology since its known for its being parsimonious (particularly economical to apply) . TAM is specifically developed to explain acceptance in information technology adoption[4].It is argued as a general model in predicting individual's behavioural action, and thus not specific enough to explain particular behavior such as new ICT or mobile internet context.Value-Based Adoption Model (VAM) proposed by [5] claimed that the previous TAM proposed by [4],was limited in explaining the acceptance of new ICT, and that new ICT users should not be recognised as simply technology users, but also as 'consumers'. Considering the importance of attitude aspect, suggest that attitude should be considered in the adoption model of mobile internet. VAM was developed to overcome the weaknesses of TAM model in explaining new ICT adoption such as mobile internet. By considering value maximization, VAM offers a simple and straightforward model in predicting mobile internet adoption. VAM is built on two basic construct to represent perceived value namely benefits and sacrifices. The benefits include usefulness and enjoyment, while sacrifice covers technicality and perceived fee. VAM aims to explain the adoption of technology based on in order to overcome the limits of TAM in a new ICT environment. Dimensions of VAM are benefits (usefulness and enjoyment) and sacrifice (technicality and perceived fee) which are so crucial in any technology adoption.Elaboration Likelihood Model, developed by[6]is a dual process theory describing the way people accept and process information.

Table 1: Summary of Theories

Theory	Summary	Key Constructs
Theoryof Reasoned Action	Perceived value is a new construct that has gained interest after service quality and satisfaction have been questioned regarding their influence on customer behaviour intentions.	Attitudes and Behaviours within human action.
Technology Adoption Model	Theory emphasizes one's behavioural intention, in which actual behavior is determined by the behavioural intention.	Perceived ease of use and Perceived usefulness
Value-Based Adoption Model	It is based on a cost – benefit paradigm which reflects the decision-making process where the decision to use is made by comparing the cost of uncertainty in choosing a new technology or product	Perceived value namely benefits (usefulness and enjoyment) and Sacrifices (technicality and perceived fee)
Elaboration Likelihood Model	People using the central route will carefully review new information and consider its merits and weaknesses, and significance. On the other hand, the peripheral route offers away to quickly accept or refuse a piece of information without active thinking.	Central Route and Peripheral Route

III. METHODOLOGY

The target population consisted of 244 technical staff members of National Construction Authority (NCA) and 17,593 registered contractors by the National Construction Authority, according to the registers maintained by the authority as at 31st December 2015. NCA is a critical player in the Kenyan built industry for improvement of the building codes approved for use in the built environment that yield efficiency and effective service delivery

For this study, multistage sampling procedure was adopted whereby; one hundred and eighteen (118) respondents out of the total 244 NCA technical staff members and 232 out of 17,593 NCA registered contractors will be selected using sample size formula below, which will represent various staff specializations in the National Construction Authority and Contractors.

A. Sample Size Formula

i) $$ss = \frac{Z^2 * (p) * (1-p)}{c^2}$$

Where:

Z = Z value (e.g. 1.96 for 95% confidence level) p = percentage picking a choice, expressed as decimal; (.5 used for sample size needed) c = confidence interval, expressed as decimal; (e.g., .04 = ±4)

(Survey Systems, 2019)

B. CORRECTION FOR FINITE POPULATION

ii) $$\text{new ss} = \frac{ss}{1 + \frac{ss-1}{pop}}$$

Where: pop = population

(Survey Systems, 2019)

Stratified and simple random sampling was then used to select the registered contractors whereby; according to Green (1991) n>50+8m (where m is the number of independent variables) needed for testing multiple correlation and n>104+m for testing individual predictors. These sample size suggestions are based on detecting a medium effect size (β >= .20), with critical α <= .05, with power of 80%. Consequently, two hundred and thirty two (232) respondents were selected from the total 17,593 registered contractors by NCA, from eight stratum based on which part of Kenya most of the contractor's work projects were undertaken in the last 5 years. The strata included: Nairobi, Central, Eastern, Coast, Western, North Eastern, Rift Valley and Nyanza. The study's sample size was therefore three hundred and fifty (350).To address validity, the research design ensured both internal and external validity. The mixed qualitative and quantitative data analysis process was relevant to the type of data collected and ensured that the conclusions are supported by the findings. The reliability was determined using Cronbach alpha (>0.7) while Validity was achieved using content and construct validity. The data collection methods including questionnaires, individual in-depth interviews and document review were used for triangulation of the findings. The review of literature also validated content and findings. For reliability, the data was collected in ways that ensured anonymity and encouraged free participation of the respondents. Names of participants were not recorded. The qualitative data analysis process was organized in the five steps as proposed by[7]. The steps include transcription, reliability analysis, coding, establishing themes and categories and writing up and interpreting results. Cronbach's alpha that provides a useful lower bound on reliability will be used. A commonly accepted rule of thumb is that an alpha of 0.7 (some say 0.6) indicates acceptable reliability and 0.8 or higher indicates good reliability. Very high reliability (0.95 or higher) is not necessarily desirable, as this indicates that the items may be entirely redundant.The data were analysed using Structural Equation Modeling (SEM). SEM is a technique which uses various types of models to depict relationships among observed variables with the goal of testing a theoretical model hypothesized by a researcher. In preparation of data for the analysis, the negatively worded items from the Institutional Integration Scales were reverse scored so all item responses reflected positive smart building integration. In addition, data were checked and screened for missing values, outliers, and normality distributions. Quantitative data was edited, coded and analyzed using the statistical package for social sciences (SPSS). In order to test the study's research questions, data analysis method based on Pearson correlation analysis and a multiple regression model was also used.

