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Multi-Dimensional Nature of e-Government: Towards Adaptive e-Government Models

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ABSTRACT

Many e-Government development models have been conceptualized based on a snapshot or current status of institutions and individuals (Agents) without considering the fact that agent statuses change over time. The implication of utilizing snapshot models to measure factors or frameworks influencing adoption or successful implementation of e-Government is that they capture what factors matter at a given point-in-time but do not look into the effect of those factors on e-Government after a period of time. This work proposes adoption of dynamic/agile development of e-Government solutions which stand a better chance of sustainability since dynamic changes in agent tastes and circumstances can determine which factors influence adoption and usage of e-Government in any given context. Understanding agile factors influencing e-Government adoption is important in designing adaptive e-Government models which are imperative for designing sustainable interventions for e-Government development. In an attempt to showcase the structural and logical limitations of snapshot models, this study utilizes the Unified Theory of Acceptance and Use of Technology (UTAUT), the Technology Acceptance Model (TAM) and TAM2 in understanding the factors that influence e-Government adoption in Zambia. The utilization of three models should normally culminate into increased explanation of factors that influence adoption of e-Government but this is not the case. The results of the study show that the factors extracted only account for 54% variance in the predictor variables and further show that there are many evolving factors given the multi-dimensional nature of e-Government which can never be captured by technology adoption models in measuring factors that sustainably influence e-Government adoption. The novelty of this research is that there is no research so far that has been proposing adaptive models for e-Government adoption.

1. Introduction

The metamorphosis of public administration to include evolving public service delivery models culminated into the conceptualization of the 'New Public Management' model – which is hinged on concepts based on agility of technology innovation with key emphasis on service efficiency [1]. As many e-Government models are being influenced by evolving technology innovations with short life-cycles, it is thus important to delve towards the development of agile adoption and assessment models. This study defines agile or adaptive e-Government adoption and assessment models as models which are highly flexible, and which may be used to measure e-Government adoption over a period of time not sorely based on technology but encompassing all other known factors influencing e-Government development in a given area.

As an enabler and main gateway to e-Government applications, technology has taken the centre stage of e-Government design and implementation [2-4]. Because of using snapshot models such as the TAM, DOI, UTAUT, etc., many developing world countries have been left out from the bandwagon of countries implementing dynamic e-Government as the key context-aware (based on a given context) factors are not know.

Dynamic e-Government entails that e-Government revolves according to technology evolution and citizens' preferences. Further, many other developing world countries have failed to effectively implement e-Government due to high set-up costs involved and because its design requires high expertise given the heterogeneity of technology environments in public-sector organisations [5, 6]. Requisite expertise may be required at the design stage to also overcome the different structural organisational incompatibilities brought about by different contextual outlays within the public sector [7, 8]. Thus, the complexity of successful e-Government implementation and development lies in its different facets of conceptualisation, design, implementation, adoption and usage. This complexity changes rapidly over a period of time [9, 10]. Appropriate measurement of e-Government needs to consider the evolving aspects of each of the different facets of e-Government and not only technology. What many models have been doing is measuring the likelihood of e-Government adoption by checking the level of acceptance and usage of technology. This approach for measuring e-Government assimilation is wrong.

This study aims to showcase the limitations of the UTAUT, TAM and TAM2 in measuring adoption of e-Government in a developing world context and therefore emphasise the need to design adaptive models in measuring e-Government development [11,12]. A mix of document review and an empirical component (data collection using questionnaires and interviews) is used to come up with positions on e-Government. This enables this study to understand as many reasons as possible which are at the center if e-Government development in Zambia. The number of key factors explaining e-Government development serves as motivating to design adaptive models for e-Government assessment. Although there are currently no global adaptive e-Government models, there is growing evidence that these have to be designed given the varying contextual settings to match up with the ever-evolving e-Government applications and solutions.

2. BACKGROUND

Understanding the gamut of e-Government is an important ingredient to one's understanding of the development and evolution projectile of e-Government applications in any given context. Although there are varying definitions of e-Government, all of them converge that e-Government involves the utilisation of ICTs to provide meaningful public services to citizens and businesses so that individuals, regardless of their status, participate in governance value chains and platforms [1,3]. E-Government principally sits at the perimeter of public administration and information systems with one leg in each space of the fields seeking their identity in the phase of multidisciplinary fields [13]. Contemporary adaptive e-Government focuses on three main arenas: adaptive and improved service provision (e-service delivery), e-democracy (digital democracy) and participation of citizens/businesses in the governance processes (e-participation) [1,2].

