Predicting User Acceptance of Electronic Learning at the University of Zululand

By Neil Davies Evans

Thesis submitted in fulfillment of the requirements for the award of the Degree of Doctor of Philosophy (Library and Information Science) in the Department of Information Studies at the University of Zululand, South Africa

Promoter: Professor C.B.J. le Roux
Co-promoters: Professor S. Mutula
Professor D. Jacobs

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DECLARATION

I declare that this study, “Predicting User Acceptance of Electronic Learning at the University of Zululand”, unless where clearly indicated, is my original work and has not been submitted for the award of any other degree, at the University of Zululand, or any other university.

……………………………………… Date: ………………………
Neil Davies Evans

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Promoter: Prof. C.J.B. le Roux

……………………………………… Date: ………………………
Co-Promoter: Prof. S. Mutula

……………………………………… Date: ………………………
Co-Promoter: Prof. D. Jacobs

DEDICATION

I would like to dedicate this thesis to my father Michael Davies Evans, who passed away before its completion. I would also like to dedicate this study to the present and future academics at the University of Zululand - may it encourage the use of pedagogies that will empower both teachers and learners.

ACKNOWLEDGEMENTS

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Finally, my sincere thanks to all academic staff and students who participated in the study.

ABSTRACT

Since the beginning of the 21st century, the ubiquitous use of e-learning resources has changed the way information, especially multimedia information is being stored, accessed and disseminated in institutions of higher learning. These institutions constantly have to review instructional policies and technical frameworks to accommodate new pedagogies and educational technologies that are required to educate a generation of students with different learning styles and needs. This research followed a positivist epistemological belief and deductive reasoning by adopting the known and validated Unified Theory of Acceptance and Use of Technology (UTAUT) and validated its application within the contextual setting of the University of Zululand where it was used to predict the acceptance, behavioural intentions and usage behaviour of the primary users of e-learning resources. The study adopted a survey research design and a non-experimental statistical method was used to analyse the quantitative data. Partial Least Squares Structural Equation Modeling (PLS-SEM) and inferential statistics were used to predict the level of acceptance of e-learning by academic staff and students and show the strengths and significances of the postulated UTAUT relationships. From the results, the study anticipates the acceptance of e-learning resources by the majority of students and academic staff at the University of Zululand. Further UTAUT demonstrated moderate predictive accuracy and relevance in explaining behavioural intentions of students (Adjusted R^2 = 0.39) and academic staff (Adjusted R^2 = 0.41) to use e-learning resources, which was below the high accuracies found in Venkatesh *et al.* (2003) study, but comparable to the predictive strengths of the eight models used to make up the UTAUT model. The expected academic performance gains in primary users proved to be significant and the strongest direct effect on the primary users' behavioural intentions to use e-learning resources at the University of Zululand. The students' use behaviour of e-learning resources is most influenced by the direct effect of the facilitating conditions, then by their behavioural intentions, while the most influential indirect effects were performance and effort expectancies and lastly social influences. For academic staff, the direct effect of their behavioural intentions to use e-

learning resources is the most influential on their use behaviour, followed by the indirect and direct effects of performance expectancy and facilitating conditions respectively, and then lastly the indirect effects of effort expectancy and social influences. The study concludes that these results indicate the importance of creating conducive facilitating conditions for students and positive behavioural intentions in academic staff to expedite the use of e-learning resources at the University of Zululand. The moderating effects hypothesised by Venkatesh *et al.* (2003) were found not to have any conclusive significant effects on primary users of e-learning resources at the University of Zululand and the study postulates that the acceptance of technologies in different sectors (industrial, financial and educational) requires their own contextualised socio-economic moderators for these to be consistently significant. The unique contextual setting and dataset of the study provides empirical findings that cannot be generalised to different tertiary education settings; however, it can be used to facilitate the use of e-learning resources at the University of Zululand and contribute to UTAUT's theoretical validity and empirical applicability to the management of e-learning based initiatives.

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LIST OF ABBREVIATIONS

A	Attitude
AD	Academic Development
API	Application Programming Interface
ATB	Attitude Toward Behaviour
AVE	Average Variance Extracted
AWS	Amazon Web Services’
BI	Behavioural Intention
CA	Cronbach’s alpha
CaaS	Computing as a Service
CBSEM	Covariance-Based Structural Equation Modeling
CBT	Computer-Based Training
CD-ROM	Compact Disk Read Only Memory
CenTAL	Centre for Technology Assisted Learning
CIPD	Chartered Institute of Personnel and Development
CMS	Content Management System
CR	Composite Reliability
DHET	Department of Higher Education and Training
DOI	Diffusion of Innovation Theory
DSTV	Digital Satellite Television
DVD	Digital Video Disk
EC2	Elastic Compute Cloud
EE	Effort Expectancy
EFA	Exploratory Factor Analysis
EM	Extrinsic Motivation
FC	Facilitating conditions
GUI	Graphical User Interface
HCI	Human-Computer Interaction
HTML	Hypertext Mark-up Language
IAI	Interactive Audio Instruction
ICT	Information and Communication Technology
IDT	Innovation Diffusion Theory
IM	Intrinsic Motivation

IRI	Interactive Radio Instruction
IS	Information System
iTE	Telematic Education
KM	Knowledge Management
IaaS	Infrastructure as a Service
LAN	Local Area Network
LISREL	Linear Structural Relationship
LMS	Learning Management System
LV	Latent Variable
MM	Motivational Model
MOODLE	Modular Object-Orientated Dynamic Learning Environment
MPCU	Model of Personal Computer Utilization
NUFFIC	Netherlands Universities Foundation for International Cooperation
NWU	North-West University
ODL	Open and Distance Learning
PaaS	Platform as a Service
PC	Personal Cpmputer
PDA	Personal Desktop Assistant
PE	Performance Expectancy
PLS	Partial Least Squares
PU	Perceived Usefulness
RSS	Really Simple Syndication
S3	Scalable Storage Service
SaaS	Software as a Service
SAN	Storage Area Network
SEM	Structural Equation Modeling
SCT	Social Cognitive Theory
SI	Social influence
SN	Subjective Norm
TAL	Technology Assisted Learning
TAM	Technology Acceptance Model
TDG	Teaching Development Grant
TPB	Theory of Planned Behaviour

TPC	Tablet Personal Computer
TRA	Theory of Reasoned Action
TV	Television
UB	Use Behaviour
UCT	University of Cape Town
UFS	University of the Free State
UJ	University of Johannesburg
UKZN	University of KwaZulu Natal
UNISA	University of South Africa
UPS	Uninterruptible Power Supply
UTAUT	Unified Theory of Acceptance and Use of Technology
UWC	University of the Western Cape
VLE	Virtual Learning Environment
VOIP	Voice over Internet Protocol
VUT	Vaal University of Technology
WAN	Wide Area Network
WBT	Web-Based Training
WUZULU	Wageningen University - Zululand University
WWW	World Wide Web
XHTML	Extensible Hypertext Mark-up Language

Chapter 1: INTRODUCTION AND BACKGROUND

1.1 Introduction

The purpose of this study is to empirically validate the Unified Theory of Acceptance and Use of Technology (UTAUT) model's ability to predict academic staff's and students' behavioural intention to accept electronic learning (e-learning) at the University of Zululand. Since the end of 2012, significant investments in e-learning have been made by the Department of Higher Education and Training (DHET) through the Teaching Development Grant (TDG) to assist in the development of a sound teaching and learning environment at the university (University of Zululand, 2012/2013). This research attempts to address some of the valid concerns as to whether expenditure in information and communication technologies (ICTs) always produces the intended results (Dillon, 2001; Lee *et al*., 2003). Resistance to change by users, and thus the adoption of new technologies, is often cited /seen as critical factors influencing a users' willingness to adopt or reject these resources (Kanuka, 2006). This study pays specific attention to the level of user acceptance of e-learning technologies at the University of Zululand.

Since the beginning of the 21st century, the abundant use of digital technologies (e-learning Africa, 2013:10) connected to digital networks (Mansell and Tremblay, 2013:iii) have changed the way information, especially multimedia information, is being stored, accessed and disseminated (Agyei, 2007:5). Users today essentially want information delivered to them (Sturges, 2006). This has been particularly pertinent to institutions of higher learning that constantly have to evaluate instructional policies and technical frameworks to accommodate new pedagogies and educational technologies that are required by a rapidly growing generation of students with different learning styles, and different needs (Siemens, 2004a).

For the purposes of this study, the term e-learning was broadly used to describe any type of teaching and learning that utilises Information and Communication Technologies (ICTs) and Information Systems (IS) in academic programmes (Stockley, 2008), while the combination of conventional face-to-face instruction in the physical classroom, experiential learning and e-learning methods is referred to as blended learning (King and McSporran, 2005:4). Blended learning is practiced in most South African universities (Boere and Kruger, 2008); with the University of South Africa's (UNISA) correspondence or distance learning programmes being the obvious exception.

User acceptance is defined as the demonstrable willingness within a user group to adopt and employ technologies for the tasks they are designed for (Dillon, 2001). In this study, it will involve measuring the level of acceptance and use of e-learning technologies by academic staff and students, hereafter referred to as primary users, at the University of Zululand. The results obtained will be disseminated to all stakeholders and the Academic Development (AD) unit to assist with the ethical integration of e-learning into the curriculum of programmes offered at the institution.

1.1.1 Conceptual Setting

Based on the assumption that people's actions are guided by their emotions or how they feel (Hayes, 2013:24), it has been theoretically shown that a user's initial reaction or attitude towards ICT and IS technologies will affect their intentions to use them, which in turn will influence their actual use of such technologies (Venkatesh *et al.*, 2003:427; Davis, Bagozzi, and Warshaw, 1989 in Theories Used in IS Research Website, 2008).

Hayes (2013:29) explains that a linear regression model is simply an equation that links one or more input variables to an output variable by exploiting information contained in the association between inputs and output. In this study, the input variables, also known as independent variables, include performance expectancy, effort expectancy, social influence and the facilitating conditions, while the output variables, also known as dependent variables, are the users' behavioural intention or initial reaction towards e-learning as well as their use of these resources.

Following a deductive research approach this study takes cognisance of a number of theories that can help to explain user acceptance and the adoption and use of both ICT and IS with special emphasis on e-learning. These theories include the original Theory of Reasoned Action (TRA) developed by Fishbein and Ajzen in 1975 and simplified in 1980 (Ajzen, 2008); the Technology Acceptance Model (TAM) by Davis, Bagozzi, and Warshaw in 1989 and; the Theory of Planned Behaviour (TPB) developed by Ajzen in 1991 (Ajzen, 2008). A more coherent or unified model known as the Unified Theory of Acceptance and Use of Technology (UTAUT) was developed by Venkatesh and others in 2003. This model outperformed the abilities of all the previous models to predict user acceptance of ICT innovations (Venkatesh *et al.*, 2003:425) and was chosen for this study.

The UTAUT model theorises that four constructs, namely, performance expectancy, effort expectancy, social influence, and facilitating conditions have a significant determination relationship with user acceptance of ICT innovations (Venkatesh *et al.*, 2003). These constructs are moderated, in varying degrees, by gender, age, experience, and voluntary or compulsory use.

By applying a user acceptance model, criteria that contribute to the primary users' reaction, their intention to use and their actual use of e-learning can be measured, thus enabling the study to predict its adoption. Venkatesh *et al.* (2003:427) illustrates the basic concept underlying user acceptance models in Figure 1.1:

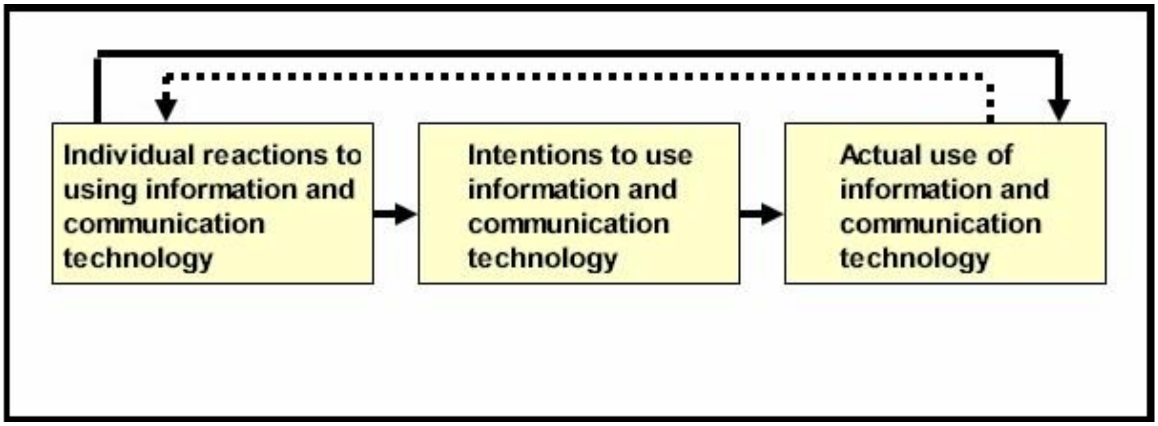

Figure 1.1: Basic Concept Underlying User Acceptance Models (adapted from Venkatesh *et al.*, 2003:427)

1.1.2 Contextual Setting

The University of Zululand is a comprehensive university with two campuses in the largely rural northern part of the KwaZulu Natal province of South Africa. The Ongoye or “main campus” is situated some 15 kilometers outside the town of Empangeni (population: 24 775) and the newer, but much smaller, Richards Bay campus is situated 30 km away in the port city of Richards Bay (population: 54 553). Richards Bay and Empangeni are collectively known as the City of uMhlathuze and this is one of the six local municipalities situated within the uThungulu District Council. The university is a traditional contact institution offering certificate, diploma and degree programmes in the faculties of Arts, Education, Administration, Commerce and Law and Science and Agriculture.

A number of e-learning projects have been initiated on the main campus since 2000, ranging from basic departmental websites, which hosted “virtual classrooms” to the actual deployment of various Learning Management Systems (LMSs) including WebCT, now called Blackboard, in 2000, MyCMT, which was developed in-house by the Department of Accounting and Auditing in 2002 and Moodle (Modular Object-Orientated Dynamic Learning Environment), which has been introduced and piloted by the author[1] in the Department of Information

[1] Neil Evans

Studies since 2007. Moodle was officially adopted as the preferred LMS on campus in 2009, with one instance installed for each of the four faculties. Since then, a total of 8 486 registered users have used the LMS, with 3 769 registered users in the Faculty of Science, 2 427 registered users in the Faculty of Arts, 1 977 registered users in the Faculty of Administration, Commerce and Law and 313 registered users in the Faculty of Education (Faculty learning management systems, 2013).

In 2006 the Wageningen University Research Centre, in cooperation with the University of Zululand launched and funded the Netherlands Universities Foundation for International Cooperation (NUFFIC) research project, which became known as the Wageningen University Zululand University (WUZULU) project. The aim of the project was to promote: "enhancing the quality and relevance of education and research in the social and natural sciences at the University of Zululand" (Definite Schedule WUR-visit, 2006). One of the themes of the project was the role of e-learning, however, a proposal for a structured e-learning initiative at the University of Zululand initially made little or no progress because of a lack of commitment from knowledgeable staff that already had heavy workloads, combined with the fact that the funding did not cover staff replacements. In an attempt to address this problem a special e-learning task team was established in 2008 to revitalise the project. After a revised proposal (Muller and Evans, 2008) was tabled and accepted by the WUZULU project, the task team drew up a strengths, weaknesses, opportunities and threats (SWOT) analysis which was presented to the university management in the form of a road show. Both the Registrar and the Vice-Rector of academic affairs subsequently agreed that e-learning should be an integrated part of the university's curricula.

In the same year (2008), the University of Zululand's e-learning task team was invited to participate in a developmental study towards effective practices in Technology Assisted Learning (TAL) by the University of Johannesburg in collaboration with Edge Hill University (United Kingdom). The study's coordinators, Boere and Kruger (2008), invited role players from twenty three (23) South African universities to use twelve so-called “lenses” of self-evaluation to review and organise their information regarding TAL or e-learning within their institutions. Fifteen (15) institutions including the University of Zululand accepted the invitation to participate. The workshop provided some valuable insight into benchmarks achieved at other institutions. From the collaboration it emerged that the University of Zululand was significantly behind benchmarked institutions such as the University of Stellenbosch (Boere and Kruger, 2008:8) and the University of Johannesburg (Boere and Kruger, 2008:13) in the twelve (12) lenses of review, which, included:

- Low computer literacy rates among academic staff, a low Personal Computer (PC) (720) (E-Learning Working Group, 2013) to student (16 582) (University of Zululand registration website, 2013) ratio (1:26).
- A general reference to the use of technologies in the University of Zululand’s Teaching and Learning Policy (2004:2) but no specific policy that refers to or promotes e-learning.
- No specific quality management processes to emphasise and enhance e-learning.
- Limited initiatives for the professional development of staff to integrate e-learning within the existing traditional curricula.
- Few structures in place for technical and system support and working with pre-determined standards.
- Few contributions from leadership and change management, hence relying on a bottom up approach in its implementation.

In 2009, the e-learning task team developed an e-learning strategy and implementation plan which recommended a two phased implementation approach (Muller and Evans, 2009). The first phase included a requirements analysis for academic staff, students and other stakeholders to determine their needs and expectations of an e-learning system. The second phase involved creating the necessary organisational changes to facilitate, support and roll out e-learning on campus. Later in 2009, the e-learning implementation strategy and plan was presented to all four faculty boards and Senate and all bodies unanimously adopted it. In 2012, the document, together with a budget proposal, was submitted, via AD, to the DHET, requesting funding through the Teaching Development Grant (TDG). The theme, Creating a Sound Teaching Environment: through E-learning, was allocated R5.6 million out of a total TDG of R15.2 million for the period 2012 to 2013 (University of Zululand teaching development proposal, 2012/2013).

This study will focus on factors that influence the primary users (academic staff and students) acceptance of e-learning, which requires special consideration for the successful planning, implementation and support of structured e-learning at the University of Zululand.

1.2 Background to the Study

The growing use of ICTs and IS to deliver and facilitate both formal and informal learning and knowledge sharing, is rapidly changing the teaching and learning environment. According to Carol (2007), much of our curricula and education systems are still products from a mechanistic and industrial past, in which pre-determined knowledge was delivered in a linear format to a mass audience. According to the author, the focus was on transferring information in a controlled sequence without accounting for the contextual settings of different learners. Many traditionally contact institutions have heeded current research, which suggests that in a rapidly changing social environment they could no longer retain their traditional structures, both in terms of facilities and delivery of content via formal lectures and class based activity alone (O'Neill *et al.*, 2004:1).

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, is recommended for the digital era (Siemens, 2004a). Within a higher education context, well-rounded learning outcomes are achieved through multi-threaded networks of research, service learning, experiential learning, face-to-face and e-learning. Moodle, unlike other popular LMSs, was specifically designed around the pedagogical concept of social constructivism of which the theoretical foundations was laid by Jean Piaget, a developmental psychologist, during the first half of the 20th century (Atherton, 2011). Broadly speaking, social constructivism refers to the concept or understanding that learning and teaching is a collective process in which we are both teachers and learners at the same time and are thus better able to understand the information we have constructed by ourselves.

Quality education requires the right combination of learning events, which constitutes a good learning strategy (Leclercq and Poumay, 2005); this in turn should promote meaningful learning through the acquisition of knowledge or skills obtained by study or experience[2]. Leclercq and Poumay (2005:1) proposed a theoretical reference model of eight learning events (see Figure 1.2) as they sought to describe and conceive the diversity of learning / teaching experiences and their underpinning psychological theories. The centrally placed “meta-learns” can be seen as self-reflection at the end of a learning process. “Creates”, as a learning event, involves creating something new such as producing work e.g. essays, projects, etc. Similarly, “experiments” allows the learner to manipulate the environment to test personal hypotheses e.g. lab work, workshops, computer simulations, or problem solving. “Practices” on the other hand involves the application of theory and its assessment, to include teacher feedback - e.g. exam, quiz, exercises, work-based learning, etc. “Explores” includes personal exploration by a learner - e.g. literature reviews, internet searches, or information handling. “Receives” allows the traditional didactic transmission of information

[2] *Concise Oxford English Dictionary* (Eleventh Edition), COED11, computer software, 2009, Oxford.

e.g. lecture / content delivery / recommended reading. “Debates” encourages learning through social interactions, collaborative, and challenging discussions - e.g. face-to-face debates, online discussions. Finally, “imitates” is as a learning event which encompasses learning from observation and imitation - e.g. where the teacher models techniques, modeling / simulation, practical work, walk through tutorials, or role plays.

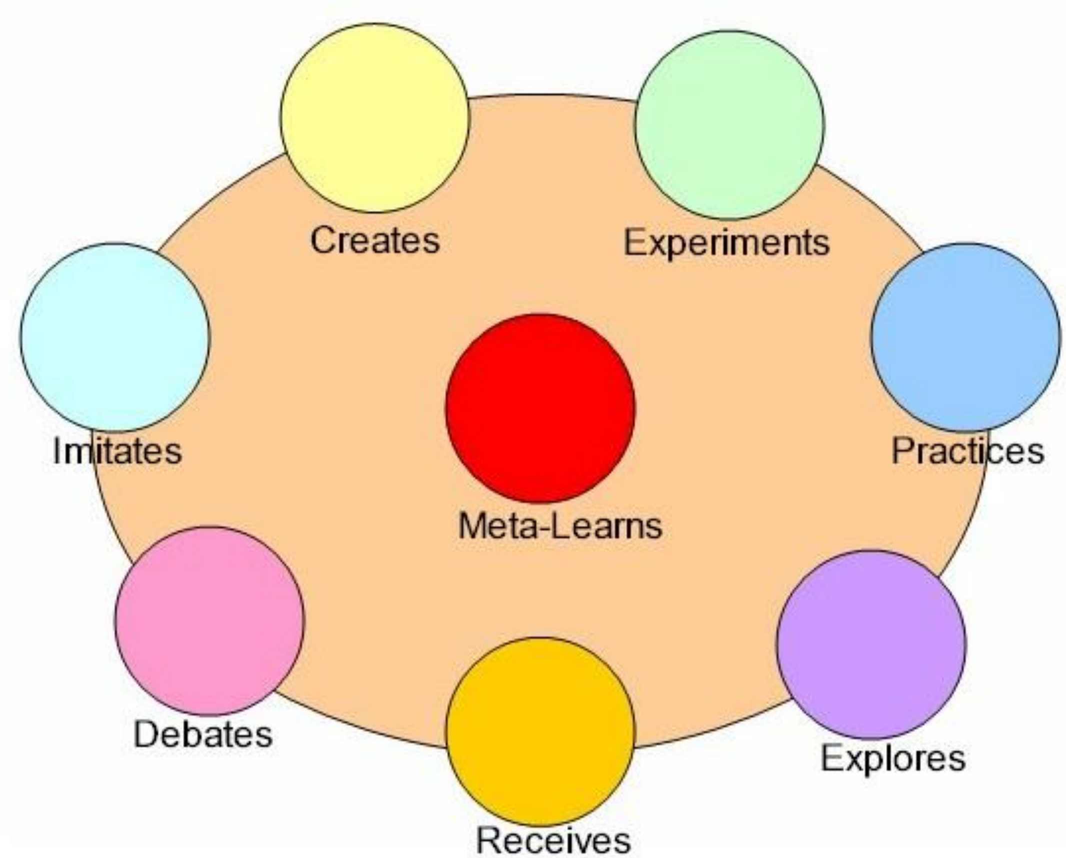

Figure 1.2: The Eight Learning Events (adapted from Leclercq and Poumay, 2005:3)

Downes (2004) and Fox (2005:13) share similar visions of how effective learning is achieved. Fox (2005:13) predicts changing expectations from learners based on their learning experiences within semantic networks as listed below:

1. The move from linear to multi-threaded learning: with internet and knowledge management, the expectation is to navigate through a web of meaning, not just causal chains of information.
2. The move from static to dynamic information: learning is a continuous resource, on demand, when and where you need it.
3. The move from content to experience: learning is achieved through interaction and application, not just delivery of information.
4. Demonstration to inference: people learn more effectively by doing, not just by being told.
5. Objectives to goals: inspiration is driven by the desire to learn to achieve something.
6. Uniformity to diversity: increasingly we expect learning configured to our personal preferences and not to be a universal solution for all.
7. Receipt to responsibility: with the rise in opportunities to configure and create our own combinations of learning components, there comes a transfer of responsibility from the instructor to the learner for quality of the individual's total learning experience.
8. Consumption to contribution: an increase in two-way communication in learning components provides exponential opportunities for learners to talk back and so to increase the total body of knowledge through email, discussion forums, chat, and more recently through the use of Blogs, Wikis, and Podcasts.

The term e-learning, which refers to the utilisation of networked ICT within educational programmes, was coined by Cross in 1998 (Cross, 2004). The idea of e-learning has appeared amongst most South African higher education institutions since the late 1990s (Ravjee, 2007:27) following global education trends of using technology and innovation to successfully skill learners for today's information society (Damoense, 2003) and its knowledge economy.

In the draft white paper on e-education in South Africa, the Department of Education recommended that e-learning should become a “mainstream activity” in all classrooms (South Africa, Department of Education, 2003:44). This recommendation corresponds with the development plans of most African governments in order to reach the Millennium Goal of “Education for all” (e-Learning Africa, 2006:4). Institutions of higher education, and the research and development community in general, have therefore a central role to play in exploring and experimenting with new e-learning technologies, methodologies and techniques to support learners, teachers and administrators in the development and implementation of their teaching and learning policies (South Africa, Department of Education, 2003:41).

1.3 Problem Statement

Integrating e-learning within higher education is inevitable as digital communication and information models become the preferred means of storing, accessing and disseminating information. Although some e-learning facilities and resources have existed at the University of Zululand since 2000, their use has remained largely unsupported and thus isolated. As indicated earlier in this chapter, this began to change in 2009 due to the efforts of individual academic staff, the official adoption of an e-learning strategy and implementation plan and the allocation of funding through the TLG.

Although the institution has begun to align its teaching and learning methods with best practices, the question remains whether academic staff and students at the University of Zululand intend to adopt e-learning in a blended learning environment and what are the factors / variables affecting this development. Identifying relationships that are important in facilitating the acceptance, adoption and use of e-learning resources in the developmental stage will result in a greater chance that firstly users take ownership and use the resources, secondly, that the resources serve their intended purpose, and thirdly, they give a good return on investment.

1.4 Research Aim and Objectives

The main aim of this study is to measure whether primary users (academic staff and students) at the University of Zululand will accept e-learning within a blended learning environment. Another aim is to investigate to what extent the UTAUT model can be efficiently utilised to predict the acceptance of e-learning by these users. The final aim of this study is to determine the impact of the various UTAUT variables or constructs on the primary user's behavioural intentions to use and their use of e-learning at the University of Zululand, as well as under what conditions these constructs operate.

Based on the above, the main research objectives can be expressed as follows:

1. To determine whether primary users (academic staff and students) at the University of Zululand will accept /adopt e-learning as a teaching and learning method.
2. To determine the efficiency of the UTAUT model to predict the acceptance of e-learning resources by primary users at the University of Zululand.
3. To determine the impact that constructs and their moderating variables in the UTAUT model will have on the acceptance of e-learning by primary users at the University of Zululand with special reference to their specific impact or influence on users' intention to use, and their use of e-learning.
4. To test the UTAUT model's theoretical validity and practical applicability.

1.5 Research Questions

The research questions are as follows:

1. Will primary users accept /adopt e-learning at University of Zululand?
2. To what level of efficiency can the UTAUT model be used to predict the acceptance of e-learning by primary users at the University of Zululand?
3. How will the constructs and their moderating variables in the UTAUT model impact on the acceptance of e-learning by primary users at the University of Zululand with special reference to their specific impact on users' intention to use, and their use of e-learning?

4. How strong is the adopted user acceptance model's theoretical validity and practical applicability?

1.6 Research Hypotheses

From a working null hypothesis approach, the research hypotheses are expressed below:

H_{01}: UTAUT will not account for any percent of variance (adjusted R^2) in students' behavioural intention to use e-learning resources.

H_{02}: UTAUT will not account for any percent of variance (adjusted R^2) in academic staff's behavioural intention to use e-learning resources.

H_{03}: UTAUT will not account for any percent of variance (adjusted R^2) in students' use of e-learning resources.

H_{04}: UTAUT will not account for any percent of variance (adjusted R^2) in academic staff's use of e-learning resources.

H_{05}: Performance expectancy will not have a significant relationship on students' behavioural intention to use e-learning resources.

H_{06}: Performance expectancy will not have a significant relationship on academic staff's behavioural intention to use e-learning resources.

H_{07}: Effort expectancy will not have a significant relationship on students' behavioural intention to use e-learning resources.

H_{08}: Effort expectancy will not have a significant relationship on academic staff's behavioural intention to use e-learning resources.

H_{09}: Social influence will not have a significant relationship on students' behavioural intention to use e-learning resources.

H_{010}: Social influence will not have a significant relationship on academic staff's behavioural intention to use e-learning resources.

H_{011}: Facilitating conditions will not have a significant relationship on students' use of e-learning resources.

H_{012}: Facilitating conditions will not have a significant relationship on academic staff's use of e-learning resources.

H_{013}: Behavioural intention will not have a significant relationship on students' use of e-learning resources.

H_{014}: Behavioural intention will not have a significant relationship on academic staff's use of e-learning resources.

H_{015}: The effect of performance expectancy on behavioural intention of students 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.

H_{016}: 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.

H_{017}: The effect of social influence on behavioural intention of students 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.

H_{018}: 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.

H_{019}: The effect of effort expectancy on behavioural intention of students 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.

H_{020}: 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.

H_{021}: The effect of facilitating conditions on students’ 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.

H_{022}: 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.

The alternate hypotheses are listed below:

H_{a1}: UTAUT will account for some percent of variance (adjusted R^2) in students' behavioural intention to use e-learning resources.

H_{a2}: UTAUT will account for some percent of variance (adjusted R^2) in academic staff's behavioural intention to use e-learning resources.

H_{a3}: UTAUT will account for some percent of variance (adjusted R^2) in students' use of e-learning resources.

H_{a4}: UTAUT will account for some percent of variance (adjusted R^2) in academic staff's use of e-learning resources.

H_{a5}: Performance expectancy will have a significant relationship on students’ behavioural intention to use e-learning resources.

H_{a6}: Performance expectancy will have a significant relationship on academic staff's behavioural intention to use e-learning resources.

H_{a7}: Effort expectancy will have a significant relationship on students' behavioural intention to use e-learning resources.

H_{a8}: Effort expectancy will have a significant relationship on academic staff's behavioural intention to use e-learning resources.

H_{a9}: Social influence will have a significant relationship on students' behavioural intention to use e-learning resources.

H_{a10}: Social influence will have a significant relationship on academic staff's behavioural intention to use e-learning resources.

H_{a11}: Facilitating conditions will have a significant relationship on students' use of e-learning resources.

H_{a12}: Facilitating conditions will have a significant relationship on academic staff's use of e-learning resources.

H_{a13}: Behavioural intention will have a significant relationship on students' use of e-learning resources.

Ha_{14}: Behavioural intention will have a significant relationship on academic staff's use of e-learning resources.

H_{a15}: The effect of performance expectancy on behavioural intention of students to use e-learning resources will be moderated by (a) gender and (b) age, such that the effect will be stronger for men and particularly for younger men.

H_{a16}: The effect of performance expectancy on behavioural intention of academic staff to use e-learning resources will be moderated by (a) gender and (b) age, such that the effect will be stronger for men and particularly for younger men.

H_{a17}: The effect of social influence on behavioural intention of students to use e-learning resources will be moderated by (a) gender, (b) age, and (c) experience, such that the effect will be stronger for women, particularly older women, in the early stages of experience.

H_{a18}: The effect of social influence on behavioural intention of academic staff to use e-learning resources will be moderated by (a) gender, (b) age, and (c) experience, such that the effect will be stronger for women, particularly older women, in the early stages of experience.

H_{a19}: The effect of effort expectancy on behavioural intention of students to use e-learning resources will be moderated by (a) gender, (b) age and (c) experience, such that the effect will be stronger for women, particularly for younger women, and particularly at early stages of experience.

H_{a20}: The effect of effort expectancy on behavioural intention of academic staff to use e-learning resources will be moderated by (a) gender, (b) age and (c) experience, such that the effect will be stronger for women, particularly for younger women, and particularly at early stages of experience.

H_{a21}: The effect of facilitating conditions on students' usage of e-learning resources will be moderated by (a) age and (b) experience, such that the effect will be stronger for older users, particularly in the early stages of experience.

H_{a22}: The effect of facilitating conditions on academic staff's usage of e-learning resources will be moderated by (a) age and (b) experience, such that the effect will be stronger for older users, particularly in the early stages of experience.

1.7 Significance of the Study

The study aims to benefit the total teaching and learning experience at the University of Zululand by investigating and understanding the criteria that effect user acceptance of e-learning resources.

The study hopes to significantly contribute to:

1. The implementation and support of e-learning at the University of Zululand, by identifying and promoting the variables that facilitate its acceptance and use, or highlighting the variables that will lead to its' rejection.
2. The provision of literature on these variables for policy development and change management.
3. The testing of the adopted user acceptance model's theoretical validity and practical applicability to the management of e-learning based initiatives with wider implications for higher education in South Africa.

1.8 Scope and Limitations of the Study

The study was limited to academic staff's and students' acceptance of e-learning at University of Zululand. Though the results of the study cannot be generalised to all institutions of higher education because their different contextual settings might lead to different acceptance decisions, the outcomes of the study may be applied to similar educational environments (Yin in Tellis, 1997).

A second limitation is the fact that the predictive power of any user acceptance model is not one hundred percent efficient. For example, in the study by Venkatesh *et al.'s* (2003), the UTAUT model was only able to correctly predict behavioural intention of seventy percent (70%) of all cases surveyed.

1.9 Dissemination of Research Findings

The research findings will mainly be disseminated by means of an e-learning portal website (http://elearn.uzulu.ac.za/survey) and this thesis. Other methods will include: electronic and paper publications in peer-reviewed journals, and presentations at conferences and workshops.

1.10 Division of Thesis

Chapter 1: Introduction and Background

This chapter starts with an introduction and background to the study the problem statement; research aim and objectives; research questions; research hypotheses; the significance of the study; the scope and limitations of the study, and the dissemination of the research findings. The chapter concludes with an overview of the overall structure of the thesis and a brief summary.

Chapter 2: Literature Review of e-learning

By reviewing related literature, this chapter will explore the term e-learning and then discuss its use within the South African higher education framework. The chapter will also investigate the origins of user acceptance of e-learning.

Chapter 3: Theoretical Framework

Chapter three reviews various technology acceptance theories to ascertain their models suitability to predict the acceptance of e-learning at the University of Zululand.

Chapter 4: Methodology and Methods

Chapter four provides a detailed description of the research design and methods; target population; research instruments; data collection procedures and ethical considerations that form the foundation for this study.

Chapter 5: Data Analysis and Presentation of Results
Chapter five reports on the data and statistics obtained from the study using tables, figures and descriptions.

Chapter 6: Discussion of Findings
Chapter six discusses the findings and interpretations of the data presented in chapter five.

Chapter 7: Summary, Conclusions and Recommendations
This chapter summarises, concludes and makes recommendations from the findings of the study.

1.11 Summary

This chapter begins by looking contextually at the current state of e-learning resources at the University of Zululand while conceptually discussing how learning styles are changing, and how e-learning can accommodate some of the students' and academic staff's new expectations in the digital age of teaching and learning. The gap between the recommended use of e-learning resources within benchmarked tertiary education and the University of Zululand leads to the statement of the problem followed by the aim, objectives, research questions, hypotheses, scope and significance of the study, which gives it its direction and value.

Chapter 2: LITERATURE REVIEW ON ELECTRONIC LEARNING

2.1 Introduction

The purpose of this chapter is to review relevant empirical literature on e-learning and the acceptance thereof. Empirical literature consists of similar studies which introduce and help explain the key terms as well as the background to the acceptance and use of e-learning, while the conceptual literature or theoretical framework of the study (chapter 3) will consider concepts and theoretical models that may be used to help predict the level of psychological acceptance of e-learning.

This chapter is organised into three parts:

Part one reviews relevant empirical literature defining e-learning and the different perceptions on its use.

Part two examines the background to e-learning including its: historical timeline, ethics, advantages and disadvantages, trends and technologies, knowledge management, implementation barriers, attitudes of users and its future use in Africa in general and at some South African universities in particular.

Part three concludes the chapter with a summary of the literature reviewed showing the strengths, weaknesses and gaps in previous research.

2.2 Defining E-learning

The fields of education and ICT are prone to confusing jargon and acronyms and further misunderstanding arises because, in such rapidly evolving fields, the meaning of these terms continue to change over time due to changes in their importance, use or meaning (Backroad Connections, 2003:3). The term e-learning was claimed to have been coined by Cross in 1998 (Cross, 2004), however it seems to have already been published by Mori in 1997 (Clark, 2007). Synonyms of e-learning are Technology Assisted Learning (TAL) (Boere and Kruger, 2008), computer-based learning, web-based learning and online learning (about e-learning website, 2007). Below are some definitions of e-learning which describe the utilisation of technologies for learning within educational and training programmes:

1. E-learning can be defined as a broad set of applications and processes which include web-based learning, computer-based learning, virtual classrooms, and digital collaboration. Much of this is delivered via the internet, intranet/extranet (LAN/WAN), audio- and videotape, satellite broadcast, interactive TV, and CD-ROM (American Society for Training and Development, 2004).
2. Similarly, e-learning is described as the use of internet technologies to create and deliver a rich learning environment that includes a broad array of instruction and information resources and solutions, the goal of which is to enhance individual and organisational performance (Rosenberg, 2006).
3. Alternatively, e-learning can refer to the use of computer-based electronic technologies of internet, e-mail, websites and CD-ROMs, and their applications, to deliver, facilitate and enhance both formal and informal learning and knowledge sharing at any time, any place and at any pace (World Bank, 2009).

From the above explanations, it emerges that the broad definitions of e-learning have not changed significantly over the years other than the technologies and digital media networks that they incorporate to enhance teaching and learning, the sharing of information and knowledge management. For the purposes of this study e-learning is broadly defined as the use of ICTs and IS in teaching and learning. At the University of Zululand this normally occurs within a blended learning environment, where traditional face-to-face teaching and learning is combined with e-learning, experiential learning, research and community engagement. E-learning resources can include office ICT, portable presentation tools for lectures, intranet, internet and wireless network services, Moodle

Learning Management System (LMS), computer labs, the library's e-resources, research databases and institutional repository etc.