C. DATA ANALYSIS

The data was run by Data cleaning, deriving of latent variables from observable variables which were later used in achieving study objectives with aid of STATA and SPSS. Data was analyzed using both descriptive and inferential statistics. Descriptive statistics comprised of mean and standard deviation. Standard deviation shows how far the distribution is from the mean. Mean is a measure of central tendency used to describe the most typical value in a set of values. This was achieved using SPSS and it was conducted for each of observable variable which was later used to find latent variables score. The study had three measured or observable variables; -Factors/Determinants, Internet of Things-Application Enablement Platform Components & Capabilities that influence the Adoption of Internet of Things Based Smart Energy Building.

With the descriptive variable, multiple linear regressions were conducted for the three latent variables in relation to dependent variable. The researchers were interested inestablishing the direct contribution of the Determinants, Enablement Platform Components and Capabilities on the influence of adoption. This was achieved through R square which is the coefficient of determination. This was conducted by adding 8 constructs for factors in the model, 8 constructs for Internet of Things – Application Enablement Platform components and 5 Internet of Things – Application Enablement Platform capabilities in the model. It should be remembered that each of constructs was derived from the observable variables.

The techniques used to run data were; SEM, Factor Analysis, Hierarchical Regression Analysis and MMR (Moderated Multiple Regressions). This was done using EFA (exploratory factor analysis) and CFA (Confirmatory Factor Analysis). Exploratory factor analysis identifies underlying factors and categorizes items that are closely related without considering any hypothesized priori model or theories. Under CFA, the observed variables are subjected factor analysis to verify that they belong to the latent variable that they are purported to be based on theoretical and empirical research. Unlike EFA, It is a verification technique of priori and hypothesised structures and relationships that are based on theoretical and empirical information.

Construct validity is confirmed by exploration of both convergent and discriminant validity. Convergent validity is a measure that confirms that the items that are meant to have relationships are actually related while discriminant validity gives a confirmation that items that are not meant to be related are actually not related. Convergent validity was measured by determining the average variances extracted (AVEs) from CFA. The exploration of discriminant validity involves the comparison of the AVEs and the squared multiple correlations. The data is said to exhibit discriminant validity if all the squared multiple correlations are less than the relative constructs AVE as was found in this study.

The second procedure was to make sure if the assumption of SEM have been met. Of importance was normality, multicollinearity, independence, Collinearity Statistics and Common method Variance. Common method variance normally occurs due to the use of the same survey participant (common source) to provide responses to the questionnaires for both the independent and dependent constructs being studied at the same time.

The third was Model Fit Indices thresholds. Model fit assessment is important in structural equation modeling to gauge how well the estimated model best fits the data. The choice of indices to assess in this study was based on coverage by ensuring that the examination of model fitness covered absolute fitness, incremental fitness and parsimony of fitness.

The next procedure was SEM on the Independent Variables. The model was fitted to achieve the objective of the study which was to identify factors, Internet of Things-Application Enablement Platform Components and Capabilities that influence the Adoption of Internet of Things Based Smart Energy Building.

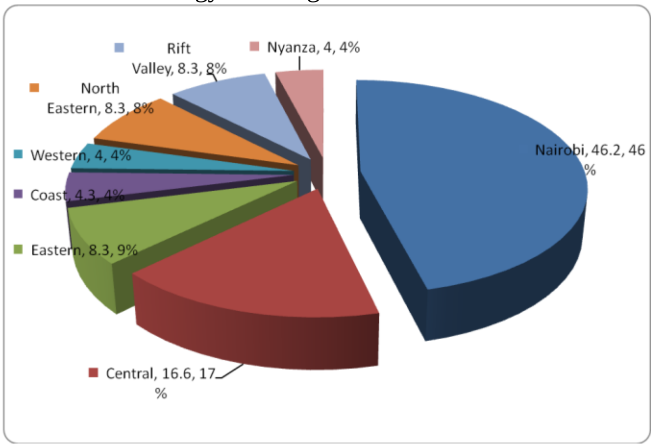

Fig. 1: Respondents' Region of majority Work Projects

This finding indicates that most of the respondents had undertaken majority of their work projects in Nairobi and Central Kenya regions. The finding is important for the study as reviewed literature pointed out that for the past decade; it has been observed that there have been an increasing number of developers considered adding "intelligence" to their buildings. The main stimulus for the development of smart buildings is that the building developers are more receptive to new technologies.

The statistics indicate that there are more building activities in regions of higher per-capita income and least in areas of low income i.e. Nairobi, Central Kenya favoured against the lake region and coast respectively that reports high and low per-capita income, [8].

This was achieved by testing hypothesized model using three regression analyses which were validated using SEM thereafter, based on the critical ratio (C.R) a suitable conceptual model for an Internet of Things Based Smart Energy Building in the World was developed.

Table 2: Coefficients for Determinant for Adoption of Internet of things

Model	Unstandardized Coefficients		Standardized Coefficients	T	Sig.
	B	Std. Error	Beta		
(Constant)	3.713	.565		6.574	.000
Awareness & Knowledge of Stake Holders	.169	.093	.091	1.815	.001
Relative Advantages	.161	.047	.171	3.464	.001
Perceived Fee	.421	.050	.468	8.502	.000
Building Codes	.105	.048	.110	2.174	.030
Technicality, Compatibility & Complexity	.404	.059	.350	6.852	.000
Perceived Usefulness & Enjoyment	.137	.054	.123	2.522	.012
Peer Firm Influence	.138	.070	.104	1.965	.050
Intention to use	.078	.034	.091	2.319	.035

Table 2 presents the findings on the contribution of each of the dimensions of determinants the values for the standardized coefficients. Focusing on the standardized coefficient column, out of eight factors dimension, only one had insignificant effect on the adoption of Internet of Things Based Smart Energy Building.

