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The adoption of E-learning systems in Zimbabwe's universities: An integration of theory of planned behaviour and technology acceptance model

Joe Muzurura[1*], Leo Mataruka[2], Josphat Nyoni[3]
[1] Midlands State University, Zimbabwe
[2] Catholic University of Zimbabwe, Zimbabwe
[3] Women University, Zimbabwe

Abstract
The education system in Zimbabwe's universities is rapidly metamorphosing, driven by technological progress, heightened competitiveness among universities, hence the need to find new sources of distinctive competences using e-learning systems. Non-controllable events such as effects of climatic changes and transboundary pandemic diseases on traditional education have been disrupting the traditional learning systems. As a result, universities are trying to augment traditional teaching and learning processes and practices by embracing e-learning systems. The purpose of this research was to examine factors that influence the probability of adopting of e-learning systems in Zimbabwe's universities. E-learning systems have steadily risen to become critical tools for effective and inexpensive way of efficient education delivery, knowledge discovery and sharing among lecturers and students. E-learning systems have the potential to improve learning outcomes of users whilst also enriching and perpetuating needed cognitive and effective skills of users. Quantitative data was collected using a structured questionnaire from a randomly selected sample of 50 university students in Harare students. The data was analysed using multinomial logistic regression equation with three dependent variables; Adopt; Not Adopt and Defer Adoption of e-learning systems. The probability of adopting e-learning systems in Zimbabwe's universities is affected by social influence, perceived control, perceived usefulness, and ease of use, facilitating conditions, performance expectance, attitude and costs. The findings also show perceived usefulness, perceived enjoyment affect the likelihood of deferring the adoption of learning system relative to not adopting. The study recommends crafting of policies that reduce complexity and cost of using e-learning systems whilst at the same time adopting add-ons that enhances relative advantages, compatibility with traditional systems, and performance expectance of users. The study contributes to literature by extending the Technology Acceptance Model and Theory of Planned Behaviour using a polychotomous regression technique to examine factors that enables the probability of using e-learning system.

Keywords: Zimbabwe, Universities, TAM, TPB, E-learning systems, multinomial regression

Introduction

In more recent years, the educational milieu in Zimbabwe's Universities has been undergoing a hurried and exogenously driven metamorphosis. The rapid diffusion of information communication technologies and increasing competitiveness of the university education ecosystem has forced many local universities to re-examine other inventive sources of attaining sustainable competitive advantages. Growing innovations in education delivery systems, social-economic volatilities, high cost of university education and accelerated demands by students and parents are also impelling universities world over to integrate electronic learning systems (e-learning) into traditional teaching and learning processes. The traditional teaching and learning approaches that heavily rely on textbooks and the lecture room are becoming redundant, costly and mismatched to advancements that have been happening in the field of education information technologies. Unlike much of the post-independent Zimbabwe where the education environment was more predictable and university-driven, today's education environment has significantly evolved. The education environment is now characterised by discontinuous and inadvertent changes, and to a large extent employer-driven. University education now demands a new paradigm shift, a new kind of learning experience that is technology-centric- one that goes beyond traditional learning and teaching systems where the lecturer and student do not always have to meet face to face. The lecture room and markers are becoming tools of yester year, obsolete, oxymoronic and perhaps now burdensome for both the lecture and student.

Globalisation of education delivery systems has gained significant traction and has accelerated knowledge growth in most developing countries. Elsewhere, in other developing countries e-learning systems are facilitating knowledge discovery, allowing students and lecturers to conveniently transfer and share knowledge in virtual lecture rooms. The fast movement of educative information, and new knowledge frontiers are being enabled by high speed and efficient wireless transmission of data. This development has been reducing the education and knowledge asymmetries that exists between students in developed and developing countries. Competing for the future now requires that universities in Zimbabwe must also leverage traditional learning systems with e-learning systems. Whilst Zimbabwe has an over 95% literacy rate, education delivery is essentially still traditional where students spend most of their time in lecture rooms. Zimbabwe's universities lag behind other universities especially those in the Sub-Saharan region. In other developing countries, the advent of education-driven technologies such as virtual e-learning platforms, e-book resources, e-learning management systems and e-learning phone applications has forced universities to abandon their teaching and learning procedures. The involvedness of the underlying knowledge domains have been increasing due to e-learning systems. As a consequence, faster knowledge discovery, knowledge mining and knowledge transferring among lectures and students now requires that Zimbabwe Universities adopt e-learning systems that match regional and global standards. Furthermore, the ever-growing minutiae of the e-commerce-world, and rapid advancement of education-related technology obliges that traditional pedagogues need to be re-visited and revamped. This has become even more germane given epistemological developments in the education sector and also ontological domain convolutions that characterise today's academic world.

Teaching and learning experience is fast becoming a collaborative interaction between the lecturer-students-content trilogy. E-learning systems enable lectures to integrate pedagogical, andragogical and heutagogical approaches in virtual lecture rooms. In this way teaching and learning experience become more joyful and meaningful to students, hence enabling students to become self-directed and self-determined. E-learning systems enable universities to develop students and the workforce that are demanded by knowledge-based economies. Continuous e- learning opportunities any time and at any place has become the foundational trait needed for graduates' employment in knowledge-based economies. More importantly, e-learning systems have become an imperative for providing uninterrupted tuition during times of political instability and transboundary pandemic diseases. For example, the on-going outbreak of coronavirus that forced most universities in Zimbabwe to shut down, has ushered in a new reality that calls for the urgent closure of the cavity between traditional teaching and e-learning systems. Zimbabwe universities unlike those in the region have been bearing the brunt of global warming and transboundary pandemic diseases. For instance, some universities in the eastern part of the country were forced to temporarily shut down in 2019 due to cyclone-induced floods. All these events have caught most universities unprepared for e-learning education in universities. Yet, in times of temporary enforced shutdowns which are becoming frequent, e-learning systems have the potential to provide faster and quality on-line tuition unlike the traditional lecture room. E-learning systems have relatively low transaction costs and integrating these systems into the teaching and learning practices in Zimbabwe universities could be an elixir for supporting students' growth and learning outcomes more so in absence of physical lecture rooms. E-learning systems have huge data storage capacity, are highly flexible and convenient to both the student and the lecturer. In contrast to traditional learning, e-learning are better positioned to facilitate experiential and transformative learning, permits student critical reflection, and also learning by solving problems. This makes e-learning systems useful devices for delivering educational instructions in Zimbabwe and to support research and development at a lower cost. Nevertheless, the paper argues that the successful adoption of e-learning systems also depends on their perceived usefulness, accessibility, reliability, ease of use, convenience, the affordability and availability of connectivity.

