

PREDICTING THE ACCEPTANCE OF ELECTRONIC LEARNING BY ACADEMIC STAFF AT THE UNIVERSITY OF ZULULAND, SOUTH AFRICA

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ABSTRACT

In this article the authors provide a quantitative method to predict the acceptance of electronic learning resources by academic staff in a blended learning environment at the University of Zululand (UNIZULU), KwaDlangezwa, South Africa. Conceptually the study followed a positivist epistemological belief and deductive reasoning, but the article will also embrace the interpretive research paradigm to include the researchers' insights on the results. Inferential statistics

were used to predict the level of acceptance of e-learning and show the strengths and significances of the postulated Unified Theory of Acceptance and Use of Technology (UTAUT) model's relationships. The results showed that the majority of academic staff accept the use of e-learning resources. The study concludes that the UTAUT model's moderate accuracy and relevance could be improved by adopting contextualised socio-economic moderators relevant to the education sector rather than adopting those found to be significant in the financial sector of Venkatesh et al.'s (2003) study. The study would thus recommend, firstly, the provision of useful resources that will improve both teaching and learning, and, secondly, the provision of appropriate skills development and support for these resources. Another recommendation is the introduction of user policies to instil mandatory use of these resources by academic staff while concluding that the social influence relationship will strengthen with the increased interactions and relationships between management, academic staff and support staff.

KEYWORDS: e-learning, Unified Theory of Acceptance and Use of Technology, inferential statistics, University of Zululand, South Africa

1. INTRODUCTION AND BACKGROUND

The authors take cognisance of the pedagogical concept of social constructivism of which the theoretical foundation was laid by Jean Piaget, a developmental psychologist, during the first half of the 20th century. It refers to the concept or understanding that learning and teaching is a collective process in which people are both teachers and learners at the same time and are thus better able to understand the information they have constructed by themselves (Atherton 2011). New pedagogies, for example connectivism, in which technology together with language and media act as conduits of information, promoting greater participation, collaboration and interaction between networked learners, who socially construct an active learning experience within different learning networks, are recommended for the 21st century (Siemens 2004). Within a higher education context, well-rounded learning outcomes are achieved through blended multi-threaded networks of face-to-face learning, research, service learning, experiential learning and e-learning. The theory also emphasises the importance of creating a blended learning network around the intent of learning, which will result in a greater change or transformation in the learner's knowledge and experience (Evans 2013, 9).

Electronic learning (e-learning) is broadly defined as the use of information and communications technologies (ICTs) and information systems (IS) in teaching and learning. The resources surveyed included office ICTs; portable presentation tools for lectures; intranet, internet and wireless network services; the Modular Object-Orientated Dynamic Learning Environment (Moodle) Learning Management System (LMS); computer laboratories; the library's e-resources; research databases;

and the institutional repository. Dillon and Morris (1996) define user acceptance as 'the demonstrable willingness within a user group to employ information technology for the tasks it is designed to support'. Dillon (2001) believes that by developing and testing models of the variables influencing user acceptance, researchers seek to provide direction to the process of design and implementation in a manner that will minimise the risk of disapproval by users of these resources.

This article focuses on the factors that influence the academic staff's acceptance of e-learning, which requires special consideration for the successful planning, implementation and support of structured e-learning at the University of Zululand (UNIZULU), KwaDlangezwa, South Africa.

2. LITERATURE REVIEW

Around the world, all levels of education are embracing technology to provide a dynamic learning environment that is more interconnected, instrumented and intelligent in order to enable an educational continuum (Rudd et al. 2009, 9). This would allow primary, secondary and tertiary education to be linked with lifelong learning to meet the demands of the knowledge economy, where knowledge is the single most important asset for learners. The authors postulate five signposts of change, including: technology immersion, personal learning paths, knowledge skills, global integration and economic alignment. These will require educational systems to respond boldly in a variety of ways to accommodate these changes. Technology immersion portrays the notion of a new generation of university students, who have grown up in the digital era of DVDs, MP3s, DSTV, laptops, tablet computers and the Internet, and are now entering tertiary institutions with this digital literacy. According to Rudd et al. (2009, 5), they expect to use technology in the learning environment just as they do in their personal lives. Downes (2005) explains that the 'born digital' generation, also referred to as 'digital natives' or 'n-gen', use ICTs and the Internet differently to work, learn and play. Drawing on their digital literacy, they prefer to randomly access 'on demand' multi-media information from multiple sources to fully absorb messages or content from friends or lecturers either locally or globally. The 'n-gen' is in search of a learner-centred education, whose design places more control and responsibility on the learner for acquiring information and knowledge and then communicating or sharing this on social networks or communities of practice (Downes 2005).

E-learning has occurred at most South African universities since the late 1990s (Ravjee 2007, 27). However, only a few seem to have set the benchmark and made full use of ICTs in their teaching and learning. These include Stellenbosch University, the University of Cape Town, the University of Johannesburg and the University of the Free State (Boere and Kruger 2008).

A number of e-learning projects have been initiated at UNIZULU since 2000, ranging from basic departmental websites, which hosted 'virtual classrooms', to the actual deployment of various LMSs including Moodle, which was introduced and has been piloted by Evans (2013, 4) in the Department of Information Studies since 2007.