The largest beta coefficient was 0.421, which is coefficient perceived fee. This values is significant (β=.421, p=.000) and also positive. This means perceived fee has the strongest unique contribution to explaining the adoption of Internet of Things Based Smart Energy Building, when the variance explained by all other variables in the model is controlled for. The second largest beta coefficient was 0.404, which is coefficient value for Technicality, Compatibility & Complexity. This values is significant (β=.404, p=.000) and also positive. This means that Technicality, Compatibility & Complexity has the second strongest unique contribution to explaining the adoption of Internet of Things Based Smart Energy Building, when the variance explained by all other variables in the model is controlled.

Another variable that also had a unique significant contribution to the model was the value for Awareness and Knowledge of Stake Holders (β=.169, p=.001) and it was followed closely by relative advantage (β=.161, p=.001). Perceived Usefulness & Enjoyment also had using significant contribution to the model (β=.137, p=.012) while building code had least significant contribution to the model (β=.105, p=.030). The other variable, which is Peer Firm Influence (P=0.050) did not make statistically significant contribution to the model. This can be attributed to the overlap with the other independent variables in the model.

Table 3: Coefficients of Components

Model	Unstandardized Coefficients		Standardized Coefficients	T	Sig.
	B	Std. Error	Beta		
(Constant)	5.659	.688		8.228	.000
External Interfaces	.119	.067	.088	1.783	.076
Analytics	.391	.046	.393	8.426	.000
Additional Tools	.419	.073	.296	5.778	.000
Data Visualizations	.681	.095	.350	7.145	.000
Processing & Action Management	.631	.122	.262	5.186	.000
Device management	.752	.069	.536	10.936	.000
Connectivity &Normalization	.341	.052	.303	6.533	.000
Database	.090	.057	.081	1.572	.117

a. Dependent Variable: Adoption framework for internet of things based smart energy building

The largest beta coefficient was 0.752, which is coefficient of device management. This values is significant (β=.752, p=.000) and also positive. This means device management component has the strongest unique contribution to explaining the adoption of Internet of Things Based Smart Energy Building, when the variance explained by all other variables in the model is controlled. The second largest beta coefficient was 0.681, which is coefficient of Data Visualizations. This values is significant (β=.681, p=.000) and also positive. This means data visualizations component has the second strongest unique contribution to explaining the adoption of Internet of Things Based Smart Energy Building, when the variance explained by all other variables in the model is controlled. The third largest beta coefficient was 0.631, which is coefficient value for Processing &Action Management. This values is significant (β=.631, p=.000) and also positive. This implies that Processing & Action Management has the third strongest unique contribution to explaining the adoption of Internet of Things Based Smart Energy Building, when the variance explained by all other variables in the model is controlled.

Other variables that also had a unique significant contribution to the model were additional tools (β=.419, p=.000), analytics (β=.391, p=.001) and Connectivity &Normalization (β=.341, p=.001). However, database (P=0.117) and external interface (P=0.076) did not make statistically significant contribution to the model. This can be attributed to the overlap with the other independent variables in the model.

Table 4: Model Summary of influence of the components on the Adoption of Internet of Things Based Smart Energy Building

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	.719[a]	.517	.505	.871	.517	42.385	8	317	.000

a. Predictors: (Constant), EI, AN,AT,DV,PAM,DM,CH,DA (**E**xternal **I**nterfaces, **AN**alytics, **A**dditional **T**ools, **D**ata **V**isualizations, **P**rocessing and **A**ction **M**anagement, **D**evice **M**anagement, **C**onnectivity and **N**ormalization, **DA**ta)

Table 5: Coefficients of Capabilities

Model		Unstandardized Coefficients		Standardized Coefficients	T	Sig.
		B	Std. Error	Beta		
1	(Constant)	2.399	.298		8.065	.000
	Data Management	.320	.052	.320	6.138	.000
	Scripting Engine	.223	.058	.204	3.844	.000
	Integration Framework	.200	.060	.184	3.338	.001
	Software Development Kits	.099	.052	.102	1.911	.057
	Web Services	.058	.050	.058	1.159	.247

The largest beta coefficient was 0.320, which is coefficient of data management. This values is significant (β=.320, p=.000) and also positive. This means data management capabilities has the strongest unique contribution to explaining the adoption of Internet of Things Based Smart Energy Building, when the variance explained by all other variables in the model is controlled. The second largest beta coefficient was 0.223, which is coefficient of scripting engine. This values is significant (β=.223, p=.000) and also positive. This means scripting engine capabilities has the second strongest unique contribution to explaining the adoption of Internet of Things Based Smart Energy Building, when the variance explained by all other variables in the model is controlled. The third largest beta coefficient was 0.200, which is coefficient value for integration framework capabilities. This values is significant (β=.200, p=.001) and also positive. This implies that integration framework capabilities have the third strongest unique contribution to explaining the adoption of Internet of Things Based Smart Energy Building, when the variance explained by all other variables in the model is controlled.

The other variables, which is Software Development Kits (P=0.057) and web services (P=0.247) did not make statistically significant contribution to the model. This can be attributed to the overlap with the other independent variables in the model.

