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Determinants of E-Resources Usage Intensity of Postgraduate Students in a Kenyan Private University

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Abstract:
The aim of this study was to ascertain the determinants of usage intensity of e-resource platforms accessible to postgraduate students of a Kenyan private university. The research applied Technology Acceptance Model (TAM) to make sense of e-resource interaction and usage by postgraduate university students within a developing country context. Cross-sectional descriptive survey design was used. The target population was 225 postgraduate students who were on session during September 2017 semester and who had completed at least one year of study. From this, 79 eligible respondents were randomply sampled. Perception data was matched against users' uniform resource locator (URL) log count. Inferences were drawn using correlation and regression technique. The study established that TAM factors explained 10.9 percent of the variability in the student's e-resource usage intensity. The results showed that perceived ease of use had no statistically significant predictive power on e-resource usage intensity. The results also indicated that perceived usefulness did not significantly predict the student's e-resource usage intensity. Similarly, perceived behavioural factors did not significantly predict the student's e-resource usage intensity. The results challenge the applicability of TAM for explaining technology acceptance and usage as far as e-resource usage is concerned. Conclusion was drawn that TAM factors are not adequate for explaining postgraduate student's e-resource usage intensity in a Kenyan private university. University librarians should be user-centric in the design of all its systems. This calls for collecting the views of users and bringing their input on board as opposed to library logic where the library staff create a system based on what they believe is good for the users. More studies that integrate objective data mined from e-resource servers with perception data using a larger dataset should be conducted to confirm or refute the findings of this research. Meta analysis of such studies can lead to the development and validation of new models for explaining e-resource usage especially in a resource-constrained country.
Key Words: Behavioral Control, E-resources, Perceived Ease of Use, Perceived Usefulness, Usage Intensity.

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I. INTRODUCTION

E-resource usage in a universitsy play a central role in the academic life of postgraduate students due to the intensity of research involved in postgraduate level of education. If a university library is to make headway when it comes to satisfying the needs of its postgraduate users, it has to align its services according to this cohort's preferences. Decision makers ought to put into consideration these preferences as they signal not just user needs but also trends (Meletiou, 2010).

With the continued advancement in technology, and the introduction of different modes of study in institutions of learning, there has been an increasing need to ensure that library resources are not only accessible from the ordinary desktop computers but also through other gadgets which library patrons and users can connect to either from within the library or remotely. Most postgraduate users will opt to use their personal gadgets to access the available resources and for this reason, the library has no option but to adjust to this trend accordingly. Tidal (2013) concurs with this statement by saying that technological trends have enabled gadgets such as Wi-Fi-enabled e-readers, computer tablets and smart phones to connect library users to the available online resources and learning institutions have had to adjust accordingly in order to meet the needs of such device users.

User preferences are not just determined based on the traditional library services but also through web resources. Gakibayo et al. (2013) note that library services have evolved from the days of closed library stacks through searches using punched cards to open access databases and repositories. Most libraries today have reinvented themselves from just being a repository of books to centers of information and communication of knowledge via open acess databases, social media platforms, websites and institutional repositories.

Recent trends in technological advancement allow librarians and other researchers to get to understand user behaviour through tracking users pathways as they interact with such open access databases, websites, institutional repositories, social media platforms and analysing the same in order to determine what content is most popular with the users, hence seek to improve ease of navigation to that content in a bid to reach out to users and guarantee them satisfaction (Vecchione et al., 2016). Understanding the determinants of e-resource usage patterns provide the evidence base upon which universities can develop a response to promote the greater adoption and usage of electronic platforms in which they invest.

