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DETERMINANTS FOR THE ADOPTION OF INTERNET OF THINGS (IOT) FOR FLOOD AND DROUGHT DISASTER MANAGEMENT IN KENYA

***Abstract**: Major disasters continue to affect millions of people worldwide every year. These disasters range from earthquakes, floods, hurricanes, cyclones, hunger, terrorist activities to collapse of buildings, among others. Floods and droughts are by far the most common natural disasters worldwide and account for the most deaths. The deadliest disaster of the 20th century was the China floods of 1931, which resulted in more than a million deaths. One common characteristic of these disasters is the poor predictability and inability to stop the occurrence of the same. This research proposes a real time IoT big data analytics system that collects a huge amount of flood and drought related information generated prior to, during, and after the disaster, and employs big data analytics and visualization techniques among others to support situational awareness and decision making by providing timely, accurate and relevant information to relevant groups of stakeholders. It is to be noted that with slight changes in the transducers and design approach, this technique employed in the study can easily be extended for use with any other disaster management. In fulfilling the first objective of the research, we carried out a survey in Kenya among experts, opinion leaders, policy makers and selected members of public on the factors influencing the increased adoption of IoT technology for flood and drought disaster management in Kenya. The results of the research indicate that Perceived knowledge (PK), Perceived Ease of Use (PE), and Relative advantage (RA) respectively are very significant in influencing the adoption of IoT technology in flood and drought disaster management in Kenya, while self efficacy (SE), and Referent's Influence (RI) constructs were moderately significant. However, perceived declining cost (PD), Facilitating conditions (FC), and utilitarian outcome (UO) were found to be least significant in explaining the* *behavioural intention to adopt IoT for flood and drought management in Kenya. Among the Key recommendations, the research proposes deliberate efforts to improve gender inclusive specialised ICT skills including IoTs, increased academia-industry linkages and collaboration in emerging ICTs, and the establishment of key regulatory interventions that support innovative implementation of IoT and other emerging technologies that are poised to support the Digital economy in Kenya.*

Key words: *Adoption, IoT, Floods, Drought, Disaster Management, Kenya.*

Language: *English*

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Introduction

Note: This study is a product of on-going multi-disciplinary research work entitled "A Model and Implementation for an Internet of Things (IoT) Based Big Data Analytics System for Disaster Prediction and Management" funded by the National Research Fund (NRF), Kenya.

1. INTRODUCTION

[1] classifies disasters under five groups as follows:

i. Geophysical: Events originating from solid earth i.e earthquakes and volcanos

ii. Meteorological: Events caused by short-lived atmospheric processes i.e storms, cyclones

iii. Hydrological: Events caused by deviations in the normal water cycle or overflow of bodies of water caused by wind set-up i.e floods

iv. Climatological: Events caused by long-lived meso- to macro-scale processes (in the spectrum from intra-seasonal to multi-decadal climate variability) i.e heat wave, cold wave

v. Biological: Disaster caused by the exposure of living organisms to germs and toxic substances i.e epidemics, animal infestation

Thus floods and droughts are classified under climatological and hydrological disasters respectively, and are considered among the most complex but least understood of all natural hazards [4][5]. For example, in sub-Saharan Africa, the droughts of the early to mid-1980s are reported to have adversely affected more than 40 million people [3]. On the other hand, in 2018 alone, flood disasters caused havoc the world over, examples being the Japan flood that claimed over 150 lives. In Africa, Kenya, Sudan, Liberia, Cote-de-Ivoire and Nigeria were affected by massive floods resulting from above-normal rainfall forcing hundreds of thousands of people out of their homes and killing scores of people in 2018 [3]. The same situation has been repeated in Kenya in the first quarter of 2020, with flooding disasters, leading many families to loose crops and livestock on which they depend for their livelihoods. Roads, bridges, and water systems were also damaged or destroyed

Literature review on IoT adoption and diffusion shows both macro and micro level [4][5][6] studies have been conducted to understand IoT deployment in disaster management in the developed world. However, only a few studies have investigated IoT interventions in flood and drought disaster management within the developing country context [1][7][15][16].

Given that Kenya perennially suffers from the effects of flooding and drought, it is imperative that research focus shifts to the use of new and emerging ICTs in managing the menace [32] . This study proposes the use of Internet of things (IoT) and Big Data analytics technology in the Management of disasters across the four phases namely: Mitigation, Preparedness, Response and Recovery [17][18] [19]with special reference to floods and drought which are the most common and destructive natural disasters in Kenya [31][32].

As a guide to evaluating of the factors affecting IoT adoption for flood and drought disaster management in Kenya, the study sought to answer the following questions.

1. What relationship exists between demographic factors and IoT adoption for disaster management in Kenya ?

2. What factors have the greatest impact in explaining variations in the intention to adopt IoT for flood and drought management in Kenya?

This research paper is structured as follows: Section 2 gives a theoretical underpinning of the study, Section 3 provides a brief discussion of the research methodology. The findings and recommendations are then presented and discussed in sections 4 and 5 respectively. Finally, limitations, future work and the conclusion of the research are provided in Sections 6 and 7 respectively.

2. THEORETICAL BASIS

In this study, the researchers adopted the diffusion of innovations theory [11]. Diffusion of Innovations theory seeks to explain how innovations are taken up in a population depending basically on the innovation's five attributes namely Relative advantage, Compatibility with existing values and practices, Simplicity and ease of use, Trialabality and Observability of results [12][13][21].