Table 6: KMO and Bartlett's Test

Test		Value
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.738
Bartlett's Test of Sphericity	Approx. Chi-Square	7196.994
	Df	435
	Sig.	0.000

The KMO value was found to be 0.738 which is a high figure that is close to 1 and acceptable. The Bartlett's test of sphericity is to test for a significant relationship among the observed indicators. A significant relationship is evident with the confirmation that the correlation matrix of the indicators is not an identity matrix which would be an indication of unrelated indicators. For the Bartlett's test in this study, the Chi-square statistic of the Bartlett's test was found to be 7196.994 with a p-value of 0.000. The p-value that is less than 0.05 is a confirmation at 0.05 level of significance that the correlation matrix of the indicators is not an identity matrix thus the indicators have an evident significance relationship as is expected for appropriate factor analysis. Further analysis of reliability and validity of the measurement model were carried out considering confirmatory factor analysis and measures of internal consistency.

Table 7: Internal consistency

Constructs	Cronbach alpha	Number Items	Status
Awareness and Knowledge	0.786	3	Reliable
Relative Advantages	0.764	4	Reliable
Perceived Fee	0.708	4	Reliable
Building Codes	0.819	3	Reliable
Technicality, Compatibility & Complexity	0.784	4	Reliable
Perceived Usefulness & Enjoyment	0.900	4	Reliable
Peer Firm Influence	0.750	4	Reliable
Intention to Use	0.777	3	Reliable
External Interfaces	0.793	4	Reliable
Analytics	0.832	4	Reliable
Additional Tools	0.844	4	Reliable
Data Visualizations	0.816	4	Reliable
Processing & Action Management	0.833	4	Reliable
Device management	0.777	4	Reliable
Connectivity &Normalization	0.880	4	Reliable
Database	0.867	4	Reliable
Data Management	0.722	4	Reliable
Scripting Engine	0.717	4	Reliable
Integration Framework	0.728	4	Reliable
Software Development Kits	0.899	4	Reliable
Web Services	0.812	4	Reliable

Reliability analysis of the data collected was carried out using Cronbach alpha measurement of internal consistency which found the data on all the constructs reliable with Cronbach alpha statistics above 0.7. Cronbach alpha ranges from 0 to 1 where values higher than one imply high reliability and values above 0.7 are considered acceptable.

Table 8: Confirmatory Factor Analysis

Item	AVE	Squared Multiple Correlation	Factor loadings				
			Determinants	Components	Capabilities	Policies and Regulations	Adoption
D1	0.770	0.382	0.763				
D2		0.288	0.720				
D3		0.686	0.815				
D4		0.602	0.846				
D5		0.697	0.806				
D6		0.438	0.745				
D7		0.499	0.788				
D8		0.768	0.675				
CO1	0.725	0.516		0.762			
CO2		0.383		0.722			
CO3		0.477		0.757			
CO		0.049		0.668			

4						
CO 5		0.455	0.834			
CO 6		0.160	0.575			
CO 7		0.490	0.758			
CO 8		0.356	0.720			
CA 1	0.810	0.049		0.804		
CA 2		0.455		0.827		
CA 3		0.160		0.818		
CA 4		0.490		0.785		
CA 5		0.356		0.818		
PR1	0.789	0.518			0.831	
PR2		0.590			0.721	
PR3		0.563			0.874	
PR4		0.556			0.839	
PR5		0.624			0.791	
PR6		0.535			0.731	
A1	0.779					0.750
A2		0.410				0.778
A3		0.723				0.792
A4		0.605				0.799
A5		0.570				0.821
A6		0.567				0.736

Confirmatory factor analysis CFA is adopted as a coherent part of SEM considering its use in verification of factor structure of a set of observed variables. It is a verification technique of priori and hypothesised structures and relationships that are based on theoretical and empirical information. Under CFA, the observed variables are subjected factor analysis to verify that they belong to the latent variable that they are purported to belong to be based on theoretical and empirical research. Under CFA, the observed items are expected to load the latent variable above 0.4.

D. MODEL OF INTERNET OF THINGS DETERMINANTS, COMPONENTS AND CAPABILITIES

Together with the determinants; Awareness and Knowledge of Smart Building Technology, Relative advantage, Perceived Fee, Building Codes, Technicality, Perceived Usefulness and Enjoyment, Peer Firm Influence and Intention to Use, IoT components and capabilities namely; External Interfaces, IoT Analytics, Additional Tools, Data Visualizations, Processing & Action Management, Device Management, Connectivity & Normalization, IoT Database, Data Management, Scripting Engine, Integration Framework, Software Development Kits and Web Services were found to be of importance for good adoption of smart building technologies which are as described in the Table. These are components which make internet of things possible; they help in integrating with existing IOT platforms. An Application Enablement Platform (AEP) is a technology-centric offering optimized to deliver a best-of-breed, industry-agnostic, extensible middleware core for building a set of interconnected or independent IoT solutions for customers. An Application Enablement Platform links Internet of Things devices and applications, delivering data to allow industrial enterprises to implement predictive maintenance, machine learning, factory automation, asset logistics, surveillance and many other applications [9].

The study developed the final model for successful adoption of Internet of Things Based Smart Energy Building follows;