The driver of information seeking is the idea of a user need or information need. Any information need can be seen as the motivation an information seeker may have when seeking for it. Users with certain information needs behave in certain ways as they interact with the available people, information resources and systems. The information seeker sees a gap between what he has, what he has experienced, and what he wants, or even wishes to experience. Users will be prompted to visit a certain site depending on the resources and information needs they may have. The queries raised through the information seeking process signals to a librarian about the user needs. In order for any librarian to successfully meet the needs of the postgraduate library users, it becomes paramount for them to be aware of the determinants of e-resource usage intensity. Prior related research suggest that perceived usefulness explain majority of the variance in postgraduate student's satisfaction with e-resource usage and that perceived usefulness and perceived ease of use mediate the relationship between computer self-efficacy and e-resource usage (Gu, Teo, & Peng, 2019; Isam & Sheikh, 2020; Islam, Leng, & Singh, 2015). A common denominator in these studies is that e-resource user's computer self-efficacy had a significant influence on their level of satisfaction. However, these studies were undertaken outside Africa and therefore may not generalize to the situation in African universities.

Research done in Africa on the factors influencing e-resource usage report different results that reveal contextual differences which most western models fail to take into account. For instance, an investigation on e-resource utilization among students of Great Zimbabwe University by Mawere and Kundai (2017) found that limited utilization of the university's e-resources was due to the students' ignorance and unawareness of e-resource facilities, lack of resources to access the e-resource facilities and high cost of data charges by the providers of internet services. Similar findings were reported in a study undertaken in a university in Nigeria (Joshua & King, 2019) and Tanzania (Mollel & Mwantimwa, 2019) suggesting that factors influencing university e-resource utilization are potentially context-specific. In fact, the study by Gor (2017) among distance learners in the University of Nairobi found no significant influence of computer self-efficacy on e-resource utilization in contrast to most studies, suggesting that the research evidence is mixed. However, the scenario in Kenya is characterized by limited scholarly knowledge resources on the subject matter, with the few available reference material existing in unpublished form (Omete, 2016; Sisimwo, 2016).

One of the scientific researches done in Kenya was undertaken Momanyi, Toroitich and Onderi (2018) who investigated student skills and utilization of e-resources at a public university. However, the study's narrow focus on information literacy programming at the university limits the generalizability of results to the gamut of factors potentially at play in a resource-constrained country like Kenya. Furthermore, the study did not mine the University's server where user log files were stored to analyze e-resource usage intensity. In order to address this knowledge gap, this study sought to investigate the factors influencing usage intensity of university library's e-resource platforms within a private university in Kenya by matching perception data against users' uniform resource locator (URL) log count. The specific objectives were to:

i) determine the influence of perceived ease of use on e-resource usage intensity of university libraries
ii) establish the influence of perceived usefulness on e-resource usage intensity of university libraries
iii) investigate the influence of perceived behavioral control on e-resource usage intensity of university libraries

II. LITERATURE REVIEW

Usage intensity is the breadth and depth of interaction between any given information user and computer-based information systems as measured by the log count record maintained in a computer system for every user (Timmers & Glas, 2010). This depicts the interaction in totality between human beings and e-resource channels (Kadli & Kumbar, 2013). The concept largely describes modalities through which information is needed, sought after, managed, provided and used in all the various contexts to fill an information gap (Kadli & Kumbar, 2013).

The definition of usage intensity extends to the way users navigate and find their way in an information institution or an information space such as within a library. This normally is depicted in the way e-resource user utilize the available varieties of informational media, information systems and people and familiarize themselves with these resources (Mandel, 2016). In a university library setting, e-resource usage can be measured by the URL counts (Wakahia, 2017). E-resource user behavior could also be seen as the way a user creates a search for information with an intention to fulfill an information need and how this same user will do a follow up on the very search he initiated.