3. THEORETICAL FRAMEWORK

Predicting the acceptance of ICT and IS and hence e-learning requires the review of psychology based theories, including the original Theory of Reasoned Action (TRA) (Ajzen 2008; Dillon and Morris 1996); the Technology Acceptance Model (TAM) (Dillon 2001; Dillon and Morris 1996); and the Theory of Planned Behaviour (TPB) (Ajzen 2008), among others, that are essentially modifications of the above mentioned. Venkatesh et al. (2003) reviewed eight prominent user acceptance models, and then formulated a unified model that incorporates validated elements across the eight models, as well as a selected subset of additional variables. Thus, the UTAUT model has condensed the 32 variables found in the eight existing models into four main effects and four moderating factors (Venkatesh et al. 2003, 467).

Taiwo and Downe (2013, 48) state that the UTAUT model has become the model of choice for measuring user acceptance, despite the fact that although the model has been extensively applied, tested and validated, the outcome of empirical studies has been inconclusive in respect to the magnitude, direction and significance of the construct and moderator relationships in the model. The objective of Taiwo and Downe's (2013) study was to investigate the validity of the UTAUT model and reveal how much this validity is substantiated in the extant literature. To do this, the authors provided a meta-analysis of 37 empirical studies that have made use of the UTAUT model highlighting those that have validated the model and those that have found differences. According to Taiwo and Downe (2013, 51), the inconsistency in the results of the above studies on the UTAUT model leaves the output of the relationships in the model inconclusive; however, on the basis of the meta-analysis study their findings confirmed Venkatesh et al.'s (2003) initial findings between the five constructs of the UTAUT model. Only the relationship between performance expectancy and behavioural intention was found to be strong, while others, although somewhat weak, were still significant.

While the UTAUT model's ability to predict academic staff's behavioural intention to accept e-learning at UNIZULU was empirically validated by Evans (2013) using a strictly positivist epistemological belief and deductive reasoning, this article presents the study's methodology and results and also attempts to interpret the level of acceptance, behavioural intention and usage behaviour of academic staff towards e-learning within this institution by inductive reasoning and the use of constructivism or interpretivism.

4. PROBLEM STATEMENT

While the incorporation of e-learning within higher education seems inevitable, predicting the acceptance and use of these resources by academic staff at UNIZULU will help to recognise, understand and support relationships that are found to facilitate this development and ensure that academic staff use the resources for their intended purpose and in order for them to show a good return on investment.

The main research question was whether academic staff accept e-learning resources at UNIZULU and the subsidiary research questions were as follows:

1. To what level of efficiency can the UTAUT model be used to predict the acceptance of e-learning by academic staff at UNIZULU?
2. How will the constructs and their moderating variables in the UTAUT model impact on the acceptance of e-learning with special reference to their specific impact on academic staff's behavioural intention to use, and their use of e-learning at UNIZULU?
3. How strong is the adopted user acceptance model's theoretical validity and practical applicability?

Due to limited space, the working null research hypotheses H_{01} to H_{11} are not expressed, but will be referred to later together with the alternate hypotheses in the discussions of the findings.

5. METHODOLOGY AND DATA ANALYSIS

The research methodology used quantitative data and foundations of positivism where fixed UTAUT relationships were surveyed in academic staff using e-learning to validate the model and to increase the predictive understanding of this development.

The target population included 310 academic staff who were stratified by their positions of contract lecturer, junior lecturer, lecturer, senior lecturer, associate professor and professor and who had email addresses on the institution's email server address book (Evans 2013, 99). The desired sample size of 150 was selected using simple random sampling (with replacement) and probability proportionate to size formulas.

The survey instruments included an emailed online questionnaire and a paper version put into internal post boxes. The questionnaire indicators for most of the constructs (performance expectancy, effort expectancy, social influence, facilitating conditions and behavioural intention) were adapted from Venkatesh et al. (2003) and Venkatesh and Davis's (2000) validated studies and slightly modified to include the term e-learning, while the indicators for measuring the use construct were customised to the contextual use of e-learning at UNIZULU. The survey questions were mapped to the constructs of the UTAUT model to measure the four independent variables

or determinants (performance expectancy, effort expectancy, social influence and facilitating conditions) and their moderating effects (gender, age, experience, voluntariness), together with the two dependent variables (behavioural intention and use). Five-point Likert scales, which make use of standardised responses (strongly disagree, disagree, neutral, agree and strongly agree), were used in the indicator questions to measure the participants' responses to key UTAUT variables. The questionnaires also contained biographical questions.

According to Urbach and Ahlemann (2010, 9), structural equation modelling (SEM) is a statistical method for testing and approximating those causal relationships based on statistical data and qualitative underlying assumptions. Hair et al. (2010, 627) call SEM a cutting-edge technique that has grown in popularity over the past 20 years because of its ability to estimate multiple dependence relationships, which are similar to multiple regression equations, while also enabling multiple measures for each concept, which is similar to factor analysis. Urbach and Ahlemann (2010, 10) explain that SEM consists of a combination of the different inner and outer sub-models. The structural model or inner model encompasses the relationships between the latent variables (LVs), which have to be found in theory. The independent LVs (performance expectancy, effort expectancy, social influence, and facilitating conditions in the UTAUT model) are also referred to as exogenous variables and the dependent LVs (behavioural intention and usage behaviour in the UTAUT model) as endogenous variables. For each of the LVs within SEM, a measurement model or an outer model has to be defined. These models represent the relationship between the empirically observable indicator variables and the LVs. Urbach and Ahlemann (2010, 10) explain that the combination of structural and measurement models leads to a complete SEM.