According to the 2012 E-learning Africa Report (2012:14), when respondents were asked to define ICT-enhanced learning and training, a wide range of answers were received, reflecting the diverse backgrounds and points of view of the participants on e-learning. Key terms that feature regularly in the definitions of e-learning are: ‘flexible and personalised’ and ‘knowledge enhancing’, in conjunction with the central theme of ‘innovation’ and ‘integration’. Other key threads that also emerged from the responses in the report are:

- The practical nature of the sector explaining it as ‘the combination of ICT training with real life projects’ that makes ‘teaching and learning more fun and enjoyable so as to motivate the learner to want to acquire more information on his or her own’.
- That ICT-enhanced learning is where ‘the learning is enabled seamlessly by technology - the participants use technology transparently without being aware that technology is present’ and the fact that ‘it makes learning easy’.
- Economic priorities are also emphasised, with respondents defining ICT-enhanced learning and training in terms of the way it ‘allows globalisation and raises the education system to the level of competition and the global economy’.
- Some gave more operational definitions that considered efficiency to be the primary defining attribute, stating that ‘it is an easy and fast way of learning, sharing and disseminating information’.
- Others again stated that connectivity is the key defining factor, suggesting that ICT-enhanced learning is ‘any kind of learning, training, knowledge-sharing, or knowledge creation that we could not do if we did not have access to the internet’.

- Finally, most respondents emphasised that ultimately the sector is about education, learning and training, with technology as the enabling tool: 'ICT is a means to an end – to provide better teaching and learning'.

Broadbent (2002:10) identifies four types of e-learning, namely: informal, self-paced, leader-led and through performance support tools. In informal e-learning, a learner could access a web site or join an online discussion group to find relevant information. Self-paced e-learning on the other hand refers to the process whereby learners' access computer based or web-based training materials at their own pace. Leader-led e-learning, as the name suggests, refers to an instructor, tutor or facilitator leading the process. This type of learning can further be divided into two categories: (1) learners accessing real-time (synchronous) learning materials and (2) learners accessing delayed learning materials (asynchronous). The fourth and last type of e-learning described is through the use of performance support tools, which refers to materials that learners can use to help perform a task (normally in software) such as using a wizard. Rich hybrids of e-learning represent a combination of any of the four types described above (Broadbent, 2002:11). The combination of face-to-face instruction in the physical classroom and online instruction is also referred to as hybrid e-learning in some literature, but in this study it will be referred to as blended learning. According to King and McSporran (2005:4) blended learning is the mixture of traditional delivery including lectures, tutorials, apprenticeship and experiential learning together with e-learning methods. The authors state that the variety in methods will lead to an increase in interest and more effective learning. Flexible learning expands choice on what, when, where and how people learn. It supports different styles of learning, including e-learning. Flexibility means anticipating, and responding to, the ever-changing needs and expectations of learners and academic staff (Backroad Connections, 2003:3). Online learning is seen as a subset of e-learning. Both, however, are about the use of specific (web and electronic) technologies, while flexible learning is defined as a philosophy and an approach, of which the use of technology is but one, albeit a very important, component (Backroad Connections, 2003:5).

Ravjee (2007:28) highlights four different perceptions in literature on the relation between ICTs and higher education change in South Africa, namely: globalisation, digital divides, market driven forces and the politics of e-learning. The author explains that the first three perspectives examine ICT in terms of its functionality, while the fourth, which questions the political meaning of higher education transformation, is often hidden in the first three perspectives.

Literature on globalisation portrays the use of ICT as an inevitable process necessary to participate in knowledgeable societies and their economies (Ravjee, 2007:28). The author states that this literature highlights the role of educational institutions in providing learners with the necessary skills to successfully compete in global knowledge economies. Internationalisation and globalisation are often used interchangeably but Smith and Smith, writing in 1999 makes the distinction that (Backroad Connections, 2003:3):

> "Globalisation [is] the integration of economies worldwide through trade, trade agreements, finance, information networks and the movement of people and knowledge between nations. Internationalisation represents those same activities occurring between two or more nation states but does not necessarily involve a whole-world view."

In digital divide literature, there are segregated points of view on ICT-enhanced higher education in South Africa, ranging from optimism to caution (Ravjee, 2007:29). These studies highlight the disparity in the ability to access ICT resources including internet connectivity, bandwidth and electricity (e-Learning Africa, 2013:10) across nations and within national contexts. Other issues, other than physical access are the numerous individual, social, cultural, economic and institutional factors that influence people's intention to use available ICT resources (Ravjee, 2007:29). The latter includes the computer literacy level of users to effectively use this technology, the funding to enroll in more expensive technology enhanced programmes and the skill readiness of academic staff to pedagogically integrate e-learning resources ethically into curriculum.

Economic perceptions in literature see ICTs and the market as a hand-in-hand force that permeates our educational institutions, leading to change (Ravjee, 2007:31). From this economic perspective, economic and business activities are characterised by changes that can explain the emergence of the knowledge based economy (Castillo-Merino and Sjöberg, 2008:3). In developed economies, this is characterised by rapid knowledge creation and easy access to knowledge, conditions that produce greater efficiency, quality and equity within societies (Foray, 2004 in Castillo-Merino and Sjöberg, 2008:3). Ravjee (2007:31) gives the rise of ICT-enhanced for-profit institutions (virtual universities), the selling of internet courses, the use of proprietary LMS software, and ICT-related intellectual property issues as examples of the increasing influence that markets have on higher education globally. The same source (Ravjee, 2007:31) finds that intellectual property issues appear most in debates about whether to use proprietary or open source software. Proprietary software (e.g. WebCT now Blackboard) is costly and rigid if there is a need to customise certain modules or functions within the LMS, however it comes with real time support. Open source options (e.g. Moodle and Sakai) are free to use and one can add to or rewrite the source code for unique or creative requirements, however support of the LMS relies on internal skills or help from its user community. Fox (2005:5) warns that learners are looking for more value for money and institutions of higher education have to re-think their offerings as the ability for learners to register anywhere in the world through virtual campuses, is rapidly reshaping the market place.

As former South African president Nelson Mandela once said: “Education is the most powerful weapon which you can use to change the world" (Gokhool, 2005:6). Today, ICTs are seen to provide working class communities and life-long learners increased access to online higher education programmes, however

Ravjee (2007:31) questions whether online or mixed-mode programmes offer the same quality education (e.g. enough focus on critical and creative thinking, ethics, etc.) compared to contact programmes. Brown (2008) and Toprak *et al.* (2010) question the ethical standards of e-learning in terms of the delivery of distance learning. Whilst e-learning, like the internet, has no geographical boundary, the quality of the student learning experience should be similar to that offered anywhere else in the world and Kistan (2005:160) recommends the need for cross border evaluation initiatives to monitor the quality of e-learning covering relevant aspects of ICT, IS, pedagogy and administration.

2.3 The Background to E-learning

2.3.1 An Historical Timeline

The roots of e-learning can be traced back to the late 19th century, where radio transmissions were used in correspondence courses (Al-Khasha, 2006:6). In the 1960s, when the use of personal computers was rare, few learners engaged in Computer-Based Training (CBT) (Martinich, 2002:136). CBT was initially leader-led and, together with the necessary technology, this made it a relatively expensive exercise (Al-Khasha, 2006:7). It was only half way through the 1980s when user friendly operating systems with Graphical User Interfaces (GUIs) appeared and the inexpensive CD-ROM became the preferred multi-media technology, did CBT catch on, but mainly in IT related courses (Cross, 2004). By the early 1990s it had however become apparent that these anytime, anywhere training programmes were not delivering the required interactivity normally associated with classroom learning. This resulted in high dropout rates and user dissatisfaction (Cross, 2004).

The meaning of e-learning changed with the invention of the World Wide Web (WWW) in the early 1990s. The term Web-Based Training (WBT) emerged as this medium introduced new geographically independent communication and information models that used email and web-browsers to efficiently communicate and access information. One change that was necessary was that the large multimedia files initially used in CBT needed to be replaced with smaller, more web friendly file formats (like .JPEG and .MPEG) due to the initial bandwidth limitations of WBT (Cross, 2004).

In the first decade of the 21st century, the next generation of web technologies and design that harnessed the power of user contribution, collective intelligence, and network effects (O'Reilly, 2006) brought about the term web 2.0 in 2004 (Graham, 2005), which further accelerated the evolution of e-learning. According to O' Reilly (2006) the term web 2.0 can be defined as:

> "…the business revolution in the computer industry caused by the move to the internet as a platform, and an attempt to understand the rules for success on this new platform. Chief among those rules is this: build applications that harness network effects to get better the more people use them".

It was not long after the term web 2.0 was coined when technology pundits were referring to e-learning 2.0 (Downes, 2005; Rosen, 2006). Downes (2005) predicts that the e-learning 2.0 application will function much the same way as a web 2.0 application where content accessed on the web is reused and blended using other interoperable applications (such as social media) according to the learner's own needs and interests, creating a personal portfolio tool to showcase their work.

2.3.2 The Ethics of E-learning

The integration of digital media into a curriculum to deliver and facilitate both formal and informal learning and knowledge sharing has changed the way many students and academic staff interact within institutions of higher education today. Ethics is a theoretical way to explain morals, or how members of society should interact or behave, and is well documented within the teaching and learning environment (Stahl, 2002:136). Stahl's (2002:146) research framework puts forward theoretical, practical, ethical and moral problems of e-learning at macro, meso and micro levels, which will be further discussed in this study, by linking them to the same levels in the development of an academic programme as represented in Figure 2.1. At a macro level the purpose of education programmes and their exit level outcomes are established by the relevant stakeholders including government, the academic institution's higher governing bodies, faculty boards, departments, professional bodies and workers. In theory both the South African government (Draft White Paper on E-education, 2003) and most universities, including the University of Zululand (University of Zululand, 2004:2), have recognised the effective use of technologies to support teaching and learning as a strategic priority (Stellenbosch University in Boere and Kruger, 2008:10). Ethical issues however arise when choosing the appropriate pedagogies to integrate the selection of media and technologies into the curriculum (North-West University in Boere and Kruger, 2008:7).

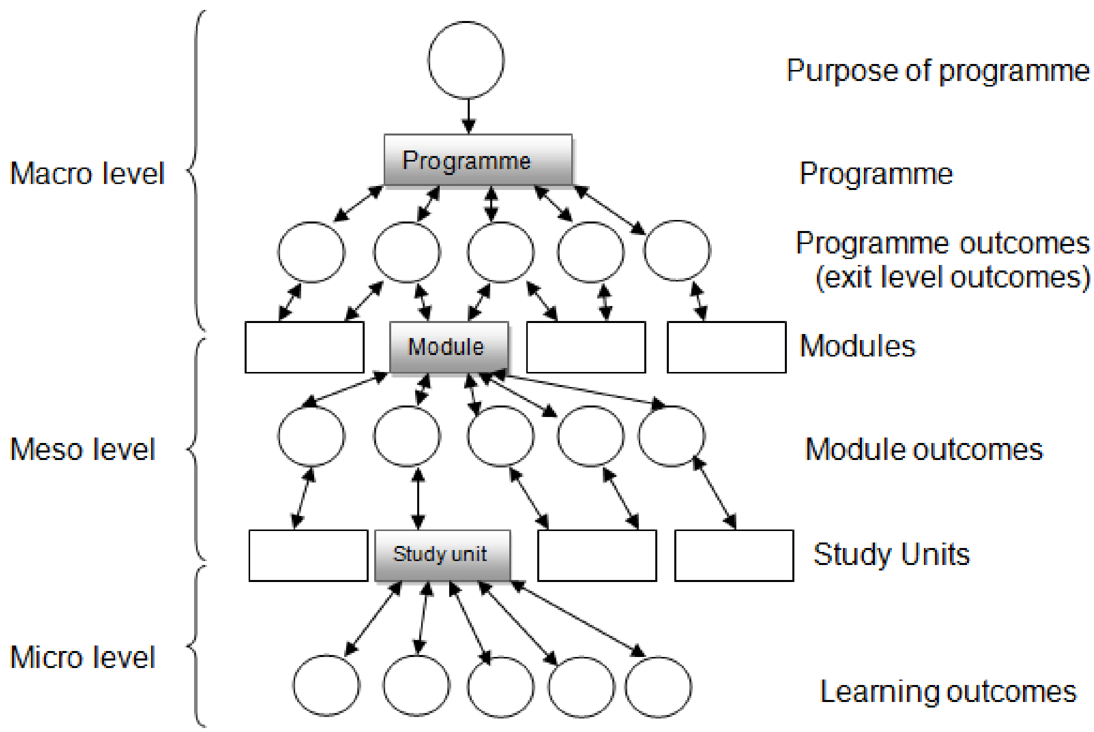

Figure 2.1: A Programme Development Model for the Macro, Meso and Micro Levels (adapted from North-West University in Boere and Kruger, 2008:5)

A pedagogic shift from teacher-centred Intructivism, adapted for the Industrial Age to learner-centred Constructivism recommended for the Information Age to Connectivism for the Digital Age, might be recommended at the macro level but is not always put into practice at the meso level, because for example academic staff has not received training in the recommended pedagogy. Practical problems of providing equitable access to infrastructure, technical training and instructional design according to recommended theories will lead to moral dilemmas and digital divides, for example the University of Zululand has around 650 (Dlamini, 2013) computers for around 16 582 students (University of Zululand, 2013) or a ratio of 1:26.

A theoretical problem at the meso level is to properly introduce e-learning to academic staff and students. Good organisation, management and budgeting to cover and distribute the costs are practical problems. Ethical considerations include fulfilling the purpose and exit level outcomes of the programme, which were determined at the macro level, by offering the right combination and quality of teaching methods. Another ethical consideration in e-learning environments is good policy to inform and protect the user's rights. For example, users' privacy can be invaded as LMSs track details of every action conducted by academic staff and students enrolled in their modules. Moral problems arise when distributing the costs of expensive infrastructure required to offer and access e-learning resources. Poor legal and regulatory frameworks for ICTs in Africa results in high rates of proprietary software piracy (Zulu, 2008:351), which highlights prevalent copyright issues within e-learning environments. Education and training using open source system and application software (Free Software Foundation, 2013) and open- access information (Kahle, 2013) can help alleviate some of these immoral practices (Ravjee, 2007:31).

A theoretical problem on the micro level involves distributing the higher costs of programmes that integrate e-learning into their curriculums to learners and whether their decision to enroll in these programmes proves to be good value for money. This can also theoretically restrict the opportunities of less advantaged learners to partake in these resource rich programmes. Practical problems include who to source to train users and whether the use of e-learning is voluntary or not. Other practical problems include user disabilities, technology skills and literacy in the different content formats used to disseminate electronic study units. Ethical problems arise if users do not agree with the e-learning systems adopted at the meso or macro levels and if they experience hardware and software conflicts. Moral problems for learners include their true and active participation within certain e-learning study units. Ethical questions of whether a username and password on a LMS can validate true identity and participation and whether biometric technology can address these problems need to be investigated within these e-learning systems. Moral problems for academic staff can arise if they invade their students' privacy through surveillance activities, emailing or SMS communication.

2.3.3 The Advantages and Disadvantages of E-learning

Broadbent (2002:29) notes that like most technological advancements, e-learning comes with its own advantages and disadvantages, which can be looked at from the perspectives of the four key stakeholders in the process, namely: the student, the academic staff, the online developer (includes instructional designer) and the manager. These roles as well as the opportunities and challenges of stakeholders, can be combined where specialist support such as instructional designers and content developers are absent and academic staff has to procure or design and develop their own content.

One of the advantages of e-learning is the technical ICT skills that it develops among e-learners (Broadbent, 2002:31). The opposite, of course, is also true in that technophobia and the unavailability of the necessary required technologies can disadvantage learners (Kruse, 2004).

According to Kruse (2004), portability has become the strength of e-learning with the proliferation of network linking points, notebook computers, personal desktop assistants (PDAs), and mobile smart phones, but for static text information, it still does not equal that of printed works such as books and other reference material.

Broadbent (2002:33) believes that e-learning allows for the pre-packaging of essential information for all students to access through LMSs, which in turn allows academic staff to concentrate on high-level activities in the delivery phase. According to Friel (2004), academic staff can reuse collaboratively prepared course material, however creating the course content can be labour intensive. He also warns that e-learning can be susceptible to cheating. Ocholla and Ocholla (2013:1) agree and warn that the advantages of ease of access to and use of web-based information resources in academia can be sometimes leveled by disadvantages, in particular reference to plagiarism of information through copying and pasting.

2.3.4 E-learning Trends and Technologies

Rosen (2006:1) believes that in every decade there is an emerging trend in the technology market, such as mainframes in the 1970s, the client-server market in the 1980s, the internet in the 1990s and web 2.0 in the 2000s, which, she says, layer on top of older established technologies to give rise to new services to a growing user base.

Today, web 2.0 applications allows online users the ability to interact and personalise web based information systems so that they cater for the specific needs of individuals in terms of accessing products, services or like-minded people (Rosen, 2006:1).

The following sections explore the latest web 2.0 trends and technologies and how these are used in e-learning activities. Most e-learning resources are accessed over a network, usually the WWW, and should be designed according to the principles and practices of good web publishing (Rosen, 2006:2). Effective e-learning courses should therefore be developed to display and deliver web friendly multi-media with an effectual organisational structure and transparent navigational structures that are consistent throughout the courses' website. According to Rosen (2006:2), web 2.0 is all about services and not software. With the internet as the platform, users make use of web browsers to reach websites that host services without having to load any client side software or plugins. O'Reilly's definition of web 2.0, where applications and their content get better the more people use them, recognises how end users can add value by sharing their learning experiences. For example, using wiki's, blogs and forums for various e-learning exercises can broaden learners outlook on particular topics while increasing collaboration, however Rosen (2006:3) warns that these are only resources and e-learning courses will still require good instructional design principles to be effective. Mashups is another term for blended learning, where the best of different media, authors, practical training, synchronous presentations, and self-paced learning is combined to provide a more enriching learning experience (Rosen, 2006:2). Deciding on what blend of learning events to use will depend on the desired exit level outcomes that need to be achieved by learners. Instructional designers and curriculum specialists need to advise and support academics when blending and developing or purchasing appropriate content for e-learning study units.

Rosen (2006:3) recommends that e-learning web services should be above the level of any single device or PC platform (Windows, Macintosh, or Linux). This trend will allow users the option to use portable devices which are able to interconnect within wireless networks, these include laptops, smart mobile phones, Tablet Personal Computers (TPC's) and Personal Desktop Assistants (PDA's) allowing 'just in time' learning. Another trend sees increasing internet bandwidths allowing the use of rich and real time media within a blend of synchronous and asynchronous instruction and mentoring.

The overall value of learning materials, and thus the acceptance and use of these within teaching and learning, will obviously depend on the professional design of these resources both in terms of their instructional and multimedia designs. Both these fields require specialised training and support for faculty to produce innovative and appropriate learning resources delivered and accessed through the latest ICTs including the latest mobile devices and their wireless networks.

New technologies enable the use of new applications which improve the dynamics and interactivity of online learning services. According to Downes (2005), the use of complementary web 2.0 tools and web services - such as Really Simple Syndication (RSS), podcasts, blogs and Wiki's - creates new e-learning 2.0 services, which are constantly being improved with faster scripting languages such as JavaScript and the redesign of HTML as HTML5. A blend thereof is often combined, structured and accessed through a LMS that tracks and reports student progress and interactions while providing a platform for facilitation and mentoring. Many of the above mentioned application services have been developed and popularised by open source communities for anyone to adopt and use.

- RSS

Really Simple Syndication (RSS) is a technology that can notify users of weblogs posted on RSS enabled websites. According to Rosen (2006:3), this pro-active technology turns blogs and news groups from posting repositories into more interactive communication.

- Podcasts

Rosen (2006:3) explains that podcasts are a delivery mechanism to store audio/video on a portable player. Institutions can produce and provide audio and video broadcasts that can be downloaded and played on portable devices such as cell phones and iPods/Pads.

- Blogs and Wikis

Blogging and Wikipedia sites are essentially Content Management Systems (CMSs) which provide users an online editor for the creation of a personal space or a collective collaboration online. Both enable users the ability to comment or contribute to or about the content of the site. This type of social networking has found a place in education settings because of its ability to encourage collaboration ,and critical feedback while overcoming the technical barriers of publishing online.

- Scripting

According to Rosen (2006:3-4), the latest generation of scripting and programming languages such as AJAX, Perl, Python, and Java now has more built-in routines that allow computer-to-computer communication, which speeds up development of more distributed applications that collect information or farm out computing to other servers such as in cloud computing.

- HTML5

The Hypertext Mark-up Language version 5 (HTML5) specification was officially adopted by the World Wide Web Consortium (W3C) in 2010 as the next version to superseded HTML4 and the Extensible Hypertext Mark-up Language version 1 (XHTML 1.1) (Le Roux and Evans, 2012:1). Driven by a new generation of web developers from the major browser vendors (like Apple, Mozilla and Opera), HTML5 brings more than sixty (60) new, modified and extended Application Programming Interfaces (APIs) to the HTML4 specification to deliver rich multimedia content over the web and mobile devices (Le Roux and Evans, 2012:2) which can improve the quality and interactivity of content for e-learning study units.

2.3.5 Cloud Computing for Delivering E-learning

Cloud computing is explained by Armbrust *et al.* (2009) in Le Roux and Evans (2010:4) to be both, the Software as a Service (SaaS), delivered over the internet, and the hardware and systems software in the data centres that provide utility computing services. In 2009 Nicholson in Le Roux and Evans (2010:4) divides the latter into three "layers" namely:

1. Infrastructure as a Service ("IaaS") where service providers offer cloud-based storage like Amazon Web Services' (AWS) Scalable Storage

Service (S3) which charges per gigabyte-month, with additional bandwidth charges per gigabyte to move data in to and out of the cloud over the internet. This offers services much the same as a campus Storage Area Network (SAN).

2. Computing as a Service (CaaS) where service providers offer access to raw computing processing power on virtual servers, such as AWS's Elastic Compute Cloud (EC2) who sells 1.0-GHz x86 ISA "slices" per hour, and a new "slice", or instance, can be added in a couple of minutes.
3. Platform as a Service ("PaaS") where certain providers are opening up application platforms to permit customers to build their own applications using that platform's underlying system(s) software, for example Google's AppEngine.

Companies, called cloud providers, with access to large data centres, rent scalable computer resources and services, on-line, to customers called cloud users or SaaS providers, who in turn can roll out various web applications over connected networks to public (public cloud) or private (private cloud) SaaS users (Armbrust, 2009 in Le Roux and Evans, 2010:4). Cloud computing offers benefits for both SaaS providers and users; for the former the elasticity of cloud computing resources to scale to the demand of the service without paying a premium for this large scale when it is not used is unparalleled in the history of Information Technology (IT) (Armbrust, 2009 in Le Roux and Evans, 2010:4). For the latter, server-side processing power demands minimal system requirements for digital devices to access responsive web applications.

Cloud computing holds tremendous promise when offering distance e-learning to a large national and international market, however most institutions would probably also want local instances of their information systems for access over their Local Area Networks (LANs) that can guarantee large bandwidths (100 MB/sec to a 1 GB/sec.) especially when limited bandwidth is noted by e-Learning Africa (2012:20) as one of the key constraints to e-learning at national level.

2.3.6 E-learning and Knowledge Management

Turning information and data efficiently into knowledge is a perquisite for the successful participation in today's knowledge economy, and requires focus on human development and the processes of learning, and not only on technological innovation and its impacts (Mansell and Tremblay, 2013:ii). Human capital, which holds both tacit and explicit knowledge, is the backbone for the successful operation of most businesses in the information age especially institutions of tertiary education. Knowledge Management (KM) is becoming increasing important to explain and share knowledge within organisations when there is a change or absence in their human capital.

According to Stacey (2000) the rationale for Knowledge Management is convincing due to the following reasons listed below:

1. The new economy thrives on producing information and passing it at unprecedented rates among partners, employees, and customers. As the size and complexity of the enterprise increases, the volume of information increases and becomes fragmented. The sheer volume of data and information can be overwhelming. The need to identify the important pieces that enable effective action in the interest of the enterprise becomes critical. Information needs to be distilled into knowledge. Turning information and data into knowledge enables effective action.

2. A major element of the enterprise's intellectual capital is its people. KM puts in place processes and systems to ensure it retains knowledge assets even when expertise leaves. Lessons learned and best practices become accessible and transferable throughout the organisation. Without a KM system, human capital spends large amounts of time reinventing the wheel and often repeating past mistakes. KM enables the enterprise to maintain, develop, and distribute the knowledge expertise of its people.

3. KM enables the organisation to quickly get partners up to speed on its products, processes, and requirements and vice versa. KM facilitates ease of partnering.

4. Reacting quickly to new opportunities requires the enterprise to distribute decision-making authority (and the competencies to do so). Organisations pursuing Knowledge Management are building a collaborative culture that moves away from traditional knowledge hoarding to a new culture of knowledge sharing. KM is a part of the new collaborative culture allowing for decentralised decision making and trust that the right decisions will be made.

5. A large part of the value adding in high tech companies is created by knowledge-based services such as product and system design, research and development, market intelligence, customer contact and relationship management, distribution, and brand management. KM systems define and provide access to these knowledge-based services and sustain their value by keeping them current.

Stacey (2000) lists four requirements for implementing KM:

1. People: to support KM the enterprise needs to define who its knowledge users, knowledge authors and knowledge analysts are.

2. Culture: creating an organisation that shares knowledge rather than hoards knowledge is a paradigm shift. Organisational status, power, and success based on collective sharing of knowledge, as opposed to knowledge sharing on a "need to know" basis are all important. If people do not want to share, they are not going to do it, even if the best technology in the world exists. People will not share if they don't see personal benefits and changes in performance and incentive systems may

be necessary to create a culture where knowledge sharing is the norm. It will be necessary to develop measurements that track knowledge contributions, development and re-use.

3. Content: creating and managing data, information, and knowledge is important to the success of the enterprise and at the heart of KM. KM goes significantly beyond storage and retrieval. KM involves extracting meaning/understanding out of data/information and then sharing/distributing it.

4. Technology: the technical infrastructure that enables the capture, storage, and delivery of content to those who need it, when they need it. Technology is an enabler not the solution. From a technical infrastructure point of view KM goes beyond storage and retrieval to include systems for collaboration and sharing along with push technologies, i.e. information systems that don't require users to pull information from a data repository but rather systems that broadcast knowledge on a daily basis.

Essentially, e-learning and KM share a common goal of sharing and exchanging knowledge within social networks.

Stacey (2000) explains that recent developments in e-learning have led to another point of intersection between these two disciplines, namely the use of learning objects repositories. The author defines learning objects as distinct parts of reusable online learning resources which can include applets, animation, streaming audio/video or other forms of online content. The author states that the advantage of creating a learning object rests in the principle of developing it once and using it many times within central repositories, by linking it appropriately in multiple places using object oriented design and metadata; this approach serves the needs of both effective e-learning and KM (Stacey, 2000).

Siemens (2004b) points out that initially the difference between e-learning and KM was in the creation of their learning objects. E-learning normally relies on tried and tested content that is well organised while KM recognises the value of the dynamic unstructured transfer of tacit knowledge through real time conversations about a current activity in a particular field. Today, these practices of collaboration and interaction are encouraged in e-learning though participation in video conferencing, chatting, blogs, and Wiki's, while blended learning easily incorporates the best of both fields to enhance the learner centered process.

2.3.7 E-learning Implementation Barriers

According to Cloete, van der Merwe and Pretorius (2003:2) the integration of e-learning within traditional curriculum of institutions of higher education involves many complex issues such as strategic management decisions; strategic information technology plans; a change management to get stakeholders to participate; the training and re-training of users; the selection of suitable learning strategies; partnership strategies and the development of relevant courseware. This section will concentrate on the implementation barriers for two of the stakeholders, namely the academic staff and students. Mihhailova (2005:275-276) lists the following reasons for a resistance amongst academic staff and students to adopt e-learning within their institution of higher education:

- Academic staff's lack of time, mainly related to preparing the e-course and adjusting existing courses into e-course format. From the other point of view a well prepared and user friendly e-course frees academic staff from lecturing and saves time for other academic activities. However unprepared or ill-prepared e-courses can on take up enormous amount of academic staff's time at a later stage.
- Lack of clarity with regards to a compensation system. E-learning is different from ordinary learning and teaching, and unfortunately, so far no clear rules have been developed for how to measure and pay fairly for the work of an e-academic staff.

- Uncertainty as to how to measure teaching quality and little interest in co-operation between e-course developers. It appears to be unclear as to how to measure teaching quality in e-learning. Similarly, the rules and guidelines on how to prepare and develop a good e-course are missing.
- Learning materials and time management. In the case of an ordinary learning situation, the planning and time management is being done for the student by curriculum administration department, but in the case of e-learning course, the student him/herself has to take an active role in it and that requires from an e-learner much more self-discipline and becomes one of the major issues why students drop e-courses. The best learning results can be achieved and number of dropouts reduced if as many technologies as possible are used. Blended learning can also reduce the negative side effects of web-learning.
- Loss of “teacher’s aura” or physical presence and the possibility of discussion. Many specific subjects (e.g. social work, law, etc.) require extensive discussion and quick feedback which raises the question as to whether these courses can be turned into 100 percent e-courses. Blended learning, with lectures in a virtual environment and seminars, practical assignments in classroom and a face-to-face environment, offers a solution to this problem.

2.3.8 Attitudes Towards E-learning

The use of e-learning will be influenced by both positive and negative attitudes of its users. Lookabaugh and Sicker (2004) state that: “education mediated by information technology rather than the classroom represents a revolution rather than an evolution in higher education.” The authors predict a fast and bumpy road ahead where changes in course and content delivery to learners will leave few traditional institutions and their staff unaffected. Kanuka (2006) argues that the unconcealed enthusiasm for e-learning ten (10) years ago was increasingly replaced by a growing dissatisfaction with the increasing use of e-learning with cynical criticisms such as:

> "…de-professionalization of faculty, erosion of academic freedom and agency, commercialization of teaching, lack of face-time between students and faculty, techno centric models are prioritized over campus culture, devaluing of oral discourse/discussion practices, centralisation of decision making and service provision, increased technological and pedagogical uniformity, and concern about the growing digital divide and downloading of costs to students".

Kanuka (2006) however concludes that e-learning, as an alternative to traditional teaching, does widen access to education in a cost effective manner under certain /specific conditions.

Sloman (2008) reports that in a 2008 learning survey of the Chartered Institute of Personnel and Development (CIPD) in the United Kingdom, respondents believe that e-learning demands a new attitude on the part of the learner (92% support). He maintains that this reminds us that e-learning is about the learner and not about the technology. Link and Marz (2006) found that age, computer use, and previous exposure to computers are more important than gender when comparing students' attitude towards e-learning. The authors conclude that e-learning must be appropriate to students' level of computer proficiency to prevent negative attitudes and that courses that improve computer literacy can improve attitudes towards e-learning. Tuparova *et al* (2006:5) found a positive attitude amongst academic staff towards using computers and the internet at their institution, however lack of academic and financial recognition, together with the time required preparing e-learning study units, were seen as negative factors.

2.3.9 The Future of E-learning in Education

Around the world, all levels of education are embracing technology to provide a dynamic learning environment that is more interconnected, instrumented and intelligent 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 which include: 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 DVD's, MP3's, DSTV, laptops, tablet computers and the internet 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 lectures either locally or globally. The "n-gen" is in search of a "learner centered" 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, 2006).

Rudd *et al* (2009:5) state that students following personal learning paths value programmes and services personalised to their abilities, lifestyle, needs and preferences. Rudd *et al* (2009:5) postulate that workers of tomorrow need different skills to compete in an increasingly services dominated job market. As demand for agricultural and industrial workers continues to decline, students need to acquire skills that prepare them for knowledge-based professions. The authors state that in response, academics and instructional designers are developing new teaching methods that can cater for new learning styles using tools for interactivity, personalisation and collaboration to engage students in real life situational experiences that convey concepts, promote learning and the development of lifelong skills. Rudd *et al* (2009:7) suggest that the fourth signpost of change in education will revolve around its global integration, where advancements in technology have destroyed the traditional boundaries of an educational institution. This will allow institutions to enlarge their enrolment within global markets as well as new service providers to enter established markets. The final signpost for the future of education is a growing understanding of the critical role that educational systems play in service-based economies and there are calls for closer alignment between educational systems and their country's or province's economic development initiatives and goals (Rudd *et al*, 2009:8).

A learning theory like connectivism (Siemens, 2004a) (see Figure 2.2 page 44) provides insight into a learning ecology for the digital era, where forming connections within expert communities using language, media and technology as conduits of information and ethics, beliefs and perspectives as filters of information, builds the skills required to work in the knowledge economies of today. The theory also emphasizes 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. At the University of Zululand this blend should include:

- Face-to-face transfer of information through theory and practical lectures; mentoring by senior or more experienced students both informally and though the Teaching and Learning Grant tutorial support programme.
- Experiential learning, where students volunteer for work experience during their holidays, and their resulting portfolios are examined for a practical course work mark.
- Research, which is an essential component of any academic programme.
- Community outreach, which allow some students to work as research assistants within sponsored community outreach projects.
- E-learning as defined within the contextual setting of the study.
- Self-learning and informal learning, which are self-explanatory.

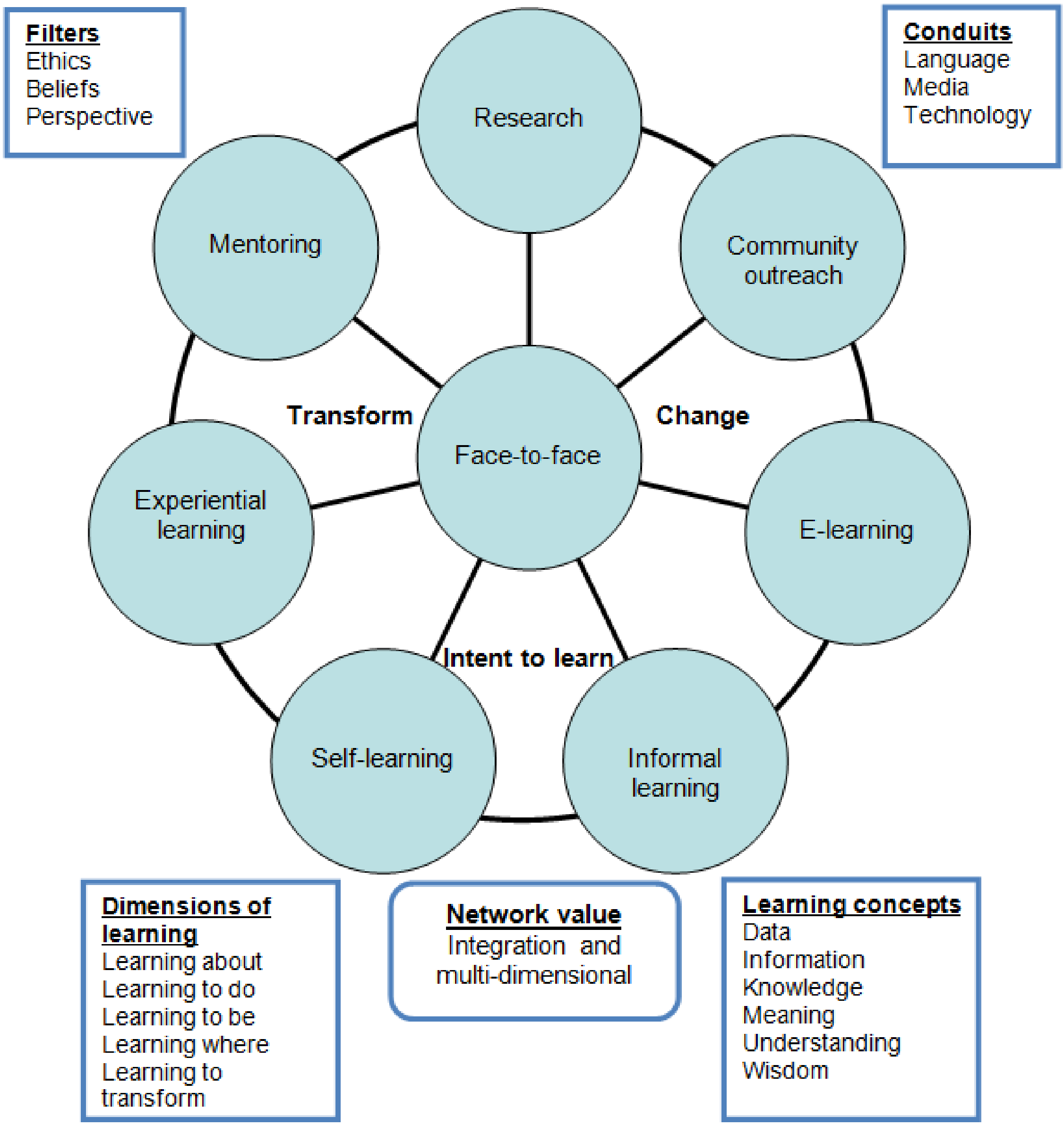

Figure 2.2: Connectivism: Process of Creating a Learning Network applied within the University of Zululand's Learning Ecology (adapted from Siemens, 2004a)

2.3.10 E-learning in Africa

The E-learning Africa Reports are collectives of e-learning experiences from African countries and were inspired by the absence of complete, reliable and consistent documentation on e-learning practice in Africa (e-learning Africa, 2012:10). The 2012 report (2012:16) established that the biggest motivating factor for forty two percent (42%) of respondents to use ICT-enhanced teaching and learning was to improve the quality of their teaching and learning. Following this, an equal proportion of respondents (18%) state that the biggest motivations are developing 21st century skills and improving access to education in remote areas. The fourth most popular response (12%) is that the promotion of creativity and critical thinking was the biggest motivation (e-learning Africa, 2012:16). For the majority of the survey respondents of the 2013 report, laptops (83%) and mobile phones (71%) are the most popular learning devices compared to computer tablets, zero client labs and smart boards. Sixty-seven percent (67%) of respondents still use stand-alone PCs, thirty four percent (34%) still use TVs and thirty one percent (31%) use radios for learning (e-learning Africa, 2013:9).

According to Kamlongera and Yasin in the E-learning Africa Report (2012:36), radio remains the most widely accessible ICT option across Africa and Interactive Radio Instruction (IRI), also known as Interactive Audio Instruction (IAI), provides one of the cheapest and most effective solutions to the challenge of providing quality education. The authors explain that IRI is a methodology and a tool that uses triangular teaching and learning processes, involving a radio or an MP3 player, to deliver educational content to learners in an active learning mode that is facilitated by academic staff. Combining the reach of the radio with this pedagogical approach has been successful in many countries in all aspects of basic education and teacher training. Kamlongera and Yasin, who cite Ligaga *et al.* (2012) in the E-learning Africa Report (2012:36), believe that the 21st century it is not just about new and innovative ICT. Well established technologies such as radio can still be utilised and the greatest educational possibilities lies in the increasing integration of different technologies across Africa, especially the radio and the mobile phone. Campus Radio stations still function as an important communication medium for students within institutions of tertiary education, however, not all radio stations would provide academic audio instruction, unless they provided distance education like UNISA. This goes to show that newer, more mobile technologies have not yet eclipsed older generation technologies and their use for teaching and learning. Social media platforms such as

Facebook, Google Plus and LinkedIn featured prominently with 60% of respondents using them, compared with 29% who use Voice over Internet Protocol (VOIP) applications such as Skype and 22% who make use of blogs, mobile apps and mobile chat (e-learning Africa, 2013:9). According to the E-learning Africa Report (2012:16), various LMSs were noted, with Moodle being the most popular.