The way the e-resource user behaves when interacting with different features of e-resource systems leads the librarian understand the user's preferences. The librarian will thus deduce the various user needs that can form his users groups based on the analysis drawn from the behavior of all these users (Prabha, 2013). Spink and Heinstrom, (2011) agree with this view and continue to opine that by linking information behavior to other instinctive genetic dispositions, such as personality differences and language, librarians can further increase the understanding of information behavior patterns and styles. The inner traits and personality dimensions of the e-resource users interacts with the contextual factors to formulate the impact in the form of motivation for information, information habits, patterns of information seeking and the nature of cognitive, affective and social utilization of information (Halder, Roy & Chakraborty, 2010). These user motivations, information habits, patterns of information seeking, social utilization methodologies are the ones that librarians anchor on to form user groups. The categories of users will vary from one library setting to another depending on the services offered. The user needs and requirements of each user group will also be divergent (Prabha, 2013). Therefore, it is left to the librarians to understand their users and know how best to profile them.

Gibbons (2012) observes that the swiftly changing education scene mainly caused by the dynamisms of technology bring along different challenges and the administration has no option but to embrace this dynamism and the challenges that come along and realign library services is a way that seeks to meet these challenges. For any university, understanding how e-resource users approach make sense of what they find plays a key role in trying to analyze their usage intensity (Case & Given, 2016; Tella, 2016).

Technology Acceptance Model (TAM) has been widely used in most studies involving ICT adoption and usage. Use and availability of e-resources is one of the development brought by ICT and TAM has been one of the widely used model in studies relating e-resource usage. TAM was developed and proposed by Davis (1986) as a theoretical model for understanding of user acceptance of computer-based information systems. The model was developed to help establish the key variables that mediate the relationship between system characteristics and actual use of such systems, and the causal relationship between the variables. The model suggests that there are a number of factors at play in the decision about when and how prospective users will use new technology (Silva, 1989). The main idea about TAM is that acceptance of technology is determined by user perception of its usefulness, the ease of its use and behavioural control users have over the technology. In this model, any human behaviour is predicted and explained through three main cognitive components including attitudes, social norms, and intentions (individual's decision do or don't do a behaviour) (Taherdoost, 2018). The model seeks to analyze and clarify the complexities of human behavior in their entirety.

Since its first conceptualization in the 1980s, the model has been the subject of continuous development. Tracing its history, Lee, Kozar and Larsen (2003) demonstrated that the theory has evolved through successive stages from validation to model extension and elaboration. For instance, a new version of the theory was introduced in the turn of the 21st century. Known as TAM 2, this new version introduced external variables of which perceptions of behavioral control was key (Venkatesh, 2000). Later, Venkatesh and Bala (2008) further developed an integrated model that they referred to as TAM 3. This version takes into account and measures the role of interventions used to promote technology acceptance and the moderators of usage post-implementation. Among these are training, experience, user participation, peer support and organizational support (Venkatesh & Bala, 2008).

The comprehensiveness of TAM was later challenged by Venkatesh, Morris, Davis and Davis (2003) who lamented the fragmented theorization of technology acceptance and usage. They thus came up with a unified model that integrates the elements of previous models into a single model. Venkatesh et al.'s (2003) Unified Theory of Acceptance and Use of Technology (UTAUT) consolidates the various factors into four basic determinants of technology usage and four moderators. The four basic determinants are performance expectancy which is more or less the same as TAM's perceived usefulness, effort expectancy which is more or less the same as TAM's perceived ease of use, social acceptance which is more or less the same as TAM2's subjective norm and facilitating conditions which expands the concept of behavioral control by including other factors that can either be an enabler or a barrier to technology usage. Four demographic factors are integrated into the model as moderators: gender, age, experience and voluntariness of use.

Due to the validity and versatility of TAM across disciplines as well as its simplicity, the theory was considered the most appropriate for the investigation of factors influencing e-resource usage in Kenya's private university sector. Specifically, the theory allows for the integration of behavioral control which in this research comprised of knowledge, confidence and ability to use e-resources as well as possession and control over e-resource devices such as laptops. The unified model was not appropriate for this study because UTAUT itself is still evolving, with UTAUT2 being its most recent version fronted by its proponents to account for hedonism, habit and price (Venkatesh, Thong, & Xu, 2013). It is important to highlight that while UTAUT has better predictive power on behavioral intentions, its predictive power on actual usage, at 52% (Venkatesh et al., 2013) actually lower than the predictive power of TAM which Davis (1986) reported as 55%.