The research relied on a combination of the Technology Acceptance Model (TAM)[9] the Unified Theory of Acceptance and Use of Technology (UTAUT), and the Value-based Adoption Model (VAM) [22] to derive the factors that were included in the five-point linkert scale questionnaire that was sent out to respondents. In addition, the researchers developed and included other IoT specific factors such as maintenance, power consumption, cost, and security and privacy for the IoT networks.

TAM was proposed by Davis et. al in 1989 [21]. It investigates perceived usefulness, perceived ease of use, and user acceptance of information technology. The UTAUT model was proposed by Venkatesh et al. in 2003[12][13]. The UTAUT model includes four critical factors (performance expectancy, effort expectancy, social influence, and facilitating conditions) which affect behavioral intention. More recently Kim et. Al in 2007, [20][22] proposed the Value-based Adoption Model (VAM) in recognition of ICT users as not just being users of technology, but consumers as well. The VAM identifies benefits (usefulness and enjoyment) and sacrifice (technicality and perceived fee) as the main factors of perceived value that drive intention to use new ICTs.

This study postulates that behavioral intention (IoTI) to adopt IoT in flood and drought disaster management is influenced by several independent variables which can be categorized into three broad groups [7][8][10][20]. These are:

(i) Attitudinal factors, which describe the individual's or organisation's perception towards IoT technologies [Relative Advantage (RA) and Utilitarian Outcomes (UO)]

(ii) Normative factors, which describe the social influences that may affect the intention to adopt IoT [Referents Influence (RI)], and

(iii) Control factors, which control or influence the ability to initiate and maintain an IoT based service [Perceived Knowledge (PK), Perceived Ease of Use (PE), Perceived Declining Cost (PD), Self Efficacy (SE), and Facilitating Conditions (FC)]

The eight constructs used in this study for the above factors are explained in Table. 1

Table 1: Definition of constructs for IoT adoption

Construct	Definition
Relative Advantage (RA)	The extent to which IoT networks are perceived to better or more advanced than traditional methods for Disaster prediction and Management [9][10]
Utilitarian Outcomes (UO)	The enhancement factors contributed by the use of IoT networks in disaster management [12][13]
Referents Influence (RI)	The influence perceived from friends, similar organisations, campaigns and advertisements and which can influence the adoption of IoT networks in disaster management [19][20].
Perceived declining cost (PD)	The extent to which declining costs of devices, networks, and maintenance influences adoption of IoT networks for disaster management [12][13]
Facilitating Conditions (FC)	The perceived level of resources, legal and regulatory support available to enhance use of IoT based networks for disaster Management [12][13]
Perceived Knowledge (PK)	The level of knowledge that one perceives to have on IoT including benefits and risks and which influences adoption of IoT networks for disaster management [12][13]
Self Efficacy (SE)	The extent to which one can successfully use and operate IoT based technology [12][13]
Perceived Ease of Use (PE)	The extent to which the deployment of IoT networks for disaster management is easy to deploy and operationalise [12][13].

3. RESEARCH METHODOLOGY

The primary survey instrument for data collection was a self administered questionnaire. Questionnaires have the advantage of being able to collect large amounts of information from a large number of people in a short period of time and in a relatively cost effective way [14]. Also, the questionnaires can usually be quickly and easily quantified by either the researcher or through the use of a software package, and to be analysed more 'scientifically' and objectively than other forms of research instruments [23].

Critics of the use of questionnaires argue that there is no way to tell how truthful a respondent is being, and that it has no provision to understand some forms of information - i.e. changes of emotions, behaviour, feelings and so on. Further, they argue that there is some level of subjectivity, both in the way the respondents understand the question, and researcher imposition, that the researcher may design the questionnaire with the desired result bias [23][25].

Despite these drawbacks of the questionnaire as a research instrument, [23] asserts that questionnaires are familiar to most people and generally do not make people apprehensive, and have the advantage that they can be completed at the respondent's convenience.

Due to the uncertainty regarding the identity of IoT subject experts, the snowballing sampling technique [28] [29] was employed. Initial subject experts from academia, the private sector, Government, students and the general public were first identified. These in turn referenced other subject matter referents. This progressively increased the sample size. This strategy led to the questionnaire being administered to a total of 120 respondents during the response period.

The initial understanding from literature review on IoT adoption provided the basis for the development of the questionnaire consisting of Twenty five (25) questions. All the 25 questions were of five-point likert scale type in nature, ranging from strongly disagree to strongly agree with a neutral option constructed to capture the adoption constructs under investigation. They were adopted from [12][13]. One of the questions was asked to rate the overall intention by respondents to keep.begin to use, or recommend IoT and Big Data based Flood and Drought Disaster Management in the next 12 months.

The conceptual model, Figure 1 assumed that the dependent variable 'IoT intention' (IoTI) is influenced by several independent variables that include the general constructs of Relative advantage (RA), Utilitarian outcomes (UO), Referents influence (RI), Perceived declining cost (PD), Facilitating conditions (FC), Perceived knowledge (PK), Self efficacy (SE), and Perceived ease of use (PE) respectively.

Prior to the dissemination of the final questionnaire, a trial study was conducted in order to determine the response rate and learn of any discrepancies within the questions, which included determining whether the format of the questionnaire and the questions was suitable. Additionally, the time required for completing the questionnaire was established.

