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Determinants of Acceptance and Use of DHIS2 in Kenya: UTAUT-Based Model

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Abstract: Background: In 2010, Kenya initiated the process of adoption and implementation of a web-based system (DHIS2) as the national HIS to facilitate management of routine health information for evidence-based decision making. To reap maximum benefit from this implementation, DHIS2 needed to gain acceptance from all categories of targeted users. This study, conducted between June and August 2014, sought to develop a new technology acceptance model that can better explain the key determinants of acceptance and use of DHIS2 in Kenya.

Methods: The model was adapted from the Unified Theory of Acceptance and Use of Technology (UTAUT). An exploratory study was conducted primarily through the use of quantitative methods, but qualitative Key Informant Interview (KII) data was also collected in a pre-study to provide the background and contextual information used in refining the model. In the main phase of the study, a questionnaire was administered to health workers through cross-sectional survey both at national and regional levels.

Results: The total number of valid questionnaires returned was 269 against the 300 that were issued. This number represents slightly more than 20% of the approximately 1,100 health workers who have been trained on DHIS2 in Kenya, and these were drawn from at least 10 of Kenya's 47 counties. Analysis of the survey data was done in two parts: descriptive analysis was performed using SPSS statistical analysis tool for the purpose of obtaining frequencies, means, standard deviation, skewness and kurtosis. Subsequently Structural Equation Modeling (SEM) and specifically Partial Least Square path modeling (PLS), was used to analyze the conceptual model and test the proposed hypotheses.

Conclusion: The resulting model revealed that social influence was the most pertinent predictor of behavioral intention in the study setting, while facilitating condition and computer anxiety play a significant role in predicting actual use of DHIS2. Findings from this case study can be extended to explain acceptance and use of health IT in other similar settings. Future research can test more variables and moderators to increase the overall predictive levels of the model.

Keywords: Technology Acceptance, DHIS2, Unified Theory of Acceptance and Use of Technology (UTAUT), Structural Equation Modeling (SEM), Partial Least Squares (PLS)

1. INTRODUCTION

Having recognized the critical role played by a functional HIS, in 2010 Kenya overhauled the existing disintegrated and inefficient system to replace it with the web-based District Health

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Information Software (DHIS2). The DHIS2 is a free and open source database application for collecting, processing, analyzing and visualizing health information for health administration purposes. Development of DHIS2 is coordinated by the University of Oslo, and by the time of this study, DHIS2 had been implemented at different levels in 46 developing countries around the world [1]. The system allows health care workers to analyze their levels of service provision, predict service needs, and assess performance in meeting health service targets, and thus has the potential to transform Kenya from the era of unreliable and fragmented HIS system to the more ideal situation of availability and use of quality health information for rational decision making [2,3].

While implementation of DHIS2 in Kenya was a leap in the right direction, there is compelling evidence to suggest that health professionals are reluctant to accept and utilize information and communication technologies (ICT) and this contributes to the lag in adoption and utilization of ICT across the health sector [4,5]. A validated technology adoption model to evaluate the complex interrelations between factors affecting user acceptance of DHIS2 is beneficial in informing policy makers, system designers and implementers on approaches that will contribute to more successful implementation and scale up of this and other related health information technologies in Kenya and in other similar developing countries' contexts.

The Unified Theory of Acceptance and Use of Technology (UTAUT) has been applied in its original or adapted form to study IT adoption in various sectors and demonstrated up to 69 percent accuracy in predicting user acceptance of new information technology [4,6,7]. However despite the large amount of work done to validate the UTAUT model, only a small proportion of it has been conducted in the healthcare context, and especially healthcare context of developing countries. Yet developing countries face unique challenges in implementing ICT in health, ranging from ICT infrastructure challenges, lack of the adequate ICT skills among health professionals, economic challenges, and other social political issues. This therefore means there is need to review existing adoption models and adapt them to include factors that are relevant to the developing countries healthcare context. The only technology acceptance research conducted in developing countries healthcare context has focused on the relatively simple and individually driven applications of ICT in health, rather than on any specific organizational-level health technology which is of greater concern at management levels [8].

This study set out to examine the applicability of an extended UTAUT to DHIS2 system as a new innovation in the Kenyan setting, and in so doing understand the key determinants of acceptance and use of this system by public health workers in the country. It extends the model's theoretical validity and empirical applicability by examining UTAUT within the context of a national health information system in a developing country context. Overall the study was implemented in three key phases: (i) an explorative pre-study through Key Informant Interviews [KII] to provide the background and contextual information used in refining the conceptual model. (ii) A pilot phase involving focus group discussions and quantitative analysis of data collected from twenty two DHIS2 users. This was used to establish the survey instrument's understandability and completion time, as well as its validity and reliability for intended study; (iii) the main study phase in which a survey was done to provide cross-sectional data on current usage, behavioural intention and acceptance of DHIS2, as well as on other factors surrounding utilization of ICT in public healthcare setting. Results from the first two phases of the study have been reported elsewhere [9,10]. This paper reports on analysis of data from the main phase to validate the extended model which explains factors that determine acceptance and use of DHIS2 in Kenya and, by extension, in related developing country settings.