Angwin, in the E-learning Africa Report (2012:16), believes that the ambitious e-learning goals in Africa can only be achieved with classroom technology that is intrinsically sustainable and that the reality of extending digital classrooms into urban or rural Africa is that IT provision must take account of unreliable power supplies. Even when interruptions can be managed with novel solutions around Uninterruptible Power Supply (UPS) back-ups or solar energy to power a classroom in a remote setting, low power consumption is going to remain key in how educational organisations manage their energy budgets. This makes thin or zero client computers very attractive as they typically only use between three (3) and (15) watts of power compared to four hundred (400) to eight hundred (800) watts consumed by a low to high end PC. Angwin concludes that African countries look set to trail-blaze other economies in their innovative use of cloud client computing on a massive scale. However, as the E-learning Africa Report (2012:20) points out, ICT-enhanced teaching and learning is often limited by the factors restricting its growth and development. Of all the many challenges faced by respondents, the most significant constraining factor is limited bandwidth (17%), followed by the lack of financial resources (11%), inadequate human resource capacity (11%) and limited electricity (11%) (e-learning Africa, 2012:20).

In the E-learning Africa Report (2012:22), respondents were asked what the most influential factors are when delivering ICT-enhanced teaching and learning within their organisation. The most influential factors at an organisational level were stated to be: access to appropriate content (18%); infrastructure, including electricity, buildings and broadband (16%); professional development and training (12%) and access to affordable and reliable computers (11%).

When asked about their experiences of failure, 49% of the 2013 respondents say they have experienced failure in e-learning, with many of these failures associated with technology and infrastructure breakdowns. The report viewed these valuable conversations on the topic of failure as important, in an attempt to promote a culture of learning and reflection, and in order to improve practice (e-learning Africa, 2013:9).

2.3.11 E-learning at South African Universities

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 technologies in their teaching and learning. These include Stellenbosch University, University of Cape Town, University of Johannesburg, University of the Free State and UNISA, which together with other universities accounts of using e-learning, will be covered in more detail below.

The Cape Peninsula University of Technology's states that one of its strategic objectives is to develop and implement strategies to use ICT as an enabler for teaching and learning for students and academic staff. The institution took a decision that all offerings will have at least a minimum web presence on their LMS (Cape Peninsula University of Technology in Boere and Kruger, 2008:4-5).

The Central University of Technology set a target to have 100% minimum web-presence by 2007 (i.e. in all of its courses). The minimum web-presence is defined as posting a study guide, using the calendar and at least one interactive tool on their LMS, Blackboard. Although this was not fully achieved, it remained their target in 2008 (Central University of Technology in Boere and Kruger, 2008:5).

At North-West University (NWU), programmes are delivered by means of blended learning methods, which can include a combination of face-to-face contact between academic staff and student, distance learning and/or e-learning. Although there is support for e-learning at the NWU, the development of technology infrastructures has preceded the readiness of the institution to fully transform some of the "old" and vested approaches to teaching and learning to the new paradigm, which results in the ineffective use of technology in some teaching and learning at the institution (North-West University in Boere and Kruger, 2008:7).

Stellenbosch University defines e-learning as using ICTs to add value to the teaching and learning process. The institution has always followed a blended ("brick and click") approach where they strive to not distinguish between "learning with technology" and "learning without technology" but rather aim to obtain the optimal blend of face-to-face and e-learning activities to achieve the outcomes of the specific module or programme. The previously dedicated e-learning applications, such as the LMS and the satellite based Interactive Telematic Education (iTE) system, are still mostly used only in teaching and learning, but now are also increasingly used in community outreach and research. These are also just two examples of the many e-learning applications in the so-called "technology basket" available to academic staff and students to support them not only in their teaching and learning, but also research and community outreach (Stellenbosch University in Boere and Kruger, 2008:8).

The University of Cape Town's (UCT) position regarding educational technology is contained in these seven points (University of Cape Town in Boere and Kruger, 2008:12-13):

1. UCT encourages and is committed to enabling the innovative and effective use of ICTs for teaching and learning in UCT courses and programmes.

2. UCT believes that the use of ICTs for teaching and learning must be driven by sound pedagogical principles and the needs of the institution's students and staff, facilitated by technological advances.
3. UCT supports an integrative approach to the use of ICTs
4. UCT is committed to the provision of an appropriate ICT infrastructure and technical support to enable effective implementation of the intentions expressed in this document.
5. UCT expects priorities regarding educational technology to be determined at faculty level.
6. UCT recognises and wishes to exploit the synergies between teaching-and-learning and research with regard to ICTs. As a research-led institution, UCT is also committed to ongoing research in the emerging field of educational technology.
7. UCT acknowledges that the changing terrain requires increased flexibility of course provision, and that ICTs can be used to support this flexibility.

UCT’s Educational Technology Policy document was approved in November 2003, and is available at http://www.cet.uct.ac.za/policy.

At the University of Johannesburg (UJ), the focus of their Centre for Technology Assisted Learning (CenTAL) is to make the integrated approach to technology-assisted learning (TAL), teaching and assessment a reality to the learning experiences of all students, and on all campuses, of UJ. It is noted that this can only become a reality when equal access to computers and the necessary infrastructural upgrades, for example increased bandwidth, are made. Their integrated approach is based on the use of different modes of delivery – learning guides, interactive CDs and web learning environments – including educational technologies, and aims to promote their use in an integrated manner to enhance the students’ learning experience (University of Johannesburg in Boere and Kruger, 2008:13).

At the University of KwaZulu Natal (UKZN), e-learning is embraced more by some than others and is incumbent upon individual enthusiasms rather than being a coherent and systematic process. In some instances, video conferencing has been used in teaching but this has not been sustained. The library service facilitates access to online resources both on and off campus and to resources such as referencing software (University of KwaZulu Natal in Boere and Kruger, 2008:19).

In 2008 e-learning was in its infancy at the Turfloop campus at the University of Limpopo, and as such it was neither centrally coordinated nor well-established. There are a few individuals within the institution who were involved in different e-learning activities such as the Web-CT LMS, which was used mainly by one department to offer their MBA classes through the web (University of Limpopo in Boere and Kruger, 2008:19).

In 2007, UNISA revised its academic model and moved from correspondence model to an Open and Distance Learning (ODL) model. It was envisaged that e-learning would play a significant role in the new ODL model, which would use a wide range of technologies ranging from paper to multimedia CDs, videoconferencing, satellite broadcasting and online teaching and learning using UNISA Virtual Learning Environment (VLE) called myUnisa (https://my.unisa.ac.za/portal). The latter LMS is based on the Communality Source Technology Framework called Sakai (http://sakaiproject.org/portal) (University of South Africa in Boere and Kruger, 2008:20-22).

In 2006, the executive management of the University of the Free State (UFS) accepted blended learning as a teaching/learning strategy for both on-campus and off-campus academic programme offerings. The blended model currently implemented at the institution implies a blend of presenting courses on a face-to-face basis, in addition to an electronic, online basis. The UFS used a variety of programme delivery methods and strategies, such as: engaged learning;

collaborative learning; experience-based learning; problem-based learning; reflective learning; community service learning; resource-based learning; e-learning; group work and directed self-study, which serve to advance lifelong learning. On-campus teaching and learning (utilising the above approaches, strategies and methods) is at the heart of the operations at the UFS. The institution states that a relatively small but significant number of UFS students are served off-campus by different forms of off-campus learning such as resource-based learning, teaching centres in the Free State, Northern Cape, Eastern Cape, and partnerships with FET institutions. Other forms of off-campus learning, such as telematic and e-learning, are attracting growing numbers of students from all over the country, but also from African and other countries (University of the Free State in Boere and Kruger, 2008:23-24).

At the University of the Western Cape (UWC), the e-learning support team acknowledges that e-learning implementation does not only encompass the delivery of training programmes, but also to familiarise educators and bring them on board (University of the Western Cape in Boere and Kruger, 2008:26).

At the University of Zululand, which is the focus of this study, only certain programmes make use of e-learning. Although all programmes contain a minimum exposure to ICT through computer literacy modules within their curricula, the use of e-learning has largely been the product of individual academic staff rather than an institutional wide effort. These initially consisted of departmental websites to dump multimedia resources, followed by the introduction of LMSs to add automated formative and summative assessment methods and upload links for digital document submissions. The first LMS introduced was WebCT (now Blackboard), however when outside funding stopped, its expensive license fees did not justify its limited use. MyCMT was then built in-house in 2002 and provided a simple but effective LMS for all of the above mentioned activities. In 2007, Moodle was introduced to provide more constructivist learning tools such as Wiki's, blogs and forums (Evans in Boere and Kruger, 2008:28).

The Vaal University of Technology (VUT) reported to have Moodle implemented on campus, and that e-learning occurs across the institution in rather individualistic ways, some areas embracing it more than others. For example, Health Sciences used it for their BTech courses with full online content; ICT makes use of chat rooms and putting additional content/articles on Moodle and the rest of VUT mostly used it for online assessment. The end user computing module is done via e-learning through SimNet (Vaal University of Technology in Boere and Kruger, 2008:28).

2.4 Summary

The purpose of this chapter was to review empirical literature on e-learning in order to understand what it is, how it is perceived and where it is used. E-learning is broadly defined and four points of view of how ICTs are influencing change within higher education, including globalisation, digital divide, market forces and politics of e-learning, are introduced. The background to e-learning begins by giving a historical timeline from the first correspondence course learning, dating back to the 1890s, to the 2000s, where the next generation of web 2.0 technologies and designs harnessed the power of user contribution, collective intelligence, and network effects. Ethical issues of e-learning are then discussed at macro, meso and micro levels of university programmes, for example, choosing the appropriate pedagogies to integrate the selection of media and technologies into the curriculum at macro level and fulfilling the purpose and exit level outcomes of the programme by offering the right combination and quality of teaching methods at meso level. Other ethical issues include access to resources, copyright of software, true identity and participation and privacy of the users. It was then established that e-learning comes with its own advantages and disadvantages, which can be looked at from the perspectives of the stakeholders in the process. Advantages for students are the technical ICT skills that they develop, while allowing access to essential pre-packaged information through LMSs, which in turn allows academic staff to concentrate on high-level activities in the delivery phase. Disadvantages for the academic staff include creating labour intensive course content and e-learning can be susceptible to cheating and plagiarising information. Emerging e-learning trends and technologies are then discussed, which layer on top of older established technologies to give rise to new services to a growing user base, for example social media hosted through cloud computing services. Literature on e-learning and knowledge management explains why turning information and data efficiently into knowledge is a perquisite for the successful participation in today's knowledge economy. The implementation barriers of integrating e-learning within traditional curriculum of institutions of higher education involves many complex issues such as strategic management decisions, strategic information technology plans, change management to get stakeholders to participate, training and re-training users, selection of suitable learning strategies, partnership strategies, development or purchase of courseware, etc. The use of e-learning was shown to be influenced by both positive and negative attitudes of its users, which in turn can be influenced by factors like age, gender and the motivation of users. The future of e-learning conceptually discusses how learning styles are changing and how e-learning can accommodate learner's new expectations in the digital age. Literature of e-learning in Africa provides a collective of e-learning experiences from African countries, which contextualised both motivations to participate, preferred technologies and experiences of failure. The chapter ends by giving examples of how e-learning is officially integrated into programme curriculum of some benchmarked South African universities, while unofficially used on a voluntary basis in others.

The strengths of the literature reviewed is that it gives a holistic overview of how e-learning is only one of the methods that can be integrated in a blended learning environment, which can enhance the learning process, especially if there is an intent to learn, as well as the motivation to pick up additional technical skills. Weaknesses in literature include the lack of peer review on some information cited from websites. Gaps exist in the literature reviewed so far when looking for specific models that can predict the psychological adoption or rejection of e-learning and the constructs that influence this decision; this is covered in the next chapter under the theoretical framework.

Chapter 3: THEORECTICAL FRAMEWORK

3.1 Introduction

The purpose of this chapter is to review relevant literature on concepts and theoretical models that may be used to help predict the level of acceptance of e-learning at the University of Zululand. The study aims to understand the factors that influence the acceptance and use of user-friendly e-learning technology because the adoption of such technologies will strengthen teaching and learning, while the adoption of user unfriendly technologies will lead to frustrated users not adopting and/or using them for their intended purposes. The large investment and future procurement of relevant user-friendly e-learning technologies has made user acceptance an increasingly critical issue for the successful implementation and management of e-learning at the University of Zululand.

3.2 Concept of User Acceptance

User acceptance is defined as “the demonstrable willingness within a user group to employ information technology for the tasks it is designed to support” (Dillon and Morris, 1996). According to Dillon (2001), the scientific concern with user acceptance is relatively recent, since traditionally, developers and buyers of new technology could rely on established authority to ensure that technology was used for its intended purpose. However, the author believes that with the current working practices, as well as a large market for recreational and educational applications, the new digital technological applications have enabled greater options among users, thus increasing the need to determine the dynamics of acceptance (Dillon, 2001). Dillon (2001) explains that by developing and testing models of the variables influencing user acceptance, researchers seek to provide guidance to the process of design and implementation in a manner that will minimize the risk of opposition to or rejection by users. Questions of how many technologies have produced noticeable benefits to the end users and how many have not been used because they were rejected on the basis of poor design and/or being unsupported can be explained by separate literature in areas of innovation diffusion, technology design and implementation, Human-Computer Interaction (HCI) and Information Systems (IS), where the concept of acceptance has been explicitly investigated (Dillon and Morris, 1996). This literature demonstrates that the nature of technological acceptance is mediated by distinct factor groups related to the psychology of the users, the design process of the technology, and the nature and quality of the technology in user terms (Dillon and Morris, 1996). As such, user acceptance of technology draws on multiple theoretical perspectives and on research subjects such as change management in organisations, human attitude formation, systems analysis, user interface design, and technology diffusion (Dillon and Morris, 1996).

Predicting acceptance requires the review of psychology based theories. Researchers from the field of social-psychology have published various theories that can help to explain the adoption of both Information and Communication Technology (ICT) and Information Systems (IS). These theories include the original Theory of Reasoned Action (TRA) by Fishbein and Ajzen (1975, 1980) (Dillon and Morris, 1996; Ajzen, 2008); the Technology Acceptance Model (TAM) by Davis, Bagozzi, and Warshaw (Dillon and Morris, 1996; Dillon, 2001; Theories Used in IS Research Website, 2008) and the Theory of Planned Behaviour (TPB) by Ajzen (1985, 1991) (Ajzen, 2008) among others that are essentially modifications of the above mentioned. Research by the above authors has generated various adoption metrics that can be used to estimate the probability of acceptance and successful implementation of ICT, IS and thus e-learning initiatives.

Dillon and Morris (1996) however noted that these potentially overlapping theories seem to exist independently of each other and that there was scope for a unifying framework to extend innovation diffusion concepts and systems design models into a formal theory of user acceptance of technology. Venkatesh *et al.* (2003) subsequently formulated a unified model, called the Unified Theory of

Acceptance and Use of Technology (UTAUT), through the review and consolidation of the constructs of eight models that earlier research had employed to explain IS usage behaviour. (Theories Used in IS Research Website, 2008). These theoretical approaches, together with the UTAUT, are reviewed under the next section.

3.3 Theoretical Approaches to Understanding the Psychology of User Acceptance

3.3.1 The Theory of Reasoned Action (TRA)

The Theory of Reasoned Action (TRA) was introduced by Fishbein and Ajzen in 1975, adapted in 1980, and subsequently published in their book *Understanding Attitudes and Predicting Human Behaviour* in 2008 (Ajzen, 2008). The well-studied TRA model originated from the field of social-psychology (Ajzen and Fishbein, 1980; Fishbein and Ajzen, 1975 in Davis, Bagozzi, and Warshaw, 1989:984) and is one of the most fundamental and influential theories of human behaviour. According to TRA, a person's performance of a specified behaviour is determined by his or her Behavioural Intention (BI), and BI is jointly determined by a person's Attitude (A), and Subjective Norm (SN) concerning the behaviour (Davis, Bagozzi, and Warshaw, 1989:984). The key application of this theory is the prediction of behavioural intention and the direct determinants of behavioural intention are one's attitude towards the behaviour and subjective norm associated with the behaviour (BI = A + SN) (Ajzen, 2008). The theory further states that attitudes and norms are not weighted equally in predicting behaviour. Thus BI = (A) W1 + (SN) W2. For example, you might be the kind of person who cares a lot about what others think. If this is the case, the subjective norms would carry a greater weight in predicting your behaviour (Ajzen, 2008).

TRA is a very general model that can be used to explain virtually any conscious human behaviour (Ajzen and Fishbein, 1980:4 in Davis, Bagozzi, and Warshaw, 1989:983), and could therefore be considered for studying the determinants of technology usage behaviour as explained in the Figure 3.1 (page 57) (Davis, Bagozzi, and Warshaw, 1989:983).

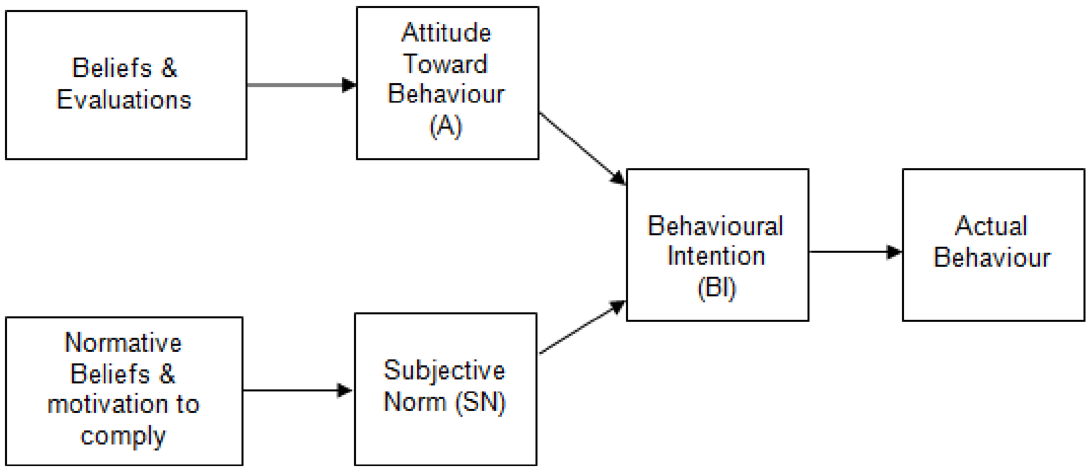

Figure 3.1: Theory of Reasoned Action (TRA) (based on Fishbein and Ajzen, 1975 from Davis *et al.*, 1989:984).

3.3.2 The Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM) is one of the most well used and cited (Dillon, 2001) adaptations of TRA and was first developed by Davis in 1986 to specifically explain computer usage behaviour and model user acceptance of IS (Davis, Bagozzi, and Warshaw, 1989:983-5). TAM used TRA as a theoretical basis for specifying the causal linkages between two key beliefs: perceived usefulness and perceived ease of use, and users' attitudes, intentions and actual computer adoption behaviour (Davis, Bagozzi, and Warshaw, 1989:983). In the context of ICT and IS, this provides an approach to study the attitude of users towards these technologies. TAM suggests users formulate a positive attitude toward the technology when they perceive the technology to be one, useful and two, easy to use (Davis, Bagozzi, and Warshaw, 1989:985). Thus, the two theoretical components "perceived usefulness" and "perceived ease of use" are the foundation of the TAM model to determine an individual's intention to use a system, with the intention to use serving as a moderator of actual system use.

Perceived usefulness is also seen as being directly affected by the perceived ease of use factor. Davis, Bagozzi, and Warshaw define usefulness as “the degree to which a person believes that using a particular system would enhance his or her job performance.” Davis, Bagozzi, and Warshaw go on to define perceived ease of use as “the degree to which a person believes that using a particular system would be free of effort” (Davis, Bagozzi, and Warshaw, 1989:985).

According to the Theories Used in IS Research Website (2008) TAM and TRA, which both have strong behavioural elements, assume that when someone forms an intention to act, that they will be free to act without restriction. However a recognised limitation of TAM is that it does not take into consideration any barriers that would prevent an individual from adopting a particular technology (Taylor and Todd, 1995:149; Theories Used in IS Research Website, 2008). In practice constraints such as time, availability of the resource, support, incentives or the lack thereof to use the resource or organisational shortcomings, and unconscious habits of the user are all factors that will limit the freedom to act (Theories Used in IS Research Website, 2008).

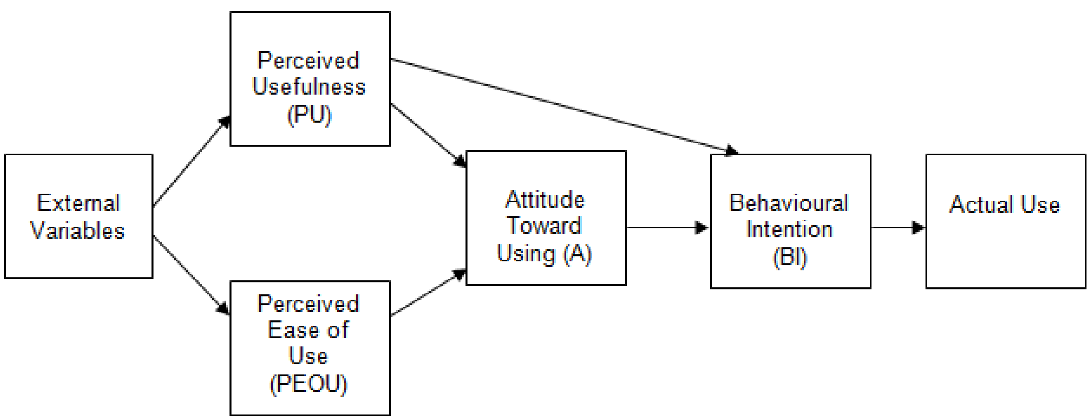

Figure 3.2: Technology Acceptance Model (TAM) [Source: Davis, Bagozzi, and Warshaw (1989:985)].

Ventakesh *et al.* (2003:428) state that TAM is custom-made to IS contexts, and was designed primarily to predict IT acceptance and usage. Unlike TRA, the final conceptualization of TAM excludes the Attitude (A) construct in order to better explain intention prudently. TAM2 extended TAM by including subjective norm as an additional predictor of intention in the case of compulsory settings (Venkatesh and Davis, 2000:188). TAM has been widely applied to a diverse set of technologies and users. The TAM2 model is illustrated in Figure 3.3 below.

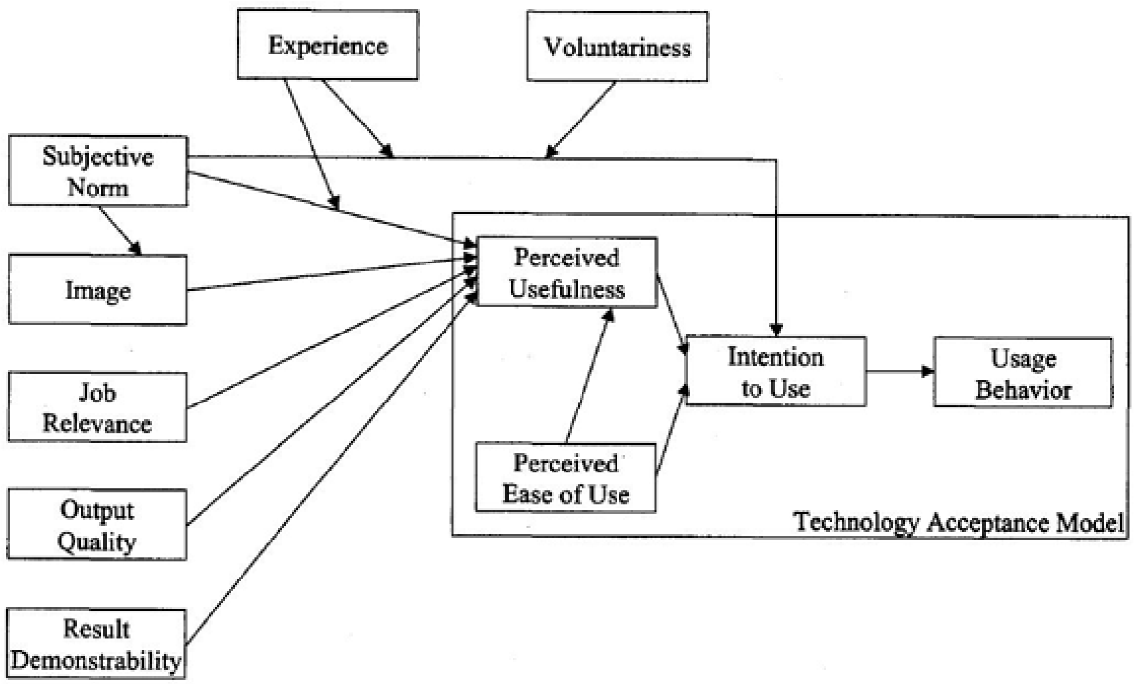

Figure 3 3: Second conceptualization of the Technology Acceptance Model (TAM2) adapted from Davis, Bagozzi, and Warshaw, 1989 [Source: Venkatesh and Davis, 2000:188)].

3.3.3 The Motivational Model (MM)

Although a significant number of studies have chosen to use TAM to explain Behaviour Intention (BI) in the use of technology, another noteworthy and somewhat parallel body of research in psychology has supported a more general motivation theory as an explanation for BI (Ventakesh *et al.,* 2003:428). Within the information systems domain, Davis, Bagozzi, and Warshaw. (1992) (Ventakesh *et al.,* 2003:428) applied motivational theory to understand the adoption and use of new technology. Referred to as the Motivational Model (MM) the core constructs of the MM include:

- Extrinsic Motivation (EM), which is the perception that users will want to perform an activity "because it is perceived to be instrumental in achieving valued outcomes that are distinct from the activity itself, such as improved job performance, pay, or promotions" (Davis, Bagozzi, and Warshaw, 1992:1112 in Ventakesh *et al.,* 2003:428). Due to the parallel nature of MM and TAM there is a close similarity between EM and Perceived Usefulness (PU) of TAM (Cocosila, Archer and Yuan, 2009:340).
- Intrinsic Motivation (IM), which is the perception that users will want to perform an activity "for no apparent reinforcement other than the process of performing the activity per se" (Davis, Bagozzi, and Warshaw, 1992:112 in Ventakesh *et al.,* 2003:428). This type of motivation occurs when users engage in an activity for exploratory, curious or playful reasons (Moon and Kim, 2001:218; Ryan and Deci, 2000:56).

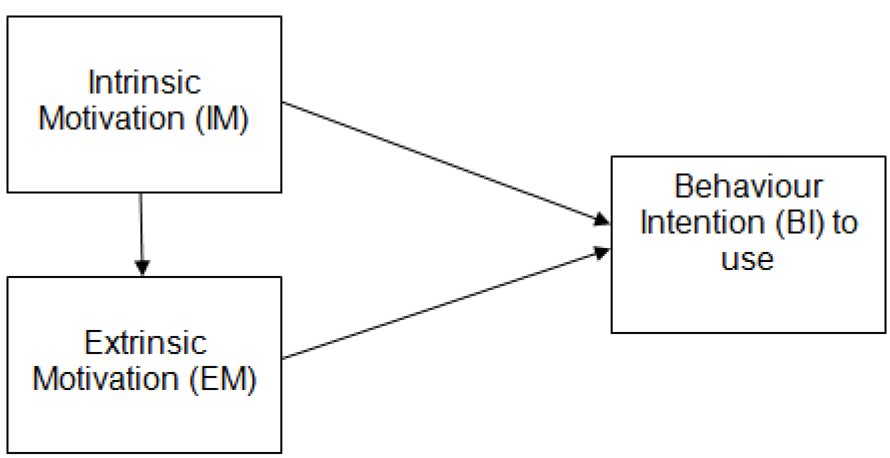

Figure 3.4: The Motivational Model (MM) (Davis, Bagozzi, and Warshaw*,* 1992) [Source: Cocosila, Archer and Yuan (2009:344)].

3.3.4 The Theory of Planned Behaviour (TPB)

The Theory of Planned Behaviour (TPB) (Ajzen, 1985, 1991) extends the TRA (Fishbein and Ajzen, 1975) to account for conditions where individuals do not have complete control over their behaviour (Taylor and Todd, 1995:149). TPB is considered an influential theory for the prediction of social and health behaviour patterns and incorporates both social influences and personal factors as predictors (Rivis and Sheeran, 2003:218). According to Ventakesh *et al.* *(*2003:429), Ajzen (1991) presented a review of several studies that successfully used TPB to predict intention and behaviour in a wide variety of settings. TPB has been successfully applied to the understanding of individual acceptance and usage of many different technologies (Harrison *et al.* 1997:172; Mathieson 1991:173; Taylor and Todd 1995:149; Ventakesh *et al.* 2003:429). Figure 3.5 below illustrates the TPB model of acceptance behaviour.

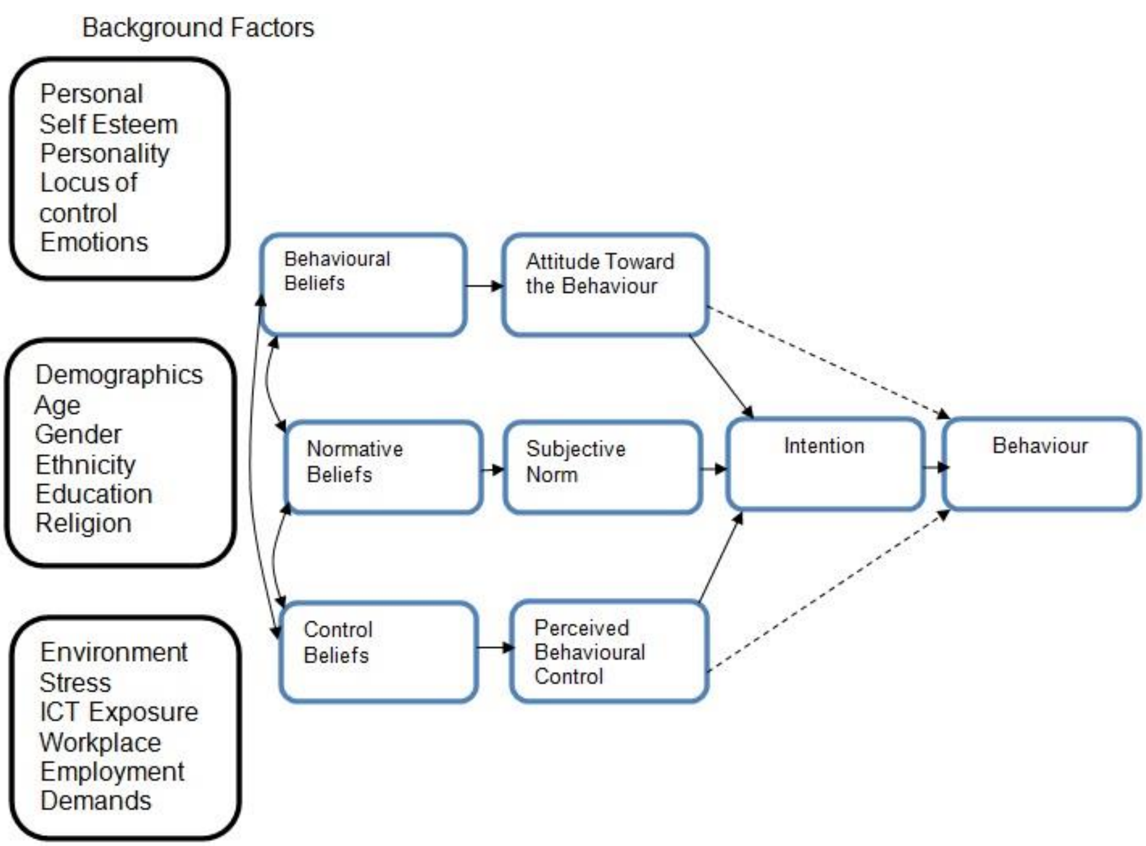

Figure 3.5: Theory of Planned Behaviour (Ajzen, 1985) [Source: Siragusa and Dixon (2009:971)].

The core constructs of the TPB include:

- Attitude Toward Behaviour (ATB), which was adapted from TRA.
- Subjective Norm (SN), which was adapted from TRA.
- Perceived Behavioural Control (PBC), which is "the perceived ease or difficulty of performing the behaviour" (Ajzen, 1991:188). In the context of IS research, "perceptions of internal and external constraints on behaviour" (Taylor and Todd 1995:149).

3.3.5 The Combined TAM and TPB (C-TAM-TPB) hybrid model

TAM and TPB have been two of the most widely used models in IS literature. Initial studies (Taylor and Todd, 1995:147) used TAM and TPB separately to compare their explanatory power (Yayla and Qing, 2007:180). Researchers then started combining the two theories to have a richer understanding of the technology acceptance behaviour. Many hybrid models of TPB and TAM were proposed and tested in the literature (Yayla and Qing, 2007:180). The C-TAM-TPB model combines the predictors of TPB with the perceived usefulness from the TAM to provide the hybrid model (Taylor and Todd 1995:148; Ventakesh *et al.* 2003:429). The core constructs of the C-TAM-TPB hybrid model, shown in Figure 3.6 below, include:

- Attitude Toward Behaviour (ATB), which was adapted from TRA/TPB.
- Subjective Norm (SN), which was adapted from TRA/TPB.
- Perceived Behavioural Control (PBC), which was adapted from TRA/TPB.
- Perceived Usefulness (PU), which was adapted from TAM.

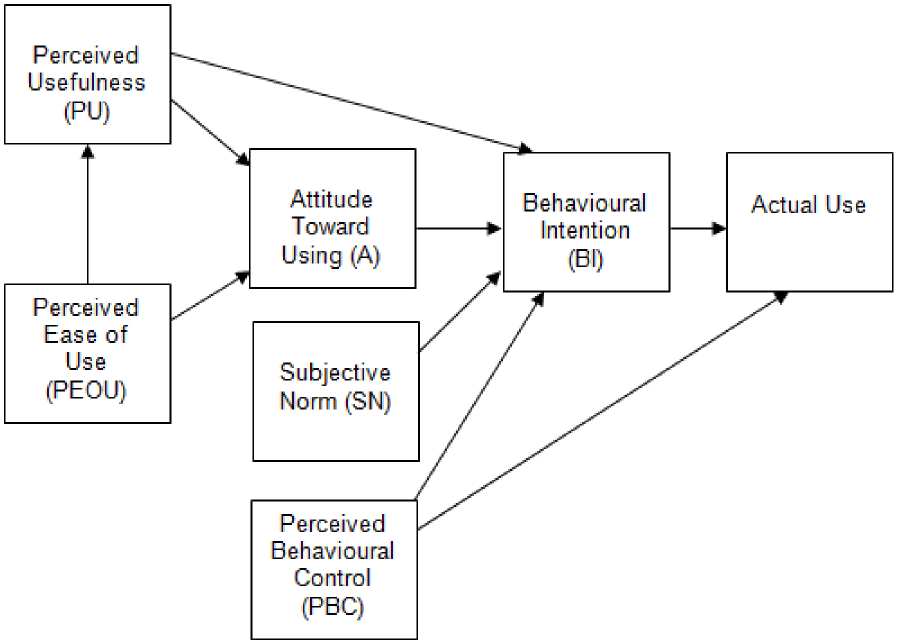

Figure 3.6: Combined TAM and TPB (C-TAM-TPB) [Source: Taylor and Todd (1995:146)].

3.3.6 The Model of Personal Computer (PC) Utilisation (MPCU)

Ventakesh *et al.* (2003:430) explain that the MPCU is derived largely from Triandis' (1977) theory of human behaviour, which presents a competing point of view to that proposed by TRA and TPB. According to Ventakesh *et al.* (2003:430), Thompson *et al.* (1991) modified and refined Triandis' model for IS contexts and used the model to predict PC utilisation. The authors purport that the nature of the model makes it particularly suited to predicting individual acceptance and use of a range of information technologies. The core constructs of the MPCU model, which is shown in Figure 3.7 below, include:

- Job-fit with PC Use, is "the extent to which an individual believes that using a technology can enhance the performance of his or her job" (Thompson *et al.*, 1991:129).
- Complexity of PC Use, which based on Rogers and Shoemaker (1971), is "the degree to which an innovation is perceived as relatively difficult to understand and use" (Ventakesh *et al.,* 2003:430).

- Long-term Consequences of PC Use, which are “outcomes that have a pay-off in the future” (Thompson *et al.*, 1991:129).
- Affect Towards PC Use, which based on Triandis, is “feelings of joy, elation, or pleasure, or depression, disgust, displeasure, or hate associated by an individual with a particular act” (Ventakesh *et al.,* 2003:430).
- Social Factors Influencing PC Use, which derived from Triandis, are “the individual’s internalization of the reference group’s subjective culture, and specific interpersonal agreements that the individual has made with others, in specific social situations” (Ventakesh *et al.,* 2003:430).
- Facilitating Conditions for PC Use, which are objective factors in the environment that observers agree make an act easy to accomplish. For example, returning items purchased online is facilitated when no fee is charged to return the item. In an IS context, “provision of support for users of PCs may be one type of facilitating condition that can influence system utilization” (Thompson *et al.*, 1991:129).

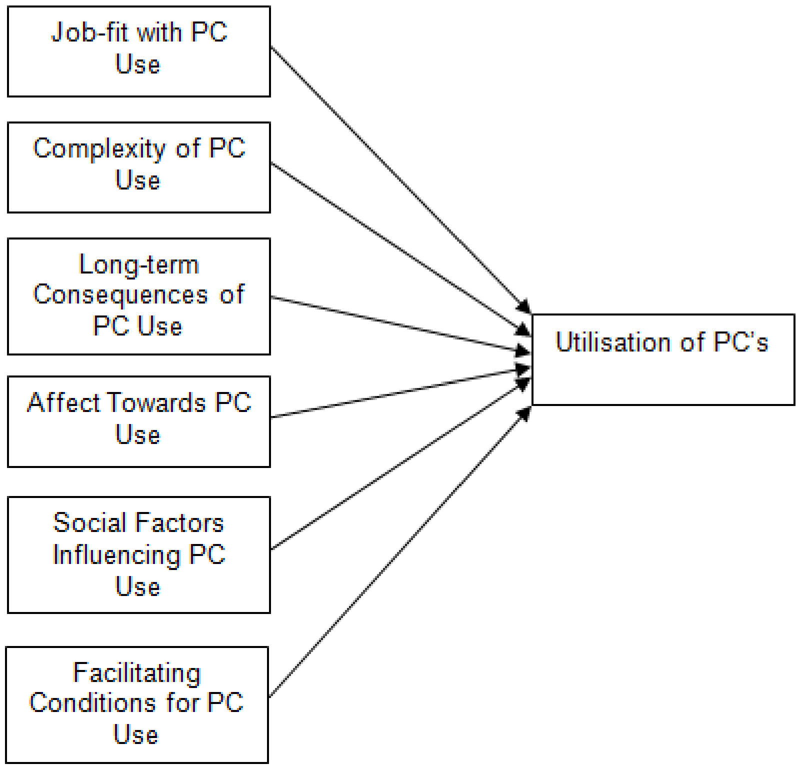

Figure 3.7: Model of Personal Computer (PC) Utilisation (MPCU) [Source: Thompson *et al.*, (1991:131)].