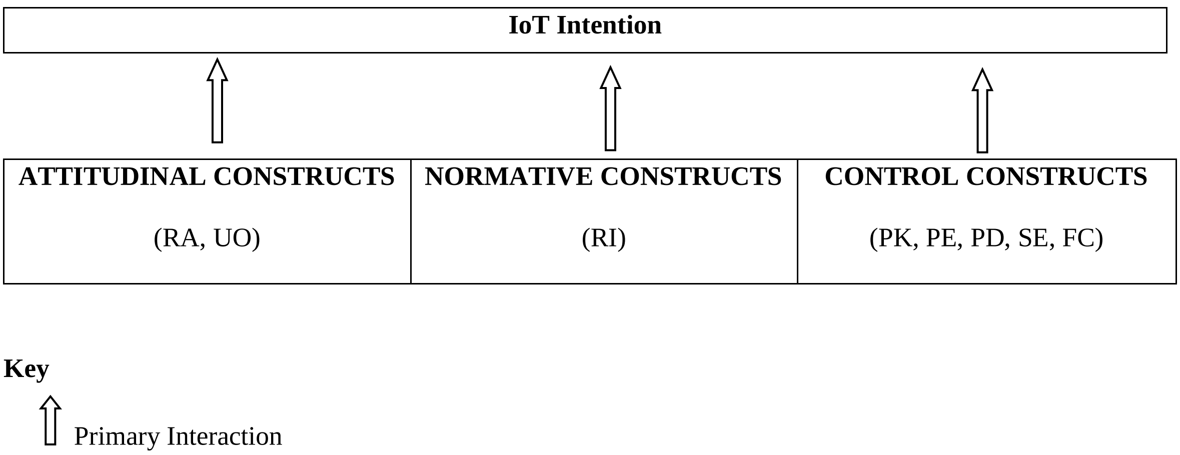

Figure 1. IoT Adoption Constructs Conceptual Model (Source-Researchers)

4. DATA ANALYSIS AND RESEARCH FINDINGS

A total of 88 responses were obtained from the 120 questionnaires sent out within the specified duration. Thus, a response rate of 73.3% was achieved. This response rate is slightly higher comparable to response rates in recent studies on technology adoption conducted in developing countries [9][10][20]. This can be attributed to the research having targeted expert subject matter respondents [22][26].

The data analysis involved classifying and uniquely identifying the responses [25]. Using SPSS (version 22), descriptive statistics were generated and reliability tests and regression analysis conducted in order to analyze and present the research data obtained from the questionnaires [24].

4.1 DEMOGRAPHIC FACTORS

Table 2 .Demographic characteristics of respondents N=88
(Source- Researchers)

Variable	Intermediate variables	No. of Respondents	Percent (%)
Gender (GE)	Male	60	68.2
	Female	22	32.8
Age (AG) in years	Below 25	0	0
	26-40	52	59.1
	41-55	24	27.3
	56-70	12	13.6
	Above 71	0	0
Sector (SE)	Private/NGO	8	9.1
	Gvt/Agency	44	50.0
	Academia	24	27.3
	Specialised Disaster Agency	8	9.1
	Other	4	4.5
Role in Organisation(OR)	Technical	28	31.8
	Administrative	4	4.5
	Policy/Manager	32	36.4
	Academic/Research	24	27.3
	Others	0	0
Education Level (ED)	High School	0	0
	College Certificate	0	0
	Bachelor's Degree	24	27.3
	Master's degree	56	63.6
	Doctorate degree	8	9.1

4.1.1 TESTING FOR NON-RESPONSE BIAS

Existence of non-response bias would result in data from the respondents being non- representative, and thus pose a threat to the external validity of the study's conclusions. Non-response bias testing typically involves a comparison of the characteristics of respondents who returned completed surveys and non-respondents [28]. [29][30] suggest three methods of handling non-response bias namely:-

(i). Comparison of early to late respondents. The assumption here is that subjects who respond late are similar to non-respondents.

(ii). "Days to respond" method. A procedure in which "days to respond" is coded as a continuous variable and is used as an independent variable in regression

(iii). Comparison of respondents to non-respondents by following up to get a given number of responses from the initial group of non-respondents, and then comparing their responses to the actual respondents.

In this study, the "comparison of responses from early to late respondent's " technique was used to test for non-response bias. The similarity results suggest that it is less likely that the findings of this study were affected due to non-response bias and hence the threat to external validity is minimised.

4.2 RELIABILITY TEST

Reliability of constructs was estimated using Cronbach's coefficient (alpha) (Table 2).

Table 2: Reliability values N=88

CONSTRUCT	No. OF ITEMS	CRONBACH'S ALPHA α
RA: RELATIVE ADVANTAGE	4	0.840
UO: UTILITARIAN OUTCOMES	2	0.943
RI:REFERENTS INFLUENCE	3	0.552
PK:PERCEIVED KNOWLEDGE	2	0.728
SE:SELF EFFICACY	3	0.671
PE: PERCEIVED EASE OF USE	2	0.596
PD: PERCEIVED DECLINING COST	3	0.867
FC: PERCEIVED FACILITATING CONDITIONS	6	0.780

[24] suggest four ranges for the reliability coefficient α; excellent reliability (α >=0.90), high reliability (0.70 < α < 0.90), moderate reliability (0.50< α< 0.70), and low reliability (α<= 0.50). In general, the higher the Cronbach's α value of a construct, the higher the reliability of it measuring the same construct.