Until recently, most of the studies on e-resource usage intensity in university libraries have been dominated by western thinking (Duffin, 2020; Lamothe, 2019; Lewellen & Plum, 2016; Mangrum & Foster, 2020). Burgeoning research is being documented in the developing world context that provides consistency and validity of TAM's application outside the western world. Mawere and Sai (2018) applied the theory in their investigation of e-resource utilization among Zimbabwean university students. Results showed that e-resource usage among respondents was very limited due to lack of resources among students and poor promotion strategies. In another study, Hamutumwa (2014) investigated the use of e-resources by distance learners at a university in Namibia. A low level of awareness and devices to facilitate e-resource usage was observed. In yet another study, the utilization of electronic information resources in a University setting was conducted (Gakibayo, 2013). The findings suggested that e-resource user self-efficacy and access device availability were key antecedents. Namisiko, Munialo and Nyongesa (2014) also studied the challenges facing e-learning in Kenyan private universities and found that availability of e-learning infrastructure; perceived usefulness and perceived ease of use of e-learning resources were important factors. All these studies seem to underscore the dominance of TAM factors to the determination of e-resource usage behavior. However, the conclusions in these studies were drawn from limited analytical rigour as most of them were largely descriptive.

Drawing from the empirical and theoretical literature, three null hypotheses were tested as follows:

H_{01}: Perceived ease of use has no influence on e-resource usage intensity of postgraduate students in a Kenyan private university.

H_{02}: Perceived usefulness has no influence on e-resource usage intensity of postgraduate students in a Kenyan private university.

H_{03}: Perceived behavioral control has no influence on e-resource usage intensity in a Kenyan private university.

III. RESEARCH METHODOLOGY

Cross-sectional descriptive survey design was used. This type of research design enables the collection and analysis of data so as to come to conclusion about a population of interest at one point in time (Lavrakas, 2008). This design was used because it provides a snapshot of e-resource usage at the time the research is undertaken. The target population was 225 postgraduate students who were on session during the September 2017 semester and who had completed at least one year of study. From this, 79 respondents were randomply sampled. This sample size was determined by performing power analysis using G*Power software (Lomax & Hahs-Vaughn, 2013). Statistical power is the likelihood that a statistical test will produce a statistically significant output (Cohen, 2013). An a priori linear multiple regression, fixed model, single regression coefficient test with three predictors was run in keeping with the number of independent variables of this study. For a two-tailed test, the obtained sample was found to have a medium effect size of 0.17 at 95% confidence level and 95% statistical power. Effect size refers to the extent to which the alternate hypothesis is far from the null hypothesis (Cohen, 2013). The sample size therefore meets the required threshold of at least 80% statistical power and at least 95% confidence that a sample size should fulfill (Cohen, 2013; Rubin, 2009).

A structured questionnaire tool was administered to postgraduate students of a private university located in Nairobi. The data was collected through drop-and-pick method. The first section contained questions that elicited demographic data about the respondents. The remaining sections contained a set of questions and statements for evaluating perceived usefulness of e-resources, perceived ease of use of the e-resources and perceived behavioural control factors.

Perceived usefulness was measured using a 7-item Likert scale that covered speed of completion of assignments, quality of research work, ease of doing assignments, control over assignments, user effectiveness in research, and relevance, accuracy and currency of the e-resources. Perceived ease of use was measured using an 8-item Likert scale that covered dimensions such as clarity and simplicity, ease of access, error frequency, user frustrations, user-friendliness and ease of navigation. Perceived behavioural control was measured using a 5-item Likert scale that covered aspects like user confidence, knowledge, access to devices, user ability and control. Reliability of the instrument was determined using Cronbach's alpha. The output of reliability test is shown in Table 1. The table shows that the the alpha coefficient of the Likert scale for exceeded the 0.7 threshold that indicates that the scales were highly reliable (Taber, 2016). E-resource usage intensity was measured by total URL count.