3.3.7 The Diffusion of Innovation Model (DOI)

The Diffusion of Innovation Theory (DOI), also referred to as the Innovation Diffusion Theory (IDT), was first developed by EM Rogers in 1962 (Rogers, 1983:38). Rogers (1983:21) explains that adoption is a decision of "full use of an innovation as the best course of action available" and rejection is a decision "not to adopt an innovation". Rogers (1983:5) defines diffusion as "the process in which an innovation is communicated through certain channels over time among the members of a social system" and innovation, communication channels, time, and social system are the four key components of the diffusion of innovations. The DOI or IDT theory thus argues that "potential users make decisions to adopt or reject an innovation based on the beliefs that they form about the innovation" (Agarwal, 2000:90). According to Lee *et al*. (2011:126), IDT/DOI includes five significant innovation constructs: relative advantage, compatibility, complexity, and trialability and observability. These characteristics are used to explain end-user adoption of innovations and the decision-making process. Figure 3.8 below illustrates the five different constructs.

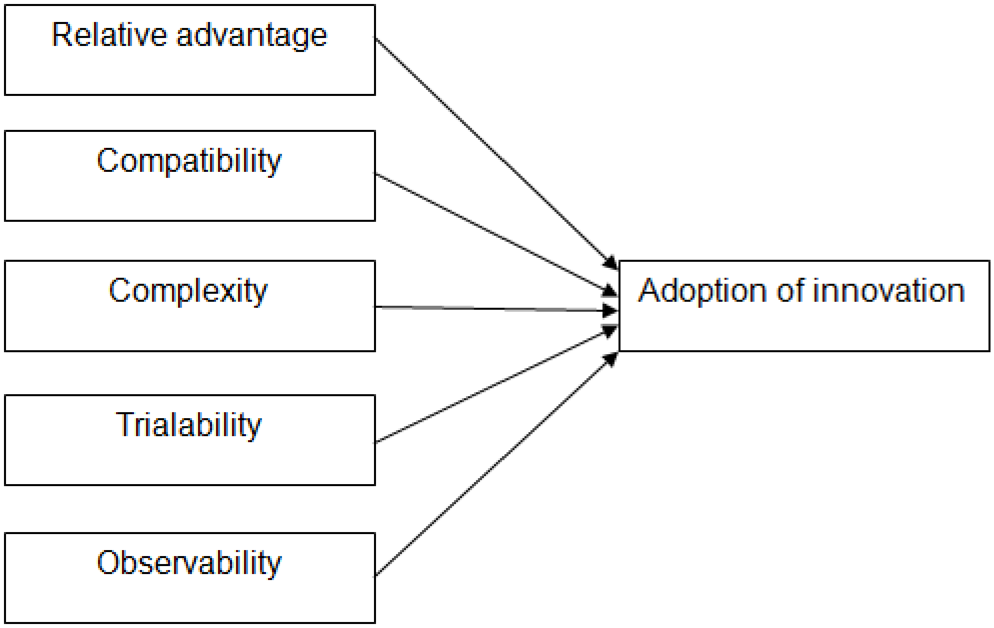

Figure 3.8: Innovation Diffusion Theory (IDT) [Source: Rogers (1995) in Lee *et al*., (2011:126)].

Lee *et al*. (2011:126) defines the five significant innovation constructs in IDT/DOI model:

1. "Relative advantage is defined as the degree to which an innovation is considered as being better than the idea it replaced. This construct is found to be one of the best predictors of the adoption of an innovation" (Lee *et al*., 2011:126).
2. "Compatibility refers to the degree to which innovation is regarded as being consistent with the potential end-users' existing values, prior experiences, and needs" (Lee *et al*., 2011:126).
3. "Complexity is the end-users' perceived level of difficulty in understanding innovations and their ease of use" (Lee *et al*., 2011:126).

4. “Trialability refers to the degree to which innovations can be tested on a limited basis” (Lee *et al*., 2011:126).
5. “Observability is the degree to which the results of innovations can be visible by other people” (Lee *et al*., 2011:126).

Within information systems, Moore and Benbasat (1991) adapted the characteristics of innovations presented by Rogers (1983) and refined a set of new constructs that could be used to study individual technology acceptance (Ventakesh *et al.,* 2003:431). Moore and Benbasat (1996) found support for the predictive validity of these innovation characteristics (see also Agarwal and Prasad 1997:558, 1998:205; Karahanna *et al.,* 1999:184; Plouffe *et al.,* 2001:209).The core constructs of their modified IDT model include:

- Relative Advantage, which is “the degree to which an innovation is perceived as being better than its precursor” (Moore and Benbasat, 1991:195 in Ventakesh *et al.,* 2003:431).
- Ease of Use, which is “the degree to which an innovation is perceived as being difficult to use” (Moore and Benbasat, 1991:195 in Ventakesh *et al.,* 2003:431).
- Image, which is “the degree to which use of an innovation is perceived to enhance one’s image or status in one’s social system” (Moore and Benbasat, 1991:195 in Ventakesh *et al.,* 2003:431).
- Visibility, which is the “degree to which one can see others using the system in the organisation” (Moore and Benbasat, 1991:195 in Ventakesh *et al.,* 2003:431).
- Compatibility, which is “the degree to which an innovation is perceived as being consistent with the existing values, needs, and past experiences of potential adopters” (Moore and Benbasat, 1991:195 in Ventakesh *et al.,* 2003:431).
- Results Demonstrability, which is “the tangibility of the results of using the innovation, including their observability and communicability” (Moore and Benbasat, 1991:195 in Ventakesh *et al.,* 2003:431).

- Voluntariness of Use, which is “the degree to which use of the innovation is perceived as being voluntary or of free will” (Moore and Benbasat, 1991:195 in Ventakesh *et al.,* 2003:431).

3.3.8 The Social Cognitive Theory (SCT)

Bandura (1986) developed and defined the Social Cognitive Theory (SCT) which suggests human functioning is explained in terms of a model of triadic reciprocal determinism (Bandura, 1989:6) Figure 3.9 below illustrates the SCT model.

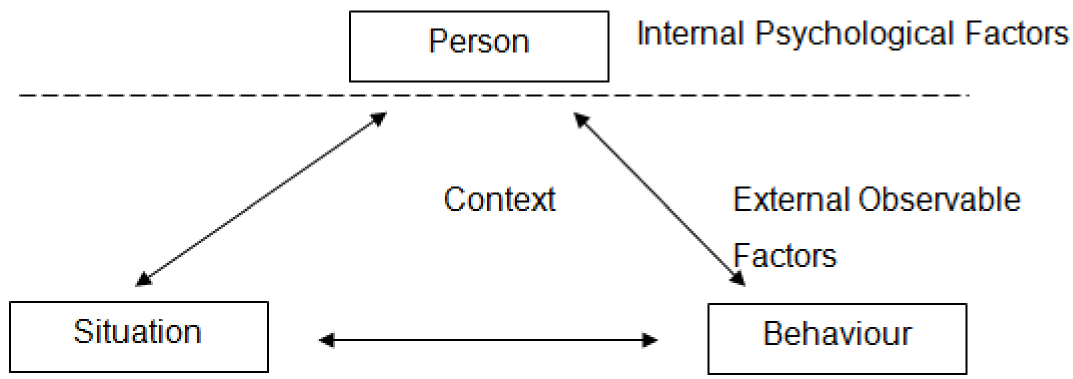

Figure 3.9: Model of Reciprocal Determinism [Source: Bandura (1977; 1966) in Bandura (1989:3)].

In this model, which can be visualized as an equilateral triangle, behaviour, cognition and other personal factors and environmental events all operate as interacting determinants of each other, while the nature of persons is then defined within this triadic perspective (Bandura, 1989:2). Reciprocal determinism recognizes that elements of the person and the environment interact in ways that may help to shape future motivations, behaviour, and well-being (Bandura, 1989:2).

Compeau and Higgins (1995b) applied and extended SCT to the context of computer utilisation. This model studied computer use but the nature of the model and the underlying theory allowed it to be extended to acceptance and use of information technology in general (Compeau and Higgins, 1995b:189). The core constructs of SCT include:

- "Outcome Expectations – Performance, which is the performance-related consequences of the behaviour. Specifically, performance expectations deal with job related outcomes" (Compeau and Higgins, 1995b:191).
- "Outcome Expectations - Personal, which is the personal consequences of the behaviour. Specifically, personal expectations deal with the individual esteem and sense of accomplishment" (Compeau and Higgins, 1995b:191).
- "Self-efficacy, which is the judgment of one's ability to use a technology (e.g., computer) to accomplish a particular job or task" (Compeau and Higgins, 1995b:191).
- "Affect, which is an individual's liking for a particular behaviour (e.g., computer use)" (Compeau and Higgins, 1995b:189).
- "Anxiety**,** which evokes anxious or emotional reactions when it comes to performing a behaviour (e.g., using a computer)" (Compeau and Higgins, 1995b:189).

3.3.9 The Unified Theory of Acceptance and Use of Technology (UTAUT)

Ventakesh *et al.* (2003) reviewed the aforementioned eight prominent user acceptance models, namely:

1. The theory of reasoned action
2. The technology acceptance model
3. The motivational model
4. The theory of planned behaviour
5. A model combining the technology acceptance model and the theory of planned behaviour
6. The model of PC utilization
7. The diffusion of innovation theory

8. The social cognitive theory

The authors empirically compared the listed models above and their extensions and then formulated a unified model that incorporated elements across the eight models, as well as a selected subset of additional variables (Ventakesh *et al.* 2003:425). The UTAUT model has thus condensed the thirty two variables found in the eight existing models into four main effects and four moderating factors (Ventakesh *et al.* 2003:467) (see Figure 3.10 page 70).

The UTAUT model was empirically tested using data from four organisations and then cross-validated using new data from an additional two organisations (Ventakesh *et al.* 2003:467). These tests provided strong empirical support for the UTAUT model, which theorizes that three direct variables determine the behavioural intent of technology use and a direct determinant of usage behaviour is the facilitating conditions (Ventakesh *et al.* 2003:467). These primary constructs are moderated, in varying degrees, by gender, age, experience, and voluntariness of use.

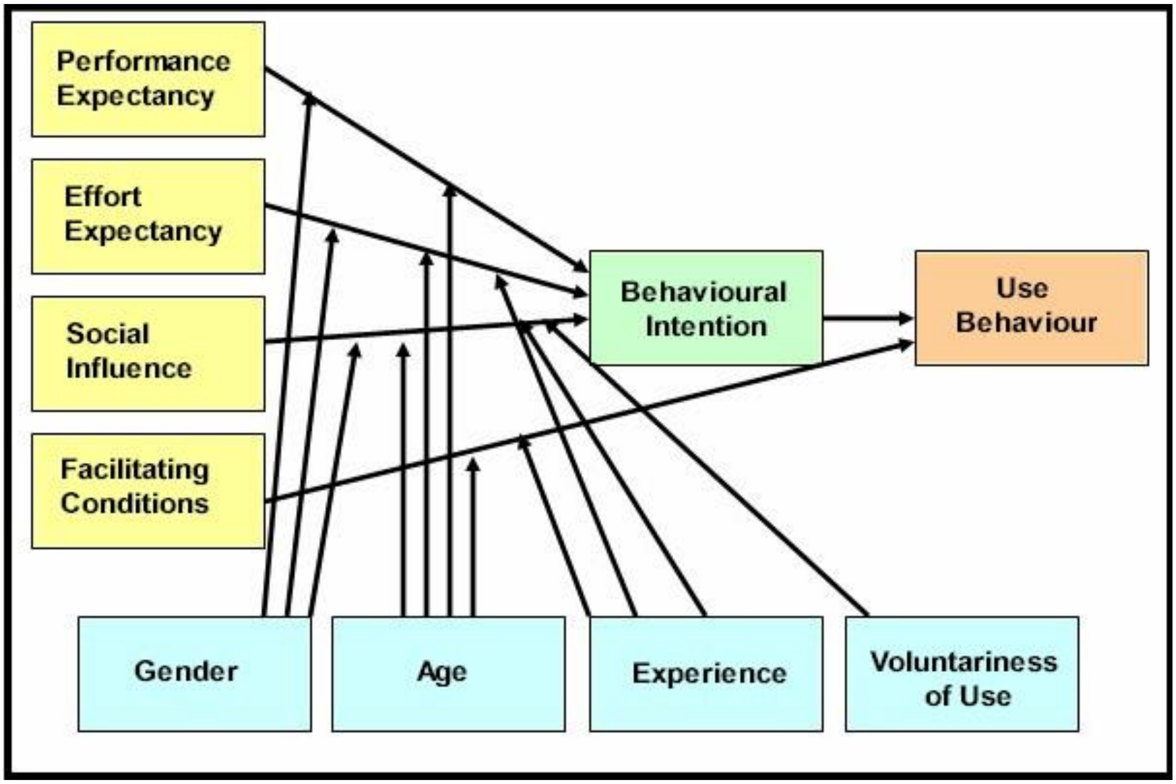

Figure 3.10: The Unified Theory of Acceptance and Use of Technology Model (UTAUT) [Source: Venkatesh *et al.* (2003:445)].

3.3.9.1 Performance Expectancy (PE)

Performance expectancy is defined as the degree to which an individual believes that using the technology will help him or her to achieve gains in performance (Venkatesh *et al*., 2003:447), in this case teaching and learning. The five constructs from the aforementioned eight models that pertain to performance expectancy are: perceived usefulness (TAM/TAM2 and C-TAM-TPB), extrinsic motivation (MM), job-fit (MPCU), relative advantage (IDT), and outcome expectations (SCT) (Venkatesh *et al*., 2003:447).

According to Venkatesh *et al.* (2003:447), the performance expectancy construct is the strongest predictor in the UTAUT Model. This according to the author was consistent with previous user acceptance model tests (Agarwal and Prasad, 1998:205; Compeau and Higgins, 1995a:118; Taylor and Todd, 1995:158;

Thompson *et al.*, 1991:129; Venkatesh and Davis, 2000:187; Venkatesh *et al.*, 2003:448).

Studies have suggested that this construct may have a gender and age bias (Venkatesh *et al.*, 2003). For instance, they determined that the effect of performance expectancy was moderated by age and gender especially males and particularly younger males. Thus, the study expects the influence of performance expectancy to be moderated by both gender and age in the study.

3.3.9.2 Effort Expectancy (EE)

Effort expectancy is defined as the degree of ease associated with using the technology. Three constructs from the aforementioned models capture the concept of effort expectancy: perceived ease of use (TAM/TAM2), complexity (MPCU), and ease of use (IDT) (Venkatesh *et al.*; 2003:450).

Venkatesh *et al.* (2003:450), drawing upon past research (e.g., Bem and Allen 1974; Bozionelos 1996; Venkatesh and Morris 2000), suggest that effort expectancy is more important for females than for males. The gender differences predicted here could be driven by cognitions related to gender roles (e.g., Lynott and McCandless 2000:6). Prior research supports the notion that constructs related to effort expectancy will be stronger determinants of individuals' intention to use the technology for females (Venkatesh and Morris 2000; Venkatesh *et al.* 2000 in Venkatesh *et al.,* 2003:450) and for older workers (Morris and Venkatesh 2000 in Venkatesh *et al.*, 2003:450). Thus, the authors proposed that effort expectancy will be most important for females, particularly those who are older and with relatively little experience with the system.

Venkatesh *et al.* postulated that the influence of effort expectancy on behavioural intention will be moderated by gender, age, and experience, to such an extent that the effect will be stronger for women, particularly older females, and particularly at the early stages of experience (Venkatesh *et al.*, 2003:450).

3.3.9.3 Social Influence (SI)

According to Venkatesh *et al.* (2003:451) Social Influence (SI) is defined as “the degree to which an individual perceives that important others believe he or she should use the new system”. The authors point out that SI, as a direct determinant of behavioural intention, is represented as a subjective norm in TRA, TAM2, TPB/DTPB and C-TAM-TPB, as social factors in MPCU, and as an image in IDT. Thompson *et al.* (1991:140) used the term social norms in defining their construct, and recognised its similarity to the subjective norm within TRA. While they may have different labels, each of these constructs contains the explicit or implicit concept that the individuals’ behaviour is influenced by the way in which they believe others will view them as a result of having used the technology.

Theoretically, females tend to be more sensitive to others’ opinions and therefore find social influence to be more important when forming an intention to use a new technology (Miller 1976; Venkatesh *et al.* 2000 in Venkatesh *et al.* 2003:453), with the effect declining with experience (Venkatesh and Morris 2000 in Venkatesh *et al.* 2003:453). As in the case of performance and effort expectancies, gender effects may be driven by psychological phenomena personified within socially constructed gender roles (e.g., Lubinski *et al.* 1983:428). Venkatesh *et al.* (2003:453) cite Rhodes (1983) whose meta-analytic review of age effects concluded that affiliation needs increase with age, suggesting that older workers are more likely to place increased significance on social influences, with the effect declining with experience (Morris and Venkatesh 2000 in Venkatesh *et al.* 2003:453). Therefore, the study expects a complex interaction with these moderating variables simultaneously influencing the social influence-intention relationship.

Venkatesh *et al.* hence postulated that the effect of social influence on behavioural intention will be moderated by gender, age, voluntariness, and experience, such that the effect will be stronger for women, mainly older women, particularly in compulsory settings in the early stages of experience (Venkatesh *et al.* 2003:453).

3.3.9.4 Facilitating Conditions (FC)

Venkatesh *et al.* (2003:453) state that facilitating conditions are defined as the degree to which an individual believes that an organisational and technical infrastructure exists to support use of the technology. The authors recognize that this definition captures concepts embodied by three different constructs namely: perceived behavioural control (TPB/ DTPB, C-TAM-TPB), facilitating conditions (MPCU), and compatibility (IDT).

The same authors (Venkatesh *et al.* (2003:453) explain that when both the performance expectancy construct and effort expectancy construct are present, facilitating conditions becomes non-significant in predicting behavioural intention.

They further state that the empirical results indicate that facilitating conditions do have a direct influence on usage beyond that explained by behavioural intentions alone. In fact, the effect is expected to increase with experience as users of technology find numerous avenues for help and support throughout the organisation, thereby removing hurdles to sustained usage (Bergeron *et al.* 1990 in Venkatesh *et al.* 2003:453). Organisational psychologists have noted that older workers attach more importance to receiving help and assistance on the job (e.g., Hall and Mansfield 1975 in Venkatesh *et al.* 2003:453). This is further highlighted in the context of harder or more complex ICT and IS tasks given the increasing cognitive and physical limitations associated with age. These arguments are in line with empirical evidence from Morris and Venkatesh (2000) and thus, when moderated by experience and age, facilitating conditions will have a significant influence on usage behaviour (Venkatesh *et al.,* 2003:453).

The authors (Venkatesh *et al.*) hence postulated that the influence of facilitating conditions on usage will be moderated by age and experience, such that the effect will be stronger for older workers, particularly with increasing experience (Venkatesh *et al.*, 2003:455).

3.3.9.5 Behavioural Intention (BI)

Behavioural intention (BI) refers to the intention of an individual to use a technology. The view of Venkatesh *et al* (2003:456) on behavioural intention is consistent with the underlying theory for all previous intention models discussed in this chapter, and expects that behavioural intention will have a significant positive influence on technology usage.

3.3.9.6 Use Behaviour (UB)

The UTAUT ultimately theorises that behavioural intention and facilitating conditions predict use behaviour. However, this seems to be the least investigated and therefore least understood construct in user acceptance models. Legris *et al.*'s (2001:196) critical review of TAM found only eleven (11) out of twenty two (22) studies where use behaviour was measured. Most studies measure use through self-reporting, while only one (1) study measured use by an automatic measuring tool, such as in Venkatesh *et al.'s* (2003) study, where system logs were used to automatically measure use. Taiwo and Downe's (2013:48) meta-analysis of thirty seven (37) UTAUT studies confirms that the correlation between Behavioural Intention and Use Behaviour (BI-UB) were only reported from thirteen (13) studies.

3.4 Seminal Studies Using the UTAUT Model

Taiwo and Downe (2013:48) state that UTAUT 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. According to Taiwo and

Downe (2013:48), because of the complexity of human behaviour in social sciences, the issue of variety in statistical significance is common and therefore, mixed results in different studies are not unusual. It does, however undermine the accuracy of the models, including the UTAUT model. The objective of their study was to investigate the validity of UTAUT and reveal how much this validity is substantiated in present literature. To do this, the authors provide a meta-analysis of thirty seven (37) empirical studies that have made use of the UTAUT model highlighting those that have validated the model and those that have found differences. Table 3.1 below summarises sixteen (16) of the thirty seven (37) case studies in Taiwo and Downe's (2013) literature review.

Table 3.1: Summary of How the Validity of UTAUT is Substantiated in Present Literature [Source: Taiwo and Downe (2013:49–51)].

Authors	**Study**	**Findings**	**Supports UTAUT?**
AlAwadhi and Morris (2008).	Adoption of e-government services using UTAUT, the survey was carried out on 880 students.	Performance expectancy, effort expectancy and peer influence determine students' behavioural intention. Facilitating conditions and behavioural intentions determine students' use of e-government services.	Yes.
Biemans, Swaak, Hettinga and Schuurman (2005).	Used the UTAUT model to examine nurses' behavioural intentions towards the use of Medical Teleconferencing Application.	The study revealed that performance expectancy and effort expectation are high predictors of behavioural intention but social influence prediction power is low.	Yes.
Oshlyansky,Cairns and Thimbleby (2007).	Cross cultural study of IT adoption	Found that performance expectancy, effort expectancy and social influence predicts use intention.	Yes.
Šumak, Polančič and Heričko (2010).	Predicting the use of an e-learning system.	Found that social influence has a significant impact on students behavioural intention to use Moodle and students' behavioural intentions is a powerful predictor of the use.	Yes.
Cheng, Liu, Song and Qian (2008).	Investigated the validity of UTAUT using 313 intended users of Internet banking in China.	The results suggest that performance expectancy and social influence are strong predictors of behavioural intention.	Yes.

Authors	**Study**	**Findings**	**Supports UTAUT?**
Cheng, Liu, and Qian (2008).	Investigated the validity of UTAUT for users of Internet banking in China.	Found performance expectancy and social influence as predictors of users' behavioural intention towards internet banking. Found that effort expectancy does not predict customers' intention to use internet banking.	Yes and No.
Fang, Li, and Liu (2008).	Predicting managers' intention to engage in knowledge sharing using Web 2.0.	Findings suggest that performance expectancy, effort expectancy and social influence significantly predict use.	Yes.
Maldonado, Khan, Moon and Rho (2009).	Examined the acceptance of an e-learning technology in secondary school in Peru, 240 Students took part in the survey.	Results from their study suggest that social influence significantly predicts the behavioural intention. In the same study, Maldonado *et al.* (2009) found behavioural intention to significantly predict use behaviour. Found facilitating conditions to be non- significant in predicting use behaviour.	Yes and No.
Carlsson, Carlsson and Hyvönen (2006).	Examined the acceptance of mobile telephones.	Found that performance expectancy, effort expectancy and social influence are predictors of behavioural intention.	Yes.
Also, Wu, Tao and Yang (200.7)	Investigated the acceptance of 3G services in Taiwan.	Found performance expectancy and social influence as predictors of behavioural intention. Also found performance expectancy, effort expectation, social influence and facilitating conditions as predictors of use behaviour.	Yes.
He and Lu (2007).	Predicting consumer's acceptances of mobile advertising.	Findings suggest that performance expectancy and social influence are predictors of behavioural intention The authors also found that facilitating condition and behavioural intention predicts use behaviour.	Yes.

Authors	Study	Findings	Supports UTAUT?
Li and Kishore (2006).	Studied the use of online community weblog systems.	Results indicated that scales for the four constructs in UTAUT, including performance expectancy, effort expectancy, social influence, and facilitating conditions, have invariant true scores across most but not all subgroups.	No, the authors expressed the need for caution when interpreting UTAUT.
Tibenderana and Ogao (2008).	Studied a structured PLS-Graph Conceptual Model predicting the intention to use electronic Library services in Ugandan Universities.	Found performance expectancy and social influence to be non-significant in predicting behavioural intention to use.	No
Heerink, Kröse, Wielinga and Evers (2009).	Investigating the acceptance of an interface robot and a screen agent by elderly users.	Performance expectancy, effort expectancy and social influence were found to be non-significant in predicting intention.	No
Šumak, Polančič and Heričko (2010).	Students behavioural intention to use Moodle	Social influence is a significant predictor of behavioural intentions. Suggested that performance expectancy and effort expectancy are non-significant predictors of behavioural intention.	Yes and No
Schaupp, Carter and Hobbs (2009).	In the context of e-Government, investigated the acceptance of eFiling by the American tax payers.	Results from the study suggest that performance expectancy and social influence predicts behavioural intention. Interestingly, the study revealed that effort expectancy is not a predictor of behavioural intention.	Yes and No

According to Taiwo and Downe (2013:51), the inconsistency in the results of the above studies on UTAUT leaves the output of the relationships in the model inconclusive; however, on the basis of the meta-analysis study their findings confirm Venkatesh *et al.* (2003) initial findings between the five (5) 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.

3.5 Summary

The purpose of this chapter is to review literature and influential studies on concepts and theoretical models that may be used to predict the level of psychological acceptance of e-learning at the University of Zululand. User acceptance was defined as "the demonstrable willingness within a user group to employ information technology for the tasks it is designed to support" (Dillon and Morris, 1996) and predicting acceptance requires the review of psychology based theories from the social psychology setting. These theories include the original TRA by Fishbein and Ajzen (1975, 1980); the TAM by Davis (1986) and the TPB by Ajzen (1985, 1991). Researchers (Dillon and Morris, 1996) noted that these potentially overlapping theories seem to exist independently of each other and there was scope for a unifying framework to extend innovation diffusion concepts and systems design models into a formal theory of user acceptance of technology. Venkatesh *et al.* (2003) subsequently formulated a unified model, (UTAUT), through the review and consolidation of the constructs of eight models that earlier research had employed to explain IS usage behaviour. Due to the complexity of human behaviour in different contextual settings, the issue of variety in statistical significance is common in social sciences, however, it does to an extent undermine the accuracy of the models, including the UTAUT model. A meta-analysis of influential studies using UTAUT confirms Venkatesh *et al*.'s (2003) initial findings between the five (5) constructs of UTAUT, however only the relationship between performance expectancy and behavioural intention has been shown to be strong, while others although weak, are still significant. Although user acceptance has received widespread attention in international research, little attention has been given to the topic in South Africa, especially in different technologies, user populations and/or institutional contexts.

Chapter 4: METHODOLOGY AND METHODS

4.1 Introduction

The main purpose of this chapter was to clearly differentiate between the methodology and methods selected for the study. The chapter includes information on the research design, the population of the study, the sample and sampling procedures, the data collection procedure, the techniques employed to ensure reliable and valid data; research questions; data analysis; and possible ethical issues related to the study.

Mouton (2009:22) acknowledges a powerful metaphor of science as being the house of science (positivism), which, like a building, needs to be built on solid foundations. The author explains that the foundations of this science were usually built from irrefutable factual statements, which are easier to verify than theoretical statements, or the bricks of the building, which may have to be replaced from time to time when cracks (in theories) develop. This interpretation views science as a phenomenon that progresses over time as the structure becomes more firmly cemented (Mouton, 2009:22).

However the works of Galileo Galilei (1564–1642) and Francis Bacon (1561–1626) both rejected the Aristotelian view that all knowledge started with a general known proposition (Moses and Knutsen, 2012:19–21). Bacon argued that traditional scientists who engaged in deductive studies were unable to produce new knowledge (Moses and Knutsen, 2012:22). While both Galileo and Bacon agreed that systematic observation could generate new knowledge (induction), Bacon also observed that human senses could not always be trusted, and that the world might not always be as it is perceived to be (Moses and Knutsen, 2012:23).

According to Barbie (2013:21), inductive and deductive thinking both play a role in our daily lives, as they do too within social research. Barbie (2013:21–22) explains that induction moves from the particular to the general, whereas deductive reasoning moves from the general to the specific. The author states that deduction moves from a pattern that might be logically or theoretically expected, to observations that test whether the expected pattern actually occurs - deduction begins with "why" and moves to "whether", which is the opposite direction to inductive reasoning (see Figure 4.1).

This study used deductive reasoning and the Unified Theory of Acceptance and Use of Technology (UTAUT) model in its attempt to explain the use of e-learning at the University of Zululand.

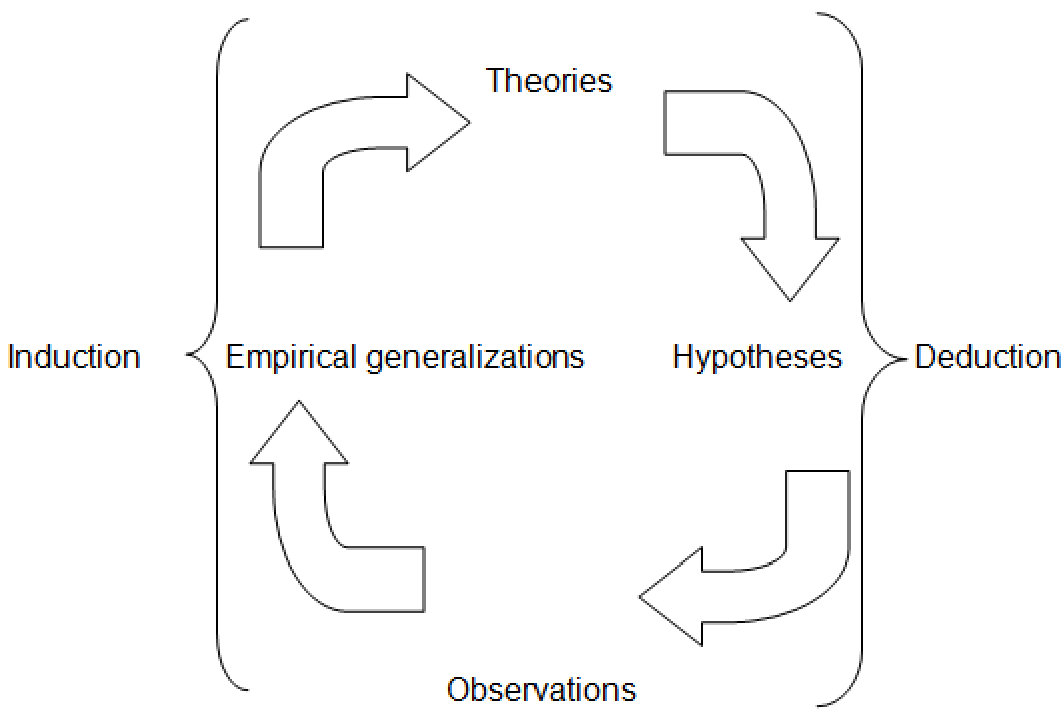

Figure 4.1: The Wheel of Science [Source: Adapted from Wallace (1971) in Barbie (2013:22)].

Mouton (2009:76) gives the following examples of inductive and deductive arguments that illustrate their difference:

Deductive: All mammals have hearts.
All horses are mammals.
All horses have hearts.

Inductive: Horse 1 - was observed to have a heart.
Horse 2 - was observed to have a heart.
Horse 3 - was observed to have a heart.
Horse n - was observed to have a heart.
All horses have hearts.

The philosopher, Karl Popper, levied two objections against logical positivism: one criticizing inductivism, and the other rejecting the verification theory. He gave the example of European observations that swans were always white, and how this inference would be falsified if any European tourist went to Australia and saw their indigenous black swan (Moses and Knutsen, 2012:23). He argued that scientific theories grow in an evolutionary way (Mouton, 2009:15). In 1962, Kuhn formulated an alternative to the positivist view and suggested people view scientific knowledge as sets of paradigms, which dictate the research agenda of the time, by defining legitimate scientific problems and more importantly, what constitute acceptable solutions to such problems. Thus, as research frameworks are faced with problems that they cannot solve, they will be replaced by another framework or paradigm (Mouton, 2009:15).

For most of the twentieth century, social scientists have adopted the view of the natural sciences (naturalism methodology), which assumes that the Real World exists independently of our experiences and that we can gain access to that world by thinking, observing and recording our experiences carefully (Moses and Knutsen, 2012:8). Despite this naturalist view dominating modern science, many social scientists were critical of this methodology, because many of their studies were seen to be dependent on human activity, and hence their adoption of the constructivism methodology, which recognises the important role of the observer and society in constructing the patterns we study (Moses and Knutsen, 2012:9). The authors explain that the constructivist methodology is known by a number of names, the most common being 'interpretivism'.

According to Bhattacherjee (2012:1), science refers to a logical and organised body of knowledge in any area of study that is learnt using "the scientific method". Bhattacherjee (2012:2) refers to scientific knowledge as a generalised body of laws and theories used to explain a phenomenon or behaviour of interest that are acquired using the scientific method, while laws are observed patterns of phenomena or behaviours, and theories are logical explanations of the underlying phenomenon or behaviour. The author distinguishes between natural science as being the study of naturally occurring objects or phenomena, such as organic or inorganic matter, earth, stars, or the human body and social science as the science of people, communities, their economies, and their individual or collective behaviour. Bhattacherjee (2012:1) explains that scientific method refers to a standardised set of techniques for building scientific knowledge, for example how to make valid observations, how to interpret results, and how to generalise those results. Scientific method allows researchers to independently, and without bias, test pre-existing theories and previous findings, and subject them to open discussion, variations, or improvements and therefore these methods must satisfy four key characteristics (Bhattacherjee, 2012:1):

1. Replicability: "Others should be able to independently replicate or repeat a scientific study and obtain similar, if not identical, results".
2. Precision: "Theoretical concepts, which are often hard to measure, must be defined with such precision that others can use those definitions to measure those concepts and test that theory".
3. Falsifiability: "A theory must be stated in a way that it can be disproven. Theories that cannot be tested or falsified are not scientific theories and any such knowledge is not scientific knowledge. A theory that is

specified in imprecise terms or whose concepts are not accurately measurable cannot be tested, and is therefore not scientific. Sigmund Freud's ideas on psychoanalysis fall into this category and is therefore not considered a "theory", even though psychoanalysis may have practical utility in treating certain types of ailments".

4. Parsimony: "When there are multiple explanations of a phenomenon, scientists must always accept the simplest or logically most economical explanation. This concept is called parsimony or "Occam's razor." Parsimony prevents scientists from pursuing overly complex or outlandish theories with endless number of concepts and relationships that may explain a bit of everything but nothing in particular".

McGregor and Murnane (2010:419) explain that a paradigm is a set of assumptions, concepts, values, and practices that establishes a way of looking at reality and although the three main sciences (natural, social and human) accept this basic view, the actual paradigm embraced by each scientific discipline is often different. Each paradigm goes with attendant methodologies and the authors warn that the intellectual integrity, trustworthiness and diversity of studies depends on researchers accounting for the methodological (philosophical) foundations of their work, not only the methods used to sample, collect and analyze data and report the results (McGregor and Murnane, 2010:419). According to Gephart (2004:455), the connection between theory and methodology is important and researchers need to use methodologies that are consistent with the assumptions and aims of the theoretical view or paradigm being articulated. Methodology refers to how logic, reality, values and what amounts to knowledge inform research, while methods are the practices and procedures followed to conduct research, and are determined by the methodology (McGregor and Murnane, 2010:420).

Willis (2007:22) reasons that in the social sciences there are a number of general frameworks for doing research and the terms qualitative and quantitative are often used to describe two of these frameworks, which wrongly imply that the main difference between the different frameworks is the type of data collected, for example numbers or interviews. The author warns that the differences are much broader and deeper than the type of data and actually involve assumptions and beliefs on several different levels, from philosophical positions about the nature of the world and how humans can better understand it, to assumptions about the proper relationships between social science research and professional practice. Willis (2007:23) believes that the terms such as world view and paradigm better capture the nature of the differences between different approaches to social science research, and the most popular paradigms today are positivism or post-positivism, interpretivism (constructivism), and critical theory. Urbach and Ahlemann (2010:9) report that Information Systems (IS) research is characterised by a number of different philosophical positions and researchers are free to decide on a philosophical position, however this should not be an uninformed decision as it has a substantial impact on the research design and the nature of the findings that the researcher can obtain in their study.

Orlikowski and Baroudi (1991:5) state that the foundations of positivist studies exist from earlier fixed relationships within occurrences or phenomenon, which are typically investigated with structured instrumentation, and such studies serve mostly to test theory, in an attempt to increase predictive understanding of these occurrences. The authors' criteria, that they adopted in classifying studies as positivist, were evidence of formal propositions, quantifiable measures of variables, hypotheses testing, and the drawing of conclusions about an occurrence from the sample to a stated population. Orlikowski and Baroudi (1991:5) state that "descriptive" studies are an exception to this where researchers attempted no theoretical grounding or interpretation of the occurrences, rather, they presented what they believed to be straightforward "objective", "factual", accounts of events to explain some issue of interest to the community. The authors state that "descriptive" articles typically included case studies, with or without simple descriptive statistics (frequencies and percentages) (Orlikowski and Baroudi, 1991:5).

Orlikowski and Baroudi (1991:5) on the other hand explained that interpretive studies (constructivism) assume that people create and associate their own subjective and inter-subjective meanings as they interact with the world and the people around them. The authors explain that constructive (interpretive) researchers thus attempt to understand occurrences through accessing the meanings that participants assign to them, thus constructive (interpretive) studies reject the possibility of an "objective" or "factual" account of events and situations, seeking instead a relativistic, although shared, understanding of occurrences. Orlikowski and Baroudi (1991:5) note that generalisation from the setting or sample to a population is not pursued, rather, the aim is to understand the deeper structure of a phenomenon or occurrence, which it is believed can then be used to inform other settings. The criteria the authors adopted in classifying interpretive studies were evidence of a non-deterministic perspective, where the aim of the research was to increase understanding of the occurrence within cultural and contextual situations, where the occurrence of interest was examined in its natural setting and from the perspective of the participants, and where researchers did not impose their earlier understanding on the situation as outsiders.

According to Orlikowski and Baroudi (1991:5–6), critical studies, on the other hand, aim to critique the existing state of affairs, through the exposure of what are believed to be entrenched, structural contradictions within social environments, and thereby alter these alienating and limiting social conditions. The criteria that the authors adopted in classifying critical studies were evidence of a critical stance towards assumptions about organisations and information systems, and an opposition analysis, which attempted to reveal the historical, conceptual, and contradictory nature of existing social practices (Orlikowski and Baroudi, 1991:5–6).

Dwivedi et al. (2008) analysed three hundred and forty-five (345) Information Systems' research articles on technology adoption, acceptance and diffusion published in nineteen high-ranking peer-reviewed IS journals from 1985 to 2007, and found that positivism was clearly the dominant epistemology used in two hundred and twenty-five (225) or seventy-five percent (75%) of the studies with descriptive / conceptual / theoretical studies comprising a further twenty-seven (27) studies or nine percent (9%).

Urbach and Ahlemann (2010:9) cite the work of Orlikowski and Baroudi (1991) and Dubé and Paré (2003) to provide a set of characteristics that classifies research as positivist:

- Ontologically, positivist research adopts an objective, physical, and social world that exists independently of humans. Furthermore, the nature of this world can be relatively easily held, characterised, and measured.
- The researcher plays a passive, neutral role and does not interfere in the phenomenon of interest.
- Epistemologically, the positivist standpoint is concerned with the empirical testability of theories. In other words, these theories are either confirmed or rejected.
- They are premised on the existence of past fixed relationships within phenomena that can be identified and tested through hypothetico-deductive logic and analysis.
- The relationship between theory and practice is seen as primarily technical.