In this study, Cronbach's α varied between 0.943 for the Utilitarian Outcomes (UO) constructs and 0.552 for the referents influence (R) constructs. The Utilitarian Outcomes (UO) construct expressed the highest reliability (α =0.943), closely followed by perceived declining cost constructs (α =0.867), Relative Advantage (α =0.840), Facilitating Conditions (α =0.780), Perceived Knowledge (α =0.728), Self Efficacy (α =0.671), Perceived Ease of Use (α =0.596), and finally Referents Influence construct (α =0.552). Considering [24][25], the aforementioned values suggest that of the Eight constructs, one possessed excellent reliability, four constructs possessed high reliability and the remaining three demonstrated moderate reliability. The implication is that all the constructs were internally consistent. Consequently, all items of each construct measured the same content universe (i.e. construct). For example, all items of PK measured the same content universe of perceived knowledge. Similarly, all items of SE measured the content universe of the self efficacy construct and so on.

4.3 DESCRIPTIVE STATISTICS

The means and standard deviations of the dependent variable, IoT intension (IoTi) and the items related to the Eight constructs included in the study for the purpose of measuring factors affecting the IoT adoption for flood and drought disaster management in Kenya are now reviewed.

4.3.1 DESCRIPTIVE STATISTICS FOR IoT INTENTION (IoTI)

Table 3: Descriptive statistics for IoT Intention N=88

Factors	Detailed Factors	Mean	Std. Dev
IoT I(IoT INTENTION)	Scale-IoT	4.318	0.635

Within the questionnaire, one question was used to measure the overall rating of the respondent's approval of their intention to keep the IoT networks , their organization's intention to adopt IoT based Disaster Management, or their recommendation to stakeholders to embrace IoT technology for Disaster Management within the next 12 months. Table 3 shows that IoTI was fairly agreed upon with a mean of 4.318 with standard deviation of 0.635.

4.3.2 DESCRIPTIVE STATISTICS FOR ATTITUDINAL FACTORS

The means and standard deviations of aggregated measures for the two constructs used to measure attitudinal factors are illustrated in Table 4. A strong agreement was made for the Relative Advantage (RA) construct with average score of aggregate measure (M = 4.343, SD = 0.673) with the respondents agreeing highly to the perceived higher reliability of IoT networks (HR; M = 4.430, SD = 0.691). This was followed by the view that IoT networks are easy to interface with other devices, systems, and networks (EI; M = 4.330, SD = 0.582), Real time advantages associated with IoT (RT; M = 4.310, SD =0.613), and lastly, the perception that IoT networks consume low power compared to other traditional networks (LP; M = 4.300, SD = 0.805).

The other construct used to measure attitudinal factors was the utilitarian outcome (UO) , which was ranked Fourth overally with the average score of aggregate measure (M = 4.285, SD = 0.623). Under this construct, the respondents highly agreed upon the easily understandable results item, UR (M = 4.330, SD = 0.620) followed by the less human intervention item EF (M = 4.240, SD = 0.625) respectively, Table 4.

Table 4: Descriptive statistics for Attitudinal constructs N=88

Factors	**Detailed Factors**	**Mean**	**Std. Dev**	**Rank**
UO(UTILITARIAN OUTCOME)	**Scale-UO**	**4.285**	**0.623**	**4**
	EF	4.240	0.625	
	UR	4.330	0.620	
RA (RELATIVE ADVANTAGE)	**Scale-RA**	**4.340**	**0.673**	**2**
	RT	4.310	0.613	
	HR	4.430	0.691	
	EI	4.330	0.582	
	LP	4.300	0.805	

4.3.3 DESCRIPTIVE STATISTICS FOR CONTROL FACTORS

The means and standard deviations of aggregated measures for the five constructs used to measure control factors are illustrated in Table 5. The self Efficacy (SE) construct scored the highest average aggregate measure (M = 4.337, SD = 0.851), and thus becoming the third most agreed upon construct overally. The respondents highly agreed to the three items used to measure this construct, namely, perceived IoT use skills (US; M = 4.550, SD = 0.585), ability to Manage IoT networks (operational expertise) (OE; M = 4.410, SD = 0.839), and finally the technical expertise to set up IoT networks (TE; M = 4.050, SD = 1.113).

The SE construct was followed by the perceived knowledge (PK) construct which was highly agreed upon with the two constructs for measuring PK, awareness of IoT networks for flood and drought management (EA; M = 4.360, SD = 0.776), and awareness of the advantages of IoT networks for Disaster Management (AA; M = 4.180, SD = 0.781) being rated highly.

The facilitating conditions (FC) construct was ranked third among the constructs used to measure the control factors and sixth overally, but was fairly agreed upon by respondents as well with the average score of aggregate measure (M = 4.138, SD = 0.941).The individual items in this construct that were highly agreed upon included, reliability of IoT networks (NR), Stability of IoT Networks (SN), and perceived security of IoT networks (SN) with an average score of aggregate measure of above 4.138, Table 5.

Next in the order was the perceived ease of Use (PE) construct with the two items on the perception that less effort is required to set up IoT networks (EO; M = 4.440, SD = 0.604), and perceived low maintenance costs (LM; M = 3.780, SD = 0.686) being rated highly.

The least agreed upon, and yet ranked fairly highly construct in this group was the perceived declining cost of IoT networks (PD; M = 4.000, SD = 0.792). Three items were used to measure this construct namely perceived declining cost of IoT networks (CD; M = 4.140, SD = 0.698); Perceived declining maintenance costs of IoT networks (CM; M = 3.950, SD = 0.772), and lastly declining initial installation costs (CI; M = 3.910, SD = 0.905) respectively,Table 5.

