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An Exploratory Factor Analysis Framework for Analysing the Challenges to the Deployment of Technologies in Higher Institutions of Learning

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Abstract

The paper provides a proposed conceptual framework for identifying challenges to the deployment of technologies in higher institutions of learning. The paper indicates how to identify these challenges using Exploratory Factor Analysis (EFA). The current body of related studies show that most researchers identify the challenges of deploying technologies in higher institutions of learning using frequencies, mean scores and related statistical tools. These statistical procedures are considered weak and inappropriate because they are less robust for the exercise. The mistaken use of these statistical tools is driven by a lack of knowledge about the role and use of EFA among researchers and the absence of standard conceptual frameworks for identifying the challenges of deploying technologies in higher institutions of learning. This paper reviews empirical and theoretical studies to identify the challenges of deploying technologies in higher institutions. Moreover, commonly cited empirical and theoretical studies are explored on EFA, with focus on how to use it to identify the challenges of deploying technologies in higher institutions. Based on the review, this paper proposes the use of EFA to screen for the manifest variables of the three constructs (i.e. infrastructure, training and access) that represent the main challenges of deploying technologies in higher institutions of learning. The framework is proposed as a paradigmatic approach to measuring and identifying these challenges. The right approach to identifying the three main challenges of deploying technologies in higher institutions of learning is using EFA to screen for manifest variables that constitute each challenge.

Keywords: *Exploratory factor analysis, higher institutions of learning, quality of teaching and learning*

Introduction

Human beings have found their way towards the deployment and leveraging of technologies in learning and teaching, resulting in a remarkable change in the quality and impact of education in most jurisdictions in recent times (Ezziane, 2007; Hussain andSafdar, 2008). Additionally, the education section sector is gradually catching up with industry in terms of the use of technologies in facilitating the accomplishment of activities and minimising the cost of hiring labour. Moreover, there is the general belief that the dynamic capabilities of technologies make them deployable in teaching and learning now and in future (Ezziane, 2007). This belief is rooted in the rapid advancement in the functions of educational technologies and the evolvement of robust technologies that address specific issues in teaching and learning (Capper, 2003; Rhema and Miliszewska, 2010). Hence, institutions failing to incorporate technologies in learning and teaching are missing out on technological innovations that play a pivotal role in institutional management and societal building. This argument is twin to the fact that many technologies are deployable in higher institutions.

Keong et al. (2005) posit that many categories of technologies are deployable in an academic environment. They however add that the bulk of technologies are information systems are used basically for disseminating information across stakeholders (i.e. university council, management, faculty, students, parents and potential students) in an academic institution. Many studies (e.g. Agyei and Voogt, 2010; Ezziane, 2007; Dağlı andÖznacar, 2013, etc.) have identified the computer and its applications, internet, intranet, mobile phones and other e-learning systems as information systems centred on information dissemination across institutional stakeholders. But along the disclosure of these and various types of technologies in these studies, the challenges under which they are adopted in academic settings are strongly acknowledged. It is admitted that identifiable challenges are still the main deadlock to the maximum relishing of technologies in teaching and learning (Capper, 2003; Obuobi et al., 2007; Amenyedzi, Lartey andDzomeku, 2011), especially in developing African countries (Obuobi et al., 2007; Amenyedzi, Lartey & Dzomeku, 2011).

Today, many challenges are reported to confront academic institutions in deploying technologies in

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teaching and learning, including administrative uses. A survey of related studies indicate that the prevalence of these challenges permeate all educational sectors (i.e. basic, secondary and tertiary). Yet, some industry experts have expressed the concern that the infusion of technologies in teaching and learning, especially in developing African countries, at the basic and secondary school level is not rigorous and sometimes informal (Adjei, 2010; Aguele, 2012). As a result, it is inappropriate to consider basic and second cycle instructions when conducting studies on the challenges of deploying technologies in teaching and learning. In view of these, possibly, most studies (e.g. Sell, 1997; Sife, Lwoga andSanga, 2007; Oye, Salleh and Iahad, 2011; Mbodila, Jones and Muhandji, 2013) have been focused on revealing the challenges of deploying technologies in teaching and learning at the tertiary educational level. However, there are colossal gaps in the academic literature of the subject.