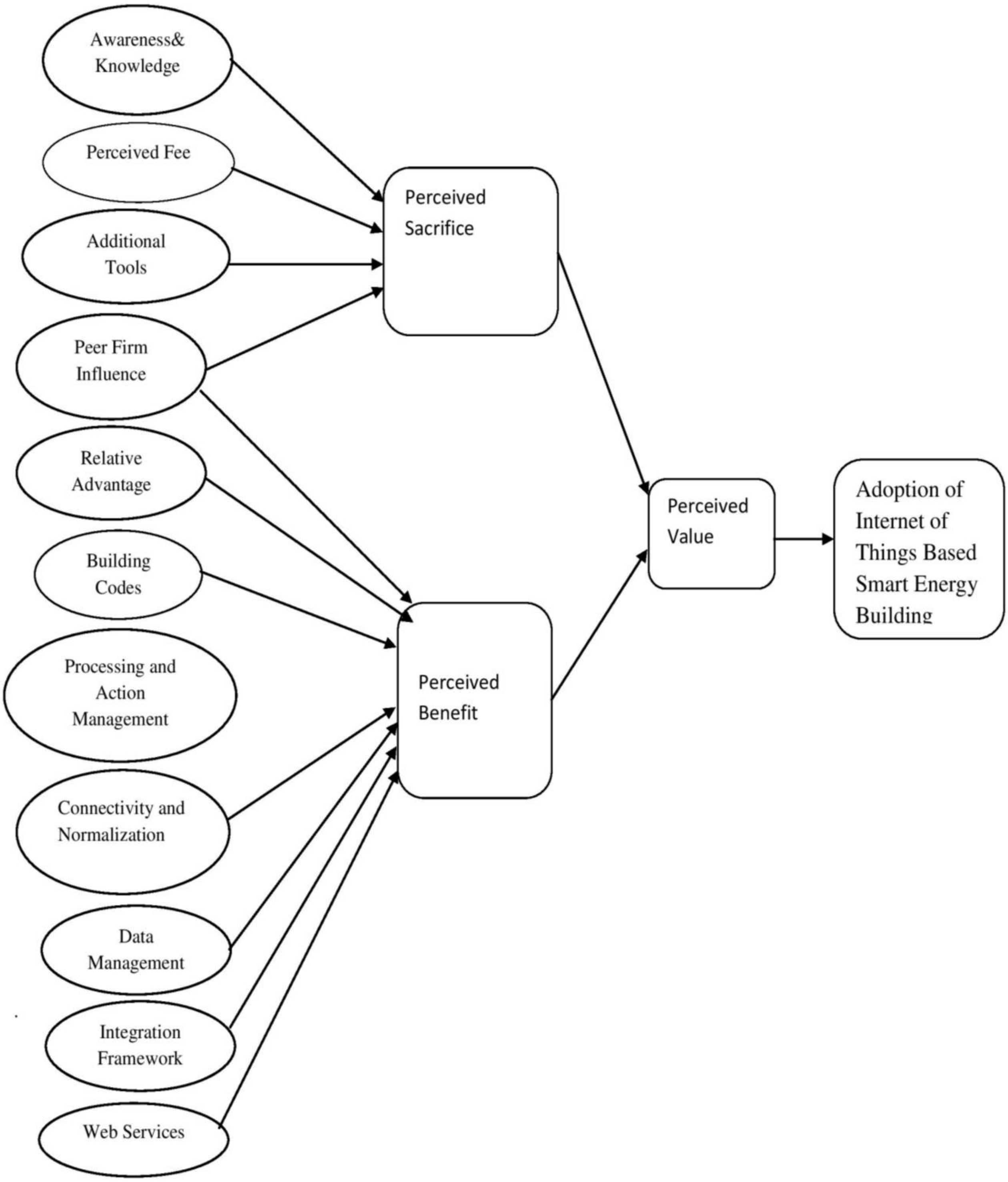

Fig. 2: The Refined Final Model for Successful Adoption of Internet of Things Based Smart Energy Building.

E. MODEL TESTING

This study verified the above variables by using partial least squares-structural equation modeling. In the verification, Pearson's correlation between the predictor variables overall hypotheses verification is used.

Table 9: Summary of Latent Variables Results using Regression

Latent Variables	Path	Estimate	Std. Error	T Value	P Value
		B	Std. Error		T
Know	Knowledge	-0.163	1.106	- 2.930	
RA	Relative advantages	0.725	0.066	13.100	0.004**

PF	Perceived fees	0.469	0.096	6.730	0.000*
LR	Legislative and Regulations	0.793	0.15	17.900	0.000*
TEC	Technicality	0.233	0.11	2.650	0.008*
PU	Perceived Usefulness	-0.032	1.120	0.419	0.676
USE-E	Usefulness and Enjoyment	-0.038	0.066	-0.460	0.646
PF	Peer firm influence	0.019	0.096	0.228	0.820
VS	Value Seeking	0.073	0.15	1.500	0.136

Source (Data Analysis, 2016)

First of all, perceived value was found to have a negative (2) relation with perceived sacrifice (b ¼ 21.63, t-value ¼ 22.930**). It had a positive (+) relation with perceived benefit (b ¼ 0.725, t-value ¼ 13.10***). In regard to perceived value, perceived sacrifice and perceived benefit had a high explanatory power of 75.3%. As a result, H1 and H2 are adopted, which supports the research by [5]and[10].As for intention to use, it had a positive (+) relation with perceived value (b ¼ 0.469, t-value ¼ 6.730***). Intention to use had a positive (+) relation with attitude (b ¼ 0.233, t-value ¼ 2.650**), but variety seeking had no effect on intention to use.

In regard to intention to use, perceived value, attitude, and variety seeking had an explanatory power of 45.4%. To summarise, H3 and H5 were adopted, but H6 was dismissed.In case of attitude, it had a positive (+) relation with perceived value (b ¼ 0.793, t-value ¼ 17.900***).Perceived value had an explanatory power of 54.6% regarding attitude, and thus H4was adopted. The hypotheses on variety seeking and intention to use (H6) and thatvariety seeking will have a moderating effect on each path in this research model (H7) were both dismissed. In the pilot test conducted prior to this study, variety seeking and intention to use had a strong relationship, but as the age of the sample grew higher, the role of variety seeking decreased. Although H6 was dismissed, the establishment of an additional tests found that perceived value acted as a full mediation for variety seeking and intention to use (Z ¼ 3.89, p-value ¼ .000, Test result: z-value ¼a*b / SQRT (b2*s2a+ a2*s2b; upon examining the path from variety seeking to perceived value, it was found that b ¼ 0.196 and t-value ¼ 4.750). This result shows that although variety seeking does not directly affect intention to use, it offers the possibility that it could act as a variable of wanting to substitute an old service with a new service through perceived value.