Table 5: Descriptive statistics for Control constructs N=82

Factors	**Detailed Factors**	**Mean**	**Std. Dev**	**Rank**
PE(PERCEIVED EASE OF USE)	**Scale-PE**	**4.11**	**0.645**	**7**
	EO	4.440	0.604	
	LM	3.780	0.686	
PK (PERCEIVED KNOWLEDGE)	**Scale-PK**	**4.270**	**0.779**	**5**
	EA	4.360	0.776	
	AA	4.180	0.781	
PD (PERCEIVED DECLINING COST)	**Scale-PD**	**4.000**	**0.792**	**8**
	CD	4.140	0.698	

	CI	3.910	0.905	
	CM	3.950	0.772	
SE(SELF EFFICACY)	**Scale-SE**	**4.337**	**0.851**	**3**
	US	4.550	0.585	
	OE	4.410	0.839	
	TE	4.050	1.113	
(FC)FACILITATING CONDITIONS	**Scale-FC**	**4.138**	**0.941**	**6**
	AC	3.950	1.071	
	GP	3.450	1.240	
	ES	3.770	1.1.72	
	NS	4.450	0.726	
	NR	4.730	0.620	
	SN	4.480	0.816	

4.2.4 DESCRIPTIVE STATISTICS FOR NORMATIVE FACTORS

The means and standard deviations of aggregated measures for the construct referents influence (RI; M = 4.424, SD = 0.707) in the normative factors category is illustrated in Table 6. Among the three items used to measure this construct, strong agreement was made for the reference by IoT experts (SE) item with the highest score of aggregate measure (M = 4.625, SD = 0.593). Respondents also agreed highly to influence to adopt IoT from Government agencies , and agencies that have adopted IoT (MR) and (OR) ((M=4.625, SD = 0.593) & (M=4.364, SD = 0.886) respectively, Table 6.

Table 6: Descriptive statistics for Normative construct N=88

Factors	Detailed Factors	Mean	Std. Dev	Rank
RI (REFERENTS INFLUENCE)	**Scale-RI**	**4.424**	**0.707**	**1**
	SE	4.625	0.593	
	OR	4.284	0.642	
	MR	4.364	0.886	

4.4 REGRESSION ANALYSIS: INFLUENCE OF INDEPENDENT VARIABLES ON IOT INTENTION (IoTI)

Ordinary Least Squares Linear Regression was employed to fit a probability model (Table 7). According to [30][33], Ordinary least squares (OLS) regression is a statistical method of analysis that estimates the relationship between one or more independent variables and a dependent variable by minimizing the sum of the squares in the difference between the observed and predicted values of the dependent variable configured as a straight line. The regression analysis (Table 9) was performed with IoT intention (IoTI) as the dependent variable and a total of eight constructs i.e, Relative advantage (RA), Utilitarian outcomes (UO), Referents influence (RI), Perceived declining cost (PD), Facilitating conditions (FC), Perceived knowledge (PK), Self efficacy (SE), and Perceived ease of use (PE) as the Independent variables[28] .

The adjusted R square of the emerging model (Table 7) was 0.703 ($F(8,87)=26.798$, $p<0.001$). table 8. Three of the predictor constructs included in the analysis were found to be very significant (Table 9). These are Perceived knowledge PK ($\beta = 0.496$, $p = 0.000$), Perceived Ease of Use PE ($\beta = 0.446$, $p = 0.001$), and Relative advantage RA ($\beta = 0.072$, $p=0.001$) respectively. These were closely followed by the self efficacy construct SE ($\beta = 0.175$, $p< 0.033$) and Referent's Influence RI ($\beta = 0.173$, $p <0.084$). However, perceived declining cost PD ($\beta = 0.100$, $p =0.212$), Facilitating conditions FC ($\beta = 0.072$, $p =0.603$), and utilitarian outcome (UO) ($\beta = 0.016$, $p =0.816$) respectively were found to be insignificant, Table 9.

The β values suggest that the Perceived knowledge construct had the largest impact in explaining the variations of IoT intention, followed by Perceived Ease of Use construct, and Relative Advantage construct respectively.

Table 7. Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.855[a]	.731	.703	.263

a. Predictors: (Constant), UO, PK, PE, FC, RI, PD,RA,SE

Table 8. ANOVA[b]

Model		Sum of Squares	Df	Mean Square	F	Sig.
1	Regression	14.880	8	1.660	26.798	.000[a]
	Residual	5.483	79	.069		
	Total	20.364	87			

a. Predictors: (Constant), UO, PK, PE, FC, RI, PD, RA,SE

b. Dependent Variable: IoTi

Table 9. Regression analysis: Coefficients (Dependent variable: IoTI)

Coefficients[a]

Model		Unstd. Coef		Std.Coef		
		B	Std.Error	Beta	t	Sig.
1	(Constant)	.060	.524		.115	.909
	FC	.050	.060	.072	.522	.603
	PD	.063	.050	.100	1.257	.212
	PE	.312	.048	.446	3.487	.001
	PK	.364	.083	.496	4.373	.000
	RA	.053	.102	.072	.522	.001
	RI	.148	.084	.173	1.748	.084
	SE	.116	.54	.175	2.175	.033
	UO	.012	.052	.016	.234	.816