A survey of studies on the subject indicates that the challenges confronting the infusion of technologies in teaching and learning are categorized into infrastructure, accessibility and training challenges. Though there is considerable consensus in studies that have identified these factors, there is a school of thought that their disclosure has been based on mere mean scores and frequencies by researchers (e.g. Sife, Lwoga and Sanga, 2007; Oye, Salleh and Iahad, 2011; etc.). Costello and Osborne (2005) consequently suggest that these types of unobservable variables are better measured using an appropriate statistical procedure like Exploratory Factor Analysis. This concern has also been expressed by Yong and Pearce (2013); they argue that the disclosure of these challenges and factors using frequencies and means is not robust. This is because these tools fail to unfold relevant information that EFA would have otherwise unfolded. Moreover, data associated with these challenges are often so large that data reduction is needed through the use of EFA (Costello and Osborne, 2005; Yong and Pearce, 2013).

Currently, there seems to be no specific conceptual framework for using EFA to identify the challenges of deploying technologies to support teaching and learning in higher educational institutions. Consequently, researchers continue to use the frequencies of respondents' "yes" or "no", mean scores and related descriptive statistics to identify these challenges. The use of this procedure conceals important information about the challenges and the factors to which they belong (Field, 2012; Yong andPearce, 2013). In essence, academic debate on the subject on this dimension is faulty.

In view of this problem, this paper indicates how challenges to the deployment of technologies in higher institutions of learning can be identified using EFA. The paper also provides a conceptual framework which can serve as a standard approach to measuring the challenges of deploying technologies in academic institutions of higher learning.

Related Work

Without doubt, technologies are very relevant to teaching and learning in higher institutions of learning. Technologies are also needed in accomplishing administrative activities in tertiary institutions. These assertions are made in view of the several research studies (e.g. Rhema and Miliszewska, 2010; Sarfo-Gyimah, 2010; Owoche, 2014; etc.) which have shown that the deployment of technologies in higher institutions of learning enhances the quality of teaching and learning. It is also made evident that the deployment of technologies yields efficiency in the accomplishment of administrative activities (Ezzaine, 2007; Owoche, 2013). Also, the infusion of technologies in higher institutions of learning helps university managements to optimise the cost of running the universities (Rhema and Miliszewska, 2010; Owoche, 2013). It is even more impressive to note that the use of technologies in higher institutions of learning could impact profitability or result in a business case (Sarfo-Gyimah, 2010; Owoche, 2013). Nonetheless, the oddity associated with the infusion of technology into teaching and learning is the fact that several challenges hinder this process (Capper, 2003; Obuobi et al., 2007; Amenyedzi, Lartey andDzomeku, 2011).

Several challenges hinder the deployment of educational technologies. The main challenges are in terms of infrastructure, access and training (Sell, 1997; Sife et al., 2007; Oye et al., 2011), where each of them represents an unobservable variable. Though all challenges faced in the deployment of technologies in tertiary institutions are driven by financial drawback (Sell, 1997; Sife et al., 2007), it is important to understand them individually.

Infrastructural challenge is made up of lack of suitable technologies, lack of appropriate technology support systems (e.g. electricity, external service partners, etc.), lack of internal technical teams and expertise and lack of an appropriate user environment. The second batch of challenges relate to accessibility (Sell, 1997; Sife et al., 2007; Oye et al., 2011). This category includes inability of

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Journal of Advances in Science and Technology Research (JASTER), Volume 1, Number 1, March 2015, pp12-19

individuals or the academic institution to afford technologies, inability of students and faculty to use them and lack of motivation for using technologies. The third category of challenges relate to training (Sell, 1997; Sife et al., 2007; Oye et al., 2011; Sell, 1997). This category includes lack of training for students and faculty on the use of technologies. Another element of this category is lack of effective training for students and faculty. Logically, there will be other manifest variables in each case of the latent variables depending on the specific academic institution involved.