Everywhere where it is implemented, e-Government continues evolving and when it is adequately developed, it has multi-modal access platforms and displays content in different formats exploring the best that contemporary multimedia has to offer [13]. Further, fully developed e-Government solutions provide bi-directional flow of information to the extent where there is synchronous interaction between government agents and e-Government consumers (citizens and businesses). Such communication capabilities allows citizens to solicit for information from government agents and able to pervasively access government services such as online application of drivers' licences, passports, etc.

Although technology has been peddled as the most important attribute in e-Government development and adoption, it is worth noting that e-Government does not solely depend on the computer power but also on the willingness of the general citizenry and businesses to adopt it [9]. The other factors influencing e-Government need to be considered in any endeavours of e-Government design and implementation. Given the short lifecycle of technology and given the fact that e-Government uses technology as its key enabler, it is worth commenting that the evolution of the nature of e-Government is rapid because technology has a short lifecycle. There is evidence that e-Government evolves rapidly and therefore there is need to understand the forces at play for e-Government evolution [14]. Unfortunately, these forces are not global and therefore each environment in which e-Government is to implemented needs to conduct empirical studies to understand what key forces can influence e-Government development in that particular context. In order to maintain relevance of e-Government solutions, it is important that e-Government keeps evolving to adapt to the ever-changing environment.

In many parts of the world, interventions towards e-Government development have been informed by studies measuring the status of adoption and usage of e-Government applications [15]. Most of these studies have been hinged on the assumption that since technology is a key enabler of e-Government, its acceptance and adoption automatically translates into e-Government adoption. However, a key flaw in this approach is that most of these studies have neglected the effect of other factors given the multi-dimensional nature of e-Government. Further, it worth mentioning and noting that technology has a shorter lifecycle meaning that its changes may have an effect on the degree of e-Government adoption and synthesis. Therefore, studies that have used e-Government development models (stage models) such as Gartner, World Bank, Howard, Deloitte and Touche, Asia Pacific, Moon, Hiller and Blanger, West, United Nations, Gartner, Chandler and Emanuel, Layne and Lee, etc., capture the snapshot status of e-Government given the status of technology at that particular point in time and may miss out on changing modules of technology and what their effect is on the overall e-Government agenda [16].

E-Government is complex as interests of each of the stakeholders represent individual instance and form of what e-Government has to achieve and take [17]. Therefore, a good approach is to obtain the common denominator of those interest and ensure that strategies or interventions put in place take care of those interests. The modelling of the different interests/factors influencing e-Government development can be mathematically represented by a multi-dimensional array with different scalars. For example, public managers are interested in ensuring that e-Government solutions make their work less demanding and much easier, citizens and businesses are generally looking for 'custom-made' public services satisfying their aspirations and service levels and reduce corruption in the government business value chains; politicians are expectant that e-Government will massively reduce the cost of public service delivery, businesses are expectant that e-Government will open up channels for them to easily engage the government and influence policy so that the business environment is levelled., etc. Satisfying the demands of each of these different stakeholders is a mammoth task [14].

Therefore, the starting point in the design of e-Government is the understanding of the different mental models of the potential (or would-be) stakeholders and to keep in point that these models keep changing over time. This study proposes that as these interests change, the development trajectory of e-Government also needs to change to accommodate the changing interests. Therefore, an agile development approach where e-Government is designed upon open interfaces and platforms which are highly scalable is desired. Momentous understanding of the factors influencing e-Government in any area (as shown in this study) is important but more important is the understanding of the evolving individual or institutional interests which calls for on-going exploration of these factors using adaptive models [14, 18].

3. THEORETICAL GROUNDING

The major concern in the preliminary analysis of this study is for the dataset to follow a normal probability density function (Gaussian bel-shaped curve) so as to determine validity of the data [19]. A study have shown that valid statistical inferences from any dataset can only be obtained if the dataset follows normality [19]. In measuring the multi-dimensional nature of e-Government, we assume the dataset obtained in this study is a multidimensional vector with X random variables conforming to multivariate normality conditions (articulated below) with mean μ and variance δ^2, the one-dimensional Gaussian normal distribution function will take the following form:

$$\varphi_x(t) = e^{it\mu - \frac{1}{2}t^2\sigma^2} \quad [1]$$

From above, we can generalize univariate normal distribution given the multivariate random dataset ($x_i = [x_{i1} \quad x_{i2} \quad \dots \quad x_{iN}]$) in this study. Since the data obtained in the empirical part of this stud is multidimensional, the multidimensional Gaussian Normal distribution density function used as the basis for testing normality will then take the following form [20]:

$$N(x|\mu,\tau) = \frac{1}{(2\pi)^{\frac{M}{2}}\det(\tau)^{\frac{1}{2}}} e^{-\frac{1}{2}(X-\mu)^T\Sigma^{-1}(X-\mu)} \quad [2]$$