1.1 Technology Adoption Studies in the Health Sector

Overall, technology acceptance research has been done widely in information systems research, with many models and theories developed and tested for ICT acceptance and use in different industries [8]. Some well-known examples of these models include the Theory of Reasoned Action (TRA); the Technology Acceptance Model [TAM] and the Theory of Planned Behavior (TPB) [11–13]. Venkatesh et al [8] capitalized on similarities of key factors in eight existing technology acceptance models to develop "The Unified Theory of Acceptance and Use of Technology" (UTAUT). UTAUT demonstrated up to 69 percent accuracy in predicting user acceptance of the new information technologies tested. It has since been applied in its original or adapted form to study IT adoption in different sectors, including in healthcare sector [4,6,7].

Despite the large volume of work done to validate the UTAUT model, only a small proportion of it has been conducted in the healthcare context, and especially in developing countries. Developing countries face a wide variety of health related challenges, including perennial struggle with limited financial and human resources, particularly in the public sector. WHO and other stakeholders have repeatedly emphasized the important role of a functional HIS in generating the information necessary to support improved health care management at all levels of these countries' healthcare system. This is in turn expected to eventually lead to improved quality of the health service provided to these countries' populations [14,15]. The newness of formal HIS in these countries can explain the very limited previous academic research conducted in this domain [16]. Undertaking studies that will explain how users adopt and use ICT in the health sector will thus play a major role in ensuring effective deployment of such systems. Therefore the opportunity to modify and adopt some of the existing technology acceptance models for application in such settings exists and is necessary.

This study set out to examine the applicability of UTAUT to DHIS2 as a new innovation in the Kenya public health setting. Subsequently the adapted model was used to measure the pertinent factors that influence acceptance and use of DHIS2 by different categories of public healthcare system in the country. In particular there is need to investigate the role played by the unique factors that have been shown to be of high importance when introducing new ICTs in developing countries. These include the targeted users' prior experience in general use of ICT, the associated Computer Anxiety; and provision of Adequate Training [17–19]. Most developing countries exhibit communal societies, so it was anticipated that that Social Influence by important others would play a critical rule in users' technology adoption decisions [20].

1.2 The Research Conceptual Model

The study model development and validation was done in three main stages. First the researchers reviewed context-relevant literature to gain more understanding of technology acceptance theories and the context in which computerization of health information systems is happening in the low-resources settings, of which Kenya is part. In the second stage a qualitative pre-study was done between August and November 2013 to inform customization of the research model and to ensure that it covers all the important elements of public health IT adoption in developing countries. In particular the researchers sought to gain an understanding, from the perspective of key stakeholders, of factors considered as critical to the successful implementation, scale up and use of DHIS2 in Kenya.

A pilot study was done between April and May 2014 to test, refine and make preliminary validation of the conceived study model. The pilot study is described elsewhere and the final study conceptual model generated is represented in figure 1 [21]. In the adapted model, the basic UTAUT model was extended to include Training Adequacy and Voluntariness of use as direct determinants of Behavioural Intention, and Computer Anxiety as a direct determinant of Use Behaviour. Technology Experience was also included and postulated to predict the individual's computer anxiety. Only two moderators were included in the model, namely gender and age. A summary of all the factors in the model is provided in the sections that follow.

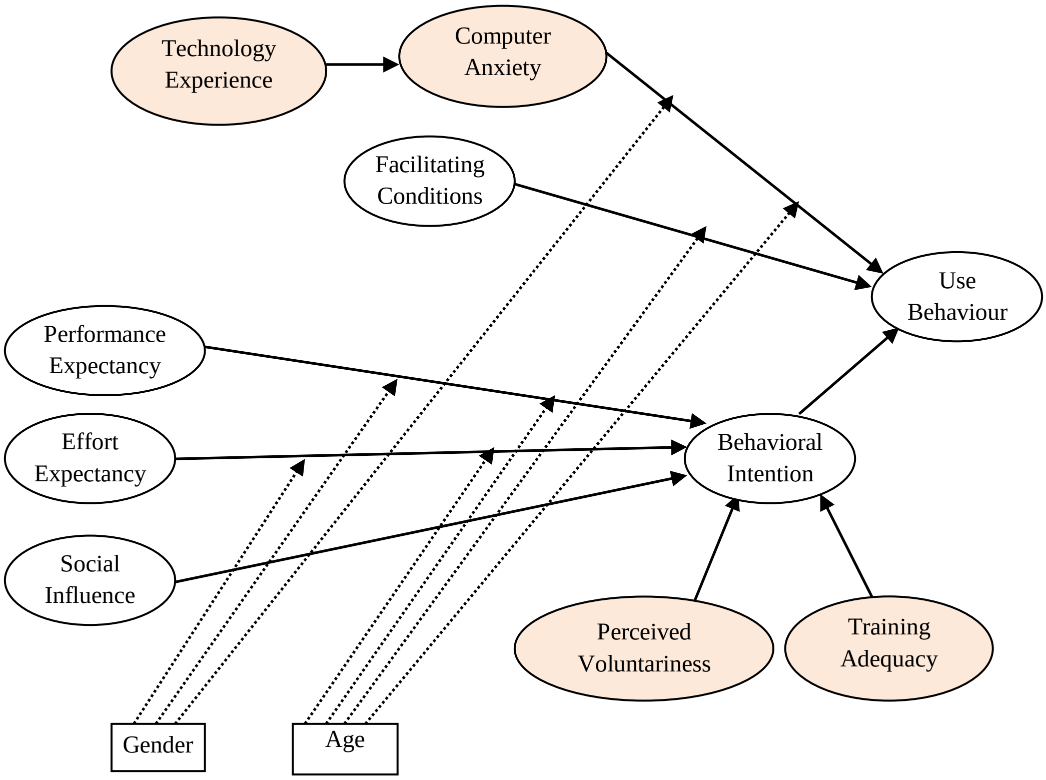


Fig 1: The Research Conceptual Model for user acceptance of DHIS2 (Adapted from Venkatesh et al, [8])

1.2.1 Factors Influencing Behavioral Intention

Performance expectancy (PE) is the degree to which an individual believes that using ICT will help him or her to attain gains in job performance [8]. It has previously been found to be a consistently strong predictor of intention. This study proposed that performance expectancy would positively affect the health worker's intention to use DHIS2. Effort expectancy (EE) is the degree of ease associated with use of a system. The influence of effort expectancy on behavioural intention is expected to be particularly significant when the technology being introduced is new and different from what the users are accustomed to.