After the data quality had been evaluated, the partial least squares (PLS) regression algorithm was run to calculate the UTAUT model parameter's estimates. The statistical output was analysed according to recommendations made by Urbach and Ahlemann (2010) and Hair, Ringle and Sarstedt (2011) for model validation, which represents the process of systematically evaluating whether or not the hypotheses expressed by the structural model are supported by the data. Urbach and Ahlemann (2010, 18) state that although the PLS does not provide an established global, 'goodness-of-fit' criterion, there are several criteria for assessing partial model structures, and a systematic application of the different criteria is carried out in a two-step process, including: (1) the assessment of the measurement model; and (2) the assessment of the structural model.

6. STATISTICAL ANALYSIS AND FINDINGS

Four tracked emails were sent and a paper copy of the questionnaire was placed in the post boxes of staff who had not responded after the second email. This elicited

a total of 98 responses on the hosting website and five paper questionnaires, giving a total of 103 responses. One of the paper copies of the questionnaires was blank, but the data from the remaining four paper questionnaires was manually captured onto the hosting website's database. Twenty-seven of the online responses were incomplete and only contained the biographical information from page one of the questionnaire and were therefore excluded from the academic staff sample, leaving a total of 75 respondents. After delivering the paper copies of the questionnaires to the postal services, it was discovered that four staff members had left the institution, one had retired and another had passed away, leaving a total possible participant pool of 144 and a response rate of 52 per cent. The responses were then filtered for those which had four or more non-random missing answers for the construct and moderator related questions on page two of the questionnaire, which were considered spoilt, and two more cases were removed leaving a final academic staff sample size of 73.

The academic staff sample consisted of fewer (29; 39.7%) females than males (44; 60.3%) and the average age of the staff who participated was 45 years with a standard deviation of 10 years. The representation of academic staff was from all four faculties including: Arts ($n = 28$; 38.4%); Science and Agriculture ($n = 25$; 34.5%); Commerce, Administration and Law ($n = 10$; 13.7%); and Education ($n = 10$; 13.7%). The stratification of academic staff was done according to their position of lecturer (45; 61.6%); senior lecturer (10; 13.7%); junior lecturer (8; 11.0%); associate professor (6; 8.2%); professor (3; 4.1%); and one other (1; 1.4%).

6.1. The measurement model

The PLS-SEM algorithm converged in six iterations in both the first PLS algorithm run and the last, showing that the algorithm could find a stable solution relatively easily. Statistical analysis led to the removal of the unreliable indicator items in the academic staff's reflective outer measurement model. The offending items, in the order that they were removed, included:

1. FC1.5 (I can get help from others when I have difficulties using e-learning resources.)
2. SI1.4 (I use e-learning resources because of the influence of my colleagues.)

Both items had indicator loadings below the recommended value of 0.70 and, because they did not adequately explain their associated latent variables, were considered unreliable for the purposes of the academic staff data analysis. The significance of the indicator loadings was also tested using the resampling method bootstrapping (Efron 1979; Efron and Tibshirani 1993 in Urbach and Ahlemann 2010, 18) and all remaining reliable indicators proved significant.

Statistical analysis of the data also showed evidence of discriminant validity between the different constructs of UTAUT for academic staff by following the

Fornell-Larcker criterion which requires an LV to share more variance with its assigned indicators than with any other LV (Urbach and Ahlemann 2010, 19).

6.2. The structural model

The path coefficients representing the hypothesised relationships between the independent and dependent constructs can be seen in Table 1. For the academic staff sample ($n = 73$), the empirical t -value has to be larger than the critical t -value (1.99) at a significance level of 5 per cent, and the p -value should be less than 0.05 for the hypothesised relationships to be significant, as seen in Table 1.

Table 1: Significance testing of the path coefficients for the structural model by bootstrapping in SmartPLS (Ringle, Wende and Will 2004)

	Path coefficients	t -value	Significance level	p -value	95% Confidence intervals	
					LLCI	ULCI
BI→USE	0.42	3.46	***	0.00	0.19	0.70
EE→BI	0.14	1.51	NS	0.13	-0.05	0.38
FC→USE	0.22	2.15	**	0.04	0.02	0.46
PE→BI	0.54	4.42	***	0.00	0.32	0.83
SI→BI	0.06	1.11	NS	0.22	-0.07	0.23

Note: NS = not significant

** $p < .05$; *** $p < 0.01$

Key: BI = behavioural intention, EE = effort expectancy, FC = facilitating conditions, PE = performance expectancy and SI = social influence

The significance testing of the total effects included the direct (PE, EE, SI on BI and BI and FC on USE) and indirect (PE, EE and SI on USE) effects as shown in Table 2 and was obtained by bootstrapping.