Most state universities in Zimbabwe are located in rural areas that have insufficient telecommunication infrastructure and often poor interoperability among different networks. In countries like Zimbabwe that are characterised by low economic growth and development, e-learning systems if adopted successfully have the ability to offer additive and transformational value-creation to university students (Serdyukov, 2017; Hung *et al*, 2017; Harvono, 2018). The education-resource gap in Zimbabwe's universities is enormous with many students still sharing books in over-crowded lecture rooms. E-learning systems can fill-in this lacuna by providing new and flexible learning channels where students and lectures can access learning content. Since e-learning systems are less expensive rural based university students are also able to bridge the financial partition between them and their urban counterparts. Despite the pervasive use of learning systems in other developing countries, the lack of user acceptance of these systems in Zimbabwe's universities have become a major source of concern. Most universities in Zimbabwe have e-learning platforms but are rarely used by students or lecturers except for registration and other mundane activities not related to learning and teaching. These platforms merely attempt to replicate lecture room experiences and do not meet students' ongoing academic support in times of crises such as obligatory shutdowns. In most cases if available in some universities the e-learning systems are prone to unexpected failures. Every so often technical and functional service quality fails. Occasionally the fault lies with universities, sometimes with the students or with a network provider. In most instances, service recovery programmes takes unnecessarily long time. This makes the use of e-learning in universities an exasperating experience for many users. Developers and deliverers of e-learning seem not understand how students perceive and react to important elements that influence the adoption of e-learning systems such as reliability, availability, student and lecturer satisfaction, usage and responsiveness. Studies that are available in Zimbabwe commonly use the Technology Acceptance Model (TAM) variables, perceived usefulness and perceived ease of use. Hitherto, behavioural factors such as subjective beliefs, personal control, attitude and self-efficacy could be also be important in explaining user acceptance. Without user acceptance of e-learning systems, their value diminishes (Blanchard, *et al*, 2016; Tarhini *et al*., 2015; Sarrab *et al*, 2015; Sung *et al*., 2016; Padmavathi *et al*, 2015). The study is significant for a number of reasons. Acceptance of e-learning systems could enable Zimbabwe's universities to become effectual in transferring knowledge among themselves, preparing and advancing student learning outcomes. The growing e-learning supporting infrastructure in Zimbabwe is likely to improve connectivity and interoperability. Resultantly, internet-enabled disintermediation in e-learning processes is likely to reduce the element of transaction costs through economies of scales. E-learning systems have the capacity to prompt university students to link their academic experiences to the real work practices after graduation. In other words, while e-learning systems heighten instructional quality, they are also capable of creating a window for strong connection between universities and the external world. The adoption and use of e-learning systems by university students is likely to reduce the learning curve associated with diffusion of technology in other sectors of the economy. In addition, the integration of e-learning systems in teaching and learning provides significant opportunities for Zimbabwe universities to mitigate sudden endogenous and exogenous shocks that might affect the provision of traditional education system.

E-learning systems also come with positive externalities such as fostering financial inclusion of geographically segmented rural university students, and facilitate collaborative efforts of universities, network providers and suppliers of e-learning resources. Once fully accepted by all users, e-learning systems may assume characteristics of a public good with a Lindahl equilibrium solution. Provided that all students have no clear incentive to understate their true preferences of e-learning systems, they may be willing to contribute their share for the provision of e-learning systems. Adopting e-learning in Zimbabwe's universities could result in considerable savings for the government which is the main funder of university education in Zimbabwe. These savings can then be channelled to other critically under-funded sectors such as social services and health. Despite the advantages of using e-learning in universities, there is a major lacuna in empirical literature that focus on Zimbabwe's universities. Yet, Zimbabwe's universities play a critical role in reducing poverty and hunger, in the knowledge production process and expediting human capital formation and development. The few studies that available tend to rely on the Technology (TAM) Acceptance or Diffusion of Innovation (DOI) models. Our contribution to literature is on the use of structural equation modelling on the adoption and use of e-learning systems in universities. The paper integrates both the widely utilised TAM and Planned Behavioural models. The later model captures the behavioural aspects of technology adoption. This study is planned as follows. The first section covers the introduction and background. The second section covers literature review whilst the third, fourth and fifth sections cover findings, conclusions and recommendations respectively.

Literature Review

In the milieu of e-learning systems services terminology adoption refers to acceptance, that is, the ability to accept a new education technology as it is introduced in education ecosystem. The term electronic-learning was first coined by Cross (1999) and later, Rosenberg (2001) use the term to refer to the utilization of internet technology to deliver learning opportunities to students. Khan (2005) refers to innovative approaches for delivering a well-designed, learner-centred, interactive, and facilitated learning environment to anyone, anyplace, anytime, by utilizing the attributes and resources of various digital technologies along with other forms of learning materials suited for open, flexible, and distributed learning environment. The usefulness of the e-learning systems for assisting quality educational delivery has been abetted by the e-learning phone, speedy penetration and rapid diffusion of communication infrastructure (Muzurura and Chigora, 2019). E-learning systems consists of portable devices such as smart phones and tablets, the internet, personal digital assistants (PDAs, and digital audio players, notebooks, netbooks, and laptops. It also include mobility of the technology, mobility of content and mobility of the learner and lecturer. These reinforce learners' sense of ownership of the learning experience. Rather than being technology-centric only, e-learning systems also foster learner-centric and teacher-centred mobility (Muzurura and Chigora, 2019). This allows both the lecturer and student to develop flexibility in how, when and where they learn or deliver teaching processes. In addition, universities are able to customize their academic and extra curricula contents according to need of students and thus, offering more flexibility in learning process. We define e-learning systems as an open-ended and systematic educational ecosystem where students and lectures can do their learning and teaching activities using any internet-enabled e-learning devices over a wireless network anywhere, anytime. Learning activities include reading, listening, emailing, text messaging, watching educational videos related to the students' learning interests, answering questions, participating in a group discussion forum using social media with their peers and teachers. In this regard, e-learning systems is not just about the use of e-learning devices in the learning and teaching processes but also about learning across contexts.

There are many theories of e-learning adoption and usage. Venkatesh *et al* (2003) propose the Unified Theory of Acceptance and Use of Technology (UTAUT). This theory unites eight popular technology adoption theories such as the Theory of Reasoned Action (TRA), Theory of Planned Behaviour (TPB), Motivational Model (MM), Technology Acceptance Model (TAM), Innovation Diffusion Theory (IDT), Social Cognitive Theory (SGT), Model of PC Utilization (MPCU), and Combined-TAM-TPB (C-TAM-TBP). The UTAUT has four key determinants of the behavioural intention to adopt a technology which are; Performance Expectancy, Effort Expectancy, Social Influence and Facilitating Conditions. In addition, the model has four moderating factors in the adoption process which are; Gender, Age, Experience, and Voluntariness of Use. Another theory that is widely used in education psychology is the Theory of Reasoned Action (TRA) which was developed by Ajzen and Fishbein, 1969, 1975, 1980). The TRA says that the individual's behavioural intention to adopt e-learning systems is determined by the individual's attitude, attitudinal and normative beliefs. Yet another theory is the Diffusion of Innovations theory (DOI) which says that an individual's decision to adopt or reject an innovation is predicated upon five key perceptions about the characteristics of such innovation: relative advantage, compatibility, complexity, observability, and trialability. The focus of this paper is to integrate the theory of planned behaviour and the Technology Acceptance Model as foundational theories that explain the adoption behaviour of university students. Hereunder, the paper reviews the two theories.