Moses and Knutsen (2012:22) state that naturalist researchers observe the world, collect empirical evidence, then analyse and order it so that they are able to reveal and collect knowledge of the regularities of the world, thereby seeking to account for individual events in the past and to predict events in the future. This understanding of how to uncover the truths of the world has resulted in a fixed hierarchy of scientific methods (see Figure 4.2), founded in the inductive procedures and experimental designs of Galileo and Bacon (Moses and Knutsen, 2012:22).

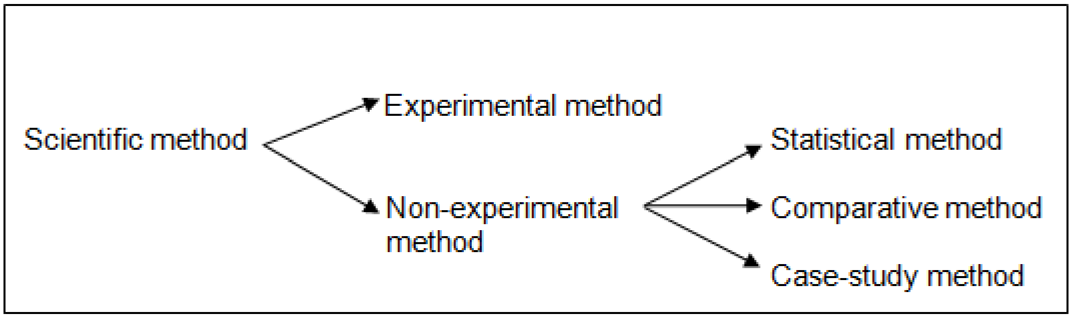

Figure 4.2: The Hierarchy of Methods in the Naturalist Tradition [Source: Lijiphart (1975) in Moses and Knutsen (2012:50)].

Moses and Knutsen (2012:50) explain that the experimental method is considered ideal for the natural sciences because of its ability to control and order causal and temporal relationships, while the other methods are less suitable in this regard. When experiments are not feasible (not practical, affordable or ethical), naturalist and social scientists fall back on the second-best approach: the statistical method, which tries to emulate the basic design of experiments (Moses and Knutsen, 2012:50). However, if there is a lack of data and the statistical method becomes unpractical, then the comparative method is used for smaller samples, while at the bottom of the hierarchy is the case-study method, used by researchers when faced with a scarcity of data (Moses and Knutsen, 2012:50).

There are two main ways in which statistical methods are used by scholars in the naturalist tradition: descriptive and inferential (Moses and Knutsen, 2012:70). According to the authors, descriptive statistics are the most frequently used to supplement narratives and illustrate claims and can also be used by the constructivist scholar, however, inferential statistics extend the inductive enterprise to infer about characteristics of a population, in order to generate predictions, provide explanations and test hypotheses (Moses and Knutsen, 2012:71). Both will be utilised in this study, the descriptive statistics to report the biographical data and survey responses, and inferential statistics to predict the level of acceptance of e-learning by academic staff and students.

Mouton (2009:36) refers to the term research methods as the means to execute a certain stage of the research and gives the following classification:

- Methods of definition: theoretical and operational definitions.
- Sampling methods: probability and non-probability methods.
- Measurement methods: scales, questionnaires and observation schedules.
- Data-collection methods: participant observation, interviewing, systematic observation, survey and unobtrusive measurement.
- Data analysis methods: statistical methods, mathematical methods and qualitative methods.

Urbach and Ahlemann (2010:9) believe that in contrast with the position adopted by the interpretive and critical philosophies, positivist researchers can empirically evaluate or predict activities or practices, but cannot deliver moral judgments or subjective opinions on them. This research study will mostly follow a positivist epistemological approach/belief. The study applies deductive reasoning by starting with the known UTAUT theory, expressing null and alternative hypotheses based on it, and then either rejecting the null in favour of the alternative or not rejecting the null based on the empirical observations of the study. A non-experimental statistical method will be used to analyse the quantitative data.

According to Taylor (2013), hypothesis testing involves the attentive construction of two statements: the null hypothesis and the alternative hypothesis. The null hypothesis is what the study is attempting to reject by a hypothesis test, i.e. the study hopes to obtain a small enough p-value that can justify rejecting the null hypothesis (Taylor, 2013). The alternative hypothesis is a statement of what a statistical hypothesis test is set up to establish (Easton and McColl, 2013). The final conclusion, once the test has been carried out, must always be given in terms of the null hypothesis, i.e. either "reject the null in favour of the alternative" or "do not reject the null", never conclude by “accepting the null”, "rejecting the alternative", or even "accepting the alternative" (Easton and McColl, 2013). If the researcher concludes "do not reject the null", this does not necessarily mean that the null hypothesis is true, it only suggests that there is not sufficient evidence against the null in favour of the alternative - rejecting the null hypothesis then, suggests that the alternative hypothesis may be true (Easton and McColl, 2013).

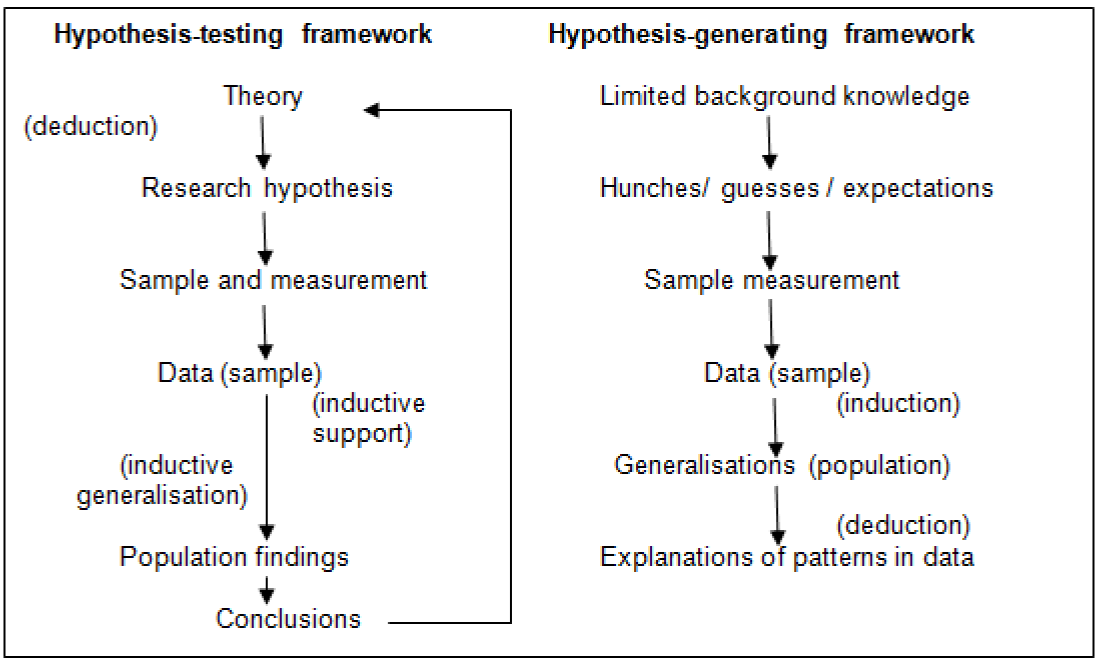

Figure 4.3: The Difference between Hypothesis-Testing and Hypothesis-Generating Studies [Source: Mouton (2009:82)].

Table 4.1 below summarises the hypothesis testing errors and according to Easton and McColl (2013) a type I Error is often considered to be more serious, and therefore more important to try avoiding, than a type II Error. The hypothesis test procedure is therefore adjusted ($\alpha = 0.05$ or 0.01) so that there is an assured 'low' probability of rejecting the null hypothesis wrongly; this probability is however never 0. This probability of a type I Error can be precisely computed as

P (type I Error) = significance level = α (Easton and McColl, 2013). If P < α, then this determines a practical significance.

Table 4.1: Hypothesis Testing Errors Summarised - Adapted from Kumar (2011:88)

H_0 True?		H_0 Rejected?	
		Yes	No
Yes	Probability	Type I Error α	Correct Result $1 - \alpha$
No	Probability	Correct Result $1 - \beta$	Type II Error β

The exact probability of a type II Error is generally unknown. If the researcher does not reject the null hypothesis, it may still be false (a type II Error) because the sample may not be big enough to identify the falseness of the null hypothesis (Easton and McColl, 2013).

According to Easton and McColl (2013), a test statistic is a quantity calculated from our sample of data, and its value is used to decide whether or not the null hypothesis should be rejected in the hypothesis test. The authors explain that the choice of a test statistic will depend on the assumed probability model and the hypotheses under question. Hair *et al.* (2010:442) state that the test or *t* statistic assesses the statistical significance between two groups for a single dependent variable.

According to Easton and McColl (2013), the critical value(s) for a hypothesis test is a threshold to which the value of the test statistic in a sample is compared to determine whether or not the null hypothesis is rejected. Easton and McColl (2013) state the critical region, or rejection region, is a set of values of the test statistic for which the null hypothesis is rejected in a hypothesis test, i.e., the sample space for the test statistic is partitioned into two regions; one region (the critical region) will lead us to reject the null hypothesis H_0 ("Reject H_0"), the other will not ("Do not reject H_0").

According to Easton and McColl (2013), the significance level of a statistical hypothesis test is a fixed probability of wrongly rejecting the null hypothesis H_0, if it is in fact true. Therefore, the probability of a type I error is set by the researcher in relation to the consequences of such an error – in social sciences for example, significance levels are normally set at five percent (5%), whereas in medical studies, they are set at one percent (1%) because of the more serious consequences involved in such studies. Easton and McColl (2013) recommend that researchers make the significance level as small as possible in order to protect the null hypothesis and to prevent, as far as possible, the researcher from inadvertently making false claims. For this study, the significance level is chosen to be 0.05 (or equivalently, 5%), i.e. Significance Level = P (type I Error) = α = 0.05

Easton and McColl (2013) state that the probability value (p-value) of a statistical hypothesis test is the probability of getting a value of the test statistic as extreme as, or more extreme than, that observed by chance alone, if the null hypothesis H_0, is true, i.e. it is the probability of wrongly rejecting the null hypothesis when it is in fact true (Easton and McColl, 2013). The p-value is compared with the actual significance level of the study and the result is significant if it is smaller, i.e. for this study the null hypothesis will be rejected if "$p < 0.05$" (Easton and McColl, 2013). The smaller the p-values, the more convincing is the rejection of the null hypothesis - indicating the strength of evidence for say, rejecting the null hypothesis H_0, rather than simply concluding that "Reject H_0' or "Do not reject H_0" (Easton and McColl, 2013).

Easton and McColl (2013) state that the power of a statistical hypothesis test measures the test's ability to make the right decision and reject the null hypothesis when it is actually false, i.e., the power of a hypothesis test is the probability of not committing a type II error and is calculated by subtracting the probability of a type II error from 1, usually expressed as: Power = 1 – P (type II error) = 1 – β. According to Hair *et al.* (2010:442), power is determined as a function of the statistical significance level (α), the sample size used in the study, and the effect size being examined. The authors elaborate that the effect size is calculated as the difference in group means, divided by the standard deviation and is comparable across studies as a generalised measure of effect (i.e. difference in group means) (Hair *et al.,* 2010:441). The maximum power a test can have is 1, the minimum is 0. Ideally, a researcher wants a test to have a power close to 1 (Easton and McColl, 2013).

Easton and McColl (2013) state that a one-sided test is a statistical hypothesis test that rejects the null hypothesis, if the values H_0 are located completely in one tail of the probability distribution, i.e. the critical region for a one-sided test is the set of values less than the critical value of the test, or the set of values greater than the critical value of the test. A one-sided test is also referred to as a one-tailed test of significance (Easton and McColl, 2013), while a two-sided /tailed test is a statistical hypothesis test in which the values for which we can reject the null hypothesis, H_0, are located in both tails of the probability distribution, i.e. the critical region for a two-sided test is the set of values less than a first critical value of the test and the set of values greater than a second critical value of the test (Easton and McColl, 2013), which is applicable for this study.

From a working null hypothesis approach, the research hypotheses are expressed below:

> **H_{01}:** UTAUT will not account for any percent of variance (adjusted R^2) in students' behavioural intention to use e-learning resources.
>
> **H_{02}:** UTAUT will not account for any percent of variance (adjusted R^2) in academic staff's behavioural intention to use e-learning resources.
>
> **H_{03}:** UTAUT will not account for any percent of variance (adjusted R^2) in students' use of e-learning resources.

H_{04}: UTAUT will not account for any percent of variance (adjusted R^2) in academic staff's use of e-learning resources.

H_{05}: Performance expectancy will not have a significant relationship on students' behavioural intention to use e-learning resources.

H_{06}: Performance expectancy will not have a significant relationship on academic staff's behavioural intention to use e-learning resources.

H_{07}: Effort expectancy will not have a significant relationship on students' behavioural intention to use e-learning resources.

H_{08}: Effort expectancy will not have a significant relationship on academic staff's behavioural intention to use e-learning resources.

H_{09}: Social influence will not have a significant relationship on students' behavioural intention to use e-learning resources.

H_{010}: Social influence will not have a significant relationship on academic staff's behavioural intention to use e-learning resources.

H_{011}: Facilitating conditions will not have a significant relationship on students' use of e-learning resources.

H_{012}: Facilitating conditions will not have a significant relationship on academic staff's use of e-learning resources.

H_{013}: Behavioural intention will not have a significant relationship on students' use of e-learning resources.

H_{014}: Behavioural intention will not have a significant relationship on academic staff's use of e-learning resources.

H_{015}: The effect of performance expectancy on behavioural intention of students 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.

H_{016}: 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.

H_{017}: The effect of social influence on behavioural intention of students 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.

H_{018}: 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.

H_{019}: The effect of effort expectancy on behavioural intention of students 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.

H_{020}: 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.

H_{021}: The effect of facilitating conditions on students' 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.

H_{022}: 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.

The alternate hypotheses are listed below:

H_{a1}: UTAUT will account for some percent of variance (adjusted R^2) in students' behavioural intention to use e-learning resources.

H_{a2}: UTAUT will account for some percent of variance (adjusted R^2) in academic staff's behavioural intention to use e-learning resources.

H_{a3}: UTAUT will account for some percent of variance (adjusted R^2) in students' use of e-learning resources.

H_{a4}: UTAUT will account for some percent of variance (adjusted R^2) in academic staff's use of e-learning resources.

H_{a5}: Performance expectancy will have a significant relationship on students' behavioural intention to use e-learning resources.

H_{a6}: Performance expectancy will have a significant relationship on academic staff's behavioural intention to use e-learning resources.

H_{a7}: Effort expectancy will have a significant relationship on students' behavioural intention to use e-learning resources.

H_{a8}: Effort expectancy will have a significant relationship on academic staff's behavioural intention to use e-learning resources.

H_{a9}: Social influence will have a significant relationship on students' behavioural intention to use e-learning resources.

H_{a10}: Social influence will have a significant relationship on academic staff's behavioural intention to use e-learning resources.

H_{a11}: Facilitating conditions will have a significant relationship on students' use of e-learning resources.

H_{a12}: Facilitating conditions will have a significant relationship on academic staff's use of e-learning resources.

H_{a13}: Behavioural intention will have a significant relationship on students' use of e-learning resources.

Ha_{14}: Behavioural intention will have a significant relationship on academic staff's use of e-learning resources.

H_{a15}: The effect of performance expectancy on behavioural intention of students to use e-learning resources will be moderated by (a) gender and (b) age, such that the effect will be stronger for men and particularly for younger men.

H_{a16}: The effect of performance expectancy on behavioural intention of academic staff to use e-learning resources will be moderated by (a) gender and (b) age, such that the effect will be stronger for men and particularly for younger men.

H_{a17}: The effect of social influence on behavioural intention of students to use e-learning resources will be moderated by (a) gender, (b) age, and (c) experience, such that the effect will be stronger for women, particularly older women, in the early stages of experience.

H_{a18}: The effect of social influence on behavioural intention of academic staff to use e-learning resources will be moderated by (a) gender, (b) age, and (c) experience, such that the effect will be stronger for women, particularly older women, in the early stages of experience.

H_{a19}: The effect of effort expectancy on behavioural intention of students to use e-learning resources will be moderated by (a) gender, (b) age and (c) experience, such that the effect will be stronger for women, particularly for younger women, and particularly at early stages of experience.

H_{a20}: The effect of effort expectancy on behavioural intention of academic staff to use e-learning resources will be moderated by (a) gender, (b) age and (c) experience, such that the effect will be stronger for women, particularly for younger women, and particularly at early stages of experience.

H_{a21}: The effect of facilitating conditions on students' usage of e-learning resources will be moderated by (a) age and (b) experience, such that the effect will be stronger for older users, particularly in the early stages of experience.

H_{a22}: The effect of facilitating conditions on academic staff's usage of e-learning resources will be moderated by (a) age and (b) experience, such that the effect will be stronger for older users, particularly in the early stages of experience.

For the sake of parsimony (Bhattacherjee, 2012:1), the moderation of voluntariness of use on the social influence to use e-learning, will not be hypothesised on in this study as the use of e-learning at the University of Zululand can be seen as both compulsory (structured lectures) and voluntary (using resources after hours) at the same time.

4.2 Research Design

The purpose of a research design is to plan and structure the study in such a way that maximises the validity of its findings, by either minimising, or, if possible removing any potential error (Mouton, 2009:108). Mouton (2009:109) stresses that validity is an epistemic criterion, which means that it is a quality of all the elements (data, hypotheses, theories and methods) of knowledge and research (conceptualisation, operationalisation, sampling, data collection and its analysis and interpretation). Kumar (2011:94) views a research design as a procedural plan adopted by the researcher to answer the research questions validly, objectively, accurately and economically.

The three primary research designs which emerged from Orlikowski and Baroudi's (1991:4) analysis of one hundred and fifty-five (155) Information Systems (IS) research articles are case studies (14%), laboratory experiments (27%) and surveys (49%) and these three designs account for almost ninety percent (90%) of these articles. Dwivedi et al. (2008) clearly found survey research to be the dominant research design (173, 58%) and will also be used to achieve the objectives of this study.

4.3 Populations of the Study

For the purpose of the study, there are two target populations who will represent the primary users of e-learning resources at the University of Zululand. The first target population includes the three hundred and ten (310) academics stratified by their positions of contract lecturer, junior lecturer, lecturer, senior lecturer, associate professor and professor (Microsoft Office Corporation, 2013) that have email addresses on the institution's email server's address book. The second population is confined to three thousand three hundred and fifty-six (3 356) students (University of Zululand registration website, 2013) stratified by their faculty and academic level who are registered for scheduled classes in the main computer laboratories at the University of Zululand in 2013. The following rationales for targeting these populations are listed below:

1. All academics at the university have ICT resources in their offices, and / or departments, which support the adoption of e-learning. The sample frame of the population can easily be determined and targeted because all academics have known contact details.
2. Although all students have access to the computer laboratories outside of the official timetabled classes (open time), and can use the limited resources (1:23 - student to computer ratio), it was decided to target those students who were involved in formal e-learning classes (clusters) timetabled in the main computer laboratories, rather than the whole student population, because, although all students have recently received email accounts, not all have activated them, therefore administering the questionnaire randomly to sixteen thousand five hundred and eighty-two (16 582) students (University of Zululand registration website, 2013) was unfeasible.

4.4 Sampling

According to Mouton (2009:110), the aim of the researcher's sampling design is to get a sample that is as representative as possible of the target population of the study. Bias, heterogeneous populations and incomplete sampling frames are all sources of sampling errors in the validity framework of research, which can only be minimised through probability sampling, stratification and an optimal sample size (Mouton, 2009:111). Babbie (2013:134) states that although probability samples obtained using Equal Probability Selection Methods (EPSEM), like Simple Random Sampling (SRS) or systematic sampling, from a list, never perfectly represents the population, they typically are more representative than non-probability samples obtained from convenience, purposive or quota sampling and can help avoid bias. Stratification is not an alternative to SRS, systematic and cluster sampling methods, but a possible modification to ensure that the sample is spread over population subgroups for obtaining a greater degree of representativeness by reducing the probable sampling error (Babbie, 2009:150). Cluster sampling is appropriate when it is impractical to compile a list of the elements making up the target population (Babbie, 2009:153). In this study, it became difficult to compile a list of e-learners so clusters of learners, within modules timetabled in the main computer laboratories were randomly selected (probability proportionate to size) after they were stratified according to the faculty they belonged to and the academic level of the module. Babbie (2009:157) explains that whenever clusters sampled are of differing sizes (different seat sizes within computer laboratories), it is appropriate to use Probability Proportionate to Size (PPS), which gives each cluster a chance of selection proportionate to its size.

The target population is firstly stratified by their role (academic staff or student) in the learning environment and then individually sampled using the most appropriate types and combinations of probability sampling. The academic staff target population's sample frame was obtained from staff email addresses stratified according to staff positions (contract lecturer, junior lecturer, lecturer, senior lecturer, associate professor and professor) at the institution and then selected using SRS (with replacement) and PPS formulas (see Table 5.2 page 127) to provide the desired academic staff sample size of one hundred and fifty (150). Stratified cluster sampling of the student target population was used to overcome the impracticality of creating and administering a questionnaire to an accurate e-learner sample frame at the institution. Stratification of modules timetabled in the main computer laboratories will occur according to one: the four faculties which the modules fall under and two: the academic level of the modules within each faculty programme. Again a SRS (with replacement) and a PPS sample design was used to select the different clusters to obtain the desired student sample size of 300 participants and above. No SRS will occur within the selected clusters. Students who are enrolled in more than one of the classes surveyed were instructed not to complete the survey more than once by the survey administrator. Replication of the study using different respondents from different faculties and in the case of the academic staff and students, at different positions and levels of study respectively, will improve the study's external validity or its ability to generalise to the university's populations (Trochim, 2002).

According to Hair *et al.* (2010:94), factor analysis is an interdependence technique used to define the underlying structure among variables in the analysis, which are the building blocks of relationships. The authors recommend that the sample size should not be fewer than 50 but preferably 100 or larger. Hair *et al.* (2010:10), however, caution against samples that are too large because at any given alpha (α) level, increasing the sample size always produces greater power for the statistical test and by having a very large sample size, smaller and smaller effects will become statistically significant. According to Chin (1997) Partial Least Squares (PLS) can be a powerful method of analysis for a number of reasons including its minimal demands on sample size. Guidelines suggested by Chin (1997), is a sample size equal to the larger of two possibilities: one, ten times the scale with the largest number of formative (i.e., causal) indicators, which equates to ten times the five (students and academic staff) indicators of performance expectancy and gives a minimum sample of fifty (50) student and fifty (50) academic staff participants, or two, ten times the largest number of precursor constructs used to determine a dependent variable, or ten times three (30), the number of constructs (performance expectancy, effort expectancy and social influence) used to determine behaviour intent. Although a minimal sample size can give results, Urbach and Ahlemann (2010:17) warn that the situation can be more complicated. They give the example where small sample sizes (e.g., $n = 20$) do not allow the discovery or validation of structural paths with small coefficients (Chin and Newsted, 1999 in Urbach and Ahlemann, 2010) and in such cases, sample sizes are required that are similar to those necessary for covariance-based approaches where samples should be greater than hundred and fifty (n > 150). Taking this into account, the study recognises the possible limitations of the minimum sample sizes (insensitive) and very large sample sizes (overly sensitive) (Hair *et al.*, 2010:10) and, where possible, aims to obtain the minimum recommended sample size from one hundred and fifty (150) academic staff and three hundred (300) students to provide a statistically strong sample size with the correct balance in power.

4.5 Operationalisation and Survey Instruments

According to Barbie (2013:71), in order to test a hypothesis, the researcher must specify the meanings of all the variables involved, in observational terms, while operationalisation literally means specifying the exact operations involved in measuring a variable. It has been noted that the statements used in the scale or questionnaire must be unambiguous and mutually exclusive and that scales must meet the criterion of unidimensionality, which means a single scale cannot be used to measure more than one aspect of a phenomenon (Mouton, 2009:110).

A survey of academic staff and students at the University of Zululand was conducted using three self-administrated questionnaires. Two online questionnaires (one for students and one for academic staff, see Appendix B) and an additional paper version (for lectures, accompanied by a letter requesting participation, see Appendix A) were used as the instruments to measure the key variables of the two target populations of the study. Multi-mode questionnaires for academic staff were administered in their internal post boxes to increase the response rate and allow those who are uncomfortable with web surveys a chance to respond on a paper questionnaire. The questionnaire indicators for most the constructs (performance expectancy, effort expectancy, social influence, facilitating conditions and behavioural intention) were adapted from Venkatesh *et al.* (2003, 2010) validated studies and slightly modified to include the term e-learning, while indicators for measuring the use construct were customised to the contextual use of e-learning by the two target populations at the University of Zululand. 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 participant's responses to key UTAUT variables. According to D. Venter (personal communication, 25 May 2011), the 5 point scale is advised over the seven point scale found in Venkatesh *et al.* (2003, 2010) studies, when participants find it hard to distinguish between terms in the larger scales, for example between disagree and somewhat disagree and agree and somewhat agree in the 7 point scale: strongly disagree, disagree, somewhat disagree, neutral, somewhat agree, agree, strongly agree. The questionnaires will also contain biographic questions.

A pilot test was administered to a small sample of both staff and students to evaluate the survey instrument and to obtain feedback on the instrument's quality. Data was coded in Microsoft Excel and then imported into SmartPLS (Ringle *et al.,* 2004), to get a feeling for the content validity of the instrument. After the pilot, three (3) use indicators were added to allow the self-measure of use behaviour of e-learning by participants and one indicator statement with low loadings for effort expectancy was removed and three (3) social influences were removed and replaced respectively to improve content validity.

4.6 Construct's Indicator Statements

According to Urbach and Ahlemann (2010:6) the Information System (IS) discipline examines socio-economic systems that are characterised by the interaction between technology (hardware and software) on the one hand, and people and institutions on the other. The authors give the example of technology adoption, acceptance, and success, as well as the conditions under which these can be achieved as being the typical issues that are addressed by this research.

They purport that these research fields are similar in that their investigation requires the researcher to cope with constructs such as the beliefs, perceptions, motivation, attitude, or judgments of the individuals involved. The authors explain that these constructs are usually modelled as latent variables (LVs) that can be measured only through a set of indicators or statements that relate to the construct. The questions used in this study are only slightly modified versions of questions used consistently in prominent research publications dealing with user acceptance models (e.g. Venkatesh *et al.*, 2003, 2010).

Survey participants were asked to indicate their response to each statement using a five item Likert scale with one (1) representing a strong disagreement and five (5) being a strong agreement with the statement.

4.6.1 Performance Expectancy (PE)

Performance Expectancy (PE) is defined as the degree to which an individual believes that using e-learning resources will help him or her to achieve gains in teaching or learning performance at the University. PE was measured using five (5) questions for students and five (5) questions for academic staff. Studies have suggested that this construct may have a gender and age bias (Venkatesh *et al.*, 2003), i.e. they determined that the effect PE was moderated by age and gender such that it was more important to younger males in particular. Thus, we expect the influence of PE to be moderated by both gender and age in the study.

4.6.1.1. Student Performance Expectancy (PE) Questions

1. Using e-learning resources in my studies enables me to complete academic tasks more quickly.
2. Using e-learning resources in my studies increases my academic productivity.
3. Using e-learning resources makes my studies easier.
4. Using e-learning resources in my studies is useful.
5. Using e-learning resources in my studies increases my marks.

4.6.1.2. Academic Staff Performance Expectancy (PE) Questions

1. Using e-learning resources enables me to complete academic tasks more quickly.
2. Using e-learning resources increases my academic productivity.
3. Using e-learning resources makes my work easier.
4. Using e-learning resources is useful.
5. Using e-learning resources increases the quality of my work.

4.6.2 Effort Expectancy (EE)

Effort Expectancy (EE) is defined as the degree of ease associated with the use of e-learning resources at the University. This construct was measured by asking four (4) questions based on the widespread literature set (e.g. Venkatesh *et al.*, 2003, 2010). Venkatesh *et al.* (2003) postulated that the influence of EE on behavioural intention will be moderated by gender, age, and experience, such that the effect will be stronger for women, particularly younger women, and particularly at early stages of experience (Venkatesh *et al.*; 2003:450).

4.6.2.1. Student Effort Expectancy (EE) Questions

1. Using e-learning resources is easy for me.
2. I find the use of e-learning resources in my studies understandable.
3. It is easy for me to become skillful at using e-learning resources in my studies.
4. I would find it easy to do what I want to do when using e-learning resources.

4.6.2.2. Academic Staff Effort Expectancy (EE) Questions

1. Using e-learning resources is easy for me.
2. I find the use of e-learning resources understandable.

3. It is easy for me to become skillful at using e-learning resources.
4. I would find it easy to do what I want to do when using e-learning resources.

4.6.3 Social Influence (SI)

Social Influence (SI) is defined as the degree to which an individual perceives that important people believe he or she should use e-learning resources at the University. Research has shown that SI is less important within voluntary contexts, however this construct becomes more significant in mandated environments, for example where it becomes policy to use e-learning resources. However, research has shown that SI is significant only in the early stages of adoption (Venkatesh *et al.*, 2003:452). According to Venkatesh *et al.* (2003:452), the role of SI in technology acceptance decisions is complex and subject to a wide range of dependent influences. Researchers theorise that SI has an impact on an individual's behaviour through three mechanisms namely: compliance, internalisation, and identification (see Venkatesh and Davis 2000:188; Warshaw 1980:157; Venkatesh *et al.* 2003:453). The authors explain that while the latter two relate to altering an individual's belief structure and / or causing an individual to respond to potential social status gains, the compliance mechanism causes an individual to simply alter his or her intention in response to the social pressure, i.e., the individual intends to comply with the social influence.

The SI construct was measured using four (4) questions for students and four (4) questions for academic staff.

4.6.3.1. Student Social Influence (SI) Questions

1. People who influence my behaviour think that I should use e-learning resources.
2. People who are important to me think that I should use e-learning resources.
3. People whose opinions I value promote the use of e-learning resources.

4. I use e-learning resources because of the influence of other students.

4.6.3.2. Academic Staff Social Influence (SI) Questions

1. People who influence my behaviour think that I should use e-learning resources.
2. People who are important to me think that I should use e-learning resources.
3. People whose opinions I value promote the use of e-learning resources.
4. I use e-learning resources because of the influence of my colleagues.

4.6.4 Facilitating Conditions (FC)

Facilitating Conditions (FC) are defined as the degree to which an individual believes that an organisational and technical infrastructure exists to support use of e-learning resources at the University of Zululand. Venkatesh *et al.* (2003) postulate that when the performance expectancy constructs and effort expectancy constructs are both present, FC becomes insignificant in predicting intention, i.e. FC will not have a significant influence on behavioural intention (Venkatesh *et al.*, 2003:455).

The authors also hypothesise that the influence of FC on usage will be moderated by age and experience, such that the effect will be stronger for older workers, particularly with increasing experience (Venkatesh *et al.*, 2003:454-5). The FC construct was measured using five (5) questions for students and five (5) questions for academic staff.

4.6.4.1. Student Facilitating Conditions (FC) Questions

1. I have the necessary resources to use e-learning.
2. I have the necessary knowledge to use e-learning resources.
3. I have the necessary support to use e-learning resources.
4. The use of e-learning resources fits my learning style (visual verbal learner).

5. I can get help from others when I have difficulties using e-learning resources.

4.6.4.2. Academic Staff Facilitating Conditions (FC) Questions

1. I have the necessary resources to use e-learning.
2. I have the necessary knowledge to use e-learning resources.
3. I have the necessary support to use e-learning resources.
4. Using e-learning fits my teaching pedagogy.
5. I can get help from others when I have difficulties using e-learning resources.

4.6.5 Behavioural Intention (BI)

Venkatesh *et al.* (2003) state that consistent with the underlying theory for all technology acceptance models incorporated into the UTAUT is that it is expected that Behavioural Intention (BI) will have a significant positive influence on technology usage. BI was measured using five (5) questions for students and five (5) questions for academic staff.

4.6.5.1. Student Behavioural Intention (BI) Questions

1. Whenever possible, I intend to use e-learning resources.
2. I perceive using e-learning resources as natural for me.
3. I plan to continue to use e-learning resources.
4. To the extent possible, I would use e-learning resources to learn.
5. To the extent possible, I would frequently use e-learning resources.

4.6.5.2. Academic Staff Behavioural Intention (BI) Questions

1. Whenever possible, I intend to use e-learning resources.
2. I perceive using e-learning resources as natural for me.
3. I plan to continue to use e-learning resources.
4. To the extent possible, I would use e-learning resources to teach.

5. To the extent possible, I would frequently use e-learning resources.

4.6.6 Use Behaviour (UB)

Use Behaviour (UB) was measured by asking participants to complete three (3) statements by filing in their usage frequency (never use, almost never use, sometimes use, often use or always use).

4.6.6.1 Student Use Behaviour (UB) Questions

1. I _______ e-learning resources during my formal lectures.
2. I _______ e-learning resources for academic tasks during open time in the computer labs.
3. I _______ e-learning resources in my residence.

4.6.6.2 Academic Staff Use Behaviour (UB) Questions

1. I _______ e-learning resources for communication and administration in my office.
2. I _______ e-learning resources during my lectures.
3. I _______ e-learning resources for research in my office

4.7 Survey and Data Collection Procedure

Static, one shot, cross-sectional studies are clearly the predominant form of research in information systems (account for 90% of the articles), while longitudinal and multiple time period studies account for only five and four percent (5% and 4%) of 155 information systems research articles, respectively (Orlikowski and Baroudi, 1990:6). This study used the more common static approach to collect the data. The online academic staff and student questionnaires were designed and hosted on www.stellarsurvey.com's website. Randomly sampled academic staff were emailed a unique online link (allowing for response tracking) to the definitions, preamble and questionnaire, while the hosting website captured participants' responses that were submitted through their web browsers. Paper questionnaires were placed in the internal post boxes for academic staff who have not immediately responded to the email request and follow ups via email and phone calls will try determine sampled participants willingness to respond or not on the different media. To administer the survey to the student sample academic staff from randomly selected modules, were asked for their permission to administer the questionnaire to their students during timetabled lectures. The fundamental ethical principles of research were observed by including a preamble for each e-questionnaire informing the respondent of the intentions of the study and assuring confidentiality of their responses (Council of American Survey Research Organisations, 2008). The three questionnaires each contained structured response formats for the close-ended questions that will provide the quantitative data. Survey participants were asked to indicate their response to each indicator statement using a five item Likert scale with one (1) representing a strong disagreement and five (5) being a strong agreement with the statement. Once the required sample sizes have been met and the academic staff paper questionnaires have been manually captured onto the hosting websites database, data was exported from www.stellarsurvey.com in a Comma Separated Value (CSV) file format. Data will then be imported in SmartPLS (Ringle *et al.,* 2004) for the data analysis.

Urbach and Ahlemann (2010:17) recommend that before starting with the model validation, the quality of empirical data collected needs to be established (Lewis *et al.* 2005 in Urbach and Ahlemann, 2010:17). The authors explain that although surveys with lower response rates do not necessarily give less accurate results than surveys with higher response rates (Visser *et al.* 1996 in Urbach and Ahlemann, 2010:17), high response rates, however usually reflect a study's thoroughness in the eyes of promoters, examiners, and readers (Van der Stede *et al.* 2005 in Urbach and Ahlemann, 2010:17). Follow-ups can effectively improve response rates and help bring the more respondents into the study

(Dillman 2008; Van der Stede *et al.* 2005 in Urbach and Ahlemann, 2010:17), which this study anticipates with the academic staff target population. Urbach and Ahlemann (2010:17) also mention that the researcher should check for non-response bias, which generally occurs when some of the target respondents do not participate in the survey and, thus, cause an unreliable representation of the randomly selected sample. The authors state that it is therefore necessary to address the issue of non-response before, during, and after data collection (King and He 2005; Van der Stede *et al.* 2005 in Urbach and Ahlemann, 2010:17). To minimise non-response before and during the data collection, Rogelberg and Stanton (2007 in Urbach and Ahlemann, 2010:17) recommend, among others, the pre-notification of participants and sending out reminder notes, while after the data collection, non-response bias can be assessed by verifying that the responses of early and late respondents are not considerably different. Urbach and Ahlemann, (2010:17) also recommend the search for outliers to analyse whether they can be regarded as acceptable cases or not. After collecting data Hair *et al* (2010:33) warn that data examination is an important initial step, where researchers evaluate the impact of missing data, identify outliers, and test the assumptions underlying most multivariate techniques. The study will not follow formalised methods of diagnosing the randomness of missing data but will simply delete offending case(s) with excessive levels of missing data (Hair *et al.* 2010:48). Other random less offensive omissions were coded -999 and the imputation method in SmartPLS (Ringle *et al.,* 2004), which is the process of estimating the missing value based on valid values of other cases in the sample (Hair *et al.* 2010:50), can either be:

- Complete Case Approach - the simplest and most direct approach for dealing with missing data is to include only those observations with complete data (Hair *et al.* 2010:51). However the authors warn that it comes with two distinct disadvantages. Firstly it is most affected by any non-random missing data processes, because cases with missing data are deleted from the analysis, and thus though only valid observations are used, the results are not generalisable to the population. Secondly, this approach results in the greatest reduction of sample size – thus, even though it is suited for instances in which the extent of missing data is small, the sample is large enough to allow for the deletion of cases with missing data, and the relationships in the data are strong enough as not to be affected by any missing data processes (Hair *et al.* 2010:51).

- Mean Substitution - the most widely used methods of imputation by using replacement values because it is easily implemented and provides all cases with complete information (Hair *et al.* 2010:53). The authors warn that although it is used a lot, it does have several disadvantages. Firstly, it understates the variance estimates by using the mean for the missing data; secondly, the actual distribution of the values is distorted by substituting the mean for the missing values, and thirdly, this method depresses the observed correlation because all missing data will have a single constant value (Hair *et al.* 2010:53).

Once the data was collected, mean substitution was chosen based on its qualities and the data characteristics like sample sizes and the extent of missing data.

4.8 Method of Data Analysis

The purpose of this research is to analyse causal relationships between variables in the UTAUT model and e-learning at the University of Zululand. 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 (similar to multiple regression equations), while also enabling multiple measures for each concept (similar to factor analysis).