Table 2: Significance testing of the total effects coefficients for the structural model

	Total effect	t -value	Significance level	p -value	95% Confidence intervals	
					LLCI	ULCI
BI→USE	0.42	3.46	***	0.00	0.19	0.70
EE→BI	0.14	1.37	NS	0.16	-0.07	0.40

	Total effect	t-value	Significance level	p-value	95% Confidence intervals	
					LLCI	ULCI
EE→USE	0.06	1.35	NS	0.16	-0.03	0.18
FC→USE	0.22	2.09	**	0.04	0.01	0.46
PE→BI	0.54	4.42	***	0.00	0.32	0.83
PE→USE	0.23	2.25	**	0.03	0.03	0.48
SI→BI	0.06	0.77	NS	0.30	-0.13	0.30
SI→USE	0.02	0.79	NS	0.29	-0.06	0.13

Note: NS = not significant

** $p < .05$; *** $p < 0.01$

The coefficient of determination R^2 , adjusted R^2 and the Stone-Geisser's Q^2 value can be seen in Table 3.

Table 3: Endogenous LV's R^2 and Q^2 values for the structural model

	R-square	Adjusted R-square	Q-square
BI	0.43	0.41	0.28
EE			
FC			
PE			
SI			
USE	0.33	0.31	0.22

Academic staff's f^2 effect sizes are shown in Table 4.

Table 4: f^2 effect size of exogenous constructs explaining endogenous constructs for academic staff

	Effect size explaining BI	Effect size explaining USE
PE	0.23	
EE	0.02	
SI	0.01	
FC		0.05
BI		0.16

Academic staff's Q^2 effect sizes are shown in Table 5.

Table 5: Q^2 effect size of exogenous constructs explaining endogenous constructs for academic staff

	Effect size explaining BI	Effect size explaining USE
PE	0.13	
EE	0.01	
SI	0.00	
FC		0.01
BI		0.09

6.3. Moderation

Having described the relationships of the UTAUT constructs for the primary users of e-learning resources at UNIZULU, attention now shifts to understanding under what conditions the constructs operate. Hayes (2013, 27) explains that a relationship between two variables, X and Y, is said to be moderated when its size and sign depend on a third variable or set of variables, M. Gender was coded as a 0/1 dummy variable consistent with previous research (Venkatesh and Morris 2000 in Venkatesh et al. 2003, 439), and age was coded as a continuous variable, consistent with prior research (Venkatesh and Morris 2000 in Venkatesh et al. 2003, 439). Experience was operationalised via a dummy variable that took ordinal values of 1, 2, 3, 4 and 5 to capture increasing levels of user experience with the system. Using an ordinal dummy variable, rather than categorical variables, is consistent with recent research (e.g., Venkatesh and Davis 2000, 197).

While conducting the academic staff's moderation analysis in SmartPLS (Ringle et al. 2004), the PLS algorithm calculation also showed slightly different results when all the moderating effects were run together. The study observed a strong correlation between experience and use of e-learning resources, with the R^2 (0.70) of USE almost doubling.

Bootstrapping, however, indicated only one moderating effect to be significant within the constructs of the academic staff's UTAUT model, which was that of experience on FC of academic staff – FC*Exper ($t = 1.98$). However, on closer inspection, the convergent validity (AVE) values did not meet the required criterion to be included in the model.

7. DISCUSSION OF FINDINGS

The academic staff sample sizes met the minimum sample size of the often cited 10 times rule (Barclay et al. 1995 in Hair et al. 2014, 20), which in the UTAUT

model's case was 30; however, the study took cognisance of Hair et al.'s (2014, 20) recommendations that the sample size should rather be determined by means of power analysis based on the part of the model with the largest number of predictors or formative constructs, which in the case of the UTUAT model was three (PE, EE, SI predicting BI). According to Cohen (1992 in Hair et al. 2014, 20), for three independent variables, the study would need either a sample size of 124, 59, 38 or 30 observations to achieve a statistical power of 80 per cent for detecting coefficients of determination (R^2) of at least 0.10, 0.25, 0.50 or 0.75, respectively (with a 5% probability of error). As the R^2 for behavioural intention (BI) was 0.43 for academic staff, this would roughly translate to around 59 necessary observations to obtain a statistical power of 80 per cent, which was obviously obtained with a sample of 73 academic staff.

The academic staff sample consisted of 15 (20%) more males than females, which might have also introduced bias when conducting the gender moderating effect analysis in academic staff, which is discussed later. There was a large age range (21–69 years) amongst the academic staff sample, which was conducive to testing the age moderating effect. The stratification of the staff, according to their positions, seemed to be dominated by lecturers (45%); however, all faculties of the institution were represented in the academic staff sample. The response rate for the academic staff's survey was 52 per cent, which could lead to some response bias.

The determination of skewness and kurtosis, which is a measure of whether the data are peaked or flat relative to a normal distribution, of all survey responses, was included in the data analysis because of previous findings of non-normal data in psychometric studies (Hair et al. 1998 in Moran 2006, 59). The researchers' choice to use partial least squares–structural equation modelling (PLS-SEM) was appropriate because of the non-normality of some of the data used and because of the relatively small academic staff sample size, which suited PLS-SEM's ability to work efficiently with smaller sample sizes (Hair et al. 2011, 140).