Based on related studies (e.g. Sell, 1997; Sife, Lwoga and Sanga, 2007; Oye et al. 2011; Mbodila et al, 2013; etc.), these challenges have been identified by researchers using frequencies, mean scores and other related descriptive statistical tools that lack robustness. Yet, Costello and Osborne (2005) and Yong and Pearce (2013) posit that identifying a cluster of manifest variables that form part of a factor, latent variable or construct using frequencies, mean scores and other related descriptive statistical tools is inappropriate. They make this argument based on outcomes of their respective studies in which they demonstrate how to use Exploratory Factor Analysis (EFA) to screen for manifest variables, which in the context of this paper represent challenges of deploying technologies in higher institutions of learning.

The problem is that the studies of Costello and Osborne (2005) and Yong and Pearce (2013) were not focused on screening for the challenges of deploying technologies in higher institutions of learning. Moreover, there seems to be no specific conceptual framework for using EFA to identify the challenges of deploying technologies in higher institutions of learning currently. Even if available, the frameworks are few and unpopular because review of several literature has produced unrelated results. Researchers (e.g. Sell, 1997; Sife et al, 2007; Oye et al,2011; etc.) therefore continue to use less robust procedures in identifying challenges faced in the deployment of technologies in tertiary institutions. If a suitable framework for measuring and identifying these challenges are not provided, future contributions to academic debate on the subject will be infiltrated with issues.

This study therefore provides a conceptual framework which can serve as a standard approach to measuring and identifying the challenges of deploying technologies in academic institutions of higher learning. We seek to indicate how challenges to the deployment of technologies in higher institutions of learning can be identified using EFA.

An Overview of Exploratory Factor Analysis

Exploratory Factor Analysis (EFA) works on the idea that observable variables called manifest variables can be reduced to fewer latent variables called constructs that share a common variation (Yong and Pearce, 2013). EFA works along a procedure termed "reducing dimensionality" (Costello and Osborne, 2005; Yong and Pearce, 2013). Thus in identifying the challenges of deploying technologies, a group of manifest variables could be reduced to become an infrastructure challenge. In this respect, several variables are reduced to one. This is the essence of reduced dimensionality in EFA.

EFA is used when a researcher intends to discover the number of factors influencing manifest variables and to analyse which manifest variables are more closely correlated (DeCoster, 1998). A group of most correlated manifest variables make a factor or latent variable (DeCoster, 1998; Yong and Pearce, 2013).

EFA is used for some common purposes. It is more often used to shrink large data (DeCoster, 1998; Costello andOsborne, 2005; Yong andPearce, 2013); thus datasets made of many manifest variables. EFA is used in this situation because data may be too large to successfully analyse (DeCoster, 1998; Costello and Osborne, 2005), and some manifest variables may be too trivial or insignificant to consider (DeCoster, 1998; Costello and Osborne, 2005; Yong and Pearce, 2013). For instance, in identifying the challenges of deploying technologies in tertiary institutions, "instability of the political environment" may be a trivial challenge relative to others in the context of the population. So, this manifest variable and similar ones would need to be taken out. Taking these variables out reduces the dimension of the data and therefore would enable the researcher to easily analyse it. EFA would be more efficient for identifying challenges of technology deployment in higher institutions because these challenges are often numerous (Obuobi et al., 2006; Oye et al., 2011). Therefore, there is the need for these variables to be either reduced to a fewer number for easy analysis or to categorise them into latent variables. Yong and Pearce (2013) quoted Rummel (1970) by stating that other uses of factor analysis include data transformation, hypothesis-testing, mapping, and scaling. Scaling, in EFA, could be used to test the reliability and appropriateness of the scale on which

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the challenges of interest are measured (Yong and Pearce, 2013).