Hair *et al.* (2010:627) explain that there are a number of statistical models, algorithms and software programmes available to estimate and explain the relationships among multiple variables based on a dataset. SEM techniques such as LISREL and PLS are second generation multivariate analysis techniques (Bagozzi and Fornell, 1982 in Gefen *et al.* 2000:3 and Fornell, 1987 in Urbach and Ahlemann, 2010:9) and differ from first-generation techniques, such as factor analysis, discriminant analysis, or multiple regressions, because SEM allows the researcher to concurrently consider relationships among multiple independent (exogenous) and dependent (endogenous) variables (Urbach and Ahlemann, 2010:9). Thus, SEM answers a set of interconnected research questions in a single, methodical, and complete analysis (Gefen *et al.* 2000:3). According to Urbach and Ahlemann (2010:9), an additional advantage of a SEM is that it supports Latent Variables (LVs), or "hypothetical constructs invented by a scientist for the purpose of understanding a research area" (Bentler 1980:420 in Urbach and Ahlemann, 2010:9). Urbach and Ahlemann (2010:9) explain that since LVs are unobservable and cannot be directly measured, researchers use observable and measurable indicator variables - also referred to as manifest variables - to approximate LVs in the theoretical model. Thus, the relationships can be analysed between theoretical variables, such as behavioural intentions, perceptions, satisfaction, or performance gains, which are important to almost every discipline. Consequently, the use of LVs has the potential to model theoretical constructs that are hard, or not possible to measure directly (Urbach and Ahlemann, 2010:9-10).

According to Urbach and Ahlemann (2010:10), a SEM consists of a combination of the different inner and outer sub-models. The structural model or inner model encompasses the relationships between the LVs, which has to be found in theory. The independent LVs (performance expectancy, effort expectancy, social influence, and facilitating conditions in UTAUT model) are also referred to as exogenous variables and the dependent LVs (behavioural intention and usage behaviour in UTAUT model) as endogenous variables. For each of the LVs within the SEM, a measurement model or 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) state that the outer measurement model also needs to be developed on a supporting theory, which in this case is the UTAUT proposed by .

Urbach and Ahlemann (2010:10) explain that the combination of structural and measurement models leads to a complete SEM. The SEM for the UTAUT model is illustrated in Figure 4.4 below.

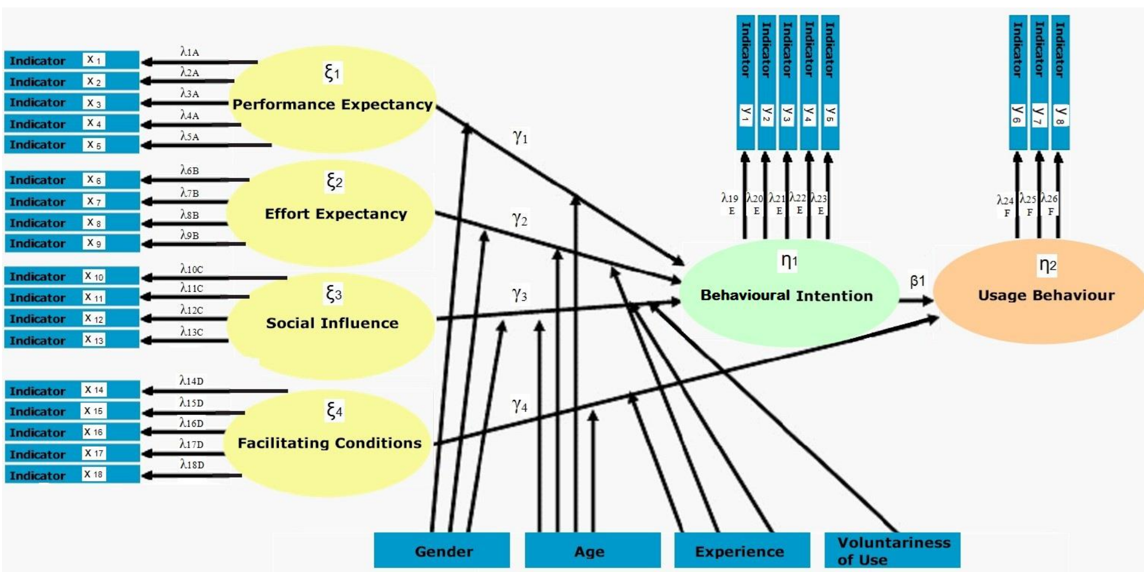

Figure 4.4: Complete Structural Equation Model for UTAUT Model

It consists of four (4) exogenous or independent variables (ξ_i) and two (2) endogenous or dependent variables (η_i). The LVs are operationalised through the measurable indicator variables x_i (i=19) and y_i (i=8). The relationships between the variables are measured by path coefficients. The path coefficients λ_i (i=27) within the measurement models are either determined by weights—for formative constructs—or loadings—for reflective constructs. The path coefficients between latent dependent variables are labeled β_i (i=1), whereas the path coefficients between independent and dependent variables are referred to γ_i (i=4).

Urbach and Ahlemann (2010:12) explain that there are presently two common approaches to SEM: one, Covariance-Based Structural Equation Modeling (CBSEM), as implemented for example in Linear Structural Relationship (LISREL) and two, the component-based Partial Least Square (PLS) approach. PLS originated in the social sciences, specifically economics by Herman Wold (1966 in Abdi, 2007:1) but became popular first in chemometrics (i.e., computational chemistry) due in part to Herman's son Svante, (Wold, 2001 in Abdi, 2007:1). Hair *et al.* (2010:775) state that PLS has become increasingly popular as an alternative to SEM (e.g. LISREL) and has been recently adopted in research in business, education and social sciences. The authors explain that although the structural model might look identical, there are substantive differences in terms of developing, estimating and interpreting a proposed model (Hair *et al.,* 2010:775). The authors state that at the core of the differences between PLS and SEM techniques are the fundamental objectives of each – PLS statistically produces parameter estimates that maximise explained variance and thus focus much more on prediction; SEM in contrast, tries to reproduce the observed covariation among measures, which makes it better suited towards finding out how well a given theory (represented by SEM model), explains the study's observations (Hair *et al.,* 2010:776). Hair *et al,* (2010:776) give the following advantages of PLS:

1. Robustness – it will provide a solution even when problems exist that may prevent a solution in SEM (poor measurement). In PLS, all recursive models are identified (do not exhibit statistical identification problems), even single item measures. Thus, whereas validating one- or two- item measures in the context of measurement theory has very little meaning with SEM, PLS is uninhibited by such concerns.
2. PLS handles both formative (measured variable cause the construct) and reflective (latent constructs cause the measured variables) constructs, while there are perceived difficulties in formative model specification in SEM. PLS does not face the model complexity that SEM does, and

therefore it is able to handle large numbers of measured variables and / or constructs easily.

3. PLS is insensitive to sample size considerations and its estimation approach handles both very small (as low as 30 observations) and large samples more easily than does SEM.

PLS regression is the statistical data analysis method used for the study results made available through specialised statistical software – SmartPLS (Ringle *et al.,* 2004).

4.9 Ensuring Validity and Reliability of Data

After data quality has been evaluated, the PLS regression algorithm is run to calculate the UTAUT model parameter's estimates. Statistical output was analysed according to recommendations by Urbach and Ahlemann (2010) and Hair *et al* (2011) for model validation, which represents the process of systematically evaluating whether the hypotheses expressed by the structural model are supported by the data or not. Urbach and Ahlemann (2010) state that although 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 one, the assessment of the measurement models and two, the assessment of the structural model (Urbach and Ahlemann, 2010:18).

4.9.1 The Measurement Model

A reflective measurement model is used in this study (latent variables cause the measured variables) and thus most of the validation guidelines suggested by Straub *et al.* (2004) and Lewis *et al.* (2005) in Urbach and Ahlemann (2010:18), Hair *et al* (2011) and Hair *et al.* (2014) was followed, namely: testing the reflective measurement models for internal consistency reliability, indicator reliability, convergent validity, and discriminant validity by applying standard rules mentioned below.

According to Gerbing and Anderson (1988), in Urbach and Ahlemann (2010:18), unidimensionality refers to an LV having each of its measurement items relate to it better than to any others, and because it cannot be directly measured with PLS, the study will rely on theory and past empirical studies' validation of measurement items adopted. Exploratory Factor Analysis (EFA) is needed to determine unidimensionality, and Urbach and Ahlemann (2010:18) explain that EFA's objective is to determine whether the measurement items converge to the corresponding constructs (factors), whether each item loads with a high coefficient on only one factor, and that this factor is the same for all items that are supposed to measure it. The authors state that the number of selected factors is determined by the numbers of factors with an Eigenvalue exceeding 1.0, and an item loading is usually considered high if the loading coefficient is above .600, and low if the coefficient is below .400 (Gefen and Straub 2005 in Urbach and Ahlemann, 2010:18).

Trochim (2006) states that in research, the term reliability means "repeatability" or "consistency". Urbach and Ahlemann (2010:18) report that the traditional criterion for assessing internal consistency reliability is Cronbach's Alpha (CA), whereas a high alpha value assumes that the scores of all items with one construct have the same range and meaning (Cronbach 1951 in Urbach and Ahlemann, 2010:18). The authors state that an alternative measure to Cronbach's Alpha is the Composite Reliability (CR) (Werts *et al.* 1974 in Urbach and Ahlemann, 2010:18), which Chin (1998b) in Urbach and Ahlemann (2010:18) recommend as superior because of CR overcoming some of CA's deficiencies of severely underestimating the internal consistency reliability of LVs in PLS structural equation models. CR takes into account that indicators have different loadings (Henseler *et al.* 2009 in Urbach and Ahlemann, 2010:18). Urbach and Ahlemann (2010:18) recommend that regardless of which coefficient is used for assessing internal consistency, values above .700 are desirable, whereas values below .600 indicate a lack of reliability (Nunnally and Bernstein 1994 in Urbach and Ahlemann, 2010:18). However, levels above .950 "are more suspect than those in the middle alpha ranges" (Straub *et al.* 2004:401 in Urbach and Ahlemann, 2010:18), indicating potential common method bias.

Urbach and Ahlemann (2010:18) explain that indicator reliability describes the extent to which a variable, or set of variables is consistent regarding what it intends to measure. The authors state that the reliability of one construct is independent of, and calculated separately from that of, other constructs by monitoring their reflective indicators' loadings to assess indicator reliability (Urbach and Ahlemann, 2010:18). Generally, it is postulated that an LV should explain at least 50 percent of each indicator's variance. Accordingly, indicator loadings should be significant at least at the .050 level and greater than .707 ($\approx \sqrt{.500}$) (Chin 1998b in Urbach and Ahlemann, 2010:18). The significance of the indicator loadings can be tested using resampling methods, such as bootstrapping (Efron 1979; Efron and Tibshirani 1993 in Urbach and Ahlemann, 2010:18) or jackknifing (Miller 1974 in Urbach and Ahlemann, 2010:18). Urbach and Ahlemann (2010:18–19) state that there may be various reasons why these requirements are not fulfilled, including:

1. The item is simply unreliable.
2. The item may be influenced by additional factors, such as a method effect (Podsakoff et al. 2003 in Urbach and Ahlemann, 2010:18–19).
3. The construct itself is multidimensional in character and thus items are capturing different issues (Chin 1998b in Urbach and Ahlemann, 2010:18–19).

In any of these cases, the measurement model needs to be adjusted by removing the offending indicators and rerunning the PLS algorithm in order to obtain revised results (Urbach and Ahlemann, 2010:19).

Construct validity refers to the degree which a variable measures what it was intended to measure (Trochin, 2006). To assure construct validity, correlations between similar construct indicator statements should show convergent validity (high correlation value), and correlations between different construct indicator statements should show discriminant validity (low correlation value) (Trochim, 2002). Urbach and Ahlemann (2010:19) define convergent validity as the degree to which individual items reflecting a construct converge in comparison to items measuring different constructs. The authors state that the Average Variance Extracted (AVE) proposed by Fornell and Larcker (1981), in Urbach and Ahlemann (2010:19), is the criterion usually applied to confirm convergent validity and an AVE value of at least .500 indicates that an LV is on average able to explain more than half of the variance of its indicators and, thus, demonstrates sufficient convergent validity (Urbach and Ahlemann, 2010:19).

Urbach and Ahlemann (2010:19) explain that discriminant validity concerns the degree to which the measures of different constructs differ from one another. The authors state that whereas convergent validity tests whether a particular item measures the construct it is supposed to measure, discriminant validity tests whether the items do not unintentionally measure something else (Urbach and Ahlemann, 2010:19). According to the authors, there are two commonly used measures of discriminant validity in SEM using PLS:

1. Cross-loading: Cross-loadings are obtained by correlating each LV’s component scores with all the other items (Chin 1998b in Urbach and Ahlemann, 2010:19). If each indicator’s loading is higher for its designated construct than for any of the other constructs, and each of the constructs loads highest with its assigned items, it can be inferred that the different constructs’ indicators are not exchangeable (Urbach and Ahlemann (2010:19).
2. Fornell-Larcker criterion: Fornell-Larcker criterion (Fornell and Larcker 1981) requires an LV to share more variance with its assigned indicators than with any other LV. Accordingly, the AVE of each LV should be greater than the LV’s highest squared correlation with any other LV (Urbach and Ahlemann (2010:19).

Table 4.2 below gives a clear summary of the validity and reliability criteria used for the assessment of the outer measurement model of the study.

Table 4.2: Assessment Criteria for the Measurement Models of the Study

Validity type	Criterion	Description	Literature
Internal consistency reliability	Composite Reliability (CR)	Attempts to measure the sum of an LV's factor loadings relative to the sum of the factor loadings plus error variance. Leads to values between 0 (completely unreliable) and 1 (perfectly reliable). Alternative to Cronbach's Alpha, allows indicators to not be equally weighted. Proposed threshold value for confirmative (explorative) research: CA > .800 or .900 (0.700). Values must not be lower than .600.	Werts *et al.* (1974), Nunally and Bernstein (1994) in Urbach and Ahlemann (2010:19)
Indicator reliability	Indicator loadings	Measures how much of the indicators variance is explained by the corresponding LV. Values should be significant at the .050 level and higher than .700. For exploratory research designs, lower thresholds are acceptable. The significance can be tested using bootstrapping or jackknifing.	Chin (1998b) in Urbach and Ahlemann (2010:19)
Convergent validity	Average Variance Extracted (AVE)	Attempts to measure the amount of variance that an LV component captures from its indicators relative to the amount due to measurement error. Proposed threshold value: AVE > 0.500.	Fornell and Larcker (1981) in Urbach and Ahlemann (2010:19)
Discriminant validity	Cross-loadings	Cross-loadings are obtained by correlating the component scores of each latent variable with all other items. If the loading of each indicator is higher for its designated construct than for any of the other constructs, and each of the constructs loads highest with its own items, it can be inferred that the models' constructs differ sufficiently from one another.	Chin (1998b) in Urbach and Ahlemann (2010:19)
Discriminant validity	Fornell-Larcker criterion	Requires an LV to share more variance with its assigned indicators than with any other LV. Accordingly, the AVE of each LV should be greater than the LV's highest squared correlation with any other LV.	Fornell and Larcker (1981) in Urbach and Ahlemann (2010:19)

4.9.2 The Structural Model

According to Urbach and Ahlemann (2010:21), once the reflective measurement models have been successfully validated, the structural model can then be analysed. Firstly, assess the structural model for collinearity, secondly, measure the significance and relevance of the path coefficients, thirdly, evaluate each endogenous LV's coefficient of determination (R^2), fourthly, calculate the effect sizes (f^2) and lastly determine the predictive relevance Q^2 and the q^2 effect sizes (Hair *et al.*, 2014:169).

Hair *et al.* (2014:123) explain that, unlike reflective indicators, which are basically interchangeable, high correlations are not expected between constructs in a formative measurement model or between formative independent constructs. According to Hair *et al.* (2014:170), collinearity issues can be assessed by looking for Variance Inflation Factor (VIF) values above five (5) and tolerance values below 0.20. This assessment was done in IBM SPSS Statistics.

Hair *et al.* (2014:169) recommend that the structural model's next assessment encompasses the evaluation of the path coefficients between the model's LVs, which checks the path coefficient's algebraic sign, magnitude, and significance. The authors explain that paths, whose signs are different to the theoretically expected relationship, do not support the pre-postulated hypotheses, while a path coefficient's magnitude indicates the strength of the relationship between two LVs (Urbach and Ahlemann, 2010:21). Some authors contend that path coefficients should exceed .100 to account for a certain effect within the model (e.g., Huber *et al.* 2007 in Urbach and Ahlemann, 2010:21) and path coefficients should be significant at least at the .050 level (Urbach and Ahlemann, 2010:21). Significance can be determined by resampling techniques such as bootstrapping (Efron 1979; Efron and Tibshirani 1993 in Urbach and Ahlemann, 2010:21), which compares the means of the coefficients in the bootstrap sample with the original means using a one-tailed t-test. The critical t-statistic for a two tailed t-test, at a significance level of five percent (5 %), and sample size of eighty (80) is 1.99. Any null hypothesis will not be rejected if the associated t-statistic is less than 1.99 for academic staff. The critical t-statistic for a one tailed t-test at a significance level of five percent (5 %), and sample size of over one hundred (100), is 1.96. Any null hypothesis will not be rejected if the associated t-statistic is less than 1.96 for students.

The coefficient of determination (R^2) measures the relationship of an LV's explained variance to its total variance (Urbach and Ahlemann, 2010:21). Urbach and Ahlemann (2010:21) recommend that the values should be high enough for the model to demonstrate a minimum level of explanatory power. Chin (1998b), in Urbach and Ahlemann (2010:21) considers values of approximately .670 substantial, values around .333 average, and values of .190 and lower, weak.

Urbach and Ahlemann (2010:21) recommend Cohen's f^2 (Cohen 1988 in Urbach and Ahlemann, 2010:21) to calculate the effect size of each path in the structural equation model. Chin (1998b), in Urbach and Ahlemann (2010:21), explain that the effect size measures if an independent LV has a large effect on a dependent LV, and it is calculated as the increase in R^2 of the LV, to which the path is connected, relative to the LV's proportion of unexplained variance. Values for f^2 between .020 and .150, between .150 and .350, and exceeding .350, indicate that an exogenous LV has a small, medium, or large effect on an endogenous LV (Chin 1998b; Cohen 1988; Gefen *et al.* 2000 in Urbach and Ahlemann, 2010:21). When calculating the f^2 effect size the following formula was used:

$$f^2 = \frac{R^2 \text{ included} - R^2 \text{ excluded}}{1 - R^2 \text{ included}}$$

Lastly, the structural model's predictive relevance can be evaluated with a nonparametric Stone-Geisser test (Geisser 1975; Stone 1974 in Urbach and Ahlemann, 2010:21), which used a blindfolding procedure (e.g., Tenenhaus *et al.* 2005 in Urbach and Ahlemann, 2010:21) to create estimates of residual variances. Urbach and Ahlemann (2010:21) explain that by systematically assuming that a certain number of cases are missing from the sample, the model parameters are then estimated and used to predict the omitted values and Q^2 measures the extent to which this prediction is successful. Positive Q^2 values confirm the model's predictive relevance in respect of a particular construct and the better the tested model's predictive relevance, the greater Q^2 becomes (Fornell and Cha 1994 in Urbach and Ahlemann, 2010:21).

Table 4.3 below gives a clear summary of the validity criteria used for the assessment of the inner structural model of the study.

Table 4. 3: Assessment Criteria for the Structural Models of this Study

Validity type	Criterion	Description	Literature
Model validity	Coefficient of determination (R^2)	Attempts to measure the explained variance of an LV relative to its total variance. Values of approximately .670 are considered substantial, values around .333 moderate, and values around .190 weak.	Chin (1998b), Ringle (2004) in Urbach and Ahlemann (2010:21)
Model validity	Path coefficients	Path coefficients between the LVs should be analysed in terms of their algebraic sign, magnitude, and significance (T-test).	Huber *et al.* (2007) in Urbach and Ahlemann (2010:21)
Model validity	Effect size (f^2)	Measures if an independent LV has a substantial impact on a dependent LV. Values of .020, .150, .350 indicate the predictor variable's low, medium, or large effect in the structural model.	Cohen (1988), Chin (1998b), Ringle (2004) in Urbach and Ahlemann (2010:21)
Model validity Predictive	Model validity Predictive	The Q^2 statistic is a measure of the predictive relevance of a block of manifest variables. A tested model has more predictive relevance the higher Q^2 is, and modifications to a model may be evaluated by comparing the Q^2 values. The proposed threshold value is $Q^2 > 0$. The predictive relevance's relative impact can be assessed by means of the measure q^2.	Stone (1974), Geisser (1975), Fornell and Cha (1994) in Urbach and Ahlemann (2010:21)

4.10 Moderation

Hayes (2013:vii) explains that analytically questions of "how" are approached through a process called mediation analysis, while questions of "when" are normally answered through moderation analysis, and analytically combining the two, leads to what the author calls conditional process analysis. The study will make use of both SmartPLS (Ringle *et al.*, 2004) and PROCESS, designed by Hayes (2013), and installed as an add on in the regression tools of IBM SPSS Statistics, to analyse the hypothesized moderating effects of the UTAUT model.

4.11 Summary

The purpose of this chapter is to differentiate between the methodology and methods selected for the study, while the general aim of the chapter is to explain how the study was planned, and conducted, in order to allow for replication, and to determine the validity and reliability of the findings. This research will follow a positivist epistemological belief. The study applies deductive reasoning by beginning with the known UTAUT theory, expressing null and alternative hypotheses based on its theory, and then either rejecting the null, in favour of the alternative, or not rejecting the null, based on the empirical results of the study. A non-experimental statistical method was used to analyse the quantitative data, and inferential statistics was used to predict the level of acceptance of e-learning by academic staff and students, while descriptive statistics was used to report on the biographical data and survey responses. Survey research was used to achieve the objectives of this study. For the purpose of the study, there are two target populations (students and academic staff) who will represent the primary users of e-learning resources at the University of Zululand. Static probability sampling of the primary users made use of Probability Proportionate to Size (PPS) and Equal Probability Selection Methods (EPSEM), like Simple Random Sampling (SRS), to randomly and proportionally select academic staff, stratified according to their positions, and students stratified according to their faculty and academic year, from their sample frames (email address book and clusters of modules on the main computer laboratories timetable). A survey of academic staff and students at the University of Zululand was conducted using three self-administrated questionnaires. Two online questionnaires (one for students and one for academic staff) and an additional paper version (for academic staff) was used as the instruments to measure the key variables of the two target populations of study. The survey questions were mapped to 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). Survey participants were asked to indicate their response to each statement using a five item Likert scale, with one representing a strong disagreement and five being a strong agreement with the statement. Once the required sample sizes have been met, data was exported from www.stellarsurvey.com in a Comma Separated Value (.CSV) file format. Data will then be imported in

SmartPLS (Ringle *et al.,* 2004) for the data analysis. PLS regression is the statistical data analysis method used for the study results made available through specialised statistical software – SmartPLS (Ringle *et al.,* 2004). After data quality has been evaluated, the PLS regression algorithm is run to calculate the UTAUT model parameter's estimates. Statistical output was analysed according to recommendations by Urbach and Ahlemann (2010:18) for model validation, which represents the process of systematically evaluating whether the hypotheses expressed by the structural model are supported by the data or not. The authors state that although 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 models and (2) the assessment of the structural model (Urbach and Ahlemann, 2010:18).

Chapter 5: DATA ANALYSIS AND PRESENTATION OF RESULTS

5.1 Introduction

The purpose of this chapter is to present the results of the study. It begins by describing the sample sizes, and the biographical details of the student and academic staff who participated, together with the summative information and descriptive statistics of their survey responses. Thereafter, the regression analysis of the outer measurement model, and inner structural model of the UTAUT, are presented followed by the theorised moderating effects.

5.2 Sample Sizes

The total available student participant pool was six hundred and ninety-two (692) students who were enrolled in ten (10) modules that were randomly selected (probability proportionate to size) from the four faculties to participate in the study (University of Zululand registration website, 2013). Table 5.1 below shows the cluster sampling details and the stratification according to faculty and academic level of the randomly selected modules. Lecturers from the four faculties, whose modules were selected for the survey, were contacted in advance and permission was sought to administer the survey to their students during scheduled lecturing / revision time. All modules were administered in this manner, except for the hydrology module (SHYD312), whose class was not being held in the computer labs during the time of the survey. In this case, a link to the survey was posted on their course on the Moodle LMS, and messages were sent to all enrolled students asking for their participation. The student survey opened on 15th of October, 2013, and closed on the 22nd October, 2013, and a total of five hundred and eleven (511) responses were captured on the hosting website. Ninety (90) of these responses were incomplete and only contained the biographical information from page one of the questionnaire. This suggests that one, the respondent may have encountered network problems when wanting to proceed to the second page (most likely from respondent feedback), or two, the respondent simply did not fill in the second page. In both cases, these responses were disqualified and removed from the sample (1011759, 1011740, 1011708, 1011681, 1011249, 1011246, 1010563, 1010562, 1010010, 1010008, 1010007, 1010004, 1010003, 1010002, 1010001, 1010000, 1009999, 1009997, 1009996, 1009205, 1008986, 1008965, 1008961, 1008957, 1008955, 1008952, 1008951, 1008950, 1008949, 1008948, 1008947, 1008946, 1008943, 1008942, 1008941, 1008940, 1008939, 1008938, 1008937, 1008936, 1008935, 1008934, 1008933, 1008932, 1008931, 1008930, 1008929, 1008928, 1008927, 1008926, 1008925, 1008924, 1008923, 1008921, 1008920, 1008919, 1008917, 1008916, 1008915, 1008914, 1008913, 1008912, 1008911, 1008910, 1008909, 1008908, 1008907, 1008906, 1008905, 1008904, 1008903, 1008902, 1008901, 1008900, 1008891, 1008890, 1008889, 1008888, 1008887, 1008883, 1008881, 1008880, 1008879, 1008878, 1008877, 1008876, 1008874, 1008863, 1008857 and 1008851).

Table 5.1: The Stratification of Randomly Selected Clusters (module names and descriptions can be found in Appendix D) and Student Enrolment

Faculty of Arts		Faculty of Commerce, Administration and Law		Faculty of Education		Faculty of Science and Agriculture	
Module code	Enrolment	Module code	Enrolment	Module code	Enrolment	Module code	Enrolment
AINF132	96	**CBIS102	132	ESCL01B	134	*SCPS122	100
AINF242	25					SCPS212	54
ACOM342	21	CMIS302	24	EACA04B	40	SHYD312	66
Subtotal	**142**	Subtotal	**156**	Subtotal	**174**	Subtotal	**220**
Total	**692**						

* Module has students from all faculties enrolled.

** Module also has students from the Faculty of Education enrolled.

This left a sample size of four hundred and twenty-one (421), which equals a response rate of fifty-nine (59) percent. Responses were then filtered for those who had 4 or more non-random missing answers for the construct and moderator related questions on page two of the questionnaire. This resulted in sixteen (16) more cases (1011737, 1011691, 1011262, 1011253, 1011229, 1009660, 1009652, 1009630, 1009598, 1009594, 1009592, 1009576, 1009256, 1009007, 1008833 and 1008816) being removed from the sample, thus leaving a final student sample size of four hundred and five (405).

From the three hundred and ten (310) academic staff listed on the institutions email address book (sample frame), and stratified according to their positions (contract lecturers, junior lecturers, lecturers, senior lecturers, associate professor and professor) at the institution, one hundred and fifty (150) were selected using SRS (with replacement) and PPS formulas as summarised in Table 5.2 below.

Table 5.2: The Stratification According to Position of Academic Staff

Stratification according to position	Frequency on sample frame	Percentage proportionate to size (%)	Simple random sample frequency
Contract lecturers	31	10	15
Junior lecturers	31	10	15
Lecturers	178	58	87
Senior lecturers	44	14	21
Associate professor	13	4	6
Professor	13	4	6
Total	**310**	**100**	**150**

The academic staff survey opened on 23rd of October, 2013, and closed on the 14th of November, 2013. Four tracked emails (23rd October, 28th October, 4th November and 12th November) and a paper questionnaire placed in post boxes of staff who had not responded after the second email on the 31st October, elicited a total of ninety-eight (98) responses on the hosting website and five (5) paper questionnaires, giving a total of one hundred and three (103) responses. One of the paper questionnaires was blank with the respondent stating that their non-response was due to the fact that they had never used e-learning resources before; the remaining four (4) paper questionnaires' data was manually captured onto the hosting website's database. As in the case of the student responses, twenty-seven (27) of the online responses were incomplete and only contained the biographical information from page one of the questionnaire and were therefore excluded (1023275, 1022933, 1015025, 1015024, 1014971, 1014909, 1014908, 1014887, 1014886, 1014856, 1014854, 1014794, 1014780, 1014776, 1014775, 1012119, 1012113, 1012111, 1012102, 1012082, 1012081, 1012068, 1012062, 1012059, 1012058, 1012055 and 1012053) from the academic staff sample, leaving a total of seventy-five (75) participants. After delivering the paper questionnaires to the postal services, it was discovered that, due to the University's Staff email database not being regularly updated, four (4) staff members had left the institution, one (1) had retired and another had passed away, leaving a total possible participant pool of 144 and a response rate of fifty-two (52%). Responses were then filtered for those who had four (4) or more non-random missing answers for the construct and moderator related questions on page two of the questionnaire and two (2) more cases (1020281 and 1015710) were removed leaving a final academic staff sample size of seventy-three (73).

5.3 Biographical Information

5.3.1 Students

The majority of the student respondents were females (245; 60.5%), with the minority being males (160; 39.5%) as represented in Figure 5.1 below.

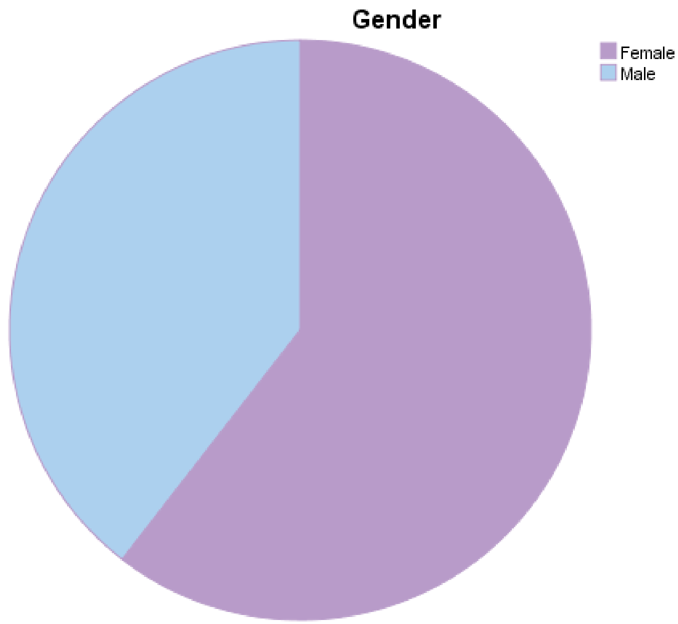

Figure 5.1 Gender Representation of Students

As seen from Table 5.3 below, most of student respondents were between the ages of eighteen (18) and twenty-three (70.1%), followed by the category twenty four to twenty nine (22.5%) and thirty to thirty five (5.9%). It was unexpected to find one student as young as sixteen (16) responding.

Table 5.3: Age Group Representation of Students

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Younger than 18	2	.5	.5	.5
	18-23	284	70.1	70.3	70.8
	24-29	91	22.5	22.5	93.3
	30-35	24	5.9	5.9	99.3
	36-41	2	.5	.5	99.8
	Older than 41	1	.2	.2	100.0
	Total	404	99.8	100.0	
Missing	(-999)	1	.2		
Total		405	100.0		

The average age of the student participants is twenty-three (23) years with a standard deviation of almost four (3.8) years.

Figure 5.2 below represents the academic level of the student sample, with the majority of participants being first year student (200; 49.4%), followed by second years (96; 23.7%), third years (79; 19.5%) and fourth years (29; 7.1%), and one (0.3%) post-graduate, whose presence in the survey was unexpected.

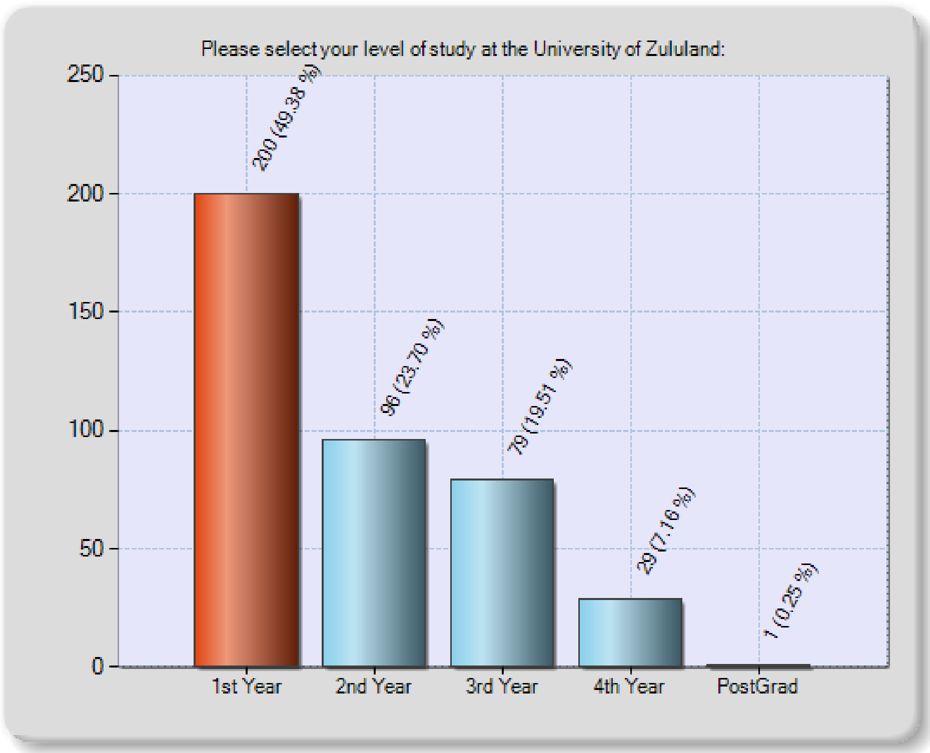

Figure 5.2: Academic Level of Students

Figure 5.3 below shows the stratification of respondents in the student sample according to the faculty of their study programmes, with the majority of participants (170; 42.0%) coming from the Faculty of Education, followed by Faculty of Arts (137; 33.8%), Faculty of Science and Agriculture (56; 13.8%), and lastly the Faculty of Commerce, Administration and Law (42; 10.4%).

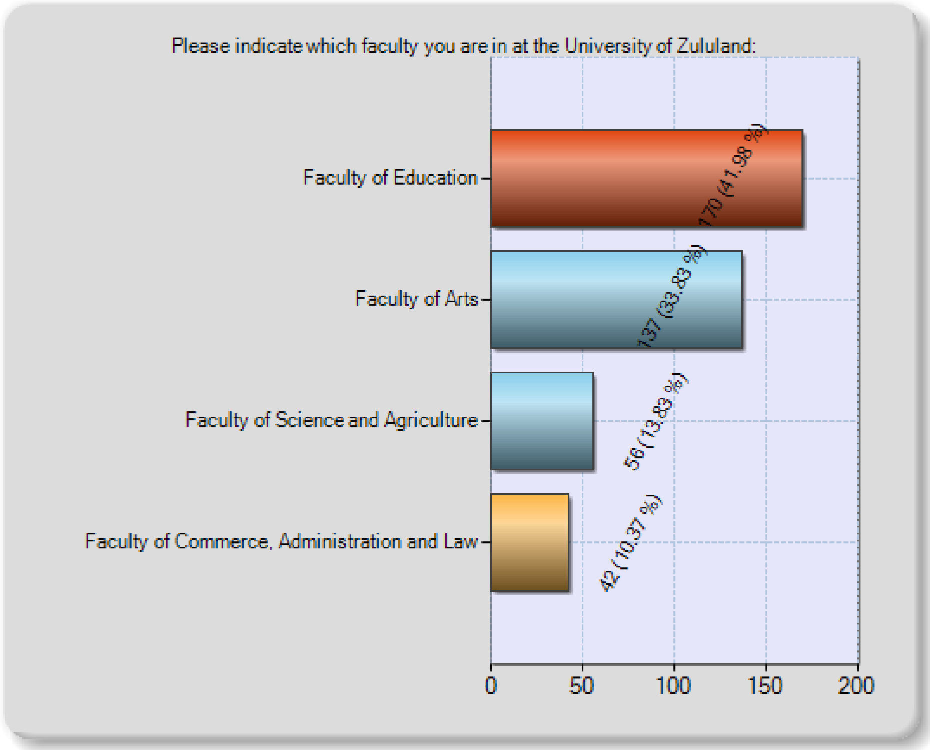

Figure 5.3: Faculty Representation of Students

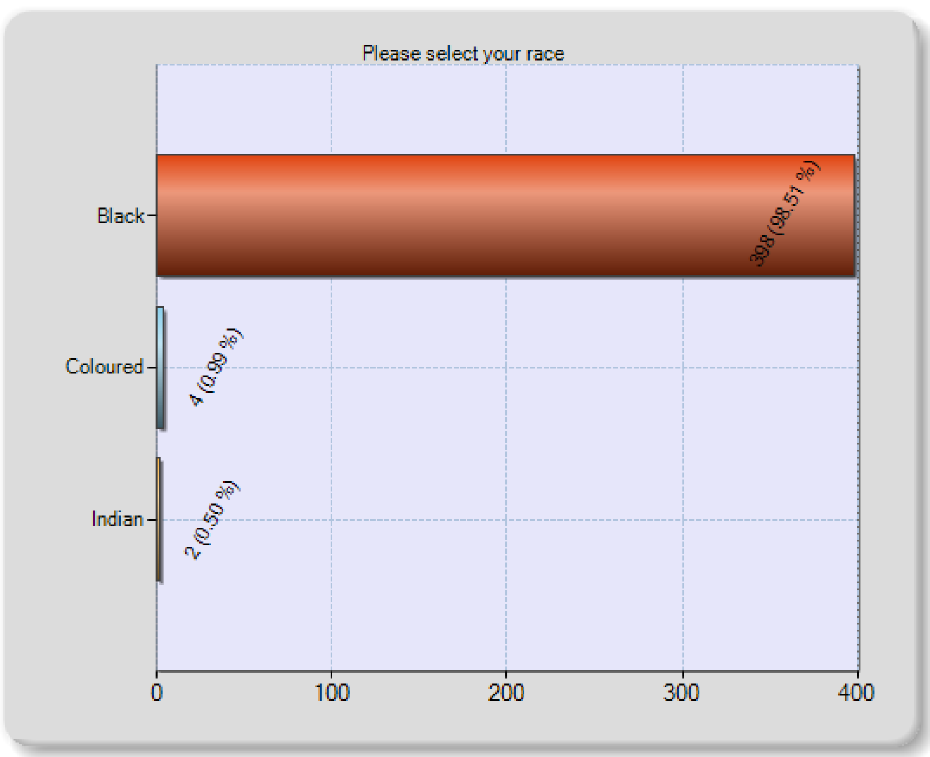

Figure 5.4: Race Representation of Students

Figure 5.4 above indicates that the vast majority (98.5 %) of the students who participated in the student survey were Black followed by a very small minority of Coloured (1%) and Indian (0.5%).

Figure 5.5 below shows that the vast majority (98%) of the students who participated in the survey are South African, while two percent (2%) reside in other African countries.