To answer the main research question, of whether the academic staff accepts e-learning resources at UNIZULU, the study had to look at both the descriptive and inferential statistics. The mode for academic staff's BI to use e-learning resources was 4, which indicates that the primary users agree that it is their BI to use e-learning resources at UNIZULU. Also, the academic staff's UTAUT model's path coefficients from exogenous LVs to endogenous LVs were positive and had LV index values greater than 3, which indicate positive relationships between these users and the UTAUT constructs. The empirical results of the study suggest the acceptance/adoption of e-learning resources by academic staff at UNIZULU. The extent of the acceptance will also depend on both understanding and supporting the effects and constructs that show positive correlations with the two endogenous LVs, namely, behavioural intention (BI) to use, and use behaviour (UB), of e-learning resources.

7.1. The UTAUT model predicting BI

In order to respond to the second subsidiary research question, of how efficiently the UTAUT model was able to predict the acceptance of e-learning resources by academic staff at UNIZULU, the study results were compared with those found in seminal studies and the extant literature. Specifically, the researchers looked at the primary users' BI coefficient of determination (R^2), which is a measure of the model's predictive accuracy (Hair et al. 2014, 174) and the Stone-Geisser's Q^2 values, which indicate the model's predictive relevance (Hair et al. 2014, 178). Hair et al. (2011, 147) state that expected R^2 values will differ from discipline to discipline; however, in general, 0.75 can be described as substantial, 0.50 as moderate and 0.25 as weak for endogenous LVs in the structural model. Hair et al. (2014, 175) warn that problems can arise if the R^2 value is used to compare models that are specified differently, that is, having the same endogenous constructs but adding additional non-significant exogenous constructs that are correlated with the endogenous LV, as this causes the R^2 values to be inflated. The authors explain that this type of impact is most noticeable if the sample size is close to the number of exogenous LVs predicting the endogenous LVs in the model. The inflation of the R^2 value was observed when adding the constructs age, gender and experience to the UTAUT model for the moderation analysis of academic staff. The original R^2 value of 0.43 with three exogenous constructs (PE, EE and SI) predicting BI, jumped to 0.61, when adding age, gender and experience, making the number of exogenous predictor constructs of BI 6, all of which proved non-significant in the current study, but significant in Venkatesh et al.'s (2003) original study. Hair et al. (2014, 176) therefore recommend that the adjusted R^2 value (R^2_{adj}), as represented in the formula below, be used as the criterion to avoid bias toward complex models.

$$R^2_{adj} = 1 - (1 - R^2) \cdot \frac{n - 1}{n - k - 1}$$

where n = sample size and k = the number of exogenous LVs.

- For the significant UTAUT staff model with three (PE, EE and SI) exogenous constructs: $R^2_{adj} = 0.40$
- For the significant but unreliable moderated UTAUT staff model with four (PE, EE, SI and experience) exogenous constructs: $R^2_{adj} = 0.36$

The first and last listed R^2_{adj} values demonstrate that although when experience was added, which proved highly correlated to UB, it increased the R^2 for UB, the more complex model, with a lower R^2_{adj} for BI, proved less successful in predicting staff's BI to use e-learning resources.

So, while the UTAUT model was unable to match the high (70%) predictive accuracy of BI as in Venkatesh et al.'s (2003) study, the explained variance in BI

was 41 per cent for academic staff. The R^2_{adj} demonstrated a moderate efficiency in predicting the academic staff's BI to use e-learning resources at UNIZULU, and matched with the predictive strength of the eight models used to make up the UTAUT model, with the variance in BI explained ranging from 17 per cent to 42 per cent (Venkatesh et al. 2003, 439). Hair et al. (2014, 183) state that Q^2 values greater than 0 suggest that the model has predictive relevance for a certain endogenous construct. For BI, the Q^2 value for the academic staff model was 0.28, which shows that the UTAUT model has predictive relevance for this dependent variable in the context of UNIZULU.

Based on these empirical results, the study rejects H_{01} in favour of the alternate hypothesis H_{a1} : UTAUT will account for some percent of variance (R^2_{adj}) in academic staff's behavioural intention to use e-learning resources.

7.2. Other UTAUT model constructs and hypotheses

The third question which the study dealt with was the impact of the various UTAUT constructs (endogenous and exogenous) on academic staff's BI to use and their UB of e-learning at UNIZULU, as well as under which conditions these constructs operate.

7.2.1. Use behaviour

The UTAUT model ultimately theorises that BI and facilitating conditions predict UB. The BI–UB relationship together with the UB R^2 and the Stone-Geisser's Q^2 values will be discussed below. Taiwo and Downe's (2013, 48) meta-analysis of 37 UTAUT studies found that the correlations between BI and UB were reported from 13 studies and classified the effect size of BI–UB to be small; however, the authors noted that it could be because few studies (35%) have actually investigated the effect of BI on UB, rather relying on the premise that a strong relationship existed between BI and UB, which Venkatesh et al. (2003) had originally postulated and found to be significant. In Venkatesh et al.'s (2003) study, UB was measured as actual duration of use via system logs, while UB was self-measured in Moran's (2006) and Brand's (2006) studies. The current study also adopted the self-measurement approach by asking academic staff how frequently they used e-learning resources.