EFA Requirements

If we should use EFA to screen for the challenges of deploying technologies, we ought to ensure that the data meets some requirements. Firstly, there must be multivariate normality in the data in the absence of multivariate outliers (Yong and Pearce, 2013). The recommended sample size for EFA is 300 respondents (Costello and Osborne, 2005; Yong and Pearce, 2013). Moreover, manifest variables in EFA should each have at least 5 to 10 observations (DeCoster, 1998; Costello and Osborne, 2005). It is generally acceptable that the ratio of respondents to variables should be at least 10:1, and the factors are considered to be stable and to cross-validate with a ratio of 30:1 (Yong and Pearce, 2013). Moreover, a larger sample size will destroy or minimise the error in the data; therefore EFA generally works better with larger sample sizes (DeCoster, 1998; Costello and Osborne, 2005). However, Guadagnoli and Velicer (1988) suggested that if the dataset has several high factor loading scores (i.e. factor loading scores > .80), a smaller size (n > 150) is appropriate. What could a factor loading be? A factor loading for a manifest variable is a measure of how much the variable contributes to the factor (Yong and Pearce, 2013). This means that high factor loading scores indicate that the dimensions of the factors are better accounted for by the manifest variables.

In addition, the correlation "r" must be .30 or greater, since anything lower suggests a generally weak relationship between the variables (Tabachnick and Fidell, 2007). It is also suggested that a heterogeneous sample is used rather than a homogeneous sample in EFA, as homogeneous samples reduce the variation and factor loadings (Kline, 1994).It is important to watch out for the presence of multicollinearity and singularity within a dataset by looking at the Squared Multiple Correlation, SMC, (Tabachnick and Fidell, 2007). Variables that have problems with singularity (i.e., SMC close to 0) and multicollinearity (SMC close to 1.0) should be removed from the data entirely.

In the context of EFA, a determining factor is based on the assumption that there is a linear relationship between the factors and the variables when computing the correlations (Gorsuch, 1983). For something to be labelled as a factor in EFA, it should have at least 3 manifest variables, although this depends on the design of the study (Tabachnick and Fidell, 2007). As a general rule of thumb, rotated factors that have 2 or fewer manifest variables should be interpreted with caution. In this respect, a factor with 2 manifest variables is only considered reliable when the manifest variables are highly correlated with each another (r > .70) but sufficiently not correlated with other manifest variables.

EFA and the Proposed Framework

Having disclosed the requirements and assumptions associated with using EFA to screen for the challenges of deploying technologies in higher institutions of learning, what ought to be additionally known is how to interpret its results, and how to use it to form a framework of factors and their retained manifest variables. Though EFA has many output features, we would only consider those primarily relevant to the formation of the needed framework.

The first basic output feature of the EFA is a table of descriptive statistics. This table should contain the total number of obviations (N) involved in the analysis, minimum and maximum values, mean values, standard deviation and standard errors of the estimates (Bartholomew et al, 2008). These researchers argue that the total number of observations included in the analysis would help others to appraise the validity of the results. The minimum and maximum values visualise the relative magnitude of mean scores and the standard deviation of the manifest variables (DeCoster, 1998). Mean scores express the relative valuation or magnitude of the manifest variables (DeCoster, 1998; Bartholomew et al., 2008).

The next batch of results consists of the correlation matrix, Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy and Bartlett's test of sphericity. This batch is far more important relative to the descriptive statistics because it helps to diagnose the validity and strength of the EFA (Costello and Osborne, 2005; Yong and Pearce, 2013). The general rule of thumb is that the correlation matrix must show clumped subgroups of manifest variables with nearly the same amount of correlations. Each subgroup must have correlation coefficients not less than 0.30; otherwise the EFA is weak or invalid (Costello and Osborne, 2005; Bartholomew et al., 2008). Afterwards, one must look at estimates for the KMO and Bartlett's tests, which come together in a single table. Naturally, the KMO does not come with a p-value, but it is required to have a value of .80 or more (DeCoster, 1998; Costello and Osborne, 2005), where a lower value is acceptable when the Bartlett's test is significant

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(Costello and Osborne, 2005). Moreover, the Anti-image correlations, which come in a separate table, must be sufficiently high, with .80 being the lowest value acceptable (Costello and Osborne, 2005; Yong and Pearce, 2013). Yet, these correlations can be smaller if the KMO and Bartlett's test are significant.