Social influence (SI) is the degree to which an individual perceives that important others believe he or she should use a certain technology. As this study's setup was in a developing country context where the cultural values of collectivism and high power-distance are expected to be quite dominant [20], it was expected that this factor would be significant in determining the technology acceptance decisions of health care workers.

For this study, Training adequacy (TA) was defined as the degree to which an individual believes that the training they received is adequate to enable them use DHIS2 effectively. This was identified as a key factor that would positively influence the targeted users' intention to use DHIS2. Voluntariness is the degree to which an individual perceives that he or she has a choice to use or not use health IT. It was expected that the more the perceived voluntariness, the more users would have a positive attitude toward DHIS2, and hence the higher their intention to use the system [22–24].

1.2.2 Factors Influencing Actual Use

According to UTAUT Actual Use is the final dependent variable representing the measurement of technology acceptance and it has two direct determinants: Intention to Use and Facilitating Conditions [11,25–27]. This study however proposed an addition direct determinant of actual use which is Computer Anxiety.

1.2.3 The Moderators

Presence of moderator variables effects some changes in the original relationship between the independent and dependent variables. For this study's model gender and age were included as moderator variables for some of the relationship paths.

3. RESEARCH METHOD

3.1 Research Design

The target population of interest included the Health Records Information Officer (HRIO) at health facility and sub-county levels; member of the sub-county and county Health Management Teams (HMT) in all 47 counties in Kenya who had been trained on the use of DHIS2, and Health Officers at the national level who have either been directly or indirectly trained on use of DHIS2. This target population consisted of approximately 1,100 members and represents the following three distinct categories of health workers:

1. **Data Management Team** – These are the HRIOs at health facilities and sub-county levels who are primarily responsible for ensuring that routine monthly reporting of health service delivery data is conducted in a timely manner from all health facilities under their jurisdiction. The target population for this group was estimated at 800 members.
2. **Regional HMT** – This group is responsible for developing health related operational plans and undertaking related health decision making in their regions. The target population among this group was estimated at 200 members.
3. **National Level Health Officers** – This is a diverse group in terms of education levels and professional orientation. The group is stationed at the national level and uses the aggregated DHIS2 data to draw conclusions related to the programs under which they serve. Some of

the reports they generate are in response to M&E requirements of external donors and other stakeholders. The target population for this group was estimated at about 100 members.

3.2 Sample Size

The main consideration in determining the sample size was that the data would be used in structural equation modeling (SEM) in an exploratory study design. This required a large enough sample to enable validation of the study model across the three different categories of public health workers. SEM requires an appropriate sample size in order to obtain reliable estimates of variables being analyzed. Guidelines regarding sample size estimation to allow generalizability of scientific results from SEM are provided by Hair et al. [28] and include the following: i) Sample sizes larger than 30 and less than 500 are appropriate for most research; ii) When samples are to be divided into sub-samples, a minimum sample size of 30 for each category is necessary; iii) In multivariate research, the sample size should be several times (at least 5 but preferably 10 times or more) as large as the number of variables in the study [28].

Additionally, Chin et al [31] recommend that when using PLS-SEM a sample size equal to the larger of two possibilities should be used: (i) Ten times the number of indicators on the most formative research model constructs. This study does not use formative constructs; hence this recommendation is not directly applicable; or (ii) Ten times the largest number of antecedent constructs used to determine a dependent variable. For this study this translates to ten times the five constructs used to determine behaviour intention or a minimum of 50 participants.

These considerations meant that at least 50 survey respondents were required for each of the three categories of health workers included in the study. To ensure that this target of 150 respondents was reached and surpassed, the researcher distributed a total of 300 questionnaires across the 3 categories of health workers.

3.3 Data Collection and Analysis

The main data collection instrument was a structured questionnaire comprising a pre-formulated written set of statements adopted from Venkatesh et al. [8], with some modifications to enable measurement of the new constructs in the adapted model. The research used the self-administered survey method whereby the researcher or their representative travels to the respondent's location and hand delivers the survey questionnaire to the respondents. This was done between June and August 2014. The resulting quantitative data was used to empirically test the research model and the associated hypotheses. Data analysis was done in two parts: descriptive analysis was performed using SPSS statistical analysis tool for the purpose of obtaining frequencies, means, standard deviation, skewness and kurtosis; with the latter two measures being used to test for distribution normality for each indicator's data. Subsequently Structural Equation Modeling (SEM) and specifically Partial Least Square path modeling (PLS), was used to analyze the conceptual model and test the proposed hypotheses. SEM was chosen because of its characteristic that allows researchers to perform path-analytics modeling of complex relationships between multiple independent and dependent variables.