From the descriptive statistics the majority (76%) of the staff perceived their UB as purely voluntary, which reflects the lack of a usage policy for e-learning resources at UNIZULU. The modes 5, 1 and 3, and 5 for the academic staff's usage indicator statements reflects that the majority of academic staff only use e-learning resources for office work, communication and research, while many never or only sometimes use these resources for teaching purposes.

The inferential statistics showed that the UTAUT model explained the 31 per cent variance in this dependent variable. This value indicates a moderate predictive

accuracy to explain UB for academic staff. The Q^2 value was 0.22, which shows that the UTAUT model has moderate predictive relevance for this dependent variable.

The path coefficient between BI and UB (BI–UB) (0.42, $t = 3.46$), was positive and significant; the Cohen's f^2 effect size for academic staff was moderate (0.16); and the Stone-Geisser's Q^2 effect size value, which indicates the relative impact of predictive relevance, was moderately weak (0.09).

Based on these empirical results, the study rejects H_{02} in favour of H_{a2} : UTAUT will account for some percent of variance (R^2_{adj}) in academic staff's use of e-learning resources; and H_{07} in favour of H_{a7} : Behavioural intention will have a significant relationship on academic staff's use of e-learning resources.

7.2.2. Performance expectancy

Performance expectancy (PE) was defined as the degree to which individuals believe that using e-learning resources will help them attain gains in their academic performance (Evans 2013, 240); however, based on the previous findings on UB, this could mainly be office work, communication and research. It has been postulated to have the most significant positive relationship with BI to use technologies in the UTAUT model (Venkatesh et al. 2003). Taiwo and Downe (2013, 52) obtained 43 correlations between users' PE and their BI (PE-BI) from 37 studies and confirmed that this relationship was reported to have the highest positive significant correlations within the UTAUT model.

The descriptive statistics showed that academic staff's responses to PE indicator statements had modes of 4 and 5, which confirms their agreement and strong agreement to expecting performance gains in their BI to use e-learning resources. The relationship between PE and BI to use e-learning resources proved both positive and significant as reflected in the study's PE-BI path coefficient for academic staff (0.54, $t = 4.42$), the indirect effect of PE on their UB was similar to the direct effects of FC, but half the direct effect of an individual's BI on UB. The Cohen's f^2 effect size for the PE–BI relationship was medium (0.23); and the Stone-Geisser's Q^2 effect size value, which indicates the relative impact of predictive relevance of the PE-BI relationship, was medium (0.13) for the academic staff.

Based on these empirical results, the study rejects H_{03} in favour of H_{a3} : Performance expectancy will have a significant relationship on academic staff's behavioural intention to use e-learning resources.

Based on the moderation analysis of gender on academic staff users' PE, a positive correlation between PE and BI to use e-learning resources was found, which is consistent with gender theory; however, it was not significant at the 95 per cent confidence interval (t -value must be greater than 1.99, and p -value less than 0.05), that is, the measured PE of males (0.60) was higher than that of females (0.42). Age, however, had no moderating effect on the PE of academic staff's BI to use e-learning resources, and was not significant at the 95 per cent confidence interval.

Based on these empirical results, the study does not reject H_{08} : The effect of performance expectancy on behavioural intention of academic staff to use e-learning resources will not be moderated by (a) gender and (b) age, such that the effect will not be stronger for men and particularly for younger men.

7.2.3. Effort expectancy

Effort expectancy (EE) was defined as the degree of ease or straightforwardness associated with the use of the e-learning resources. Taiwo and Downe (2013, 52) obtained 42 reported correlations between EE and BI (EE–BI) from 36 studies, which is very similar to the number of PE–BI relationships studied (43). The authors' meta-analysis showed a significant positive EE–BI relationship, although weaker than the PE–BI and BI–UB relationships, roughly the same strength as the social influence-behavioural intention (SI–BI) relationships but stronger than the facilitating conditions-use behaviour (FC–UB) relationships. These findings confirm that the straightforwardness of technologies support individuals' BI to use them, as initially postulated by Venkatesh et al. (2003, 450); however, the authors' study also revealed that the construct's relationship with BI becomes insignificant over periods of prolonged usage, which was also consistent with previous research that also suggested that this EE–BI effect diminishes with increased experience (e.g., Agarwal and Prasad 1997, 570, 1998, 205; Thompson, Higgins and Howell 1991, 140; Venkatesh et al. 2003, 450).

From the descriptive statistics, the mode for three out of four of their EE indicators was 4, revealing that most academic staff agree that they do not need to exert much effort to use e-learning resources; the exception was where most staff were neutral about the idea of becoming skilful at using e-learning resources.

The inferential statistics showed that the EE–BI path coefficient was positive and not significant (0.14, $t = 1.51$), the weak EE–BI relationship could suggest that the academic staff's greater experience diminishes the EE effect on BI as postulated by Agarwal and Prasad (1997, 570), Agarwal and Prasad (1998, 205), Thompson, Higgins and Howell (1991, 140), and Venkatesh et al. (2003, 450). Similar non-significant results were found in Brand's (2006, 67) study on the adoption of online desktops. The indirect effect of EE on their UB was small and insignificant (t -value = 0.06, p -value = 1.35). The Cohen's f^2 effect size for the academic staff's EE–BI relationship was small (0.02); and the Stone-Geisser's Q^2 effect size value, which indicates the relative impact of predictive relevance for the EE–BI relationship, was small for academic staff (0.01).