Where τ represents the covariance matrix of the multivariate data and μ represents the multivariate mean vector of the dataset represented as a one-dimensional array as shown in equation 3

$$\mu = [\mu_{x_1} \quad \mu_{x_2} \quad \dots \quad \mu_{x_N}] \quad [3]$$

Therefore, the covariance matrix, $\sum$, is represented as follows:

$$\Sigma = \begin{pmatrix} {\rho_{x_1}}^2 & \rho_{x_1x_2} & \cdots & \rho_{x_1x_N} \\ \rho_{x_1x_2} & {\rho_{x_2}}^2 & \cdots & \rho_{x_2x_N} \\ \vdots & \vdots & \ddots & \vdots \\ \rho_{x_1x_N} & \rho_{x_2x_N} & \cdots & {\rho_{x_N}}^2 \end{pmatrix} \quad [4]$$

Further assuming that the mean equals zero ($\mu = 0$), multivariate normal distribution is then defined by the linear combinations of univariate normal distributions. In other words, if the dataset in this study were to be analysed using univariate regression analysis, it is important to ensure that each of the univariate distributions follow normality. Many multivariate normality testing is based on Mardia's testing approach for Kurtosis ($\beta_{1,p}$) and skewness ($\beta_{2,p}$) given a dataset with multiple variables. The Mardia's test was used in the study to confirm the normality test obtained using Q-Q plots and histogram observation and other parametric tests used in this study. In a given multivariate distribution

$$\beta_{1,p} = \phi\{\Sigma^{-1}(x-\mu)(y-\mu)^{-1})\}^3 \quad [6]$$

Given a scenario where x and y are independent of each other. It follows that

$$\beta_{2,p} = \phi\{\Sigma^{-1}(y-\mu)(y-\mu)^{-1})\}^2 \quad [7]$$

In a multivariate normal distribution, it is assumed that $\beta_{1,p} = 0$ and $\beta_{2,p} = p(p+2)$. Given a sample size n observation (in this case, N=408), using Mardia's multivariate test, we can thus rewrite equations 6 and 7 as

$$\check{\beta}_{1,p} = \frac{1}{m^2}\sum_{i=1}^{m}\sum_{j=1}^{m} g_{ij}^3$$

$$\check{\beta}_{2,p} = \frac{1}{m}\sum_{i=1}^{m} g_{ii}^2 = \frac{1}{m}\sum_{i=1}^{m} d_i^4 \quad [8]$$

The equations above give the basis for understanding kurtosis and skewness in line with the Mahalanobis Distance Method where $g_{ii} = d_i^2 \text{ and } g_{ij} = (y-\check{y})'S_n^{-1}(y_j-\check{y})$ is a scalar giving the squared Mahalanobis Distance between y_i and (μ which is equal to $\check{y}$) which literally translates to the vector dispersion (how far) the observed data is from the center of joint distribution μ representing the centroid in the multivariate data space [8]. Once the Mahalanobis distance of each observed data case is known, it is now possible to construct the Q-Q plot using the estimated mean vector $\check{y}$ and the covariance matrix τ to make a visual representation of the data. In this study, the Q-Q (P-P) plot presents a visual representation of the dispersion in the dataset and can be visually used to show the extreme cases in the dataset. Skewness is thus approximated as χ^2 with p(p+1)(p+2)/6 degrees of freedom, and Kurtosis

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approximated with mean p(p+2) and variance 8p(p+2)/n for sample n>20 [which holds in this study].

In the main empirical part of the study, a questionnaire with both open and closed-ended questions informed by reference from the UTAUT, TAM and the TAM2 was used as the main data collection tool. With reference to the context, the constructs from the three models included in the study's conceptual framework in order predictive capacity. Some interviews were conducted with not more than 15 individuals to complete the data obtained from the questionnaire. The measurable constructs in this study are: Perceived Usefulness (PU), Perceived ICT Ease of Use (PEOU), Behaviour Intention (BI) to use, availability of ICT infrastructure, language and content, system usage, computer self-efficacy, access cost, availability of appropriate legal and regulatory frameworks, user support, trust, and continuance usage [21].