The Theory of Planned Behaviour

The theory of Planned Behaviour (TPB) is closely associated with TRA which was developed by Ajzen, (1980) and; Fishbein (1975). The TPB compensates for the weaknesses that are inherent in the TRA. Unlike the TRA, the TPB assumes that an individual's behaviour is not voluntary. The theory suggest that only those specific attitudes toward the behaviour in question can be expected to predict a behaviour. The TPB suggests that the behavioural intention to adopt a new technology or innovation is predicated on the behavioural, normative and control beliefs. These three influence an individual's attitude towards a new innovation, the perception of control and subjective norms which all have a direct impact on the behavioural intention. The theory of planned behaviour postulates three conceptually independent determinants of intention; attitude towards the behaviour, subjective norm and behavioural control. Attitude toward the behaviour is defined in the theory as the degree to which a person has a favourable or unfavourable evaluation or appraisal of the behaviour in question. Subjective norm is a social factor which refers to the perceived social pressure to perform or not to perform the behaviour. The third antecedent of intention is the degree of perceived behavioural control which refers to the perceived ease or difficulty of performing the behaviour. In the model perceived behavioural control is assumed to reflect past experiences with the use of a new technology as well as anticipated impediments and obstacles. Arguably, the more favourable the attitude and subjective norm with respect to a behaviour, and the greater the perceived behavioural control, the stronger should be an individual's intention to perform the behaviour under consideration (Fishbein, 1975).The comparative significance of subjective norm, perceived behavioural control and attitude in predicting the intention to use a new technology varies across behaviours and contexts. As shown in the original theory of reasoned action, a central factor in the theory of planned behaviour is the individual's intention to perform a given behaviour such as adoption of e-learning systems. According to Fishbein (1975), intentions are expected to capture the motivational factors that influence an individual's behaviour. Intentions therefore indicate how hard people are willing to try, of how much of an effort they are planning to exert, in order to perform the behaviour. The stronger the intention to engage in a behaviour, the more likely should be its performance (Fishbein, 1975). As observed by Locke *et al* (1978), intentions would be expected to influence performance to the extent that the person has behavioural control, and performance should increase with behavioural control to the extent that the person is motivated to try. Perceived behavioural control is compatible with Bandura (1982) perceived self-efficacy and is concerned with value judgements of how well an individual can execute courses of actions such as adoption of e-learning. For instance, Bandura (1982) shows that an individual's behavioural intention to adopt a new technology is strongly influenced by perceived behavioural control that their confidence in their ability to perform. According to Bandura, self-efficacy can influence choices of activities, preparation of for an activity, thought patterns, emotional reactions and effort exerted during performance.

Technology Acceptance Model (TAM)

The TAM by Davis (1989) is one of the most well-known technology adoption theory used for many e-learning adoption studies (see Sanchez-Prieto *et al*., 2017; Sarrab *et al*., 2016; Armey, 2016; Davison and Lazaros, 2015; Kowzlowski *et al*., 2015). The TAM was developed based on the Theory of Reasoned Action (TRA) by Fishbein and Ajzen (1975) and planned behaviour model by Ajzen (1991). The TAM theory makes a distinction between beliefs, attitudes, and intentions and also maintain that beliefs govern attitudes and attitudes govern intentions. The major aim of TAM was to provide an explanation on the factors that determine technology acceptance by end-users. Many TAM-based studies on e-learning systems employ the traditional constructs of TAM that is, Perceived Usefulness (PU) and Perceived Ease of Use (PEOU). However, many studies also augment the two traditional constructs by adopting additional constructs such as self-efficacy, personal Innovativeness, Social Influence, Facilitating Conditions, and Perceived Enjoyment which they adopt from other theories of technology adoption. A variety of supplementary constructs specific to e-learning such as Perceived Mobility and Learning Autonomy have also been used (Pramana, 2018). Almost all findings in empirical literature found that Perceived Usefulness and Perceived Ease of Use are important determinants of behavioural intention to adopt e-learning in many developing countries. Similar positive results were also found for other factors that influence the behavioural intention to adopt e-learning such as Perceived Innovativeness (Liu *et al*., 2010), Social Influence (Sarrab *et al*., 2016), Perceived Enjoyment (Huang *et al*., 2015) and Perceived Mobility (Rehman *et al*., 2016). The TAM model proposed that perceived ease of use and perceived usefulness are the major factors that drives the acceptance of technology. The model says that perceived usefulness refers to the extent to which the user believes that the use of the technology such as the e-learning would enhance her job performance. According to TAM, perceived ease of use refers to the degree to which a user believes that the use of a particular system would be effortless. From this model it is apparent that the perceived ease of use has also a direct impact on the perceived usefulness. Both factors determine the student attitude to the use and the behavioural intention to use the system and also the actual usage of the system. The direct influence in TAM of perceived usefulness on behavioural intention to use a new technology discords with the theory of reasoned action but is justified by empirical evidence of direct belief-intention links (Davis *et al*., 1989). TAM also posits that perceived ease of use influences perceived usefulness. That is, an easier-to-use system if it is perceived as more useful. Perceived usefulness measures productivity increase, time savings, performance increase, effectiveness and job performance whilst perceived ease of use determines, ease of understanding, ease of use, clarity, flexibility of use, ease of control and ease of control of the technology or system (Bozalek *et al*., 2013; Asiimwe and Gronlund, 2015; Crompton *et al*., 2016). The TAM model have gone through a number of metamorphoses with a number of researchers adding other factors such as risk and security, convenience, trust, culture, cost constraints, system quality, ubiquity and exogenous circumstances such as availability of infrastructure and network (Huan *et al*., 2015; Khanh and Sim, 2014; Rambe and Bere, 2013; Duman *et al*., 2015).