Based on these empirical results, the study does not reject H_{04} : Effort expectancy will not have a significant relationship on academic staff's behavioural intention to use e-learning resources.

For the academic staff, a PROCESS (Hayes 2013) analysis of the moderating effect of gender on the EE effect of academic staff's BI to use e-learning shows a

small positive value, which indicates that the EE effect of females (0.31) was actually lower than that of males (0.50). The moderating effect was however not significant at the 95 per cent confidence interval (t -value = 1.22; p -value = 0.23). Another analysis of the moderating effect of age on the EE effect of academic staff's BI to use e-learning resources showed no effect and was not significant at the 95 per cent confidence interval (t -value = 0.41; p -value = 0.68). The analysis of the moderating effect of experience and its significance on the EE effect of the academic staff's BI to use e-learning yielded a small negative relationship and was not significant at the 95 per cent confidence interval (t -value = -0.53; p -value = 0.60).

Based on the above empirical results, the study does not reject H_{09} : The effect of effort expectancy on behavioural intention of academic staff to use e-learning resources will not be moderated by (a) gender, (b) age and (c) experience, such that the effect will not be stronger for women, particularly for younger women, and particularly at early stages of experience.

7.2.4. Social influence

Social influence (SI) on academic staff's BI to use e-learning resources refers to those whom the individual perceives as being important influences towards e-learning at UNIZULU. Taiwo and Downe (2013, 52) obtained 36 correlations between SI and BI to use technologies (SI-BI) from 31 studies, which the authors noted was fewer than the number of PE-BI and EE-BI relationships obtained in their study. A positive relationship of the same magnitude as the EE-BI effect was revealed in their meta-analysis. Venkatesh et al. (2003, 452) explain that the role of SI in technology acceptance decisions is complex and subject to a wide range of dependent effects, which impact on an individual's behaviour through three mechanisms, namely: compliance, internalisation, and identification (Venkatesh and Davis 2000, 199; Warshaw 1980, 158). The authors state that the latter two relate to changing an individual's belief structure and/or causing an individual to respond to potential social status attainments, while the compliance mechanism causes an individual to simply alter their intentions in response to the social pressure, for example, policy implementation from management (Venkatesh et al. 2003, 452).

The descriptive statistics of the four indicator statements used to measure the effect of SI on academic staff's BI to use e-learning resources at UNIZULU showed mixed modes (3, 3, 4, 3), reflecting a neutral viewpoint on any SI on their BI towards using e-learning resources. This possibly reflects few of the three necessary social mechanisms at play, including compliance, because the use of these resources is voluntary for academic staff, unless they had scheduled classes in one of the computer laboratories and internalisation or identification (Venkatesh and Davis 2000, 199; Warshaw 1980, 158), because there are no incentives or policies encouraging or supporting the use of e-learning resources by academic staff (Evans 2013, 246-247).

From the inferential statistics, the relationship between SI and BI of academic staff can be observed through the SI–BI path coefficient, which was a small positive (0.06) value but not significant ($t = 0.77$) at the 95 per cent confidence interval. The indirect effects of SI on their UB were small and non-significant (0.02; $t = 0.79$). The Cohen's f^2 effect size for academic staff's SI–BI relationship was small (0.01); and the Stone-Geisser's Q^2 effect size value was non-existent for academic staff (0.00) at UNIZULU, which indicates the little predictive relevance of the primary users' SI–BI relationship.

Based on these empirical results, the study does not reject H_{05} : Social influence will not have a significant relationship on academic staff's behavioural intention to use e-learning resources.

The results of the PROCESS (Hayes 2013) moderation analysis of the SI construct in academic staff show that the moderating effect of gender (coded 0 = Female and 1 = Male) has a path coefficient with a very small negative value, which indicates that SI effects in females (0.05) are slightly higher than those of males (0.04); the moderating effect is, however, not significant at the 95 per cent confidence interval (t -value = -0.03 ; p -value = 0.98). The PROCESS (Hayes, 2013) moderation analysis of age on the social influence relationships of academic staff's behavioural intentions results in a path coefficient that shows no effect and is not significant at the 95 per cent confidence interval (t -value = -0.26 ; p -value = 0.79). Another PROCESS (Hayes 2013) moderation analysis of experience on the social influence effect of academic staff's BI to use e-learning resources results in path coefficient with a small negative value; the effect was not significant at the 95 per cent confidence interval (t -value = -1.79 ; p -value = 0.08).

Based on the above empirical results, the study does not reject H_{010} : The effect of social influence on behavioural intention of academic staff to use e-learning resources will not be moderated by (a) gender, (b) age, and (c) experience, such that the effect will not be stronger for women, particularly older women, in the early stages of experience.