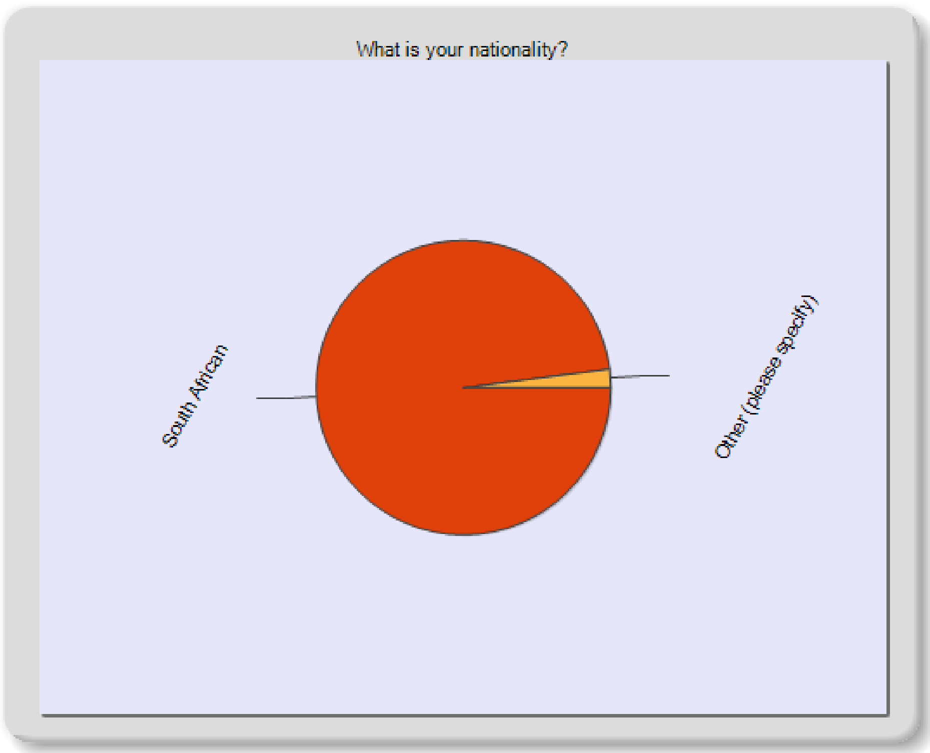

Figure 5.5: Representation of Nationality in Students

5.3.2 Academic Staff

The academic staff sample consisted of fewer (29; 39.7%) females than males (44; 60.3%), as represented in Figure 5.6 below:

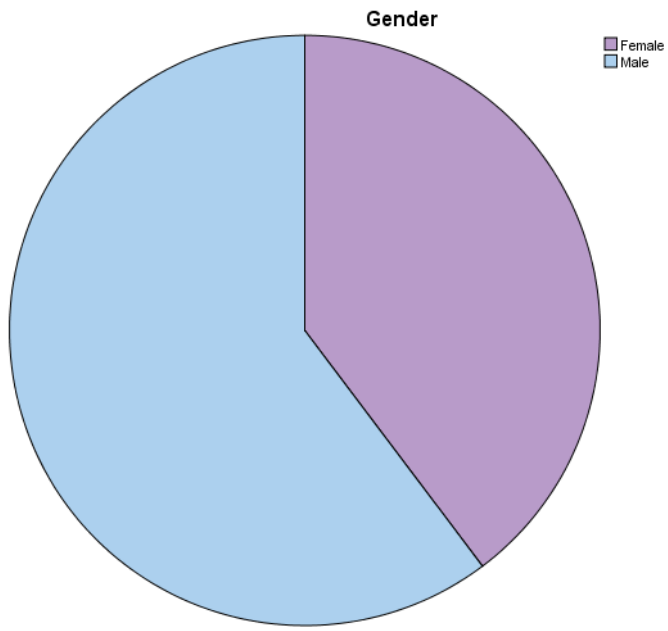

Figure 5.6: Gender Representation of Academic Staff

As seen from Table 5.4, most (25; 34.2%) of academic staff who participated were in the age groups of fifty to fifty nine (50–59), followed by the forty to forty nine (40–49) age group (20; 27.4%), thirty to thirty nine (30–39) age group (18; 24.7%), twenty one to twenty nine (20–29) age group (6; 8.2%), and lastly the sixty to sixty nine (60–69) age group (4; 5.5%).

Table 5. 4: Age Group Representation of Academic Staff

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	21 - 29	6	8.2	8.2	8.2
	30 - 39	18	24.7	24.7	32.9
	40 - 49	20	27.4	27.4	60.3
	50 - 59	25	34.2	34.2	94.5
	60 - 69	4	5.5	5.5	100.0
	Total	73	100.0	100.0	

The average age of the staff who participated was 45 years with a standard deviation of 10 years.

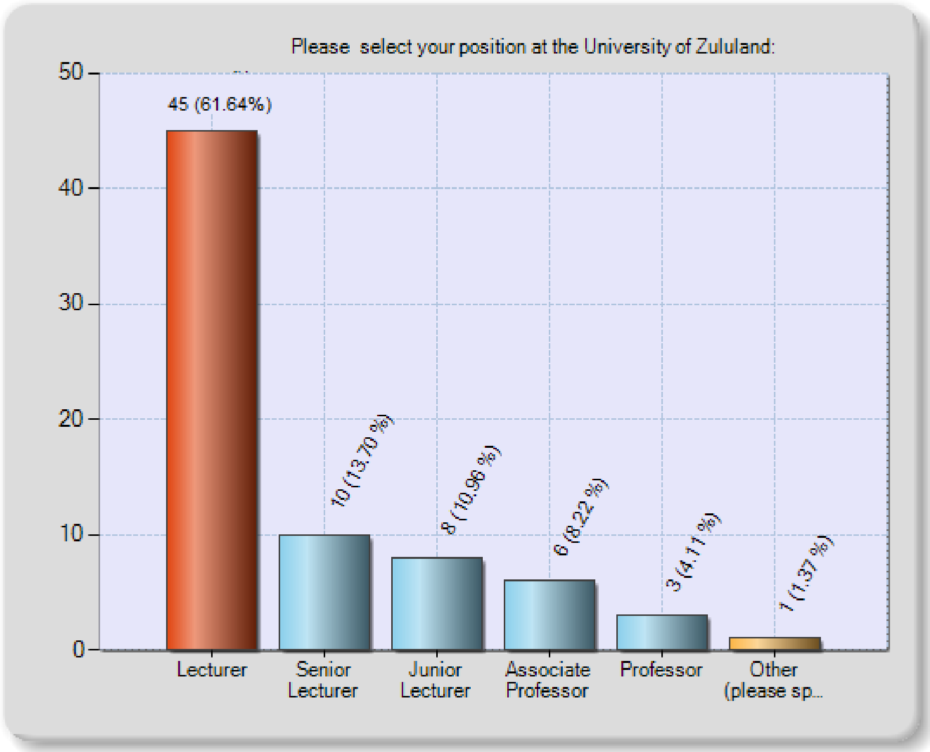

Figure 5.7: Stratification of Academic Staff According to Their Position

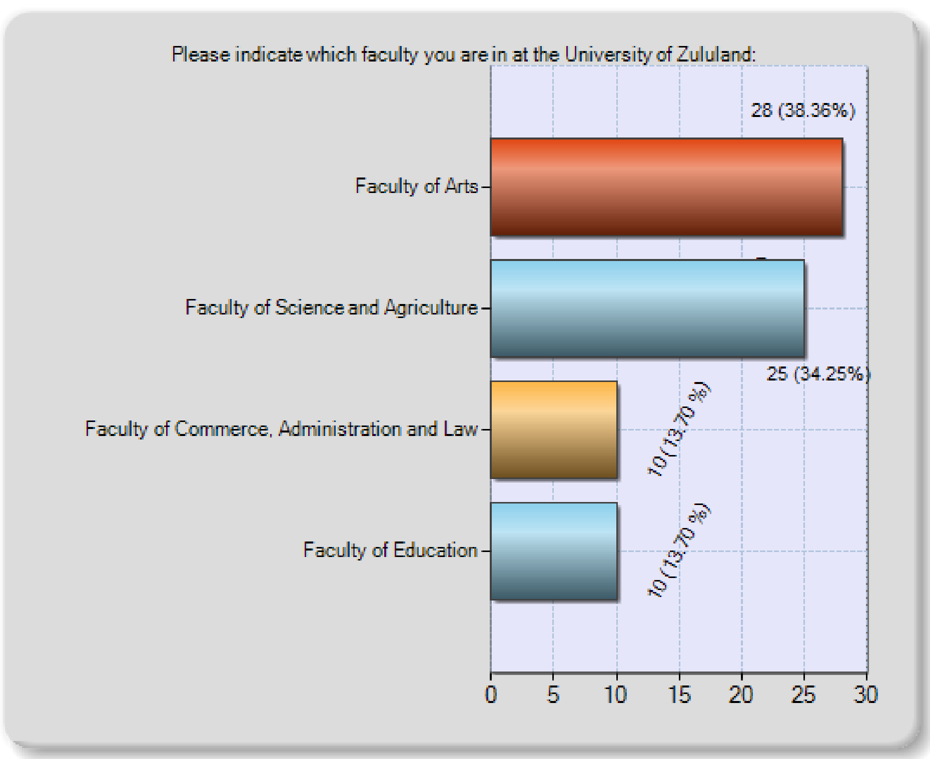

Figure 5.8: Faculty Representation of Academic Staff

Figures 5.7 and 5.8 above show the stratification of staff by their position and faculty respectively, with the majority of participating academic staff being lecturers (61.6%), who come from the Faculty of Arts (38.4%).

Figure 5.9 shows the race representation of the academic staff who participated in the lecturer survey, with the majority being Black (57.5%), followed by White (30.1%), Indian (9.6%) and Asian (2.7%).

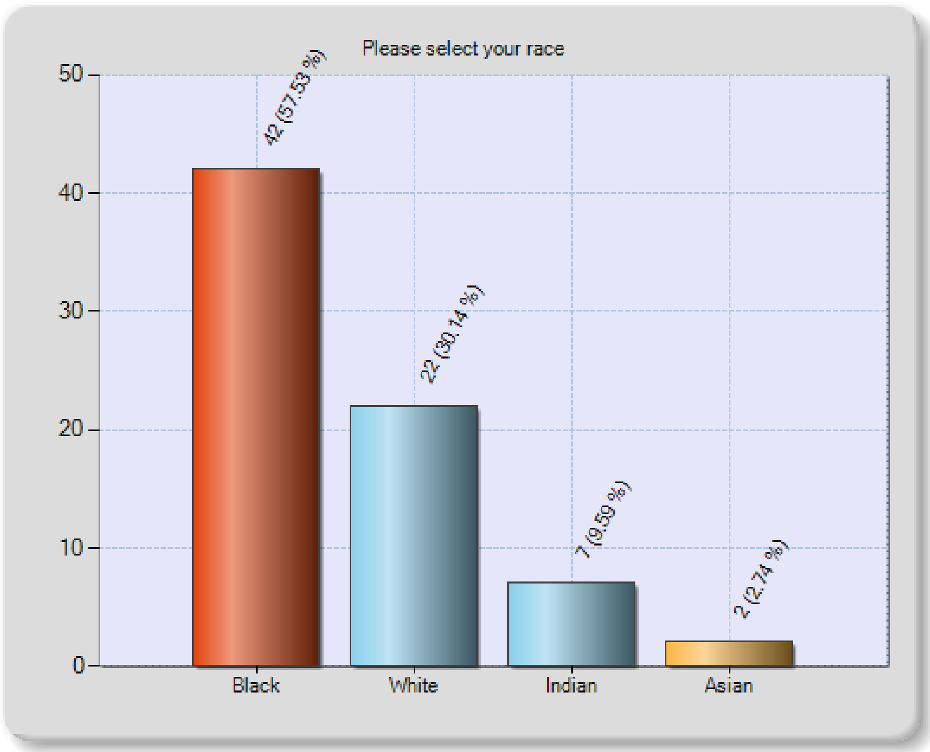

Figure 5.9: Race Representation of Academic Staff

Figure 5.10 below shows that most (84%) of the staff are South African, while a fifth (16%) are from other countries.

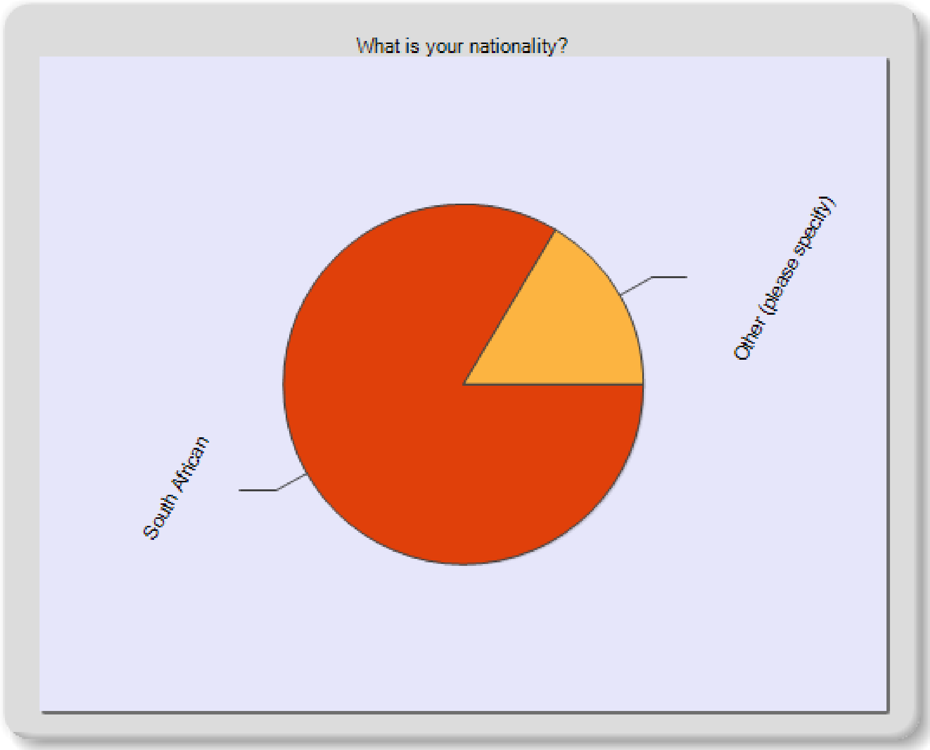

Figure 5.10: Representation of Nationality of the Academic Staff

5.4 Survey Responses

Brown (2011:13) explains that Likert items and Likert scales (made up of multiple items) are reported in different ways and that Likert items, whether nominal, ordinal or interval is irrelevant when using Likert scale data, which can be taken to be interval. Brown (2011:13), however, recommends that if a researcher presents the means and standard deviations (interval scale statistics) for individual Likert items, they should also present a percent, or the frequency of people who selected each option (a nominal and ordinal scale statistic), and allow the reader to interpret the results at the Likert-item level. The following sections, therefore, presents both ordinal (in bar charts and modes in tables) and interval scale (means and standard deviations in tables) statistics for the individual indicator statements used to measure the various latent variables in the two individual populations' SEM. The study takes cognisance of Hair *et al.*'s (2014:8) explanation that it is not appropriate to calculate arithmetic means or variance for ordinal data because the researcher cannot assume that the differences in order are equally spaced. However, with a well-structured Likert scale with appropriate categories (1=strongly disagree, 2=disagree, 3=neutral, 4=agree and 5=strongly agree), the inference is that the “distance” between categories 1 and 2 is the same as between 3 and 4 (Hair *et al.,* 2014:8–9). The descriptive statistics outputs were from the Stellar Survey website and IBM SPSS Statistics.

5.4.1 Use Behaviours

5.4.1.1 Students

It can be seen in Figure 5.11 below that almost half (45.7%) of the students consider their use of e-learning resources as both voluntary and compulsory, followed closely by forty percent (39.5%) of students who considered it compulsory, and the minority (14.8%) who regarded their use as purely voluntary.

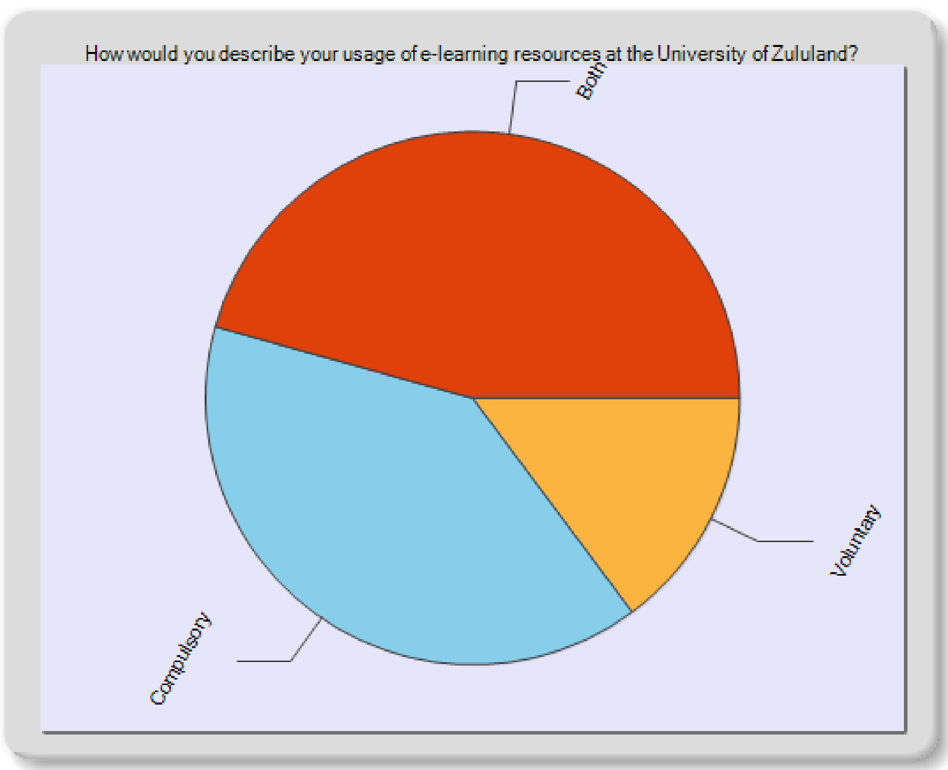

Figure 5.11: Students’ Voluntary and Compulsory Usage of E-learning Resources

Figure 5.12 below represents the students' self-reported prior experience levels of using e-learning resources, with two fifths (43.8%) of the participants stating they were moderately experienced, followed by a fifth who were extremely experienced (19.7%), followed by just under a fifth (15.2%) of the participants who considered themselves slightly experienced, followed by a similar amount (14.0%) who considered themselves somewhat experienced and lastly, the minority (7.5%) who stated that they were not experienced at all.

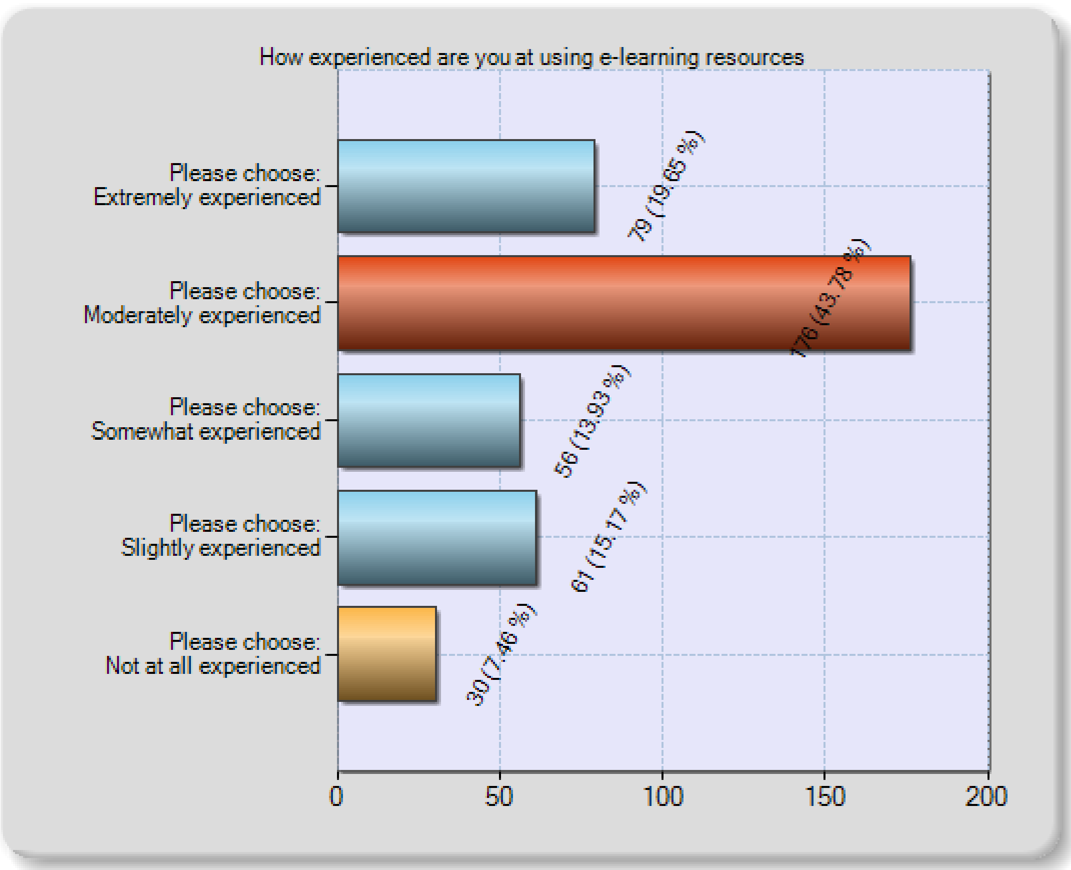

Figure 5.12: Students' Prior Experience Using E-learning Resources

The descriptive statistics of the three indicator statements that were used to collect a self-reported measure of use can be seen in Figures 5.13, 5.14 and 5.15 below. The mode for Use1 and Use2 is three (3), which indicates that most students only sometimes use e-learning resources during formal lectures and for academic tasks during open time in the computer labs. While the mode for Use3 is one (1) indicating that the largest number of students never used e-learning resources in their residences.

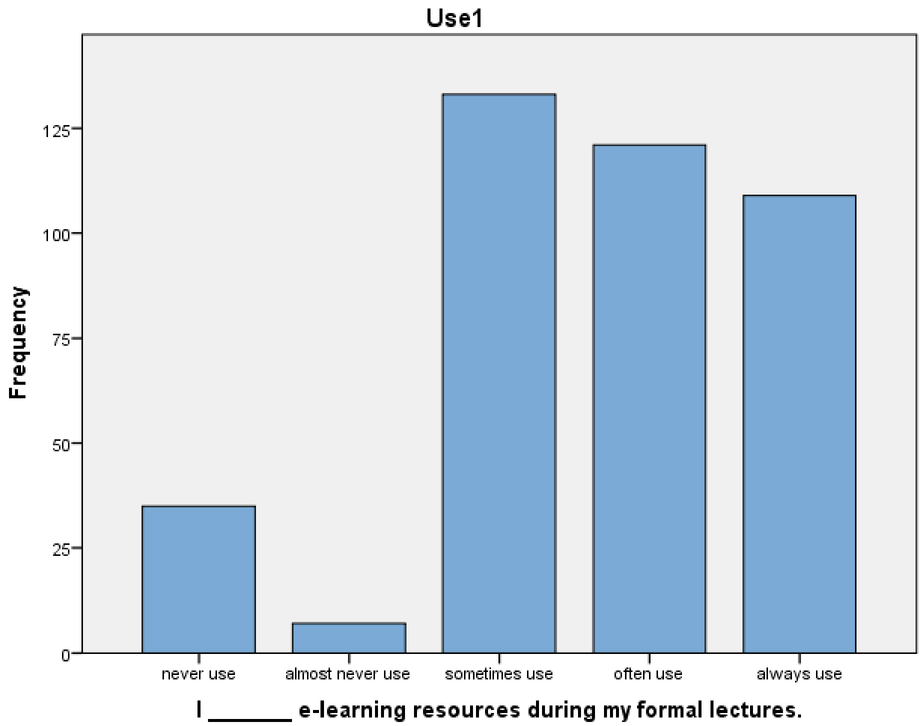

Figure 5.13: Students' Use of E-learning Resources during Formal Lectures

The finding that some thirty-five (35) students responded that they have never used e-learning resources during formal lectures (see Figure 5.13), and another nineteen (19) indicated that they never use e-learning resources for academic tasks during open time in the computer laboratories (see Figure 5.14), was unexpected because all these students have scheduled classes in the computer laboratories that require them to use e-learning resources in both instances.

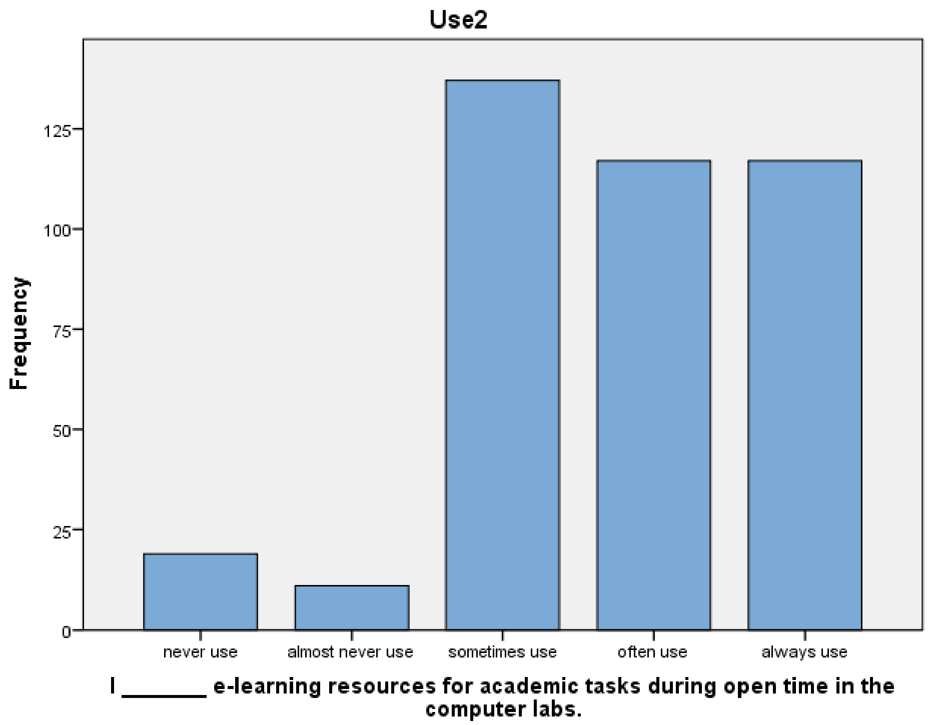

Figure 5.14: Students' Use of E-learning Resources in the Computer Laboratories during Open Time

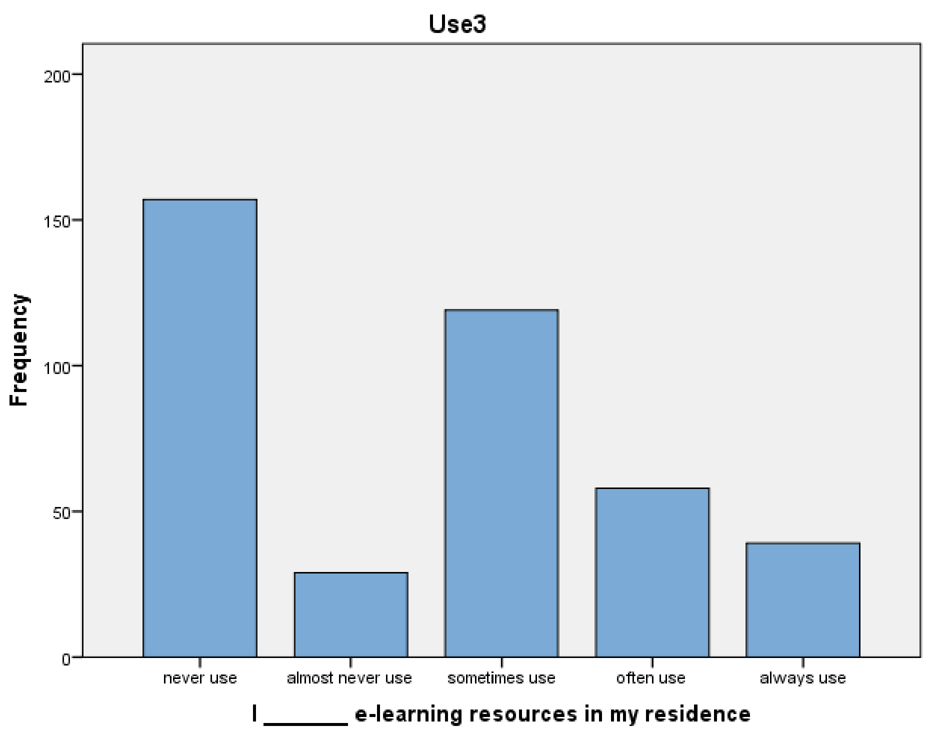

Figure 5.15: Students' Use of E-learning Resources in their Residences

A summary of the descriptive statistics of the three individual indicator statements, that were used to collect a measure of use behaviour of e-learning resources by students, can be seen in Table 5.5 below.

Table 5.5: Descriptive Statistics of Students' Use Behaviour Indicators

*Used in SEM		*Use1	*Use2	Use3
N	Valid	405	401	402
	Missing	0	4	3
Mean		3.65	3.75	2.49
Mode		3	3	1
Std. Deviation		1.150	1.054	1.381
Skewness		-.721	-.613	.305
Std. Error of Skewness		.121	.122	.122
Kurtosis		.078	.106	-1.184
Std. Error of Kurtosis		.242	.243	.243

Hair *et al.* (2010:71) explain that the shape of any distribution of data can be described by two measures: kurtosis and skewness, where the former refers to the height of the distribution, and the latter the balance of the distribution. According Hair *et al.* (2010:36), skewness is a measure of the symmetry of a distribution normally in comparison with a normal distribution (bell shaped curve). A skewness value of zero indicates that a distribution looks the same on the right and left of the centre point. A negative Skewness value (see Use1 and 2 in Table 5.5) indicates that there are relatively few small values and the left histogram tail is long compared to the right histogram tail (see Figure 5.16 below). A positive value indicates that the right tail is longer than the left tail (See Figure 5.17 below), and there are relatively few large values (Hair *et al.,* 2010:36). Skewness values falling outside the range of -1 to +1 indicate substantially skewed distributions (Hair *et al.,* 2010:36).

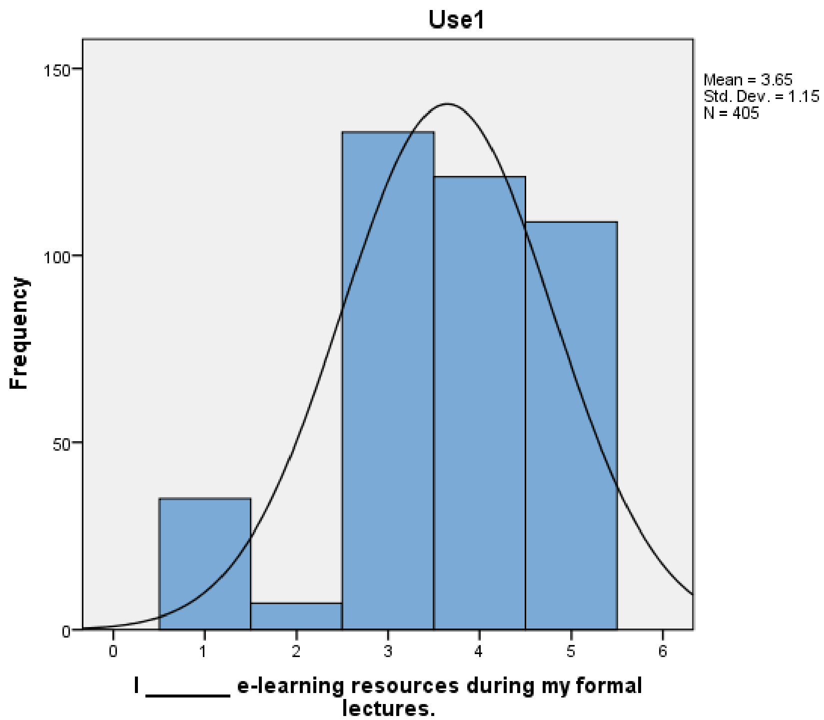

Figure 5.16: Students' Histogram Showing a Negative Skewness and Small Positive Kurtosis in their Use1 Data

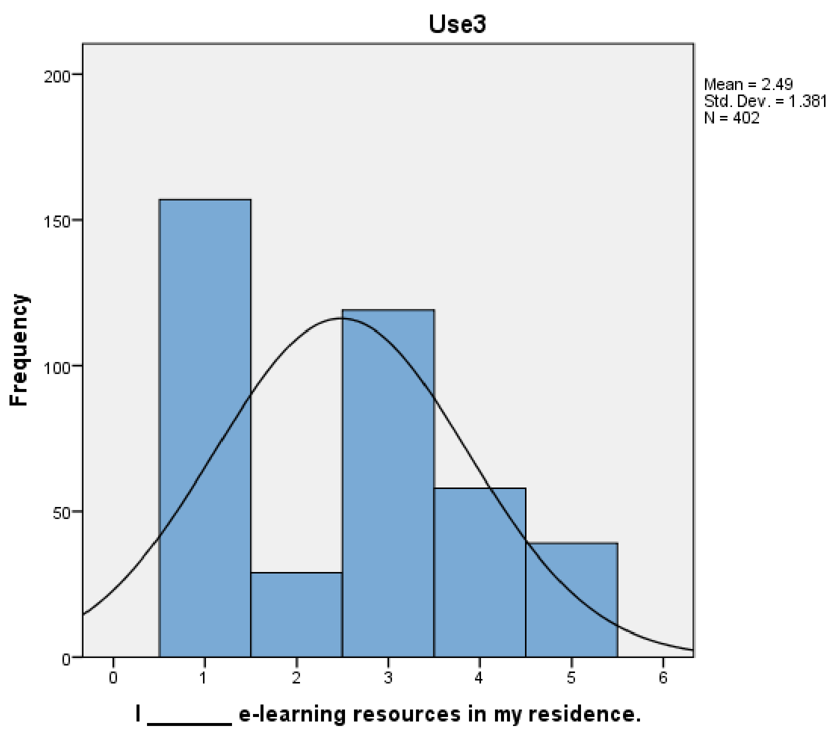

Figure 5.17: Students' Histogram Showing a Positive Skewness and Negative Kurtosis in their Use3 Data

Hair *et al.* (2010:36) explain that Kurtosis is the measures of the peakedness or flatness of a distribution when compared with a normal distribution. Data distributions with positive kurtosis have a high peak near the mean (see Figure 5.16) with a heavy tail in one direction termed leptokurtic (Hair *et al.,* 2010:71), while negative kurtosis would be a flat top (see Figure 5.17) near the mean (Hair *et al.,* 2010:36), also termed platykurtic (Hair *et al.,* 2010:71).

5.4.1.2 Academic Staff

As seen in Figure 5.18 below, the majority (76.4%) of academic staff who participated in the survey consider the usage of e-learning resources at the University of Zululand as being voluntary, while about a fifth (16.7%) consider their usage as both voluntary and compulsory, and the minority (6.9%) who consider their usage as being compulsory.

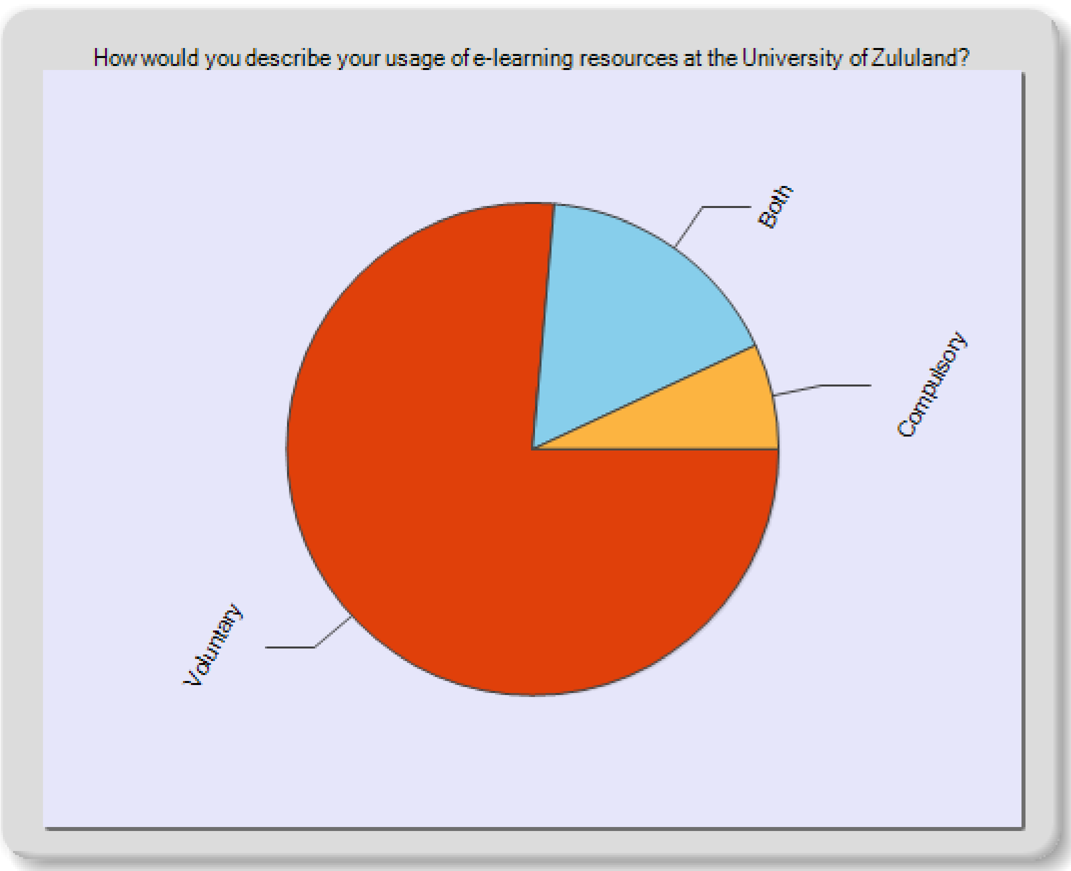

Figure 5.18: Academic Staff's Voluntary and Compulsory Usage of E-learning Resources

Figure 5.19 represents the academic staff's prior experience levels of using e-learning resources, with about a third (34.3%) stating they were moderately experienced, a fifth (21.9%) somewhat experienced, another fifth (21.9%) slightly experienced, a tenth (13.7%) not experienced at all, and the minority (8.2%) regarding themselves as extremely experienced.