Sarrab *et al* (2016) investigate the behavioural intention to adopt e-learning systems in the Middle East using the TAM model. They used perceived innovative characteristics, such as ease of use, usefulness, enjoyment, suitability, social, compatibility and cost. Their findings report that suitability, usefulness were some of the factors that led to the adoption of e-learning systems in the Middle East. As a consequence, several later TAM studies recommend the incorporation of subjective norm (see Taylor and Todd 1995; Venkatesh and Bala 2008; Venkatesh and Davis, 2000). Perceived behavioural control, a key part of the theory of planned behaviour, has also been included in some extensions to TAM by Koufaris (2002). Second, some studies have aimed to identify moderators that capture aspects of the context important to technology acceptance. For instance, Schepers and Wetzels (2007) show that subjective norm has a larger impact on intention to use technology in Western than non-Western settings, but that the impact of subjective norm on actual use is smaller in Western than non-Western settings. The finding by Schepers and Wetzels not only shows that the relation between intention to use and actual use may be more complex, but also identifies culture as a moderator in TAM studies. Karahanna *et al* (1999) investigate adoption over time and find that experience with a system is an important moderator in understanding use. For example, the shift from adoption to continued use makes the influence of subjective norm insignificant and the influence of perceived usefulness stronger (Karahanna *et al*., 1999). Third, the original TAM did not elaborate the antecedents of perceived usefulness and perceived ease of use. Studies have subsequently proposed and tested a great many antecedents to reveal how these perceptions are formed and how they can be manipulated to foster actual use. Yousafzai *et al* (2007a) in their review of literature list 79 external variables that have been proposed as antecedents of perceived usefulness or perceived ease of use. The antecedents include accessibility, awareness, computer anxiety, computer attitude, compatibility, end-user support, intrinsic motivation, management support, objective usability, perceived enjoyment, self-efficacy, social pressure, system quality, task characteristics, training, and voluntariness. Lee *et al* (2003) include a subset of these antecedents in their review and find that they all exert a significant influence on perceived usefulness or perceived ease of use. However, the influence of many of the antecedents varies across studies, thereby yielding mixed results. Fourth, it is generally acknowledged that TAM is mainly concerned with technology acceptance in utilitarian settings. However, some studies go beyond utilitarian settings by aiming to incorporate intrinsic motivation such as perception of pleasure, computer playfulness and satisfaction from performing a behaviour in TAM. (Serenko *et al*., 2007; Sun and Zhang 2006; van der Heijden 2004). Venkatesh and Bala (2008) combined various models of technology acceptance to come up with an integrated model known as TAM3. They included variables like system characteristics, social influence, and facilitating conditions which are major determinants of perceived usefulness and perceived ease of use. In the TAM3 research model, the perceived ease of use to perceived usefulness, computer anxiety to perceived ease of use and perceived ease of use to behavioural intention were moderated by experiences. The TAM3 research model was tested in real-world settings of IT implementation and have been proven to be successful (Venkatesh *et al*., 2012). The TAM was originally built to ease managing information system activities in the workplace by measuring the quality of delivered systems (Davis, 1989). According to Yang *et al* (2012), the primary emphasis of the TAM-related research perspectives in many empirical literature remained confined to the interpretation of the adoption process within organizational settings. However, other researches such as Pham and Daim (2011) argue that although TAM is purportedly used to explain the technology adoption within organization, the constructs of the model are actually meant to be general and universal. Benbasat and Barki (2007) posited that more attractive factors should be added to TAM in order to arrive at more complete understanding of what influences the intention to adopt information systems (IS) in general and in particular, e-learning systems services. The TAM has been frequently in many recent studies of technology acceptance in the education sector (see Sarrab *et al*., 2016; Sarrab *et al*., 2015; Dahlstrom *et al*., 2014; Adediha *et al*., 2013). Despite various improvements on the TAM, some of the weaknesses of the TAM like its utilitarian setting led to the development of the Unified Theory of Acceptance and Use of Technology model (UTAUT) (Venkatesh *et al*., 2012).

Methodology

This paper proposes a different approach where we infused two well-known and widely used theories that is, the TPB and TAM. The TPB was more pertinent in the context of Zimbabwe's universities because it added more external factors that influence the intention to adopt new technology. The PBM theory is well supported by empirical evidence (Doll and Ajzen, 1990; Ajzen and Driver, 1990; Watters, 1989; Schifter and Ajzen, 1985; Ajzen and Madden, 1986; Beck and Ajzen, 1990). In addition, intentions to perform behaviours of different kinds can be predicted with high accuracy from attitudes toward the behaviour, subjective norms, and perceived behavioural control; and these intentions, together with perceptions of behavioural control, account for considerable variance in actual behaviour. Attitudes, subjective norms, and perceived behavioural control are shown to be related to appropriate sets of salient behavioural, normative, and control beliefs about the behaviour (see Schifter and Ajzen, 1985). However, we caution that the exact nature of these relations in university education is still indeterminate. Expectancy value formulations are found to be only partly successful in dealing with these relations. Like earlier studies, we offer also optimal rescaling of expectancy and value measures as a means of dealing with measurement limitations (see Fishbein, 1975). However, our comfort lies in the fact that the theory has high predictive probability in comparison to the ceiling imposed by behavioural reliability.

To compensate for the shortcomings, we also integrate in this paper the TAM. Using TAM, it is possible to include factors such as complexity of technology, relative advantages, efficacy, normative influence, compatibility and facilitating conditions. According to Davis *et al* (1989), the key purpose of TAM is to provide a basis for tracing the impact of external factors on internal beliefs, attitudes, and intention. We thus in this paper modify the TAM in four main ways. First, we incorporate subjective norm, proxied by attitude and perceived behavioural control proxied by self-efficacy in our model from the theory of planned behaviour. This in part is influenced by that fact that the basis of TPB is TRA that postulates that the behavioural intention of an individual is determined by attitude and subjective norm, not solely by attitude. TAM stresses that any external variable may influence behaviour only indirectly by influencing perceived usefulness or perceived ease of use. Second, we identify moderators such as facilitating conditions, performance expectancy and trust of the e-learning system in order to capture aspects of the context important to technology acceptance model. Third, the original TAM did not elaborate the antecedents of perceived usefulness and perceived ease of use. In this study, the paper recognises various antecedents to the use of e-learning systems such as perceived usefulness and perceived ease of use such as accessibility, awareness, computer anxiety, computer attitude, compatibility, end-user support, intrinsic motivation, management support, objective usability, perceived enjoyment, self-efficacy, social influence, system quality, task characteristics, training, and voluntariness. Some of these variables will not be tested for simplicity reasons. Fourth, recognising that TAM is largely concerned with technology acceptance in utilitarian settings, the paper goes beyond utilitarian settings by incorporating intrinsic motivation factors such as perception of enjoyment from performing a behaviour in TAM.

The TAM has been frequently in many recent studies of technology acceptance in the education sector (see Sarrab *et al*., 2016; Sarrab *et al*., 2015; Dahlstrom *et al*., 2014; Adediha *et al*., 2013). We therefore conceptualise our model as follows. We propose the following conceptual framework that will be used in conjunction with a polychotomous equation.