a. Dependent Variable: IoTI

5. DISCUSSION AND RECOMMENDATIONS

With regard to demographic factors, 60 out of the 88 respondents (68.2%) were male while 28 (31.8%) were female. This raises the issue of gender parity in emerging technologies. With just about thirty (30) per cent female respondents as compared to about two-thirds male respondents, there is a definite pointer to the requirement for deliberate efforts to promote women and girls in science ,technology and emerging ICTs. With regard to age, there were no respondents below the age of 25, while the majority (59%) were aged between 26 and 40 years, with a further 27 percent aged between 41 and 55 years; 24 of the respondents or 27% were aged between 56-70 years, with no respondent above 71 years. The age factor points to an element of the requisite experience in specialised ICT fields like IoT combined with the relevant educational qualifications. In the level of Education category, 56 respondents had a Master's degree representing nearly two-thirds of the respondents. There were no respondents below a Bachelor's degree. Undergraduate respondents were 24 (representing 27%), while respondents with a Doctorate degree were eight (representing nine per cent). This also points to the specialized IoT knowledge, skills and expertise being domiciled within the higher end educational qualifications. This calls for the need to deliberately step up efforts to drive this kind of knowledge and other 21st Century skills to the younger generation by integrating advanced technologies such as IoT, Big data, Block chain, among others into undergraduate, college, and high school curriculum. With respect to sector affiliation, half of the respondents worked with Government or a Government agency, about quarter of the respondents worked in the academic/research sector while just about a tenth (8per cent) worked for a specialized disaster management agency. The corresponding roles in the organization was distributed among Policy (36.4%), Technical (31.8%), and academic/research (27.3%) respectively, with respondents performing administrative duties taking up the remaining 4.5 percent. We see here the need for the transformation of IoT and other advanced ICT knowledge into practical application since most of the IoT expertise is still domiciled within the institutions of higher learning, whereas this knowledge should be transformed into practical application to solve real world problems like the flood and drought disasters in discussion. Further, these institutions, with proper funding, could establish specific centres of excellence in IoTs and other emerging technologies to carry out research to inform policy decisions and practical applications of these technologies. This is premised on the research finding that out of the five institutions of higher learning from which responses were obtained, only one, Strathmore University, has a specialised section. namely @iLabAfrica that carries out specific research, consultancy, and implementation of IoT and other emerging technologies related projects.

With regard to the constructs used in this research, the appropriate level of internal consistency of the measures used , and the ability of the constructs to measure the same content universe is demonstrated by the cronbach's reliability α values of the various constructs ranging from 0.552 for Referents Influence (RI) to 0.978, with nearly all the constructs possessing moderate and above reliability.

The predictive power of the regression model of this study, with adjusted R^2 of 0.703 (Table 7), suggests the appropriate level of explained variance [24][28][33]. This means that the independent variables considered in this study are important for understanding IoT adoption for Flood and Drought Management in Kenya [25][31].

The findings of this study therefore, generate a number of policy recommendations in the disaster management eco-system.

With regard to demographics, considering the study findings, it is recommended that deliberate efforts be made to promote women and girls in science ,technology and emerging ICTs. Furthermore, it is recommended that steps be taken to incorporate both theoretical and practical skills in IoTs and other emerging technologies by integrating advanced technologies such as IoT, AI, Big data, Block chain, among others into undergraduate, college, and high school studies and curriculum.

In line with the finding that IoT and other advanced ICT knowledge is largely domiciled within our institutions of higher learning, there is need to tap onto this knowledge through enhancing academia-industry linkages and collaborations as per the recommendations of the National ICT Policy, 2019 [34]. Further more, the Government and private sector should be encouraged to fund the establishment of centres of excellence in research in public and private Universities and institutions of higher learning to carry out specific research on emerging technologies as the case cited for iLabAfrica@Strathmore University in Kenya. Again this is in line with the national ICT Policy,2019 [34] which calls for the setting of priority technology research areas every two years among Government agencies and departments in Kenya. These specialised research centres will be key for the discovery and dissemination of specialised technology knowledge and skills.

In this study, Perceived knowledge (PK), and Perceived Ease of Use (PE) were found to be most significant in influencing IoT intention for flood and drought disaster management. Naturally, Perceived knowledge would lead to Perceived Ease of Use and hence greater user acceptance of a technology. They both have much to do with what a user thinks they know about the technology in question including the risk factors, which influences their decision to adopt the technology[12][13][15]. Perceived Knowledge may be objective, i.e what is taught or subjective knowledge, acquired mainly though experience and from self awareness. Therefore, PK and PE can both be improved through inclusion of IoT and other emerging technologies in school, college and university studies and also through experience working with these technologies. Further, short specialised courses and practical oriented exercises offered at centres of excellence would help improve PK and PE respectively. For example, to raise awareness among the wider populations, the proposed constituency innovation hubs in Kenya could offer basic training on IoTs and other emerging technologies. However, the application of IoT technologies to solve real world problems such as floods and drought management would also require specialised skills imparted post school or university education. This can be availed as short specialised courses offered by special trainers, at institutions of higher learning and at specialised centres of excellence. Certification in these courses would be an added advantage.

The Relative advantage (RA) of IoT based technologies over the traditional flood and drought disaster management systems was found to moderately influence user acceptance for IoT adoption. Some of the advantages of IoT based systems over other systems were found to based on the fact that IoT systems provide real time data transfer, higher reliability, less human intervention and low power consumption respectively. In this regard, further research, especially in local institutions to improve certain aspects of IoT deployment including power consumption, security, reliability, connectivity and reduction in latency among others would greatly influence the uptake of IoT for disaster management and for other applications.This finding agrees with a recent research conducted by Bain & Company consulting in 2018 [2], which found that enterprise customers would be willing to purchase and deploy more IoT devices if their concerns about cybersecurity risks were addressed. In general, the report asserts that improving IoT Relative advantage could greatly grow IoT solutions deployment [2].