One must endeavour to exclude variables that are just simple derivatives of other variables in the analysis (Field, 2012),for instance: X_2 = variable X_1 + 6. The same applies to variables that are very highly correlated (i.e. multicollinearity), and when this occurs the statistical software takes a turn and consequently cannot produce valid factor loading values. A simple way of assessing this is to inspect a particular summary measure of the correlation matrix called the determinant and check to see if it is greater than 0.00001 (Costello and Osborne, 2005; Field, 2012). After taking these diagnostic measures, one should then look at the following estimates to identify factors and their manifest variables:

Factor loadings: According to Field (2012), a factor loading is the correlation between a specific observed variable (in this context challenge) and a specific factor (i.e. a group of challenges). Higher values mean a closer relationship. They are equivalent to standardised regression coefficients (i.e. β weights) in multiple regression (Field, 2012). The higher the value of the factor loading associated with a manifest variable, the better.

Communality: This is the total influence on a single observed manifest variable from all the factors associated with it (Costello and Osborne, 2005; Filed, 2012). It is equal to the sum of all the squared factor loadings for all the factors related to the observed variable. The value ranges from 0 to 1, where 1 indicates that the variable can be fully defined by the factors and has no uniqueness. This means that a value of 0 indicates that the variable cannot be predicted at all from any of the factors. Like the factor loading scores, the communality is expected to be as large as possible; thus it should be close to 1 (Bartholomew et al., 2008). With respect to the communality, uniqueness for each observed variable is that portion of the variable that cannot be predicted from the other factors or latent variables (Filed, 2012). Its value is generally the difference between 1 and the communality.

Variability explained: This indicates how much of the variability in the data has been modelled by the extracted factors. This value depicts the variation accounted by each factor that is made up of a group of manifest variables (Yong and Pearce, 2013; Filed, 2012). The total variability or variation that can be explained is 100%. Generally, the variance accounted is proportional to the Eigen values (Filed, 2012); the higher the variance, the higher the Eigen values.

After identifying the variation accounted by each factor, there is the need to identify the manifest variables that best constitute these factors. This can be done by looking at the "Component Plot in Rotated Space", in which items of each factor are clustered at a point. The manifest variables and their Factors can also be identified in the "Rotated Factor Matrix". In this case, manifest variables belonging to a factor are those having a common set of high factor loads. Though there are several other interpretations in EFA, screening for manifest variables and classifying them under factors or latent variables are primarily accomplished by interpreting the communalities, factor loading scores, variability explained by each factor, the Component Plot in Rotated Space and the Rotated Factor Matrix. After this interpretation, one needs to visualise results using a special figure. This can be done in another session of analysis called Structural Equation Modelling (SME), but some of the estimates realised with respect to the above procedure can be used to develop this figure.

Figure 1 shows a general framework of challenges that would be reached when the EFA is used as discussed earlier. In the figure, 13 manifest variables that represent challenges (see Table 1) are reduced to 3 factors. The variations accounted for by each factor would reveal which set of manifest variables or challenges pose a higher influence, and therefore knowing the seriousness of the challenges. Researchers can introduce more manifest variables based on the population or social setting of interest. Yet, the expectation of their quest would be structured as shown in Figure 1.