Conceptual Framework

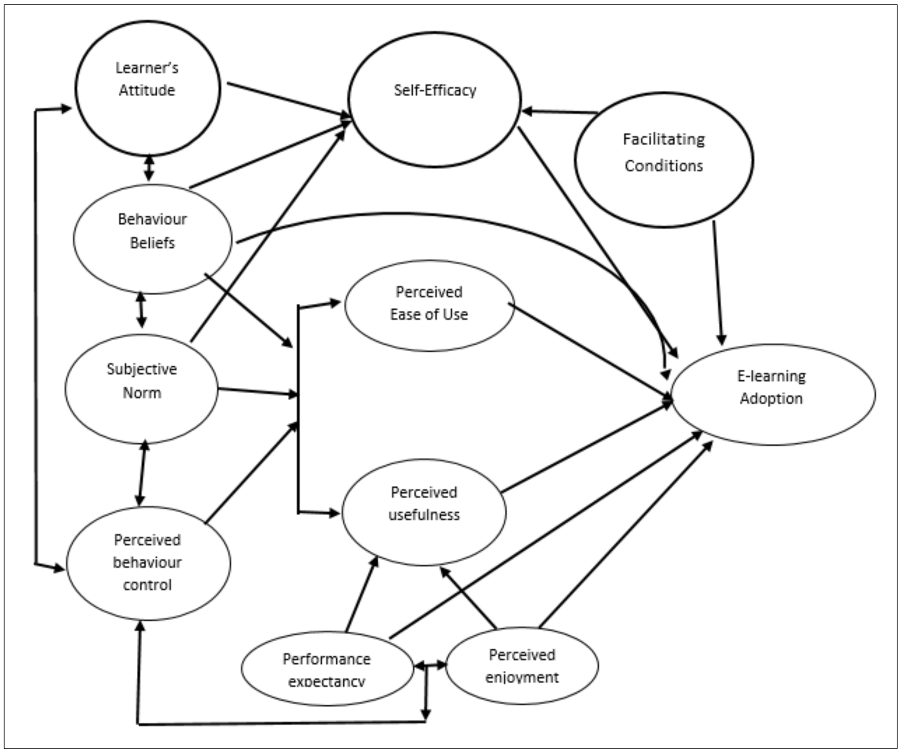

Fig 1: modified theory of Planned Behaviour and Technology Acceptance Model
Source: Own Source adapted from Fishbein (1975)

Data was collected using a structured questionnaire that was administered in two universities that are based in Harare.

Multinomial Logit (MNL) Model

Many empirical studies on the adoption of e-learning assume linear decision making. This paper takes a different approach and argue that the adoption of e-learning systems have cognitive, affective and behavioural push factors. Faced with a decision to adopt e-learning systems we assume three outcomes; (1) adopt e-learning now (AELS); (2) do not adopt e-learning (NAELS) and (3) defer adoption of e-learning (DAELS). The later decision can lead to defer and later adopt and defer and do not adopt e-learning outcomes. For minimalism purposes we reduce the outcomes associated with deferment to simply one outcome, defer e-learning systems (DAELS). Having three dependent variables suggest the probability of adopting e-learning systems in Zimbabwe's universities can be analysed using polychotomous models such as the multinomial logit (MNL) or multinomial Probit (MNP). These models are complex and have not been used in many studies that focus on the adoption of e-learning systems. We chose the MNL for this study for the following reasons. Compared to binary models such as Probit, Tobit and Logit and also to linear models such as the OLS, the MNL has easily interpretable diagnostic statistic tests. Furthermore, it is also more robust to violations of assumptions of equal variance-covariance matrices across groups (Muzurura, 2018).

We generalised our framework from models by Aldrich and Nelson (1984), Hosmer and Lemeshow (2000) and Long (1997). Data was arranged so that students that chose the decision to adopt e-learning systems that is, AELS were assigned a value of 1, not to adopt e-learning systems, NAELS were allotted 2, and those that deferred DAELS were given value of 3. The three dependent variables were unordered and not hierarchical. Any of the three outcomes was not necessarily better or worse than the other hence, assuring an equi-probability outcome.

A major consequence of using multiple discrete choice models is the fundamental assumption of independent of irrelevant alternatives (IIA) (see Alvarez and Nalgler, 1995; Fry and Crompton, 1996, 1998; Keane, 1992; Lacy and Burden, 1999; Keane, 1992; Small *et al*, 1985; Haussmann and McFadden, 1984; Green, 2002). The IIA assumption entails that the ratio of the choice probabilities of any two alternatives is unaffected by the systematic utilities of any other available alternatives. Thus, the odds for any pair of an individual decision outcomes such as "AELS" or "DAELS" are determined without reference of any other alternative such as "NAELS".

According to, if the IIA assumption is violated, it consequently follows that the MNL model cannot be used or is invalid (Haussmann and McFadden, 1984. In this paper, we utilised the Haussmann and McFadden (HM) test and the Small and Hsiao (SH) test to check for IIA. A second test that was carried out was the Wald Combination and the Likelihood ratio test. These test was to ensure that three dependent variables could not be collapsed into one to two suggesting the inapplicability of MNL in this study. For parsimony of the model we also carried out multicollinearity test.

MNL Model Specification

Using the MNL the predicted probabilities were calculated using the formula;

Starting from the formula

$$P_{ij} = \text{Prob } (y_i = jx_i = \frac{\exp\,(x_i\alpha_j)}{\sum_{j=0}^{2} \exp\,(x_i\alpha_j} \qquad (1)$$

Where y_i and jx_i depict the probability of adopting e-learning systems in universities. We expand equation (1) into three equations that represented the three dependent variables as follows;

$$P_{ijt},1 = P\big(Y_{ijt} = 1\big) = [\frac{\exp\{X'_{ijt}\alpha\}}{\{1+\exp\{X'_{ijt}\alpha_2\}+\exp\,\{X'_{ijt}\alpha_3\}}] \qquad (2)$$

$$P_{ijt},2 = P\big(Y_{ijt} = 2\big) = [\frac{\exp\{X'_{ijt}\alpha_2\}}{\{1+\exp\{X'_{ijt}\alpha_2\}+\exp\,\{X'_{ijt}\alpha_2\}}] \qquad (3)$$

$$P_{ijt},3 = P\big(Y_{ijt} = 3\big) = [\frac{\exp\{X'_{ijt}\alpha_3\}}{\{1+\exp\{X'_{ijt}\alpha_3\}+\exp\,\{X'_{ijt}\alpha_3\}}] \qquad (3)$$