Table 1. Reliability Statistics

Predictors	Cronbach's Alpha	N of Items
Perceived usefulness	.798	7
Perceived ease of use	.902	8
Perceived behavioral control	.839	5

Official perrmission was obtained from the University to collect this data by mining the server where access platform known as ezproxy was installed to examine user log files. The log files idenified the individual users based on the Internet Protocol address and the student registration numbers.

A total of 48 questionnaires were successfully filled and returned out of 79 respondents that were targeted. This translated to a response rate of 61 percent. This was considered sufficient response rate to undertake analysis. The respondents were distributed demographically as follows: 40(80%) of the respondents were Master's students and 8(16.7%) were PhD students; majority (27, 56.3%) of the students hailed from the School of Humanities and Social Sciences, 13(27.1%) were from School of Leadership, Business and Technology and 8(16.7%) came from School of Theology. Majority (40, 83.3%) of the respondents had been enrolled in their program at least one year prior to the research. Further, 68% (33) of the students had received orientation of e-resource usage, 28(54.8%) of the respondents reported having moderate computer self-eficacy skills, 25(51.6%) of the respondents had moderate internet self-efficacy.

Data was analysed using Spearman's rank correlation and multiple linear regression techniques. The use of the Statistical Package for the Social Sciences (Version 24) was made. The following regression model was used:

$ERUI = \beta_0 + \beta_1 PEOU + \beta_2 PU + \beta_3 PBC + e$

Where; ERUI = E-Resource Usage Intensity

β = Beta coefficient

β_0 = Intercept of ERUI

PEOU = Perceived Ease of Use

PU = Perceived Usefulness

PBC = Perceived Behavioural Control

e = Error term

All ethical protocols of research were followed in accordance with the requirements for conducting research in Kenya as laid out by the National Commission of Science, Technology and Innovation (NACOSTI).

IV. RESULTS

Usage intensity (URL log count) was correlated with the composite mean scores for 7 perceived usefulness dimensions, 8 perceived ease of use dimensions and 5 perceived behavioral control dimensions using Pearson's product moment correlation coefficient at $p<.05$. The results are presented in Table 2. The table shows that the correlation between usage intensity and perceived ease of use (r=.159, p>.05) as well as perceived usefulness (r=.073, p>.05) were not statistically significant though a weak positive correlation was obtained between e-resource usage intensity and perceived ease of use. This suggests that neither perceived ease of use nor perceived usefulness had an influence on respondents e-resource usage intensity.The table however shows that usage intensity was significantly correlated to behavioral control factors (r=.289, p<.05). This means that usage intensity increased with increased behavioral control factors such as knowledge, confidence and ability to use e-resources as well as possession and control over e-resource devices such as laptops. The table further indicates that there was a strong positive correlation between behavioral control and perceived ease of use (r=.632, p<.01) which in turn, significantly correlated to perceived usefulness (r=.504, p<.01). This implies that perceived behavioral control increased with rise in perceived ease of use. Further, perceived usefulness also increased with increase in perceived ease of use.

Table 2. Correlation of Determinants of E-resource Usage Intensity

Determinants			1	2	3	4
1.	Usage intensity	Pearson Correlation	1			
		Sig. (2-tailed)				
		N	48			
2.	Perceived Usefulness	Pearson Correlation	.073	1		
		Sig. (2-tailed)	.620			
		N	48	48		
3.	Perceived Ease of Use	Pearson Correlation	.159	.504**	1	
		Sig. (2-tailed)	.280	.000		
		N	48	48	48	
4.	Behavioral Control	Pearson Correlation	.289*	.268	.632**	1
		Sig. (2-tailed)	.046	.065	.000	
		N	48	48	48	48

*. Correlation is significant at the 0.05 level (2-tailed).