H1: Knowledge of Smart Building Technology will have significantly positive effect on intention to adopt Smart Building Technology H2. Knowledge of adopting Smart Building Technology was measured with three observable variables, T1 and T2 and T3. The variable T1 accounted for 0.27 (27%) of the overall model structure, it had the strongest path estimate compared to T2 and T3. T2. Relative advantage was measured with four observable variables P1 and P2 and P3 and P4 accounted 0.10, 10% of the overall structure of the model, while the least was P3 accounted 0.20 and P4 accounted for 0.107 which is 10.7% of the overall structure model,, Fees=Perceived Fees as latent variables was measured with four observable variables, C1 and C2 and C3 and C4. Perceived Fees had 4 indicators (P1 - overall structure 30%, P2 - overall structure 10 %, path estimate 0, P3 – overall structure 10%, estimate 0.24 and P4 overall structure 10% path estimate of 0.21), Tech=Technicality was measured with three observable variables which are (S1 - overall structure 21%, S2 - overall structure 26%, S3 path estimate of 25%. Tech=Technicality was measured with four observable variables which are (C1 - overall structure 21%, C2 - overall structure 26%, C3 path estimate of 25% AND C4 a path of 25%), Usefulness had 2 indicators (P1, path estimate of 30% path estimate 0.77 while P2 has a path estimate of 9.7.0% and P3 has path estimate of 24% path estimate 0.71. Peer influence=Peer Influence was measured with three observable variables which are E1has path estimate of 24%, E2 with path estimate of 30% and E3 with path estimate of 36%. Regulations = Building Codes had latent variables measured with two observable variables namely B1 path estimate of 30% and B2 with path estimate of 30% again. Lastly, Top management = Top management has latent variables as measured with four observable variables, D1, D2, D3 and D4. Top management had four indicators (D1 – overall structure 15%, D2 overall structure 10%, D3 overall structure 20% and D4 overall structure 20%). The estimated path coefficients are given along with the standardized regression weights. Overall, the fit statistics indicated a moderate fit between the data and the theoretical model.

F. MODEL VALIDATION

Based on separate models from the literature we developed a new theoretical model describing the underlying concepts of the adoption of structured and standardised recording. Using a questionnaire built upon this model we gathered data to perform a summative validation of model for adoption of internet of things based smart building. Validation was done through partial least squares structural equation modeling (SEM). The quality of both levels defined in -SEM analysis, i.e., the measurement model and the structural model, were assessed on performance measures defined in literature. Based on separate models from the literature we developed a new theoretical model describing the underlying concepts of the adoption of structured and standardised recording. Using a questionnaire built upon this model we gathered data to perform a summative validation model for adoption of internet of things based smart building. Validation was done through partial least squares structural equation modeling (PLS-SEM). The quality of both levels defined in PLS-SEM analysis, i.e., the measurement model and the structural model, were assessed on performance measures defined in literature.

Table 10: Goodness of fit thresholds

Index	Desired (good fit) Cut-off/ Thresholds
Chi-square	p-value <0.05
NFI	≥0.9
CFI	≥0.9
GFI	≥0.9
SRMR	≤0.08
RMSEA	≤0.08
PGFI	≥0.5
PNFI	≥0.5

Model fit assessment is important in structural equation modeling to gauge how well the estimated model best fits the data. The choice of indices to assess in this study was based on coverage by ensuring that the examination of model fitness covered absolute fitness, incremental fitness and parsimony of fitness. Absolute fit indices are used to test how well the priori (hypothesised) model fits the sample data and include the Chi-Squared test, RMSEA, GFI, AGFI, the RMR and the SRMR. The recommended cut-off of the GFI requires values above 0.9. The NFI is a measure of goodness of fit that compares the model chi-square to that of the null model and has recommended values above 0.9 for adequacy. The CFI also have recommendations of values above 0.9 and is a measure which is a revision of the NFI to take the sample size into account.

Model fit assessment is important in structural equation modeling to gauge how well the estimated model best fits the data. It is essential to test for model fitness since the assessment of how a specified model fits the data is one of the most important steps in SEM. There is abundance in available fit indices and a wide disparity in agreement on which indices to report the cut-offs for the various indices. The choice of indices to assess in this study was based on coverage by ensuring that the examination of model fitness covered absolute fitness, incremental fitness and parsimony of fitness.

Absolute fit indices determine how well *a priori* model fits the sample data[11], and show which of the models have the best fit and include the Chi-Squared test, RMSEA (Root Mean Square Error of Approximation), GFI (Goodness of fit index), AGFI (Adjusted GFI), the RMR (Room Mean Square) and the SRMR (Root Mean Squared Residual). They demonstrate how well the model fits in comparison to no model at all [12]. A chi-square test is the most common fit measure, but it is only recommended with moderate samples of 100 to 200, [13]. Absolute fit indices do not rely on comparison to any baseline model but are measures of model fitness without comparison [12]. Absolute fitness considered the assessment of the Chi-Squared, RMSEA, GFI, and the SRMR. The cut-offs used are based on empirical uses. Chi-Square test is the traditional measure goodness of fit and is used to assess the discrepancy between the sample and fitted covariances,[14], where a good fit would be reflected by a significant Chi-square at 0.05 level of significance with a p-value less than 0.05. The Goodness of fit index (GFI) which is considered an alternative to the Chi-square is a value of the proportion of variance that the estimated population covariance accounts for. The recommended cut-off of the GFI requires values above 0.9. The RMR is calculated as the square root of the difference between the residuals and the hypothesized model's covariance matrix. Interpretation of the RMR is made difficult where the collection instrument considers varying number of items per construct, a problem addressed by assessing the standardized root mean squared residual (SRMR) instead. According Hoyle, SRMR values ≤ .08 reflects an adequate fit.