Where equation (2) represents the probability that the ith student will choose alternative j (j = 1, (AELS); equation (3) represents the decision NAELS. Equation (4) represents DAELS X'i are student's-specific regressors as shown in the conceptual framework. The elasticities α_1, α_2 and α_3 are the coefficient vectors which are assumed to have positive signs. There is one set of coefficients for each choice alternative or variable. In order to guarantee identification of the equation, equation (3) or αj is set to zero for the referent or baseline category, which is the firm's decision to NAMLS outcome. Setting $\alpha_0 = 0$ and computing the predicted probabilities yields the equation (5) below;

$$Pijt = \Pr\,(y_i = j\text{I}x_i = \frac{\exp\,(x_i\alpha_j)}{\exp\,(x_i + \sum_{j=0}^{2} \exp\,(x_i\alpha_j} \qquad (5)$$

$$= \frac{\text{ex}\,(x_i\alpha_j)}{\sum_{j=2}^{2} \exp\,(x_i\alpha_j} \qquad (6)$$

Equation (6) (baseline category NAELS) can be expanded as below into equation 8 and 9. (See Liao, 1994; Selim, 2008)

$$Pijt = \Pr(y_i = jx_i = \frac{\exp\,(x_i\alpha_j)}{\exp(x_1 3) + \sum_{j=0}^{2} \exp\,(x_i\alpha_j} \qquad (7)$$

$$Pijt = \text{P}\,(y_i = jx_i = \frac{1}{1+\sum_{j=1}^{2} \exp\,(x_i\alpha_j} \qquad (8)$$

Risk relative rations for the baseline category (NAELS) are given by the following equation;

The relative risk ratio (RRR) indicates how the relative risk of the alternative compared to the benchmark option changes with a unit increase in the explanatory variable and was specified as follows.

$$RRR = [\frac{P\{Y_{ijt}=h\text{I}Y_{ijt}+1\}/P\{Y_{ijt}=3\ \text{I}Y_{ijt}+1\}]/P\{Y_{ijt}=h\text{I}Y_{ijt}\}}{P\{Y_{ijt}=3\text{I}Y_{ijt}]\text{I}}, j = 1 \ldots N{:}\ \text{I} \neq j; t = 1 \ldots T \qquad (10)$$

Equation (10) shows that an increase of the explanatory variable increases or decreases the likelihood of student, compared to the benchmark or baseline category the not adopting e-learning systems. The final equation was specified as follows;

$$P\,(1,2,3) = \partial_0 + \partial_1 PU + \partial_2 PEOU + \partial_3 SI + \partial_4 FC + \partial_5 LA + \partial_6 PerE + \partial ATT_7 + \partial_8 PSE + \alpha_9 PE + \alpha_{10} PC + \varepsilon_{18} \qquad (9)$$

Justification of independent variables

Perceived usefulness (PU): is the degree to which a user believes that using e-learning systems would improve learning task. It means accessibility, portability, and flexibility in having a choice of learning and teaching rather than relying on traditional classroom, chalks, blackboards and hard cover textbooks. $H_{1.}$ PU has a positive effect on the probability of adopting e-learning systems in rural secondary schools. Perceived ease of use (PEOU) - High perceived ease of use should translate to increased adoption of an e-learning system (Tan *et al*., 2016; Handal *et al*., 2013; Hustad *et al*., 2013). E-learning systems improve utility value that is learning performance, effectiveness and productivity and contribute to perceived performance expectancy. Thus the hypothesis, $H_{2.}$-the higher the degree of perceived ease of use the higher the probability of adopting e-learning systems in universities. Social Influence (SI) - applying TPB we define social norms, subjective norms or normative pressures resulting from the society and other students that will influence the adoption of e-learning systems. Prior studies has confirmed the importance of this variable (Mbengo, 2015; Anni *et al* 2018; Crompton *et al*, 2016). In universities social influence is important for behavioural intention to adopt and use of e-learning systems and hence, H_3: SI positively influences the probability of adopting e-learning systems in rural secondary schools. Facilitating Conditions (FCs)- refers to the extent to which a user believes that organisational and technical infrastructure such as telecommunication networks that support the use of e-learning systems exists. Prior studies using TAM have confirmed the significance of this variable to user attitudes on the adoption of e-learning systems, Zimbabwe universities face huge impeding barriers such as; electricity shortages, poor connectivity and interoperability of networks and inadequate technical backup H_4: FC lower the probability of adopting e-learning systems in universities. Learner's Autonomy (LA) - allows users of e-learning to set their own learning objectives and be fully in charge of their educational progress. One of the main advantages of e-learning is that it gives users flexibility and convenience. Convenience is a combination of time utility and place utility that can have an impact on the user's decision to use e-learning. This variable is a major component of TPB and has also been incorporated in some TAM studies (Sarrab *et al*., 2015; Mbengo, 2015; Haji *et al*., 2013). $H_{5.}$: LA has a positive effect on the probability of accepting e-learning systems in universities.

Performance expectancy (PerE)

PerE can be defined as the extent to which a user believes that using e-learning will help him or her to attain benefits in education performance (Venktesh *et al*., 2012). Althunibat (2015) and Sanchez-Prieto *et al* (2017) say that the performance expectancy construct has a strong relationship with behavioural intention to adopt e-learning systems at universities. H_6: has a positive effect on the probability using e-learning in universities. Attitude (ATT) - Simply acquiring a new education technology is insufficient for the integration e-learning into teaching and learning practices. The more positive the attitude about education technology, the higher the actual usage. Attitudinal impediments in most countries are exacerbated by poor training, bandwidth challenges, time delays in downloading content and high cost of connectivity. Lectures in Zimbabwe's universities have also higher teacher-student ratio, and may perceive that using e-learning systems while managing higher workloads may be difficult. Hence, H_7: attitude has a positive effect on the probability of adopting e-learning in universities. Perceived self-efficacy (PSE)-refers to the confidence that users have in using e-learning in performing educational tasks. This variable has been used in empirical literature to assess the behavioural intention to adopt internet technology in developing countries (see Venkatesh *et al*., 2012 Hanafizadeh *et al*., 2014; Ramdhony and Munien, 2013) [31]. The higher the extent of perceived self-efficacy among users, the more probable that e-learning will be adopted faster. $H_{8.}$ The higher the perceived self-efficacy the higher the probability of behavioural intention to adopt e-learning in universities. Perceived Enjoyment (PE) - PE has been given as an example of intrinsic motivation that is known to influence user acceptance on new technology (Sarrab *et al*., 2015; 2016). Prior studies showed that PE is an influencing determinant of PEOU and also behavioural intention to adopt e-learning in secondary and universities (Osakwe *et al*., 2016; Handal *et al*., 2013; Andrew, 2011; Sarrab *et al*., 2015Andreea & Cristina, 2012). PE is likely to allow students and teachers to enjoy learning activities using their e-learning devices since the same devices can be used for playing games. $H_{9.}$: Perceived Enjoyment has a positive effect on the probability of adopting e-learning systems in universities. Perceived Cost (PC) - refers to the extent to which a student believes that using e-learning systems will result in lower costs. The cost of using e-learning has been integrated in most modified TAM models as a predicting factor for adoption (Sarrab *et al*., 2016 (Govender and Sihlali, 2014)). Perceived cost of bundles coupled with weak band provides a behavioural perspective of a user's economic motivations for using e-learning. In low income countries like Zimbabwe the cost of internet access is likely to be integral on the probability of using e-learning systems. Thus, H_{10}: Perceived cost (PC) has a negative affect the probability of using e-learning in universities.