7.2.5. Facilitating conditions

In the study, the facilitating conditions (FC) are defined as the amount of technical and organisational resources, support and knowledge, which academic staff believe exist at UNIZULU to facilitate the use of e-learning resources. Taiwo and Downe (2013, 52) obtained only 16 correlations between FC and UB (FC–UB) from 13 studies, and the authors noted that the FC–UB and BI–UB effects have the equal highest negative non-significant correlations compared to the other UTAUT effects. Venkatesh et al. (2003, 454) found that when both PE constructs and EE constructs are present, FC become non-significant in predicting BI; however, when moderated by age and experience FC will have a significant influence on UB, such that the effect will be stronger for older users, particularly with increasing experience.

The academic staff's descriptive statistics of the five FC indicator statements showed four modes of 4, which reflects that most staff agreed that they do have sufficient knowledge, a suitable teaching pedagogy and necessary resources to use the e-learning resources at UNIZULU; however, staff were neutral (mode = 3) as to whether they receive enough support to use the e-learning resources.

The inferential statistics show that the primary users' relationships between FC and UB (FC–UB) was positive (0.22) and significant ($t = 2.15$). The Cohen's f^2 effect size for academic staff was small (0.05); and the Stone-Geisser's Q^2 effect size value for academic staff was small respectively (0.01), indicating low predictive relevance of the academic staff's FC–UB relationship.

Based on these empirical results, the study rejects H_{06} in favour of H_{a6} : Facilitating conditions will have a significant relationship on academic staff's use of e-learning resources.

The results of the PROCESS (Hayes 2013) moderation analyses of the FC construct in academic staff indicated that the moderating effect of age and FC showed virtually no effect on UB, and this effect was also not significant at the 95 per cent confidence interval (t -value = 1.60; p -value = 0.11). The moderation analysis of experience of academic staff and FC showed a small negative effect on UB and was not significant at the 95 per cent confidence interval (t -value = -0.68 ; p -value = 0.50). SmartPLS (Ringle et al. 2004) found the same negative relationship (-0.09), but bootstrapping found this to be significant (t -value = 1.97), leading to the first inconclusive result; however, the convergent validity (AVE) values did not meet the required convergent validity criterion and was considered too unreliable to be included in the model.

Based on the above empirical results, the study does not reject H_{011} : The effect of facilitating conditions on academic staff's usage of e-learning resources will not be moderated by (a) age and (b) experience, such that the effect will not be stronger for older users, particularly in the early stages of experience.

7.3. Limitations of the results

The concept of e-learning at UNIZULU encompasses a number of hardware and software resources used within different contexts and having a number of different levels of acceptance and use. The study's enquiry into the acceptance of all e-learning resources could lead to some respondents over or under scoring UTAUT constructs based on their UB or BI to use different resources within different contexts.

The users' self-reported responses to the UTAUT constructs' indicator statements were a limitation because this data is merely a proxy measure of an individual's perceptions and if misrepresented could threaten the internal validity of the measurement in the study's data analysis (Campbell and Stanley 1963 in Moran 2006, 102).

8. CONCLUSION AND RECOMMENDATIONS

The UTAUT model was partially validated by academic staff users of e-learning resources at UNIZULU. The theory showed moderate predictive accuracies and relevance towards their behavioural intention to using these resources; however, the study concludes that the UTAUT model's accuracy and relevance could be improved by adopting contextualised socio-economic moderators relevant to the education sector rather than adopting those found to be significant in the financial sector of Venkatesh et al.'s (2003) study.

Most staff only used e-learning resources for administration and research, while only a few use these resources for formal teaching, leading to the conclusion that there is a lack of these resources available in many classrooms at the university. The recommendation would be firstly, providing useful resources that will improve both teaching and learning, and secondly providing appropriate skills development and support for these resources.

The most significant effect on academic staff's behavioural intention to use e-learning resources at UNIZULU was their performance expectancy from the resources. The study concludes that the acquisition of quality e-learning resources, combined with relevant skills development, should support performance gains, and hence the academic staff's behavioural intention to use e-learning resources at the institution.

The relationship between effort expectancy and academic staff's behavioural intention to use e-learning resources proved insignificant. The study concludes that these results are consistent with previous findings that the effect of this construct diminishes with increased experience (Agarwal and Prasad 1997, 570, 1998; Thompson, Higgins and Howell 1991, 140; Venkatesh et al. 2003, 450). The study takes cognisance of the finding that although the majority of academic staff agreed that they find it easy to use e-learning resources, there was a minority who said they did not, and in future, recommends that these users should be flagged using a similar instrument in the ongoing quality promotion processes for the provision of the necessary skills development and support.

The effect of social influences on the primary users' behavioural intention to use e-learning at UNIZULU resources was found to be insignificant probably because most academic staff considered the use of these resources to be voluntary. The study recommends the introduction of user policies to instil mandatory use of these resources by academic staff and concludes that this relationship will strengthen as relevant skills development and support become more salient, because of the increased interactions and relationships between management, academic staff and support staff.

Facilitating conditions had half the direct effect as behavioural intention on use behaviour of e-learning resources. The study concludes that these results indicate the importance of creating positive behavioural intention in academic staff to facilitate

the use of e-learning resources, such as incentives to develop online course materials. The moderation analysis of experience of academic staff on the relationship between facilitating conditions and use behaviour showed a negative value and significance was inconclusive, possibly indicating that the more experienced academic staff become at using e-learning resources, the less content they are in terms of the facilities and support at UNIZULU.

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