To assess incremental fitness, the study considered the normed fit index (NFI) and the comparative fit index (CFI) whose cut-offs also required values above 0.9. Incremental fit indices, also known as comparative [15], or relative fit indices [11], are a group of indices that do not use the chi-square in its raw form but compare the chi-square value to a baseline model. For these models the null hypothesis is that all variables are uncorrelated. The NFI is a measure of goodness of fit that compares the model chi-square to that of the null model and has recommended values above 0.9 for adequacy[16].The CFI also have recommendations of values above 0.9 and is a measure which is a revision of the NFI to take the sample size into account.

The average ability for the model to fit diverse data patterns referred to as model fitting propensity (FP) are accounted for by adjusted Parsimony fit indices that are goodness of fit indices. The study considered the Parsimony Goodness-of-Fit Index (PGFI) and the Parsimonious Normed Fit Index (PNFI) which covered parsimony of both absolute and comparative fitness. The cut-off for the parsimony fitness were set at 0.5 as it is noted for possibility to obtain parsimony fit indices within the .50 with other goodness of fit indices being over .90.

Table 11: Goodness of Fit Thresholds

Index	Desired (good fit) Cut-off/ Thresholds
Chi-square	p-value <0.05
NFI	≥0.9
CFI	≥0.9
GFI	≥0.9
SRMR	≤0.08
RMSEA	≤0.08
PGFI	≥0.5
PNFI	≥0.5

Model 2: SEM with Policies and Regulations as a Predictor

The study also sought to determine the moderating effect of policies and regulations. A structural equation model was fitted including policies and regulations as a predictor in the model via additive. This model would determine the direct effect that policies and regulations have on adoption of Internet of Things Based Smart Energy Building. The fitted model was also tested for goodness against the set cut-offs as shown in table 12.

Table 12: Goodness of Fit Test for Model 2

Index	Model		Desired (good fit) threshold	Status
Chi-square	Statistic	1022.605	p-value <0.05	Good fit
	P-value	0.000		
NFI	0.860		≥0.9	Acceptable fit
CFI	0.912		≥0.9	Good fit
GFI	0.852		≥0.9	Good fit
SRMR	0.066		≤0.08	Good fit
RMSEA	0.078		≤0.08	Good fit
PGFI	0.586		≥0.5	Good fit
PNFI	0.634		≥0.5	Good fit

(Data Analysis, 2019)

This model was also found to at least meet absolute fitness and incremental fitness. It was found to be of good fitness based on both absolute and relative fitness tests. The traditional chi-square goodness of fit statistic was 1022.605 with a p-value of 0.000 which is less than 0.05 implying significant fitness at 0.05 level of significance. Both RMSEA and the SRMR (standardized root mean squared residual) were found to have values less than 0.08 as required as was the CFI a comparative fit index which was also found to have values greater than the required threshold of 0.9. The NFI and GFI were however both found to be 0.860 and .852 respectively which are below the desired 0.9. According to Hooper, the values are however relatively close to 1 and that the GFI has been proffered to be acceptable as low as 0.8. Notwithstanding the relatively acceptable GFI and NFI indices, the PGFI and PNFI which are parsimony tests for both fitness indices were above 0.5 implying good fit.

Table 13 presents the estimated path coefficients of the fitted model with the standard errors (S.E.), the critical ratios (C.R.) and the p-values of the CRs for this model. This fitted model also based on maximum likelihood estimation considered significance test based on the standard normal critical point of 1.96 at 5% level of significance.

Table 13: Path Coefficient Estimates for Model 2

Variable path			Estimate	S.E.	C.R.	P
AD	<---	Awareness and Knowledge	1.805	0.524	3.444	***
AD	<---	Relative Advantage	0.589	0.126	4.674	***
AD	<---	Perceived Fee	0.814	0.224	3.633	***
AD	<---	Building Codes	0.326	0.025	13.04	***
AD	<---	Technicality, Compatibility & Complexity	0.152	0.125	1.212	.085
AD	<---	Perceived Usefulness & Enjoyment	0.037	0.022	1.629	.064
AD	<---	Peer Firm Influence	0.100	0.033	3.061	***
AD	<---	Intention to Use	-0.047	0.03	-1.564	.079
AD	<---	External Interfaces	0.193	0.041	4.768	***

AD	<---	Analytics	0.019	0.036	0.510	.753
AD	<---	Additional Tools	-0.033	0.030	-1.119	.091
AD	<---	Data Visualizations	0.072	0.024	2.942	***
AD	<---	Processing & Action Management	0.070	0.028	2.5	***
AD	<---	Device management	-0.081	0.131	-0.618	.892
AD	<---	Connectivity & Normalization	0.098	0.030	3.267	***
AD	<---	Database	0.068	0.133	0.511	.987
AD	<---	Data Management	0.148	0.029	5.139	***
AD	<---	Scripting Engine	0.034	0.024	1.434	.064
AD	<---	Integration Framework	0.134	0.034	3.904	***
AD	<---	Software Development Kits	-0.179	0.136	-1.316	.091
AD	<---	Web Services	0.080	0.044	1.802	.070
AD	<---	National government legislations	0.140	0.029	4.912	***
AD	<---	County Governments By-Laws	0.093	0.136	0.683	.896
AD	<---	National Construction Authority laws	0.100	0.031	3.182	***

(Data Analysis, 2019)

From Table 13, out of five constructs of policies & regulation and determinants, two of them were significant in the second model. These constructs had their C.R.s greater than 1.96, they include national government legislations (β=0.140, C.R=4.912) and National Construction Authority laws (β=1.000, C.R=3.182). The remaining one (County Governments By-Laws) had its CR less than 1.96 (0.683).