4. RESULTS

Out of the 300 questionnaires distributed in the survey, 273 responses were received resulting in a high response rate of 91%. Four of the responses were however disqualified because the questionnaires were only partially completed. Thus, a total of 269 valid responses were available for use in the data analysis. This number represents approximately 24% of the target population, and the respondents were drawn from at least 10 of Kenya's 47 counties to ensure a good representation of the entire country.

4.1 Respondents Characteristics

A review of the respondents' characteristics revealed some distinct differences across the three categories of health workers identified in the study. For example: 97.1% of the Data Management group was made up of HRIOs and 72.5% of respondents in this group were educated only up to diploma level. In contrast, over 80% of the National Level group were holders of a University degree, and this is despite the fact that the group had 47.1% of its members who identified themselves as HRIOs professionally. Additionally, the national level group was more advantaged with regard to access to ICT infrastructure and access to DHIS2 as compared to sub-national groups.

4.2 Preliminary Analysis of the Model Variables

Descriptive analysis of the data was done using PASW version 18 software (commonly known as SPSS) for the purpose of obtaining frequencies, means, standard deviation, skewness and kurtosis. Table 1 provides the definition of each of the constructs in the model, along with the measurement items (indicators) that were used to represent them.

Table 1: Constructs and the Measurement Items

Construct Definition	Measurement Items (Indicators)	Construct Definition	Measurement Items (Indicators)
Performance Expectancy (PE): – the degree to which an individual believes that using DHIS2 will enable them to attain gains in job performance	PE1:Using DHIS2 will enable me to accomplish tasks more quickly PE2:Using DHIS2 will allow me to accomplish more work than would otherwise be possible PE3:DHIS2 will enable me to make work related decisions based on better evidence PE4: If I use DHIS2, I will increase my chances of getting a promotion. PE5: Overall, I would find DHIS2 useful in my job.	**Training Adequacy (TA):** the degree to which an individual believes that the training he or she received is enough to enable him or her use DHIS2 effectively	TA1: The training received on DHIS2 is very helpful in my use of the system TA2: I have training reference documents that I can consult in my use of DHIS2 TA3: I feel the training received is adequate for my efficient use of DHIS2 TA4r: I need further training on DHIS2 to enable me use the system efficiently TA5: My training on basic use of computers is adequate for using DHIS2 TA6: The DHIS2 training was well organized and easy to follow TA7r: I need some further training on Internet and the World Wide Web to enable me use DHIS2 efficiently
Effort Expectancy (EE): the degree of ease of use associated with the use of DHIS2	EE1: My interaction with DHIS2 is or would be clear and understandable. EE2: It would be easy for me to become skilful at using DHIS2. EE3: Learning to operate DHIS2 is easy for me EE4: Overall, I would find DHIS2 easy to use	**Voluntariness of Use (VO):** the degree to which an individual believes that his or her use of DHIS2 is voluntary	VO1. Although it might be helpful, using DHIS2 is not compulsory in my job (i.e. my use of DHIS2 would be voluntary) VO2r My use of DHIS2 would be for mandatory routine reporting VO3. My use of DHIS2 would be for voluntary analysis of the health facility/sub-county data for informed decision making
Computer Anxiety (ANX): the degree to which anxious or emotional reactions are evoked when using computer technology	ANX1: I feel nervous about using computer systems ANX2: It scares me to think I could cause loss of data in the system by hitting the wrong key ANX3: I would hesitate to use DHIS2 for fear of making mistakes I cannot correct ANX4r: The challenge of learning about computers is exciting. ANX5: DHIS2 is somewhat intimidating to me ANX6r: I look forward to using a computer. ANX7r: I am able to keep up with important technological advances in computers. ANX8: I feel nervous when using internet-based applications	**Facilitating Conditions (FC):** the degree to which an individual believes an organizational or technical infrastructure exist to support use of DHIS2	FC1: I have the resources (e.g. reporting forms, computer, antivirus, etc) necessary to use DHIS2 FC2: Access to the Internet is available any time I want to use DHIS2 FC3: I have the knowledge necessary to use DHIS2. FC4: DHIS2 is compatible with other systems that I use at my work. FC5: DHIS2 experts are available for assistance with DHIS2 difficulties FC6: I have knowledge sources (e.g. books, documents, consultants) to support my use of DHIS2 FC7: I think that using DHIS2 fits well with the way I like to work
Social Influence (SI): degree to which an individual perceives that their peers, supervisors, and important others believe they should use DHIS2	SI1: People who are important to me think that I should use DHIS2 SI2: My colleagues think that I should use DHIS2. SI3: The senior management has been supportive in the use of DHIS2 at my duty station SI4: In general, use of DHIS2 has been supported and encouraged at my duty station	**Technology Experience (Exp):** the duration of past use of computer and internet; and the current frequency of using both.	Exp1: For how long have you been using a computer? Exp2: Approximately how many hours per week do you use a computer? Exp3. How long have you been using the Internet? Exp4: Currently, how often do you use the Internet?
Behavioral Intention (BI): the degree to which an individual intends to use DHIS2	BI1: I intend to use [or continue using] DHIS2 in the next 3 months. BI2: I predict I will use [or continue using] DHIS2 in the next 3 months. BI3: I plan to use [or continue using] DHIS2 when I have access to computer and internet	**Use Behavior (UB):** Frequency of using DHIS2; and average duration of each use session.	UB1: On average, how often do you use DHIS2? UB2: When you do use DHIS2, on average how much time do you spend on the system?