The self efficacy (SE) construct, which was found to moderately influence IoT adoption for flood and drought disaster management is closely related to the Perceived Knowledge (PK) and the Perceived Ease of Use (PE) constructs and can be addressed by similar measures cited for for PE and PK respectively. Referents Influence (RI), which has previously been found significant in technology adoption studies including internet and computer adoption in households [8][9][10][13]was however, not very significant in this study. It can be inferred that this construct would come into play once the PK, PE and SE factors are addressed, due to the expected resulting growth in IoT deployments.

Lastly, IoT depolyment is an emerging technology area, and there is always need to balance regulation and support for innovative technology deployments such as IoT for flood and drought disaster prediction and management [26][34]. The general absence of universal regulations and standards governing IoT deployments and other emerging technologies globally, could explain the low significance of the Facilitating Conditions (FC) construct in this research. For example, in Kenya, a taskforce was appointed in 2018 to explore and analyse emerging digital technologies that demonstrate high potential to transform Kenya's economy, including potentially disruptive technologies that are currently shaping the global economy such as Distributed Ledger Technologies (DLT) (which includes Blockchain and hash-graph), Artificial Intelligence (AI), emerging broadband wireless technology and the Internet of Things (IoT). The said task force report recommends a supportive ecosystem and effective regulation to balance citizen protection and private sector innovation. This assertion is supported by the findings of this research, namely, the establishment of key regulatory interventions necessary for the successful implementation of IoT and other emerging technologies in Kenya that are key for the digital economy, taking note of concerns with regard to human, ethical and security implications.

6. LIMITATIONS AND FUTURE WORK

Since IoT technology deployment is still at embryonic stage in Kenya, the sampling methodology was limited to snowballing technique in order to generate sufficient and useful feedback on the subject. Hence the homogeneity of target respondents may not necessarily be suitable to provide a complete picture to generalize for the Kenyan population as a whole. Future research, subject to the diffusion of IoT, could emphasize more on conducting a cross-country survey on the adoption of IoT. Further, this study does not take into consideration cross-construct or item correlation. Therefore, it is recommended that future research moderate constructs in order to examine cross-relationships among the adoption factors.

This work presented the results of the first objective of the research, namely to determine the factors that contribute to increased adoption of IoT networks for flood and drought disaster prediction and management in Kenya. The research work is on-going with the next steps being to determine the metrics for the specification of an IoT based big data analytics model for disaster prediction and management, to derive and validate an approriate IoT based big data analytics model, and finally to implement on a pilot basis, the IoT based big data analytics model for flood and drought disaster management in Kenya.

7. CONCLUSION

This study examined the factors affecting IoT adoption for flood and drought disaster management in a developing country context. Based on the findings and discussions above, eight constructs based on a pre-validated research instrument were identified to explain behavioral intention to adopt IoT for flood and drought disaster management in Kenya. These are self efficacy (SE), relative advantage (RA), facilitating conditions (FC), perceived knowledge (PK), perceived declining costs (PD), perceived ease of use (PE), , utilitarian outcomes (UO), and referents influence (RI). Thus the two research questions presented in the introductory section have both been answered. A relationship has been established between demographic factors and IoT adoption for disaster management in Kenya as explained in the findings section. As per the second research question with regard to the factors that have the greatest impact in explaining variations in the intention to adopt IoT for flood and drought management in Kenya, statistical analysis has showed that three of the constructs are very significant in explaining the behavioural intention to adopt IoT for flood and drought management in Kenya namely Perceived knowledge (PK), Perceived Ease of Use (PE), and Relative advantage respectively. These were closely followed by the self efficacy construct (SE), and Referent's Influence (RI) constructs which were moderately significant. However, perceived declining cost (PD), Facilitating conditions (FC), and utilitarian outcome (UO) were found to be least significant in explaining the behavioural intention to adopt IoT for flood and drought management in Kenya,

These findings lead to the recommendations proposing deliberate efforts to improve gender inclusive IoT general and specialised skills, increased academia-industry collaboration and linkages, and the establishment of key regulatory interventions that support innovative implementation of IoT and other emerging technologies in Kenya.

Attention of all stake-holders in the disaster management eco-system is drawn to the factors that are reported as significant and the attendant recommendations in order to improve the adoption and diffusion of IoT for flood and drought disaster management in Kenya.

References:

1. Muthoni, M. & Antoine, B. (2010). *A framework for predicting droughts in developing countries using sensor networks and mobile phones*. Conference Paper · January 2010 DOI: 10.1145/1899503.1899551
2. Ali, S., Bosche, A., & Ford, F. (2018). *Cybersecurity Is the Key to Unlocking Demand in the Internet of Things, Bain and Company.*
3. Okiror, S. (8 May 2018). *"Lethal flash floods hit east African countries already in dire need"*. The Guardian. Retrieved 18 September 2019.
4. Simm, J., Gouldby, B., Sayers, P., Flikweert, J-J., Wersching, S., & Bramley, M., (2009). *Representing fragility of flood and coastal defenses:* Getting into the detail, Flood Risk Management: Research and Practice – Samuels et al. (eds).
5. Allsop, W., Kortenhaus, A., & Morris, M. (2007). Failure Mechanisms for Flood Defense Structures. FLOODsite Report. T04_06_01.
6. Kingston, G., Rajabalinejad, M., Gouldby, B., & Van Gelder, P. (2010). *Computational intelligence methods for the efficient reliability analysis of complex flood defense structures. Structural Safety in press.*
7. Gouldby, B., Sayers, P., Mulet-Marti, J., Maam H., & Benwell, D. (2008). "A methodology for regional-scale flood risk assessment." *Proceedings of the Institution of Civil Engineers-Water Management* 161(3): 169-182.
8. Lhomme, J., Sayers, P., Gouldby, B., Samuels, P., Wills, M., & Mulet-Marti, J.R. (2008). *Recent development and application of a rapid flood spreading method*. Proceedings of the Flood Risk 2008 Conference, Oxford, Taylor and Francis Group, London, 2008.
9. Choudrie, J., & Dwivedi, Y. K. (2006). Investigating factors influencing adoption of broadband in the household. *Journal of Computer Information Systems*, 46(4), 25–34.
10. Dwivedi, Y.K, Khoumbati, K.,Williams, M.D., & Lal, B. (2007a). Factors affecting consumers' behavioural intention to adopt broadband in Pakistan. *Transforming Government People, Processes and Policy*, 1, (3), 285-297.
11. Rogers, E.M. (2003). Diffusion of Innovations, Fifth Edition 2003, Free Press, New York.
12. Brown, S., & Venkatesh, V. (2005). Model of adoption of technology in households: A baseline model test and extension incorporating household life cycle. *MIS Quarterly*, 29(3), 399–426.
13. Venkatesh, V., & Brown, S. (2001). A longitudinal investigation of personal computers in homes: Adoption determinants and emerging challenges. *MIS Quarterly*, 25(1), 71–102.

14. Holmström, J., Ketokivi, M., & Hameri, A. (2009). *Bridging Practice and Theory: A Design Science Approach*. John Wiley & Sons, Inc 2009.
15. Mwape, Y. P. (2009). An impact of floods on the socio-economic livelihoods of people: A case study of Sikaunzwe community in Kazungula District of Zambia. *University of the Free State Faculty of Natural and Agricultural Sciences Journal*, 1(1): 1-87.
16. Devalsam, E, I., Atu, J. E., Oko, C., & Ekwok, I. (2011). Flood and its impact on farmland in Itigi, Abi Local Government Area, Cross river State, Nigeria. *International Journal of Humanities and Social Sciences*, 1(9): 98-104.
17. Lu, J., & Whitehouse, K. (2007). Flash flooding: Exploiting the capture effects for rapid flooding in wireless sensor networks. *Department of Computer Science, University of Virgina Journal*, 1(1): 1-9.
18. Khalequzzaman, M. D. (2009). Flood control in Bangladesh through best management practices. *Department of Geology and Physics Journal* 3(7): 1-13.
19. Moriandi, D., Sicari, S., Pellegrini, F.D., & Chlamatic, I. (2012). Internet of Things. Vision, Applications and Research Challenges. *Ad Hoc Networks*, Vol. 10, no.7
20. Mugeni, G.B., Wanyembi, G.W., & Wafula, J.M. (2012). Evaluating Factors Affecting Broadband Readiness in Kenya: A Pilot Study. *International Journal of Information and Communication Technology Research*, Vol. 2, No. 6, pp.491-498.
21. Davis, F. D. (1989). "Perceived usefulness, perceived ease of use, and user acceptance of information technology", Management systems research centre, Carlson school of Management, University of Minnesota. *MIS Quarterly* 13(3): 319–340.
22. Dwivedi, Y. K., Choudrie, J., & Brinkman, W. P. (2006). Development of a survey instrument to examine consumer adoption of broadband. *Industrial Management & Data systems*, 106(5), 700–718.
23. Fowler, F. J. Jr. (2002). *Survey research methods.* London: SAGE Publications Inc
24. Hinton, P. R., Brownlow, C., McMurray, I., & Cozens, B. (2004). *SPSS explained*. East Sussex, England: Routledge Inc.
25. Straub, D. W., Boudreau, M-C., & Gefen, D. (2004). Validation guidelines for IS positivist research. *Communications of the Association for Information Systems*, 13, 380-427.
26. Ahsan, F. S. (2003). Knowledge Management for Disaster Scenario: An Exploratory Study. *Research Journal of Recent Sciences* ISSN 2277-2502 Vol. 2(10), 61-66.
27. Arun, K., & Jabasheela, L. (2014). Big Data: Review, Classification and Analysis Survey. *International Journal of Innovative Research in Information Security (IJIRIS)* ISSN: 2349-7017(O).
28. Creswell, J.W. (2003). *Research Design: Qualitative, Quantitative, and Mixed Methods Approaches.* (2nd ed.). Thousand Oaks: Sage Publications.
29. Hakim, C. (1987). *Research Design: Strategies and Choices in the Design of Social Research*. Unwin Hyman Ltd., London.
30. Holliday, A. R. (2007). *Doing and Writing Qualitative Research*, 2nd Edition. London: Sage Publications.
31. Naama, A. W. (2010). *National Policy on Disaster Management, Presentation at the drought risk reduction in the horn of Africa workshop*, Nairobi 11th- 12th May, 2010.
32. Ocen, G. G., Mugeni, G.B., & Matovu, D. (2016). Role of ICT in Disaster Response and Management: A Review Study of ICT Challenges and Adoption Approaches by Developing Nations, *International Journal of Advanced Research in Computer Science and Software Engineering*, Volume 6, Issue 5, May 2016 ISSN: 2277 128X, www.ijarcsse.com
33. Patton, M.Q. (1990) .*Qualitative evaluation and research methods*. SAGE Publications Newbury Park London New Delhi 1990
34. (2019). National ICT Policy,2019, MoICT, Kenya available at www.ict.go.ke retrieved 15th January, 2020.