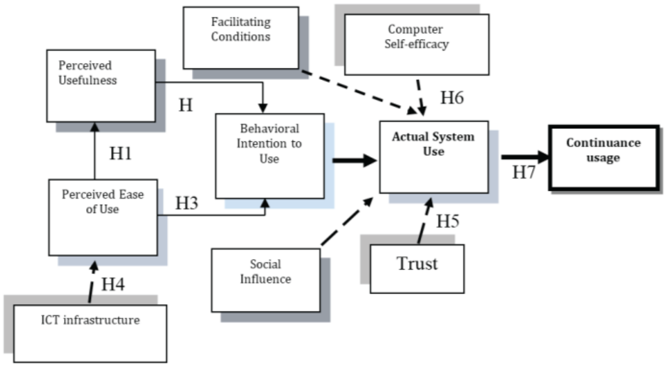


Figure 1: Conceptual model for e-Government adoption assessment in Zambia

In order to make sense of the conceptual framework in figure 1, the following hypotheses were constructed:

***H1**: Perceived ease of use of e-Government websites will positively influence the perception of usefulness of e-Government websites and applications.*

***H2**: Perceived usefulness of e-Government websites will positively influence citizen's adoption (actual usage) of e-Government websites and applications.*

***H3**: Perceived ease of use (usability) of e-Government websites will positively influence citizen's adoption of e-Government websites and applications.*

***H4**: Appropriate ICT infrastructure and lower costs to access the basic ICTs impacts positively on usability and correspondingly on Perceived Ease of Use (PEOU);*

***H5**: Trust directly influences engagement or non-engagement in e-Government applications;*

***H6**: The level of computer self-efficacy will impact on the actual use of an e-Government system by an individual.*

***H7**: Positive ICT developments will facilitate actual usage and correspondingly continuance usage of e-Government applications.*

***H8**: Appropriate ICT infrastructure coupled with higher PEOU will culminate into improved overall Perceived Usefulness (PU).*

4. RESEARCH PROCESS

A total of 721 questionnaires were distributed with 411 of them returned for analysis and 3 dropping out during the data screening stage. Therefore, 408 questionnaires were included in the final analysis. The study targeted 3 towns in Zambia: of Kitwe, Livingstone and Lusaka. To make the research management easier, two research assistants were recruited to distribute and collect the questionnaire from the participants [22]. The main researcher conducted all the interviews himself. For the interviews, a total of 20 policy-makers, government leaders, businessmen and other ordinary citizens were involved. The study used semi-structured interviews to enable flexibility during the interview schedule. The data obtained from the research process was analysed with the help of SPSS version 10. Apart from the questionnaire, the study also used semi-structured interviews to valid data obtained using questionnaires or to obtain data not gathered using questionnaires such as data on policy and government interventions on e-Government. This study ensured that all standard ethical principles and guidelines such as voluntary participation in the research (informed consent), voluntary withdraw at any time of the research process, questions not embarrassing or insulting, anonymity of responses, non-involvement of minors, etc., were observed during the research process [23,24].

The data collected was subjected to preliminary testing to ensure that it conformed to the basic statistical assumptions to obtain valid and reliable statistical inferences in the analysis. Because of the negatively skewed data observable in the dataset during preliminary testing, it was important to perform data transformation using an optimally chosen logarithmic function, Log_{10} (6-X), to remove negative skewness. The transformed data was then subjected to normality testing and homoscedasticity. Many approaches in multivariate normality testing have considered skewness and kurtosis tests employing the Shapiro-Wilk statistic and the Kolmogorov-Smirnov goodness of fit test and the Rosenblatt transformation [20]. This study employs the Kolmogorov-Smirnov and the Shapiro–Wilk tests to measure multivariate normality [25,26]. Parametric tests such as the Kaiser-Meyer-Olkin measure (KMO-test), the Shapiro-Wilk test, and Bartlett's Test of Sphericity were performed on the dataset to confirm normality in the dataset and to check whether the data can be subjected to rigorous statistical inferential analysis. With acceptable values of 0.7 and above, the KMO test measures the adequacy of the sample to justify readiness of the data for statistical analysis. This study had a KMO value of 0.919 as shown in Table 1.