4.3 Measurement Model Reliability and Validity

Reliability is defined as the degree to which a test consistently measures what it is supposed to measure. Using PLS-SEM, reliability assessment is concerned with ensuring that the block of items selected for a given construct are suitable to operationalize it. Reliability of each construct is calculated separately and is independent of the reliability of the other constructs [29]. For this research, two sets of reliability measurements were obtained using SmartPLS path modeling software.

Indicator reliability values were obtained by squaring the outer loading of each manifest variable. A reliability value of 0.7 or higher is recommended, however in exploratory research a value of 0.4 or higher is acceptable [30,31]. Indicators with loadings lower than 0.4 are however dropped from the study model [32]. For this study, it was necessary to drop one performance expectancy indicator (PE4), two computer anxiety indicators (ANX4r and ANX6r), two facilitating condition indictors (FC1 and FC5); and three training adequacy indicators (TA2, TA4r and TA7r) in order to achieve the recommended level of indicator reliability. Evaluation of construct reliability is done by examining the internal consistency reliability (Cronbach's alpha), however an alternative measure named 'Composite Reliability' is recommended when using PLS-SEM [33,34]. Table 2 shows that both measures were higher than the recommended minimum level of 0.7 indicating a highly reliable measurement instrument [35,36].

Table 2: Full Dataset Model's Reliability and Validity Measures

Latent Variable	Indicators	Loadings	Indicator Reliability [= Loadings^2]	Composite Reliability	Cronbach's Alpha	AVE
Behavioural Intention	BI1	0.967	0.935	0.966	0.948	0.905
	BI2	0.959	0.919			
	BI3	0.928	0.862			
Computer Anxiety	ANX1	0.827	0.683	0.906	0.876	0.618
	ANX2	0.797	0.636			
	ANX3	0.833	0.694			
	ANX5	0.732	0.536			
	ANX7R	0.772	0.596			
	ANX8	0.749	0.562			
Effort Expectancy	EE1	0.855	0.731	0.914	0.876	0.727
	EE2	0.866	0.750			
	EE3	0.812	0.659			
	EE4	0.876	0.768			
Facilitating Conditions	FC2	0.663	0.439	0.863	0.8023	0.558
	FC3	0.821	0.674			
	FC4	0.727	0.528			
	FC6	0.787	0.619			
	FC7	0.727	0.529			
Performance Expectancy	PE1	0.878	0.771	0.929	0.898	0.766
	PE2	0.902	0.813			
	PE3	0.848	0.718			
	PE5	0.873	0.761			
Social Influence	SI1	0.823	0.677	0.890	0.836	0.670
	SI2	0.831	0.690			

	SI3	0.788	0.621			
	SI4	0.831	0.691			
Technology Experience	Exp1	0.870	0.757	0.903	0.855	0.700
	Exp2	0.753	0.567			
	Exp3	0.914	0.836			
	Exp4	0.799	0.638			
Training Adequacy	TA1	0.848	0.718	0.900	0.854	0.692
	TA3	0.815	0.665			
	TA5	0.796	0.633			
	TA6	0.867	0.752			
Use Behaviour	UB1	0.928	0.860	0.911	0.806	0.837
	UB2	0.902	0.813			
Voluntariness	VO1	0.950	0.903	0.951	0.925	0.867
	VO2r	0.956	0.913			
	VO3	0.886	0.785			

Construct validity ensures that the measurement items selected for a given construct collectively provide reasonable operationalization of the construct. Using PLS-SEM reflective indicators, this validity focuses on convergent and discriminant validity. Convergent validity was measured by examining factor loadings of the measurement indicators and confirmed when the items loaded more highly on their pre-defined underlying constructs than on any other construct, and when the value of each latent variable's Average Variance Extracted (AVE) was at least 0.5 [34,35]. AVE measures the variance shared between a construct and its measures, and this value should be greater that than the variance shared between the construct and other constructs. The measurement instrument for the study exhibited a high level of convergent validity. Additionally all the latent constructs AVE were greater than the recommended 0.5 threshold as shown in table 3.

Discriminant validity measures the extent to which constructs differ from each other and is considered adequate when a construct shares more variance with its measurement variables than with other constructs in the model. Fornell-Larcker criterion states that discriminant validity is confirmed when the AVE of each latent construct is higher than the construct's highest squared correlation with any other latent construct [35]. This requires comparison of the square root of the AVE with the absolute values of the correlations between each construct and all the other constructs in the model. The diagonal elements in table 3 are the square-root of AVE while the off-diagonal elements in the corresponding rows and columns represent absolute values of the correlations between the constructs. Sufficient discriminant validity is confirmed if the diagonal elements are greater than the off-diagonal elements in the corresponding rows and columns, as was the case in this study.