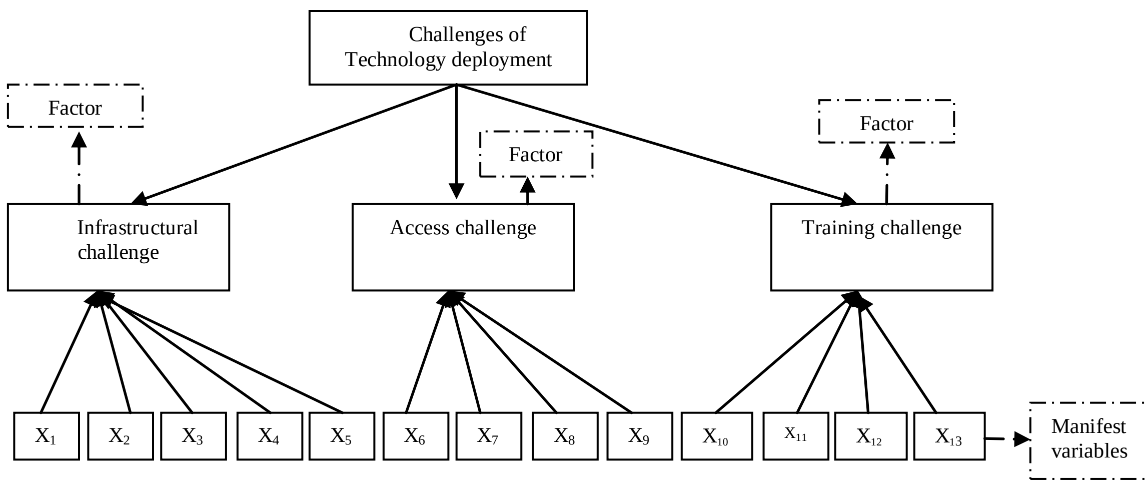

Figure 1. A Conceptual Framework of Challenges in Deploying Technologies in Higher Institutions

Table 1. Key to Conceptual Framework

Symbol	Manifest Variable
X_1	Lack of appropriate and suitable technologies
X_2	Lack of appropriate technology support systems (e.g. electricity, etc.)
X_3	Lack of technical teams and expertise
X_4	Inadequate technology user environment
X_5	Lack of full management commitment
X_6	I cannot afford technologies because they are expensive
X_7	I cannot use technologies because I know little about them
X_8	The university does not provide access to all needed technologies
X_9	I feel over-burdened using technologies
X_{10}	I have not personally acquired any training on technologies
X_{11}	Technology training in my university is deficient and poor
X_{12}	I would be able to use technologies better if I had sufficient training on them
X_{13}	I will be more willing to use technologies if I had sufficient training on them

In the context of this paper, the challenges of deploying technologies in tertiary institutions are identified using EFA. Based on the EFA procedure discussed so far, these challenges can be conceptualised as shown in Figure 1. The challenges have already been empirically identified outside the application of EFA by several researchers (e.g. Sell, 1997; Sife et al, 2007; Oye et al, 2011; Mbodila et al, 2013). But we argue that the use of EFA would better screen these challenges and indicate the variation contributed by each (in terms of communalities) and the latent variables (factors) formed by them. The use of EFA to generate the framework of Figure 1 or its estimates would be the most reliable research approach to identifying the challenges of deploying technologies in higher institutions.

Discussion and Conclusion

Though the challenges of deploying technologies in higher institutions of learning have been found in several studies (e.g. Sell, 1997; Sife et al, 2007; Oye et al, 2011; Mbodila et al,2013), the EFA procedure discussed earlier and the framework shown in Figure 1 is considered by Yong and Pearce (2013) and Costello and Osborne (2005) as a more robust way of identifying them. The role of EFA in the context of the proposed framework is validated by the fact that the methods used by previous studies in identifying the challenges of deploying technologies in higher institutions of learning are not robust and are consequently inappropriate. As a result, many researchers (e.g. Opuni et al, 2014; Yong and Pearce, 2013; Costello and Osborne, 2005) have used the EFA and related frameworks in screening and analysing many variables. Though the variables used by these researches are different, Field (2012) is of the view that EFA does not discriminate on the basis of the number or type of variables used. EFA does not also discriminate on the basis of the sector from which data was collected (Costello and Osborne, 2005; Field, 2012). This means that EFA is applicable in any situation where variables to be analysed are many and basic requirements and assumptions about the dataset are met.

The existing findings on the challenges of deploying technologies in tertiary institutions are questionable on the basis of statistical procedures and models used to identify them. With ample evidence from the studies of Yong and Pearce (2013) and Costello and Osborne (2005), and the application of EFA by Opuni et al. (2014) in similar analysis, the proposed framework of Figure 1 and its associated EFA procedure can be followed to measure, identify and analyse challenges of deploying technologies in higher institutions of learning.

Future researchers would therefore have to identify the challenges of using emerging technologies in tertiary institutions by following the EFA procedure spelt out in this paper. When the proposed framework is used as a guide, it is believed that related future studies would be more reliable and would therefore contribute better to academic debate on the subject.

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