Findings and Discussions

The findings from various model diagnostic test are shown below.

Independence of Irrelevant Alternative (IIA) Test

The Haussmann and Small-Hsiao diagnostic test for IIA are shown in Table 2 below. The AELS decision has a coefficient of -11.88 and NAELS (-320.18) whilst DAELS has a coefficient of -228.11. The hypotheses that the three outcomes, AELS, NAELS AND DAELS did not affect the variables considered important for the behavioural intention to e-learning systems in universities was rejected. The *p-value* for the decision to AELS is statistically significant at 95% level whilst the decision to DAELS and NAELS are statistically significant at 99% level of confidence. Hence, using either the p-value or coefficients of the independent variables, the assumption of IIA could also not be rejected.

Table 1: Haussmann and Small-Hsiao Test for IIA

mlog test, Haussmann smhsiao base						
*** Haussmann tests of IIA assumption (N=50)						
Ho: Odds (Outcome- J) vs Outcome-k) are independent of other alternatives						
Omitted	**Chi 2**	**df**	**P>Chi1**	**Evidence**		
AELS	-1.88	12	--------	------		
DAELS	-6.45	12	--------	------		
NAELS	0.00	12	1.000	for H_o		
Note: if chi2<0, the estimated does not meet asymptotic assumptions of the test						
H_o Odds(outcome-J) vs Outcome-K) are independent of other alternatives						
Omitted	**lnL(full)**	**lnL (omit)**	**Chi2**	**df**	**P>chi1**	**Evidence**
AELS	-11.88	-5.07	12.50	12	0.04	against Ho
NAELS	-320.18	-0.00	19.71	12	0.000	against Ho
DAELS	-288.11	-0.00	11.46	12	0.000	against Ho

Source: Own Computations

Combining Dependent Categories-The Wald Test

As indicated by the *p-value*, the Wald test is statistically significant at 95% level of confidence. These findings show that AELS, NAELS and DAELS are separate user decisions and independent of each other, hence the model was properly specified. In other words, a user can either decide to adopt, or to defer the adoption or not to adopt e-learning systems.

Table 2: The Wald Test

.mlogtest, combine ***Wald test for combining alternatives (N=50) H_o: All coefficients except intercepts associated with a given pair of alternatives are 0, that is alternatives can be combined				
Alternative Tested		**Chi-SQ**	**df**	**P>chi-squared**
AELS	DAELS	15.65	11	0.029
AELS	NAELS	13.60	11	0.035
DAELS	NAELS	11.88	11	0.046

Source: *Own computations*

Multicollinearity Test
Table 4 below shows the results of multicollinearity tests. As shown all predictor variables did not move together in systematic ways that could influence the parsimony of the MNL model. Therefore, the effects of independent variables on dependent variables can be isolated.

Table 3: Multicollinearity Tests

	PE	PEU	SI	FC	LA	PerE	ATT	PSE	PE	PC	PCOST
PE	1.00										
PEU	-0.11	1.00									
SI	-0.25	0.18	1.00								
FC	0.18	-0.14	-0.09	1.00							
LA	-0.17	0.11	-0.06	-0.08	1.00						
PerE	-0.05	0.08	-0.03	0.25	-0.15	1.00					
ATT	0.30	0.01	0.07	-0.02	0.06	0.07	1.00				
PSE	-0.16	-0.02	-0.08	-0.01	-0.09	-0.02	-0.06	1.00			
PE	0.25	-0.01	-0.11	0.02	0.02	0.05	-0.03	-0.22	1.00		
PC	-0.15	0.05	0.01	0.09	0.09	0.08	0.02	0.03	-0.21	1.00	
PCOST	0.19	0.01	-0.02	0.11	0.11	0.04	0.02	-0.02	0.05	-0.04	1.00

Source: Own Computation

Model Fitness Test
Findings from likelihood-ratio variable fitness test for variables that were used in the MNL regression model are shown in Table 4. Perceived self-efficacy, learner autonomy, perceived enjoyment determined to be insignificant and thus were dropped from further analysis. Other variables specified in MNL model were found to be statistically significant at various level of significance's universities.

Table 4: Model Fitness Test

.mlogtest, Ir **likelihood-Ratio test for independent variables (N=50) Ho: All coefficients associate with given variable(s) are 0			
Regressor	**Chi-squared**	**df**	**P>Chi-squared**
Perceived usefulness	8.54	8	0.03
Perceived ease of use	9.67	8	0.01
Social influence	8.60	8	0.00
Facilitating Conditions	9.80	8	0.01
Learner Autonomy	2.06	8	0.97
Performance Expectancy	8.10	8	0.02
Attitudes	8.15	8	0.01
Perceived Self efficacy	11.50	8	0.65
Perceived Enjoyment	9.25	8	0.45
Perceived Control	6.78	8	0.00
Perceived cost	8.70	8	0.01

Source: Own computation

Relative Risk Ratio (RRR)
Table 6 shows the findings from RRR. The tables shows that the RRR of not adopting e-learning systems in Zimbabwe's universities are caused by perceived usefulness, perceived ease of use, social influences, facilitating conditions, learning autonomy, cost and personal innovativeness.

The relative risk ratio of deferring the probability of deferring the adoption of e-learning systems in rural secondary schools are as a result of perceived self-efficacy, relative advantage, age and gender. Detailed discussions of these findings will be done in the next section.

Table 5: Relative Risk Ratio

AELS	RRR	Std. Error	z	P>IzI	95%CI	interval
Perceived Usefulness	0.55	0.01	2.99	0.00	1.45	6.45
Perceived Ease of use	0.70	0.03	2.80	0.03	1.86	5.78
Social Influence	0.11	0.01	4.05	0.00	0.45	1.65
Facilitating Conditions	0.35	0.44	-6.91	0.05	4.66	9.85
Learner autonomy	0.22	0.01	1.88	0.35	2.85	8.14
Performance expectancy	0.07	-0.06	3.10	0.00	2.46	3.55
Attitude	0.80	0.44	5.78	0.02	2.25	4.19
Perceived self-efficacy	0.45	0.39	1.25	0.66	2.45	3.65
Perceived enjoyment	0.18	0.32	1.40	0.55	3.12	6.65
Perceived control	0.06	0.29	3.85	0.03	6.56	18.25
Perceived cost	0.11	0.14	1.87	0.95	2.44	4.56
NAELS referent						
DAELS Decision						
Perceived Usefulness	0.15	0.01	3.65	0.01	12.45	18.31
Perceived ease of use	0.45	0.05	0.65	0.30	2.85	3.33
Social Influence	0.03	0.02	-0.45	0.45	7.85	15.65
Facilitating Conditions	0.40	0.12	-3.58	0.00	3.65	4.89
Learner Autonomy	0.48	0.02	1.14	0.25	1.35	2.75
Performance expectance	1.05	0.09	2.89	0.02	2.87	3.92
Perceived self-efficacy	1.42	0.33	1.65	0.75	1.66	8.44
Perceived enjoyment	0.35	0.03	-1.06	0.00	-5.05	-7.12
Perceived control	0.21	0.09	0.78	0.00	2.85	5.35
Perceived cost	1.12	0.10	1.15	0.15	-5.22	-6.17