Table 1: The KMO and Bartlett's tests

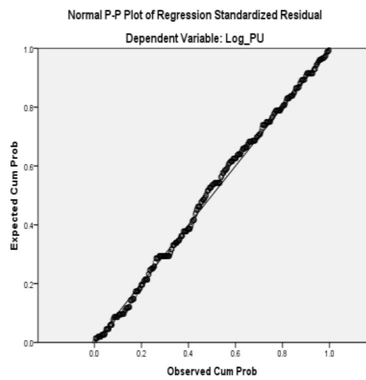
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.919
Bartlett's Test of Sphericity	Approx. Chi-Square	2701.097
	Df	66
	Sig.	.000

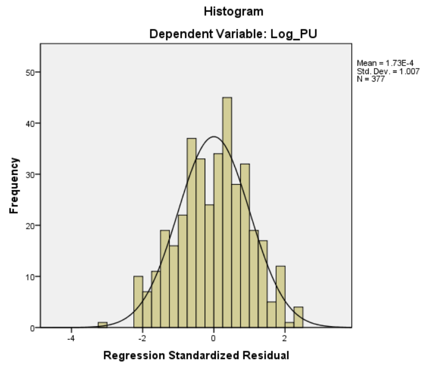
Each of the hypothesis were tested using parametric tests such as Bartlett, Kolmogorov-Smirnov, the Shapiro-Wilk, and analysis of variance (ANOVA) tests to understand which aspects of the measured variables are as hypothesised and which ones don't hold. Table 2 shows that all the factors investigated are statistically significant to the level 0.005 and can therefore be used in the analysis.

Table 2: Tests for Normality on all measured factors

Idenitified Factors		Kolmogorov-Smirnov[a]			Shapiro-Wilk		
		Statistic	Df	Sig.	Statistic	Df	Sig.
1.	ICT_infra ICT Infrastructure	.132	374	.000	.901	374	.000
2.	PEOU	.142	377	.000	.972	377	.000
3.	PU	.117	401	.000	.930	401	.000
4.	Comp_SE	.178	405	.000	.880	405	.000
5.	Social Influence	.129	405	.000	.899	405	.000
6.	Trust	.149	377	.000	.951	377	.000
7.	Facilitating Conditions	.147	374	.000	.924	374	.000

a. Lilliefors Significance Correction





The data was further checked for multicollinearity and singularity and the presence of outliers using histograms, the P-P plots and the scree plot. The results were further checked for normality using the P-P plot of standard residuals. It is evident from the two figures that the data approximately follows a normal distribution function and that it follows linearity. Therefore, the data conforms to statistical validity and can be used for further statistical analysis.

Figure 2: Histogram and linearity of PU on PEOU

On each of the seven independent variables, was subjected to analysis of variance (ANOVA) with statistical significance level of 0.05.

Table 3: ANOVA of measured variable

Model	Sum of Squares	Df	Mean Square	F	Sig.
1 Regression	34.884	6	5.814	15.701	.000[a]
Residual	131.089	354	.370		
Total	165.974	360			

Table 3 shows a regression analysis, predicting the transformed variable, logarithmic value of the Perceived Usefulness (Log_PU) from PEOU, which was highly statistically significant with $F(6) = 15.701$, $p < .001$. The residual statistics from the dataset confirmed that the Mahalanobis distance has an acceptable value for one independent variable and does not exceed the Chi-square critical value for 1 degree of freedom which is 10.828 as shown in Table 4.

Table 4: Residuals Statistics

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	.1461	.4267	.2794	.05538	377
Std. Predicted Value	-2.407	2.661	.000	1.000	377
Standard Error of Predicted Value	.007	.020	.010	.003	377
Adjusted Predicted Value	.1470	.4361	.2794	.05542	377
Residual	-.42674	.34197	.00002	.13991	377
Std. Residual	-3.071	2.461	.000	1.007	377
Stud. Residual	-3.104	2.464	.000	1.010	377
Deleted Residual	-.43611	.34289	.00000	.14073	377
Stud. Deleted Residual	-3.141	2.481	.000	1.012	377
Mahal. Distance	.016	7.081	.997	1.454	377
Cook's Distance	.000	.106	.003	.007	377
Centered Leverage Value	.000	.019	.003	.004	377

a. Dependent Variable: Log_PU

[On Table 4, please note that N=377 as some outlier cases were removed from the final analysis]. The study managed to explain only 54% of variance of the factors influencing e-Government adoption and usage in Zambia. These factors were at a higher level of abstraction and their influence on individual's adoption and usage of e-Government is not constant thus changing with changing circumstances.