Table 3: Discriminant Validity of the Full Dataset Model

	B.I.	C.A.	E.E.	F.C.	P.E.	S.I.	T.E.	T.A.	U.B.	Vol
Behavioral Intention [BI]	**0.952**									
Computer Anxiety [Anx]	0.172	**0.786**								
Effort Expectancy [EE]	0.414	0.242	**0.852**							
Facilitating Conditions [FC]	0.217	0.276	0.413	**0.747**						
Performance Expectancy [PE]	0.406	0.150	0.609	0.250	**0.875**					
Social Influence [SI]	0.492	0.044	0.449	0.352	0.446	**0.818**				
Technology Exp. [Exp]	0.104	0.322	0.025	0.236	0.067	0.007	**0.836**			
Training Adequacy [TA]	0.350	0.248	0.485	0.583	0.420	0.383	0.134	**0.832**		
Use Behavior[UB]	0.199	0.307	0.198	0.419	0.205	0.184	0.387	0.449	**0.915**	
Voluntariness [Vol]	0.121	0.085	0.092	0.142	0.128	0.207	0.057	0.191	0.304	**0.931**

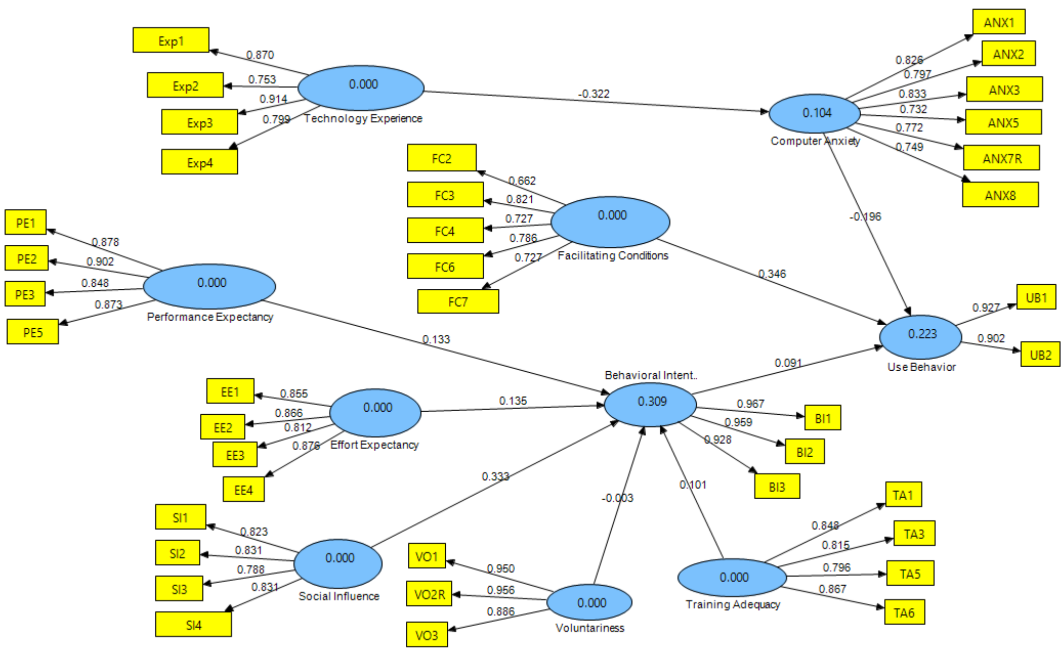
4.4 Structural Model Evaluation

The final measurement model demonstrated sufficient robustness to test relationships among the independent and dependent variables. The model's causal structure was subsequently assessed to determine the strength of these relationships through the estimation of coefficient of determination (R^2), path coefficient (β), and effect size (f2).

4.5 Coefficient of Determination (R^2)

The explanatory power of a conceptual model is ultimately determined by assessing the causal or predictive relationships between constructs. The strength of these relationships is demonstrated by the amount of variance explained (R^2) in the dependent variables as well as the inner model's path coefficient sizes and their significance [31]. As illustrated in figure 2, R^2 for the first level dependent variable (Behavioral Intention) was 0.309 while for the Use Behavior was 0.223. This means that the five latent variables: Performance Expectancy, Effort Expectancy, Social Influence, Voluntariness of Use and Training Adequacy were able to explain 30.9% of the variance in Behavioural Intention, while the latent variables Behavioural Intention, Facilitating Conditions and Computer Anxiety collectively explained 22.3% of the variance in Use Behaviour. Technology Experience explained 10.4% of the variance in Computer Anxiety.

Fig 2: Causal Model for the full dataset (all health workers)



4.6 Path Coefficients (β)

Path coefficients indicate the direction and strength of the relationships between latent variables. The general suggestion is that the magnitude of standardized path coefficient has to be more than 0.1 if a significant path relationship exists between the variables. This criterion was met in all the structural path relationships for this research model, except for the relationship between Voluntariness of Use and Behavioural Intention. The bootstrap procedure of Smart PLS was additionally used to test the significance of the structural path relationships using T-statistics and a summary of the results is given in Table 4. The procedure for this test is described by Hair et al. [32]

Table 4: T-Statistics for Full Dataset Model

Causal Path	Path Coefficients[ß]	T Statistics
EE -> BI	0.1347	1.8642*
PE -> BI	0.1326	1.7898*
SI -> BI	0.3328	5.2189***
TA -> BI	0.1009	1.59
VO -> BI	-0.0033	0.0949
BI -> UB	0.0908	1.5636
ANX -> UB	-0.1957	2.8203***
FC -> UB	0.3457	5.6719***
Exp ->Anx	-0.3218	5.4235***

Note: The Critical T-values are 1.65 for a significance level of 10% (*); 1.96 for a significance level of 5% (**); and 2.58 for a significance level of 1% (***) in a two-tailed test

Evaluation of the inner model containing the first level dependent variable revealed that Social Influence has the strongest effect on Behavioral Intention (β = 0.333); The beta coefficients of the paths from Effort Expectancy and Performance expectancy were also found to be significant, thought at a lower level of significance. For this full data set model the effects of Voluntariness of Use was found to be weak and insignificant. The effect of Training Adequacy was slightly higher at 0.10, though non-statistically significant.