**. Correlation is significant at the 0.01 level (2-tailed).

Multiple linear regression test was run to establish the predictive power of TAM on e-resource usage intensity. The regression output is presented in Table 3.The table shows that TAM factors explained 10.9% of the variability in the student's e-resource usage intensity (R^2=.109). The ANOVA results suggests that the explanatory power of the model was not statistically significant (p>.05). It was hypothesized that perceived ease of use has no influence on e-resource usage intensity of postgraduate students in a Kenyan private university. Consistent with this hypothesis, the table shows that perceived ease of use had no statistically significant predictive power on e-resource usage intensity (B=8.649, p>.05). Therefore, the null hypothesis was supported. It was also hypothesized that perceived usefulness has no influence on e-resource usage intensity of postgraduate students in a Kenyan private university. The results indicate that perceived usefulness did not significantly predict the student's e-resource usage intensity (B=16.360, p>.05). Therefore, the hypothesis was supported. It was further hypothesized that perceived behavioral control has no influence on e-resource usage intensity in a Kenyan private university. The table shows that perceived behavioural factors did not significantly predict the student's e-resource usage intensity (B=20.346, p>.05). This hypothesis was also supported.

Table 3: Regression of E-resource Usage Intensity on TAM Factors

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.330[a]	.109	-.018	62.998

a. Predictors: (Constant), PBC, PU, PEOU

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	10191.506	3	3397.169	.856	.479[b]
	Residual	83343.534	21	3968.740		
	Total	93535.040	24			

a. Dependent Variable: Log Count
b. Predictors: (Constant), PBC, PU, PEOU

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	-96.385	102.426		-.941	.357
	PU	16.360	35.004	.120	.467	.645
	PEOU	8.649	30.512	.088	.283	.780
	PBC	20.346	26.619	.199	.764	.453

a. Dependent Variable: Log Count

V. DISCUSSION

The results from this research challenge the applicability of TAM for explaining technology acceptance and usage as theorized by Davis (1986). As this study has shown, all the null hypotheses were supported and therefore none was rejected. This contradicts the results of Namisiko et al. (2014) which suggested that perceived ease of use and perceived usefulness were important antecedents to e-resource usage intensity. However, that percieved behavioural control factors similarly was not significant in explaining e-resource usage intensity, was consistent with the findings of the study by Gor (2017) among distance learners in the University of Nairobi. Two possible explanations can be offered for this surprising finding. Firstly, each university is potentially endowed differently with respect to the e-resources and related support infrastructure and programs. This uniqueness from one university to another limits generalization of research findings to every university. The second reason is methodological. It is noteworthy that most TAM studies rely on self-report to gauge technology acceptance and usage despite the vulnerability of self-report questionnaires to social desirability bias (Demetriu, Ozer, & Essau, 2015). In contrast, the current study used URL count as a measure of e-resource usage intensity by examining the user log files, which is arguably a more objective indicator of actual usage. The implication of this is that the use of self-report for evaluating e-resource usage needs rethinking, especially in light of availability of objective data that can be obtained through data mining.

VI. CONCLUSION

This study set out to investigate the factors influencing usage intensity of university library's e-resource platforms within a private university in Kenya by matching perception data against user's URL log count. The problem of the research was that prior studies have relied exlusively on user self-report data which are inherently subjective. From the results of the current study, conclusion can be drawn that TAM factors are not adequate for explaining postgraduate student's e-resource usage intensity.

VII. RECOMMENDATION

University librarians should be user-centric in the design of all its systems. This calls for collecting the views of users and bringing their input on board as opposed to library logic where the library staff create a system based on what they believe is good for the users. More studies that integrate objective data mined from e-resource servers with perception data using a larger dataset should be conducted to confirm or refute the findings of this research. Meta analysis of such studies can lead to the development and validation of new models for explaining e-resource usage especially in a resource constrained country.

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