IV. CONCLUSIONS AND ECOMMENDATIONS

A. Conclusions

The Final Model for Adoption that considered the following eleven latent variables (Awareness and Knowledge, Perceived Fee, Additional Tools, Peer Firm Influence, Relative Advantage, Building Codes, Processing and Action Management, Connectivity and Normalization, Data Management, Integration Framework and Web Services) that influence the adoption of Smart Buildings. Kenya Smart buildings go far beyond saving energy and contributing to sustainability goals. They impact the security and safety of all resources, human and capital.

The study found out that current codes and practices for building and infrastructure design work under the assumption that the climate will not change. However, in the next ten years or so, buildings will have to make the transition to a new climate, something similar to Washington DC. New codes and practices will have to require us to build for a warming climate and account for its unpredictability. The study found out that the existing policies do not fully support the implementation of smart buildings. The question is no longer how can we build energy-efficient, water-efficient, or economical buildings based on the climate of the previous 30 years, but how can we design these high-performance buildings for the projected climate across their anticipated over 50 year lifespan? The study is significant to the governments that have a big stake in the construction industry, the Built industry that need building codes so as to bring sanity to the industry that has been very hard to effectively regulate and to the academia that needs to do further research in order to improve the fast evolving built industry.

B. Recommendations

The researchers strongly recommend that a broad range of aggressive and continually improving energy codes and standards be adopted to greatly accelerate the widespread deployment of highly efficient buildings and equipment. To this end they recommends hastening of the Eurocode implementation by KEBS (Kenya Bureau of Standards) and other concerned parties like NCA and County governments; Developing Eurocodes and standards that are more stringent and more comprehensively cover energy-consuming applications; Improving Eurocode compliance and enforcement, and improving Eurocodes research and analysis once they are in place. So as to get better smart buildings that will help mitigate climate change for using energy more efficiently is an essential part of our strategy for lowering carbon emissions in the world today.This will ensure a moderate climate to plant seeds for higher yields that will ensure food security. The study vouches for many more embedded and M2M devices to be interconnected virtually and physically and realize the convergence of building science, big data real time analytics and IT telecommunications virtually to allow the devices reach critical mass.

REFERENCES

[1] Ayemba, D. (2016); Building smart; Construction Review Online

[2] Pe´rez-Lombard, L., Ortiz, J., Pout, C. (2007), A review on buildings energy consumption information, www.sciencedirect.com

[3] Sheth, J. N., Newman, B. I. and Gross, B. L., 1991, Why we buy what we buy: a theory of consumption values, Journal of Business Research, vol. 22, no. 2, pp. 159-170.

[4] Davis, F. D., Bagozzi, R. P. and Warshaw, P. R., 1989, User acceptance of computer technology: a comparison of two

theoretical models, Management Science, vol. 35, no. 8, pp. 982-1003

[5] Kim H. W., Chan, H. C. & Gupta, S. (2007) Value-based Adoption of Mobile Internet: An empirical investigation, Decision Support Systems, 43, 111 –126.

[6] Petty, R. E., &Cacioppo, J. T. 1986a.Communication and Persuasion: Central and Peripheral Routes to Attitude Change. New York,NY: Springer-Verlag

[7] Schloss and Smith, (1999Schloss, P. J. & Smith, M. A. (1999).; Conducting research . New Jersey, NJ: Prentice- Hall.

[8] Kenya National Bureau of Statistics, (2015). 'Republic of Kenya Economic Survey 2015'.Available at: http://www.knbs.or.ke/index.php?option=com_phocadownload& view=category&id=107:economic-survey-publications&Itemid=1181 (accessed October 2015)

[9] Hilton, S. (2018); IoT Platform Insights, The top 4 industrial enterprise requirements of IoT application enablement plat (A forms EP)

[10] Lin, CH, Sher, PJ & Shih, HY, 2005, Past progress and future directions and conceptualizing perceived customer value, International Journal of Service Industry Management, vol. 16, no. 4, pp. 318-336.

[11] McDonald, R. P. & Ho, M.-H. R. (2002), "Principles and Practice in Reporting Statistical Equation Analyses," Psychological Methods, 7 (1), 64-82.

[12] Jöreskog, K. &Sörbom, D. (1993), *LISREL 8: Structural Equation Modeling with the SIMPLIS Command Language*, Chicago: IL: Scientific Software International Inc

[13] Kääriäinen, M., O. Kanste, S. Elo, T. Pölkki, J. Miettunen and H. Kyngäs (2011), 'Testing and Verifying Nursing Theory by Confirmatory Factor Analysis', *Journal of Advanced Nursing*, 67 (5), 1163-72

[14] Hu, L. T. and Bentler, P. M. (1999), "Cutoff Criteria for Fit Indexes in Covariance Structure Analysis: Conventional Criteria Versus New Alternatives," Structural Equation Modeling, 6 (1), 1-55

[15] Miles, J. &Shevlin, M. (2007), "A time and a place for incremental fit indices," Personality and Individual Differences, 42 (5), 869-74.

[16] Bentler, P.M. and Bonnet, D.C. (1980), "Significance Tests and Goodness of Fit in the Analysis of Covariance Structures," Psychological Bulletin, 88 (3), 588-606.

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