5. RESULTS AND INTERPRETATIONS

The descriptive statistics were analysed given the associations of the different parts of the conceptual framework as stated in the hypotheses. The analysis of the data revealed the following:

1) The majority of the respondents have the requisite ICT skills to effectively engage in e-Government although the actual usage off e-Government applications is low as only 27% of the respondents indicated having ever used e-Government applications. Most of the respondents who had adequate ICT skills and did not ever use e-Government solutions in Zambia showed ignorance of ignorant of e-Government being implemented in Zambia. Five years down the line, the number of citizens with very low ICT skills is going to change as there are so many schools and interventions working towards improving ICT skills of citizens and upping their computer self-efficacy capabilities;

2) A total of 49% of the people surveyed indicated that they were not aware of e-Government being implemented in Zambia, with 30% being moderately aware of available e-Government services;

3) 61% of the respondents indicated that most e-Government websites or platforms are not reliable and that they cannot generally trust e-Government platforms with 84% pointing out lack of security policies and a further 84% of the respondents indicating that they would not be comfortable in sharing their information with government platforms; and

4) Over 50% of respondents are in agreement that under-developed ICT infrastructure in Zambia is negatively impacting on e-Government development in Zambia.

Specifically, information obtained with regards to the construct associations in the conceptual model reveals the following

1) The PEOU of e-Government websites positively influences the PU of e-Government websites and applications in Zambia. If an e-Government platform is difficult to use, it becomes very difficult for the citizens to engage in e-Government;

2) This study failed to state with appreciable degree of confidence that PU will positively impact on adoption and usage of e-Government applications in the case of Zambia. The strong correlation in the coefficients in the Pearson's Correlation matrix and the higher statistical significance ($p<0.001$) and the acceptable value of R^2 at 24.6% the study posits that at higher maturity levels of e-Government implementation, it is evidently possible that PU has a direct positive impact on PEOU and correspondingly e-Government adoption;

3) Because of the linearity in the dataset and the higher statistical correlation ($R^2 = 0.238$), PEOU will positively influence citizens' adoption of e-Government services;

4) The existence of requisite ICT infrastructure and low costs alone cannot guarantee positive influence on the PEOU of e-Government services

5) With evident linearity and R^2 value of 0.085 showing some degree of variance caused by engagement of citizens and businesses in e-Government applications;

6) The study confirms that an individual's leveI of Computer Self-Efficacy will positively influence his/her involvement in the utilisation of e-Government services;

7) With transformed variables to remove the effect of the three distinct outliers, the dataset showed normality and R^2 value of 0.076, it therefore follows that positive ICT developments and actual sage will culminate into positive continuance usage of e-Government applications;

8) The study further shows that appropriate ICT infrastructure coupled with higher PEOU will culminate into improved PU for the case of Zambia's e-Government development.

The conceptual model utilised in the study was able to identify factors influencing individual adoption and usage of e-Government at a given particular point in time but may not be very useful since most of the identified factors effect evolve with time. Therefore, future studies will need to design adaptive models that can be used to identify factors without the limiting factor of time.

6. CONCLUSIONS AND LIMITATIONS

This study aimed to explore the effectiveness of static models in measuring the adoption and usage of e-Government in Zambia. A conceptual model comprising constructs from the TAM, TAM2 and the UTAUT was used to identify factors influencing individual adoption and usage of e-Government applications. The seven factors identified as contributing highest variance (explanation) of the factors influencing adoption and usage only accounted for 54% of variance. This is a clear indication that the models cannot capture inherent individual factors which may be different from each participant. These factors change with time as the individual's preferences and technology evolve. Therefore, there is need to think of adaptive models which are not only going to identify individual factors but also track the evolving changes in the assessment of the factors. The major limitations of the study are: 1) Does not measure actual participants' behaviour but measures 'behaviour intention' although perceived to have a direct causative relationship and 2) The sample is limited and confined to the major cities along the line of rail in Zambia. The statistical inferences in this paper are for demonstrations purposes only proving glimpse of what may be the complete story in Zambia as the study may not be representative of the entire population in Zambia. Further, there is need for more empirical studies designed within the realm of adaptive e-Government models be it assessment or implementation models. Adaptive models are a future for e-Government given the short lifecycle of e-Government applications. Adaptive models are a meaningful innovation for studying the development of future e-Government applications.

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