Source: Own Computation

Discussions
In contrast to binary and linear regression models, a positive/negative sign on a coefficient on a MLN regression equation does not show that an increase/decrease in the independent variable corresponds to an increase/decrease in the probability of choosing an outcome (see also Cameron and Trivedi, 2005; Muzurura, 2019).

Adopting E-Learning Systems Relative to Not Adopting.
Perceived Usefulness (PU)
If perceived usefulness of the e-learning system was to increase by one unit, the relative risk for adopting the system relative to not adopting would be expected to decrease by a factor of 0.55. If users find e-learning useful to them in terms of accessibility, portability, flexibility and rich content they are likely to adopt it.

Perceived usefulness is also linked to personal innovativeness and learner autonomy. This result suggests that perceived usefulness may be linked to personal innovativeness and user autonomy which are also important antecedents for the growth of cognitive and affective skills. Perceived Ease of Use (PEOU) - If the perceived of use of e-learning system was to increase by one unit, the relative risk for not adopting e-learning systems would be expected to decrease by 65%. Ease of use of learning systems is likely to be affected by other factors such as compatibility with traditional learning systems, lack of complexity, trialability, awareness knowledge and relative advantages of other existing alternatives. Availability of supporting infrastructure is likely also to enhance ease of use. Social influence (SI) - If negative social influences were to increase by one unit, the relative risk ratio of not adopting e-learning systems would be expected to decrease by 11%. Social influences is enhanced by cultural and social norms, by beliefs that others are finding e-learning useful. Sarrab *et al* (2016) and Essary (2014) also find similar results using the TAM model. Facilitating Conditions (FC)-if conditions that facilitate the adoption of e-learning systems were to increase by 1 percent, the relative risk ratio of not adopting e-learning systems would be expected to decrease by 35%. The availability of related resources such as technical help, internet infrastructure, increased mobility, training and trials, hardware, software, training, online help users to easily work with e-learning systems. Performance expectancy-if performance expectance were to increase by 1% adoption of e-learning systems would increase by 105%. Performance expectancy can be increased by trial runs and is also affected by trust, belief in e-learning and having positive attitude towards e-learning. Credibility of e-learning, reduce perceptions of risk and insecurity and heighten performance expectancy on late adopters. Users are also likely to evaluate the benefits against the cost as a measure of performance expectance. Unsuccessful trial runs might also influence students not to adopt e-learning systems (see Rambe and Bere (2016) for South Africa and Sarrab *et al* (2015) for Jordanian schools.

Attitude (LA): if a user's attitude towards the adoption of e-learning were to increase by 1%, the relative risk ratio of not adopting would be expected to decrease by a factor of 80%. Simply having e-learning systems in universities is not sufficient, users need to have the right attitude in order to integrate e-learning into teaching and learning practices. Negative attitude can become socialised into cultural beliefs and norms through social influences or decrease performance expectancy. Slow access, excessive delays in downloading content and frequent breakdowns can lead to negative attitudes.

Perceived Costs: If the costs of using e-learning systems were to increase by 1% the relative risks of not adopting e-learning systems would increase by 150%. Most users in many developing countries like Zimbabwe have low disposable incomes and illegal photocopying of text books are likely to be cheaper than using e-learning systems. The results suggest that cost of acquiring e-learning devises, bundles and airtime data affect the probability of using e-learning systems could be a major factor that may hinder the adoption of e-learning systems. Similar findings are also shown in some studies that used TAM and focus on Zimbabwe (see Mbengo, 2015 and Ndluvu, 2018).

Deferring E-learning Adoption Relative to Not Adopting Decision

As shown in table 7, perceived usefulness, facilitating conditions, learner's attitude and perceived cost are likely to cause a user to defer the adoption of e-learning systems.

Perceived Usefulness (PU): If a user's perceived usefulness of e-learning were to increase by one percent, the relative risk of deferring the e-learning adoption process would be expected to decrease by 15%. Users are likely not to defer the adoption of e-learning systems if they perceive it more useful in their daily educational routines or meet their performance expectancy. Complexity, lack of compatibility, network reliability, inadequate user support and training can cause users to reduce their perception of usefulness of e-learning systems.in addition if other alternatives have relative advantages over e-learning systems, perceived usefulness also declines and users might prefer to wait long during the adoption process. The finding also imply that trial runs may be use to allay fears such as perceived risk, reachability, convenience, compatibility, complexity and safe to use and at the same time increasing the likelihood of immediate adoption.

Perceived Enjoyment: If the enjoyment that comes from using e-learning systems were to increase by 1% the relative risk of deferring the usage of e-learning banking would be expected to decrease by 35%. The results suggest e learning systems that are too complex, not compatible with other traditional learning practices, very expensive and not useful are hardly enjoyable. This variable has been confirmed by a number of prior studies that focus on universities (Osakwe *et al*., 2016; Handal *et al*., 2013; Andrew, 2011; Sarrab *et al*., 2015Andreea & Cristina, 2012).

Conclusions and Recommendations

The main conclusion is that all hypotheses were supported in this study. Perceived usefulness, perceived ease of use, social influences, perceived control, perceived costs, subjective norms (attitude), perceived costs, facilitating conditions and performance expectance are the major factors that affect the probability of accepting e-learning systems in Zimbabwe's universities not to adopt e-learning systems. On the other hand factors such as perceived enjoyment and perceived usefulness are likely to affect the probability of adopting and using e-learnings. Recommendations from the findings are as follows; Zimbabwe universities should pay special attention to issues like the cost of using e-learning, the perceived usefulness, ease of use, compatibility, complexity, learner and teachers' attitudes, when making decisions to use these systems. E-learning systems should be portrayed as useful and ease to use and compatible with current economic challenges as well as customers' values, lifestyles, norms, needs and past experiences of users. Trial runs and social influences should be used to motivate laggards and late adopters of e-learning systems. Policy makers should ensure that the use of e-learning systems in universities remains affordable to users. This can be done through subsidies on bandwidth during e-learning sessions.

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