For the second level dependent variable, the effect of Behavioural Intention on Use Behaviour was found to be quite weak at 0.091, especially compared with the stronger effect of Facilitating Conditions at 0.346. The effect of Computer Anxiety on Use Behaviour was statistically significant with a beta value of -0.196. As was expected, Technology Experience had a statistically significant negative effect on Computer Anxiety.

4.7 Testing the Moderator Variables

In addition to testing the direct effects of the independent variables on the dependent variables, this study also sought to establish the effects of two moderating variables on the inter-constructs relationships. A moderating effect is said to be evoked by variables whose variation influence the strength or the direction of a relationship between other variables. The group comparison approach suggested by Hensler and Fasott (2010) was applied for this purpose and it encompassed the following steps:

1. First the data was split into two dataset based on the value of the gender moderating variable. This resulted in dataset for male respondents only (n = 144) and another for female respondents only (n = 145).
2. Both datasets were then loaded onto SmartPLS for further analysis of the measurement and structural model. The age variable was then added as a moderator for each of the data sets.
3. After confirming the validity and reliability of the measurement models for both dataset, bootstrap function of SmartPLS was run to generate the path coefficients along with the related t-statistics and standard errors.

In summary the effect of effort expectancy on behavioural intention was found to be moderated by gender and age, such that the effect will be stronger for women and particularly for younger women. However the effect of computer anxiety on Use Behaviour was not found to be moderated by either gender or age. The influence of performance expectancy on behavioural intention was moderated by gender and age, and this effect was found to be stronger for older men rather than for younger men.

4.8 Model Validation for Different Health Workers' Categories

Though the full dataset model was representative of health workers trained on use of DHIS2 in Kenya's public health sector, it was recognized that this is not a homogenous group as confirmed by the diverse demographic characteristics observed from the data. Three distinct heath workers categories were already recognized according to their assigned roles and functions. These three groups were: (i) Data Management Group; (ii) A Regional HMT Group and (iii) A National Level group. The generated model was thus tested for each of these group to enable understanding of the factor relationships that are most important for each group, and thus make appropriate study recommendations.

The variance explained in the two main dependent variables (Behavioral Intention and Use Behavior) increased when the data was separated into the 3 categories, and the path coefficients for some of the structural paths in each model also increased. This variance explained increased from approximately 30% to 40% in each of the models representing the 3 different health workers' categories.

In summary it was observed that:

1. Perceived Usefulness was a significant contributor to Behavioural Intention for the National Level and Regional HMT groups, but not for the Data Management group
2. Social Influence had a positive effect on Behavioural intention for all the 3 groups, but only significantly so for the Data Management group and the National Level officers
3. The positive effect of Effort Expectancy on Behavioural Intention was only significant in the Data Management group. Even the negative effect of Computer Anxiety on Use Behaviour was only found to be significant in this group
4. Facilitating Conditions was a pertinent contributor to Use Behaviour for the Data Management and Regional HMT groups; but not for the National Level group
5. The effect of Training Adequacy on Behavioural Intention was significant for both the Data Management and the Regional HMT groups
6. The effect of Behavioural Intention on Use Behaviour was only significant in the Data Management group.

5. DISCUSSION

A key finding from the study was that the strength of factors that determine acceptance and use of DHIS2 varies across different health workers' categories. This is consistent with prior literature findings that the influence of individual factors depend on perception of autonomy by different cadres of health workers – for example it is expected that physicians and health managers will be more autonomous in their decision making than the other categories of health workers, hence social influence will not be the most important factor in predicting their actions [7,16,37,38]. On the other hand, lower cadre health workers act less autonomously and it is therefore quite plausible that they are more prone to influence by their peers and superiors in determining their technology acceptance decisions [4,39,40]. This finding confirms that health workers in developing countries are not a homogenous group across functions and cadres, and this must be taken into account when considering factors that affect their acceptance of particular health technologies.

The study also provides evidence that though the factors defined in the UTAUT model do contribute to predicting the intention to use and actual use of HIS in developing countries, they alone are not adequate and thus there is need to examine the contribution of other context-specific factors. This contributes to the body of knowledge that focuses on technology adoption by extending the UTAUT theory and validating it in a new context both in terms of technology (HIS) and low resources (developing countries).

Another contribution from the study is the unique extended model that identified and validated new factors (constructs) which impact on behavioral intentions and actual use of HIS: These new factors are: Perceived Training Adequacy, Computer Anxiety and users' prior Technology Experience. The new factors were combined with existing factors in UTAUT to produce a unique research model for predicting acceptance and use of DHIS2 among public health workers in Kenya as illustrated in figure 3.

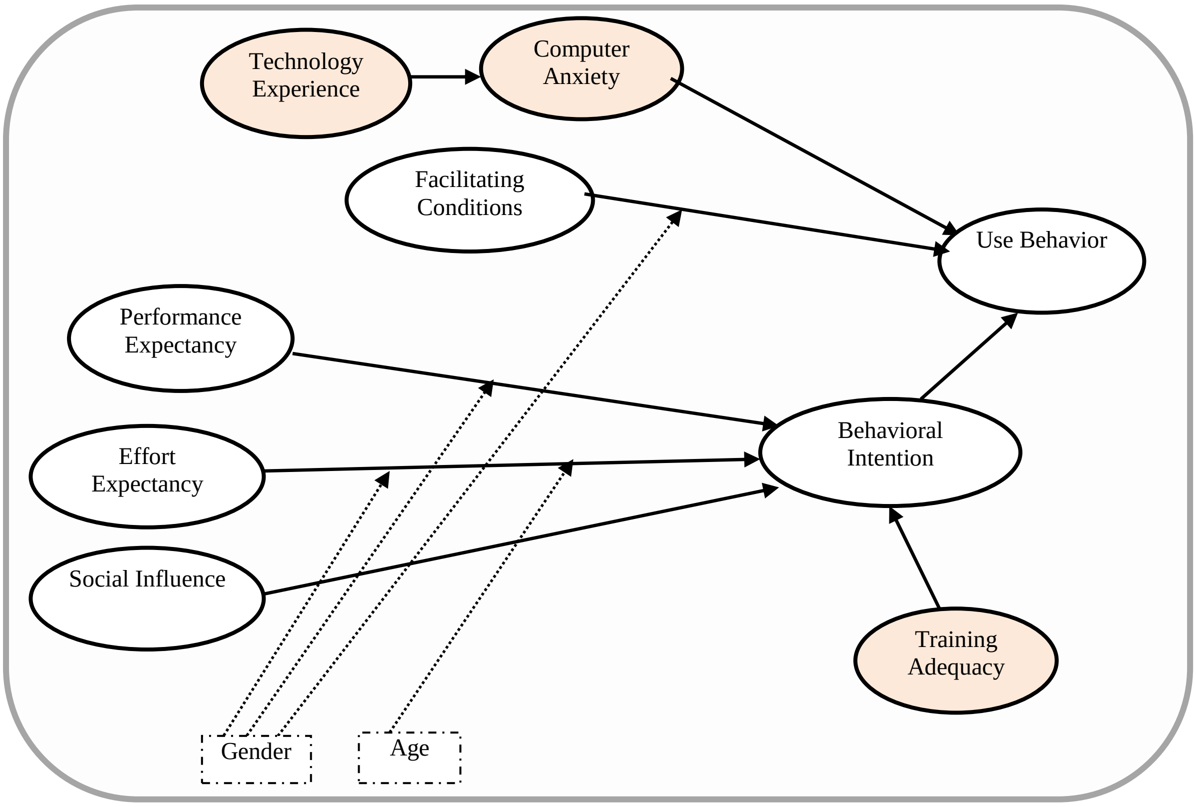


Fig 3: Revised Model for Acceptance and Use of DHIS2

Overall the most predictive factor for behavioral intention was found to be Social Influence, collaborating the findings from the exploratory study which had identified related items such as the need for champions, and the fact that most health workers will do as required of them by higher authorities[9]. This finding is contrary to that of studies conducted in developed countries contexts where performance expectancy was deemed most important factor [13,27]. All together the four factors of performance expectancy, effort expectancy, social influence and training adequacy contributed up to 30.9% of the variance in behavioral intention, and up to 37% when moderated by age and gender.

Evidence from literature suggests that computer anxiety may be more salient in Kenya and other developing countries' context [9]. This is as a result of the low levels of computerization of health systems in these countries as well as inadequate exposure of most of the health workers to the use of computers and the internet. This study confirmed that Computer Anxiety does indeed play a significant role in actual use of HIS in a developing country context. However the influence of computer anxiety was minimized by the extent to which intended users have prior experience in use of ICTs.

The organizational and technical infrastructure required to run ICT systems are hardly ever adequate in developing countries context [41,42]. This study confirmed that such facilitating conditions are even more influential on use behavior than behavioral intention, which again is contrary to findings of studies done in developed countries' context [25,26]. This provides evidence that facilitating conditions play an important role in resource-limited settings and must be taken into account when introducing new technology artifacts. Analysis of the adapted model revealed that technology acceptance models which are only tested in developed countries, or only in the limited settings of a few industries, cannot be directly applied to developing countries without specific contextual modifications. Though the original factors existing in UTAUT were also included in the new model, it was apparent that the strength of contribution of most of these factors was contrary to what had been found when UTAUT model was tested in different contexts.

One limitation of this study was that the target population was limited to the only those health workers trained on DHIS2. Another was that the data collection was done using a cross-sectional approach which, though it has its advantages, it does not have the benefit of examining the change in construct relationships across time.

6. CONCLUSION AND RECOMMENDATION

This research study set out to extend the UTAUT model by including new constructs and measures, to create a new model capable of evaluating user acceptance and actual use of HIS in developing countries context. The findings from this study contribute to the technology adoption literature by examining theoretical validity and practical applicability of UTAUT in a different country setting and in the rarely examined area of a national-level public health IT adoption. In conclusion, the study does confirm that UTAUT model is applicable to developing country context, but the factors currently included in UTAUT were not found to be adequate to explain acceptance and use of HIS in developing countries. There is hence need to include and test other relevant determinants as informed by contextual findings in literature and through conducting exploratory studies.

With the increasing effort by many developing countries especially those in Sub-Saharan Africa to computerize their national HIS, this study has important implications for the customization and deployment of such systems, and of other public health IT systems in similar settings. Ultimately addressing the factors that affect adoption of DHIS2 will lead to enhanced data demand and use by all the targeted stakeholders. It is recommended that future research tests more variables and moderators to increase the overall predictive levels of the model. Additionally, another similar study conducted within 3-5 years after this one could illustrate what determinants have changed over time and perhaps help identify if any interventions may have contributed to these changes.

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