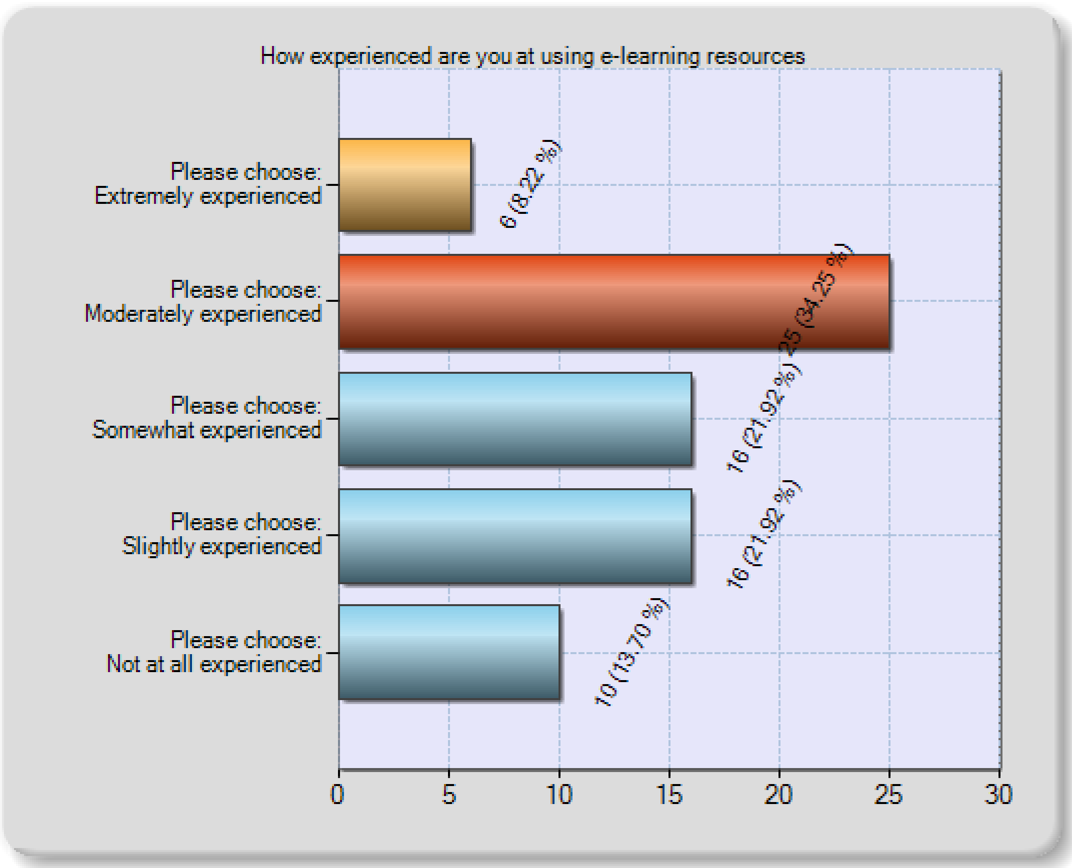

Figure 5.19: Academic Staff's Prior Experience Using E-learning Resources

The descriptive statistics of the three individual indicator statements, that were used to obtain a self-reported measure of academic staff's use behaviour, are shown in Figures 5.20, 5.21 and 5.22 below. The mode for Use1 and Use3 is five (5), indicating that most academics always use e-learning resources for communication, administration and research in their offices. While the mode for Use2 is one (1) and three (3), indicating that there is a tie for the largest numbers of academics that either never use or sometimes use e-learning resources during their lectures.

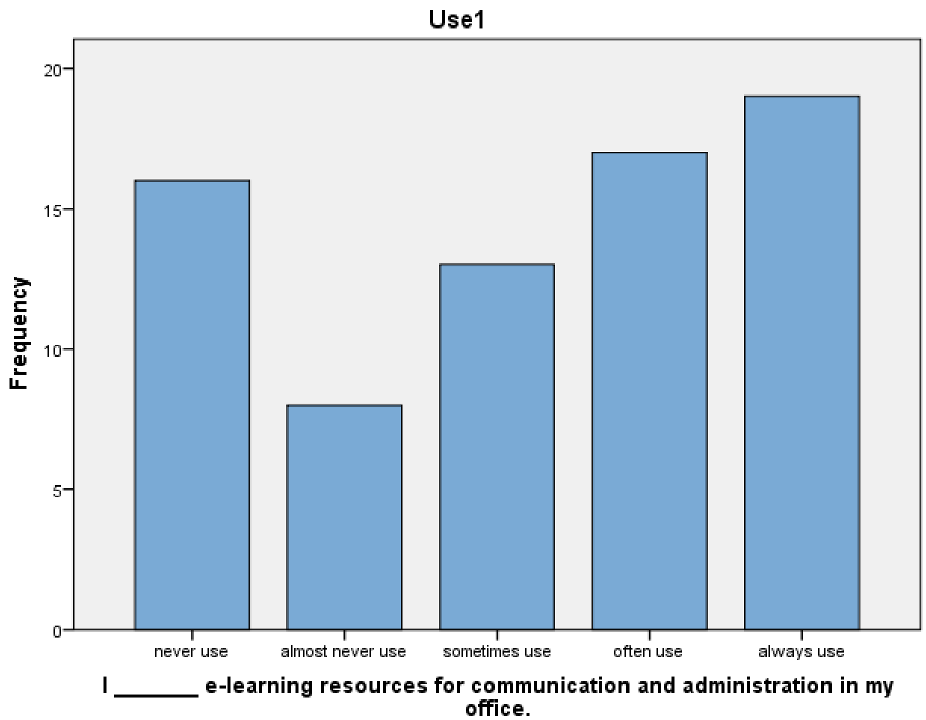

Figure 5.20: Academic Staff's Usage of E-learning Resources for Communication and Administration in their Offices

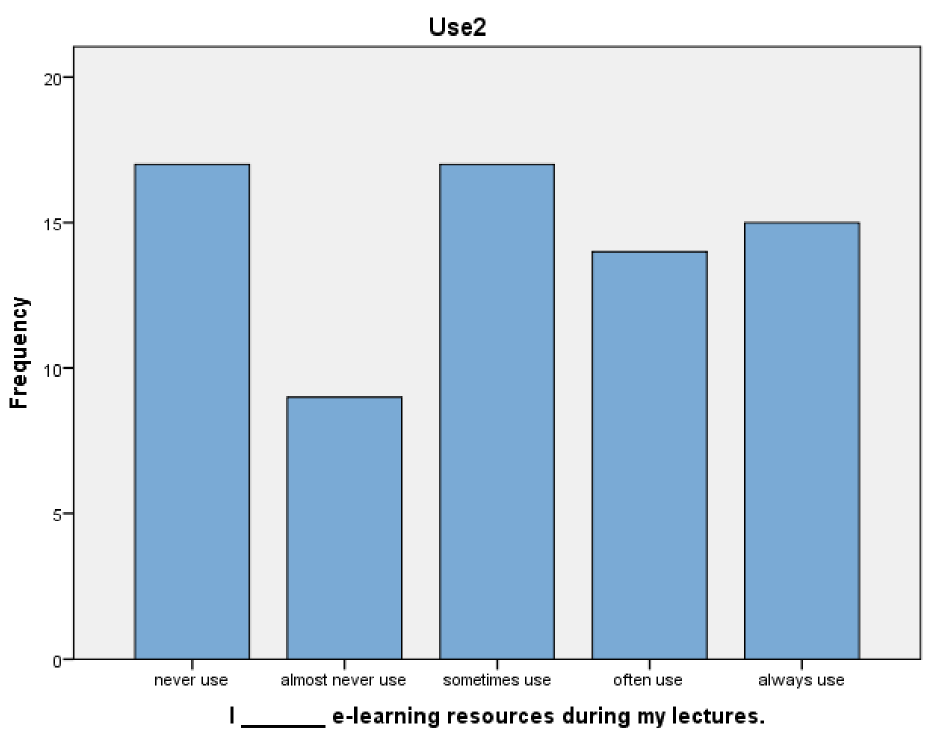

Figure 5.21: Academic Staff's Usage of E-learning Resources during Lectures

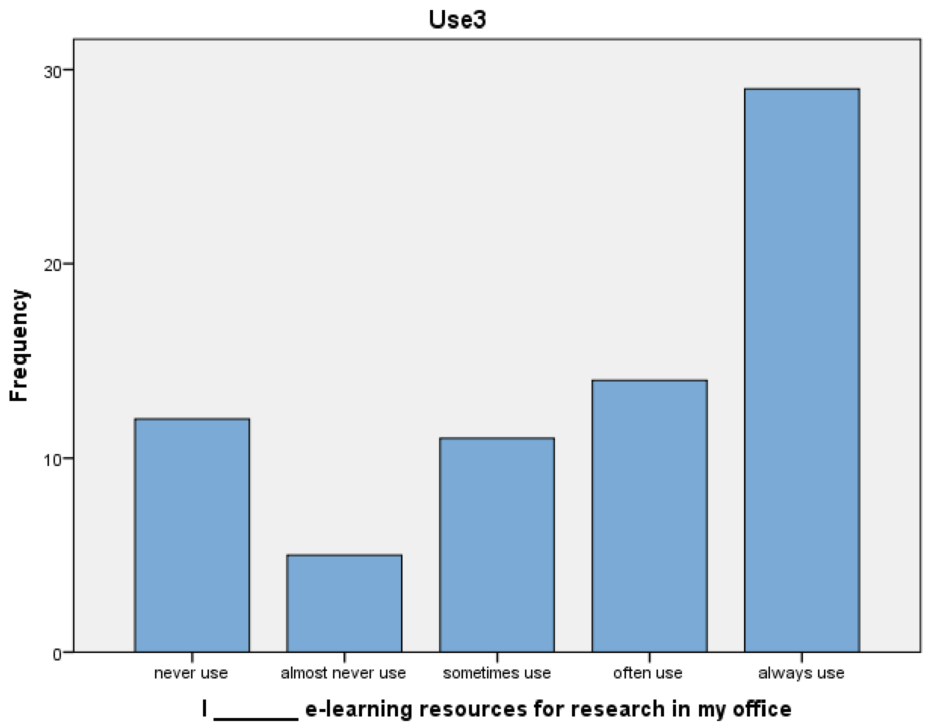

Figure 5.22: Academic Staff's Usage of E-learning Resources for Research

The finding that some sixteen (16) staff reported that they never use e-learning resources for communication and administration in their offices (See Figure 5.20 above) was unexpected, because all academic staff should have networked computer resources in their offices and many had used these to respond to the study's online survey instrument.

The summary of the descriptive statistics of the three individual indicator statements that were used to collect a self-reported measure of use for academic staff are summarised in Table 5.6 below.

Table 5.6: Descriptive Statistics for Academic Staff's Use Behaviour Indicators

*Used in SEM		*Use1	*Use2	*Use3
N	Valid	73	72	71
	Missing	0	1	2
Mean		3.21	3.01	3.61
Mode		5	1[a]	5
Std. Deviation		1.500	1.458	1.497
Skewness		-.286	-.081	-.683
Std. Error of Skewness		.281	.283	.285
Kurtosis		-1.340	-1.315	-.973
Std. Error of Kurtosis		.555	.559	.563

a. Multiple modes (1, 3) exist. The smallest value is shown.

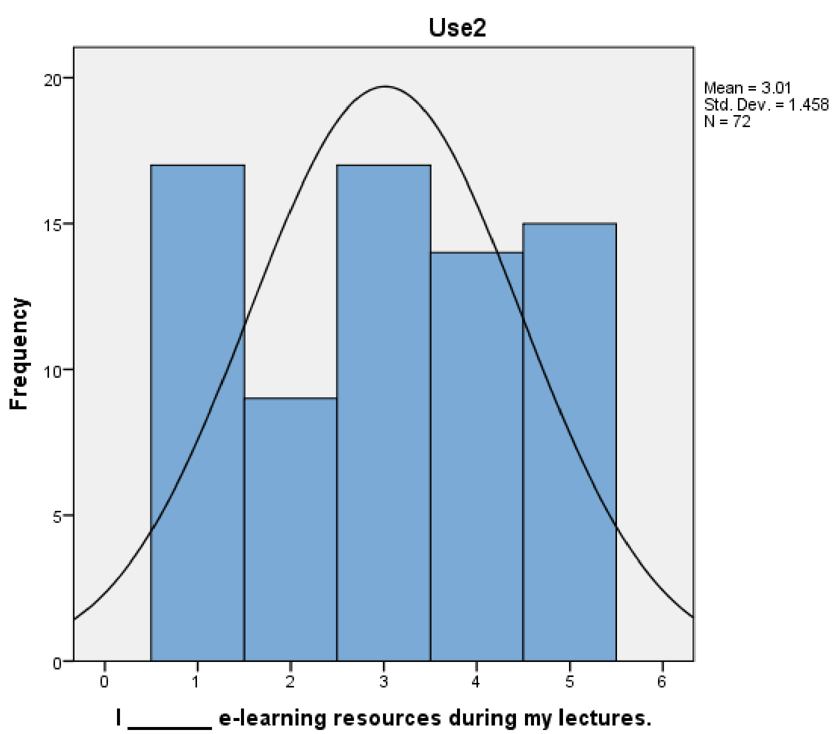

Figure 5.23: Academic Staff's Histogram Showing a Slight Negative Skewness and a Negative Kurtosis in their Use2 Data

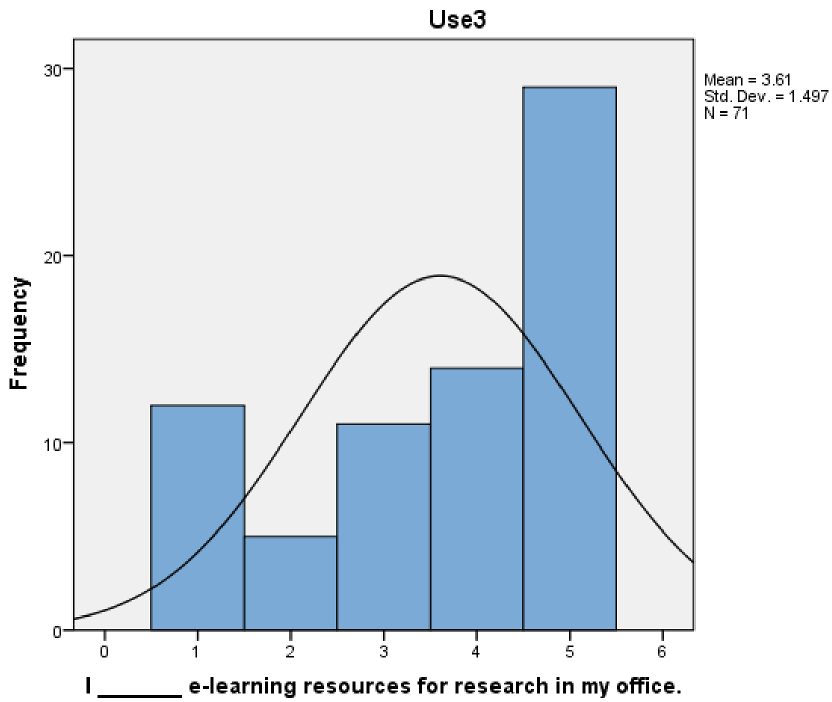

Figure 5.24: Academic Staff Histogram Showing a Negative Skewness and a Negative Kurtosis in their Use3 Data

A slight negative skewness in the distribution of data of academics usage of e-learning resources in lectures can be seen in Figure 5.23 above, where the mean is very close to the median and a normal distribution (symmetrical around the mean). While Figure 5.24 above shows more negative skewness where most values are concentrated on the right of the mean, extreme values are to the left. All three use behaviour indicators statements have a negative kurtosis, which indicates that their data distributions have a flat top near the mean.

5.4.2 Behavioural Intentions

5.4.2.1 Students

Figures 5.25 to 5.29 below indicate the student responses to the behavioural intention indicator statements. The mode for all indicators is four (4), indicating that most students agree that it is their intention to use e-learning resources.

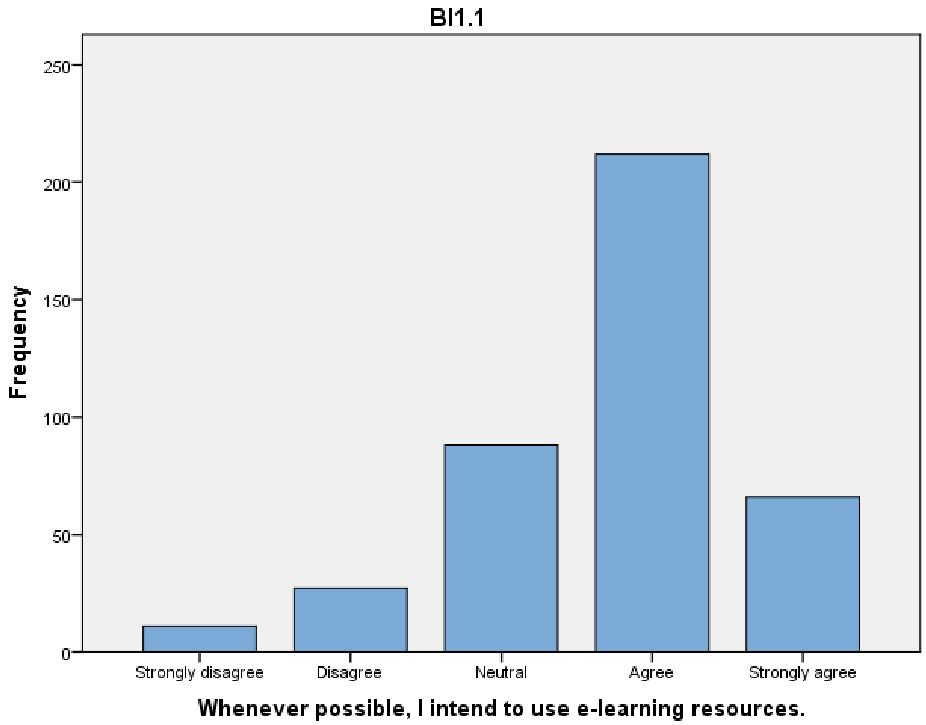

Figure 5.25: Students' Intentions to Use of E-learning Resources Whenever Possible

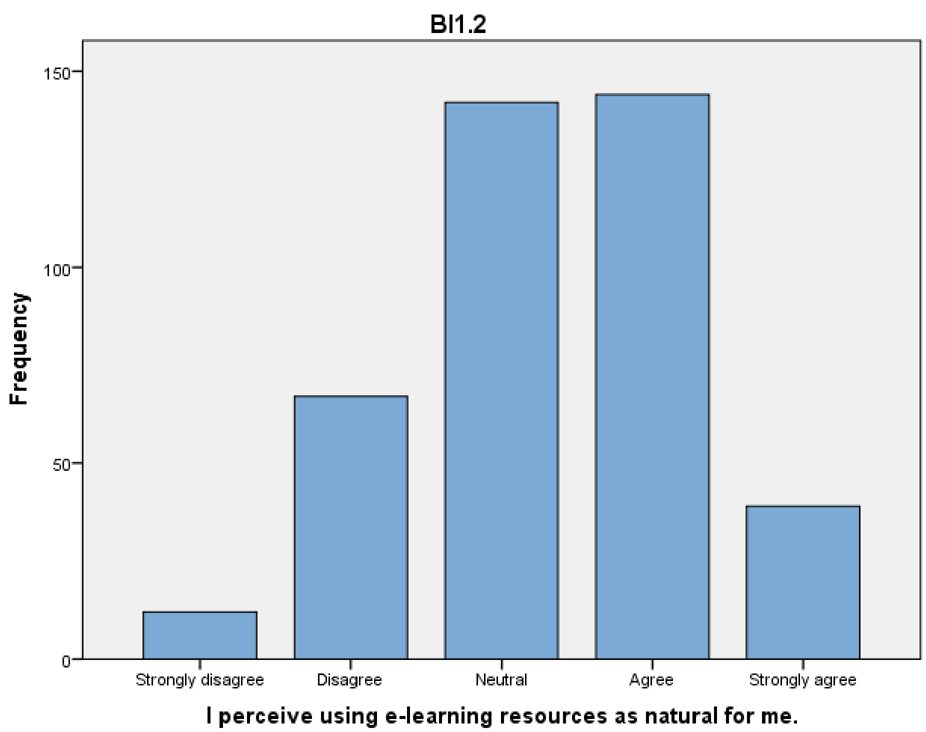

Figure 5.26: Students' Perceptions of Using E-learning Resources Naturally

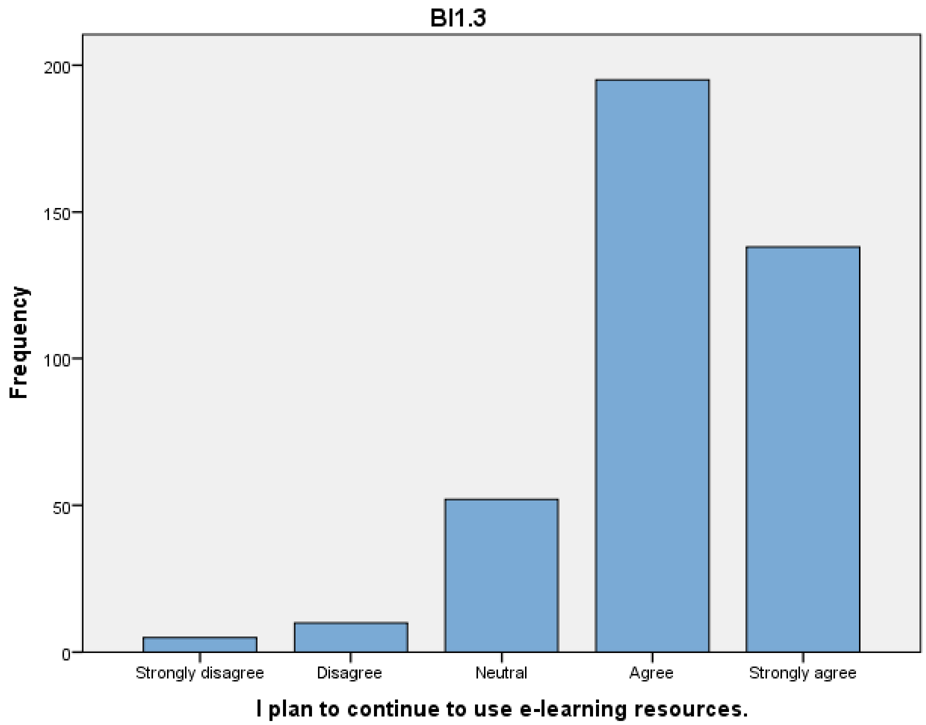

Figure 5.27: Students' Intentions to Continue Using E-learning Resources

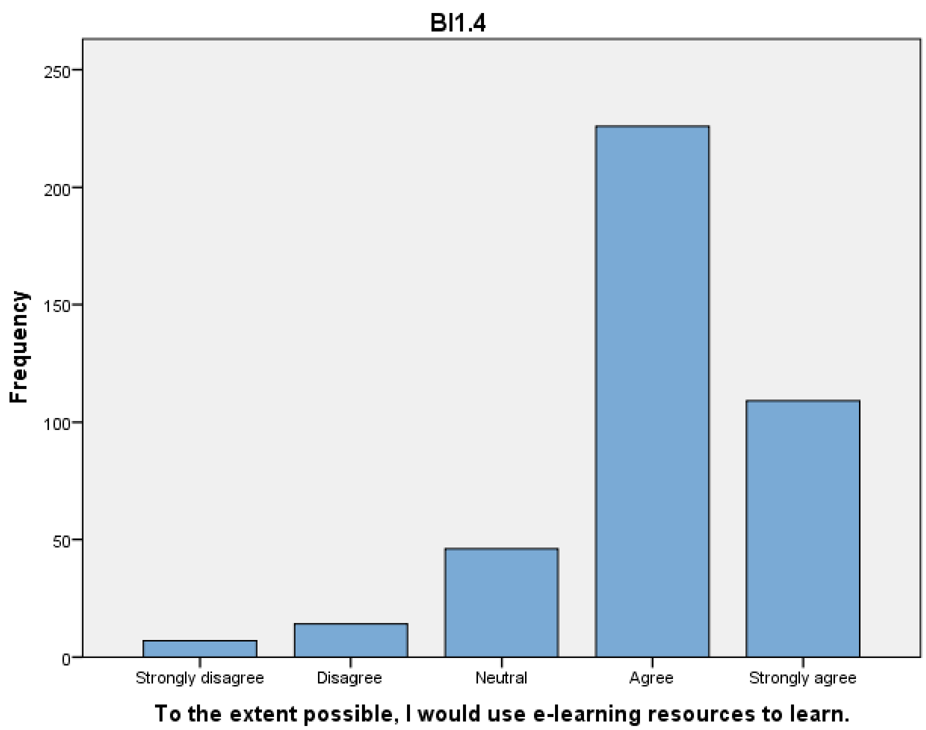

Figure 5.28: Students' Intentions to Use E-learning Resources to Learn

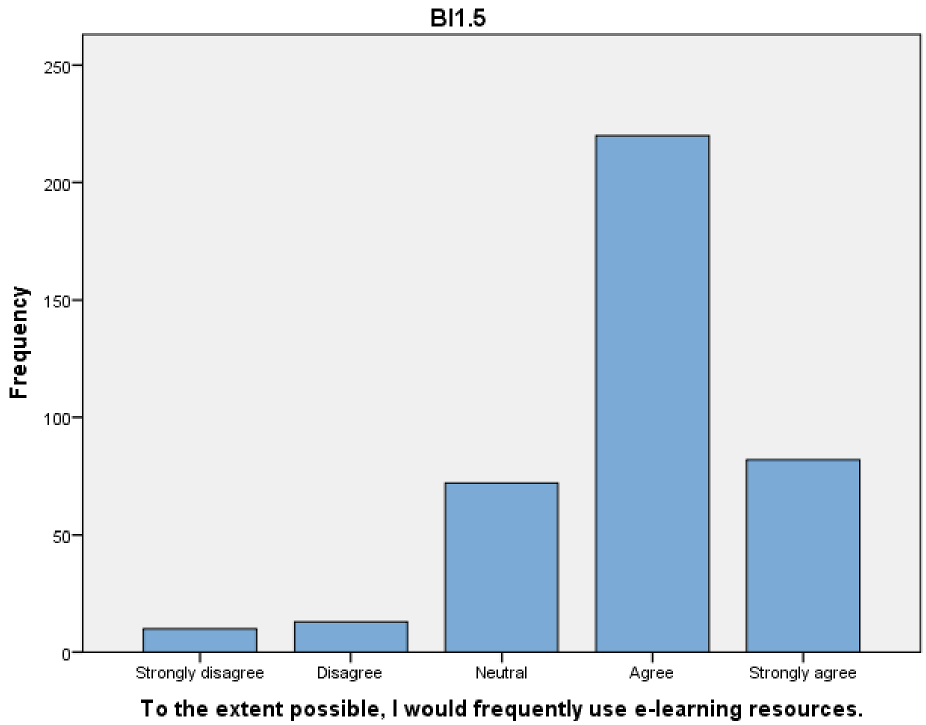

Figure 5.29: Students' Intentions to Frequently Use E-learning Resources

A summary of the descriptive statistics of the five (5) individual indicator statements, that were used to collect a self-reported measure of the behavioural intentions of students to use e-learning resources, are shown in Table 5.7 below.

Table 5. 7: Descriptive Statistics of Students' Behavioural Intention Indicators

*Used in SEM		BI1.1	BI1.2	*BI1.3	*BI1.4	*BI1.5
N	Valid	404	404	400	402	397
	Missing	1	1	5	3	8
Mean		3.73	3.32	4.13	4.03	3.88
Mode		4	4	4	4	4
Std. Deviation		.907	.961	.820	.826	.857
Skewness		-.864	-.233	-1.061	-1.186	-1.059
Std. Error of Skewness		.121	.121	.122	.122	.122
Kurtosis		.887	-.383	1.738	2.316	1.864
Std. Error of Kurtosis		.242	.242	.243	.243	.244

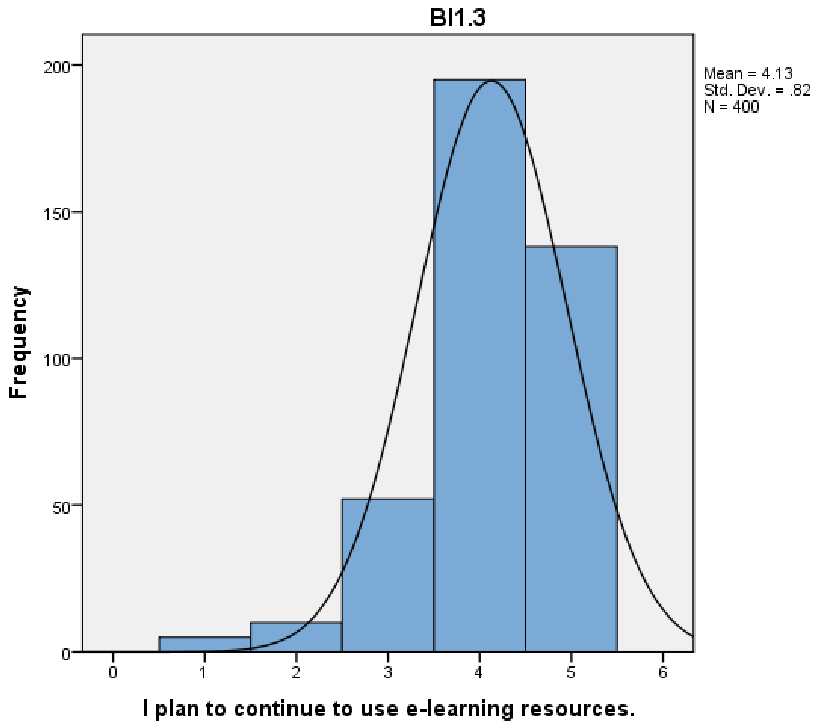

Figure 5.30: Student Histogram Showing a Negative Skewness and Positive Kurtosis in BI 1.3 Data

Figure 5.30 above shows the trend of a negative skewness in the distribution of behavioural intention data of students using e-learning resources, which indicates that there are relatively few small values and the left histogram tail is long compared to the right histogram tail. Most behavioural intention indicators statements have a positive kurtosis, with a relatively high peak near the mean (see Figure 5.29 above), and a heavy tail in the left direction, except for the data on the students' perception of the use of e-learning resources as being natural, which had a negative kurtosis with this data distribution having a flat top near the mean.

5.4.2.2 Academic Staff

Figures 5.31 to 5.35 below graphically represent the academic staff's responses to their behavioural intention indicator statements. The mode for all responses is four (4), which indicates that most academics also agree that it is their intention to use e-learning resources.

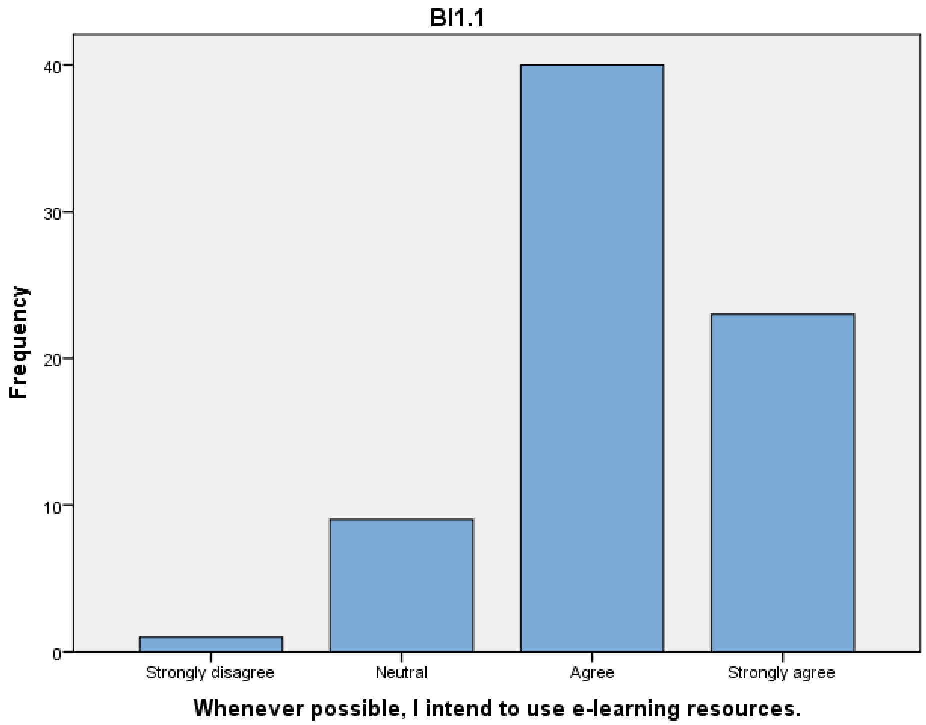

Figure 5.31: Academic Staff's Intentions of Using E-learning Resources Whenever Possible

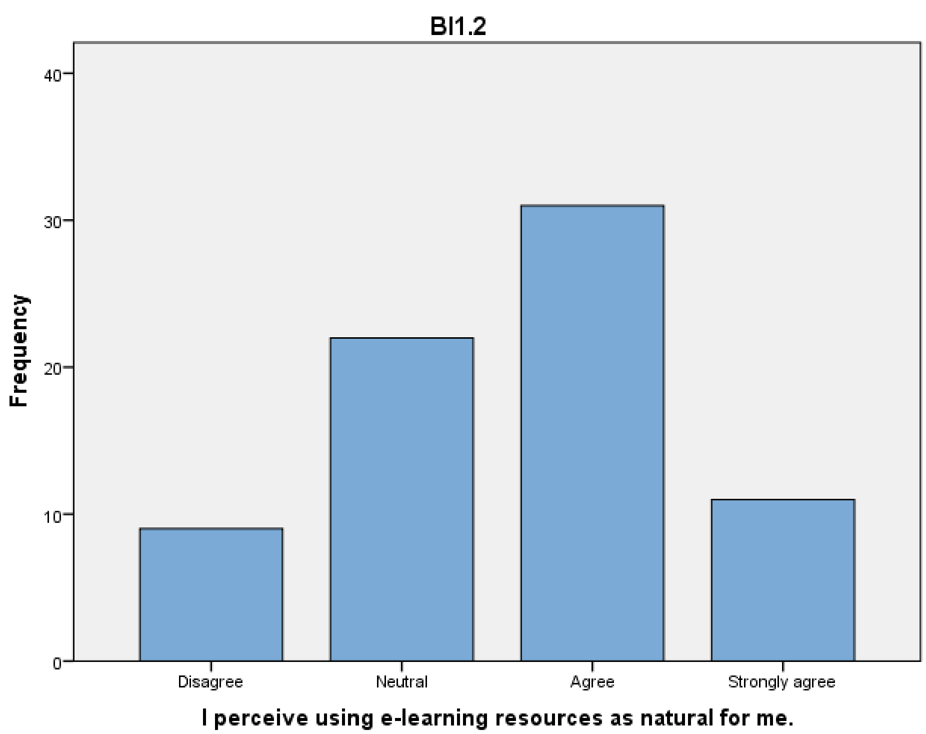

Figure 5.32: Academic Staff's Perceptions of Naturally Using E-learning Resources

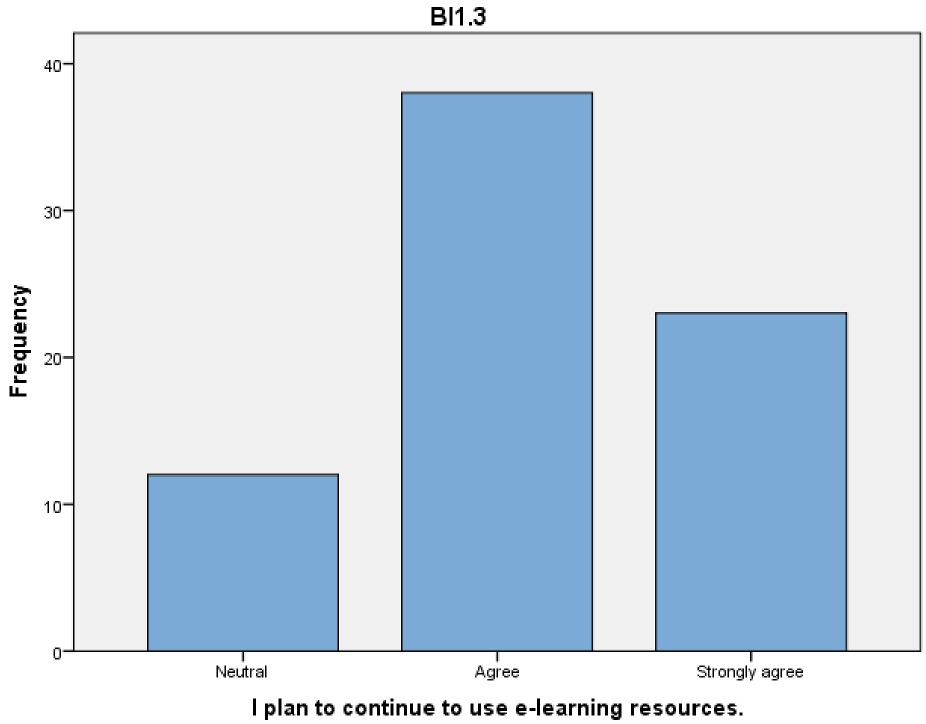

Figure 5.33: Academic Staff's Intentions to Continue Using E-learning Resources

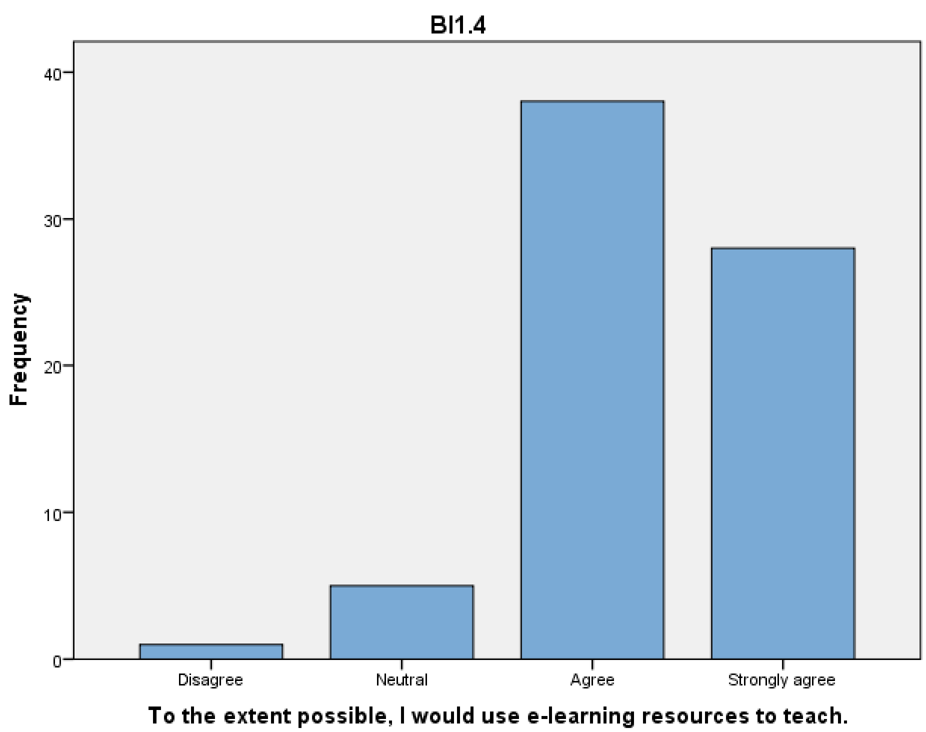

Figure 5.34: Academic Staff's Intentions of Using E-learning Resources to Teach

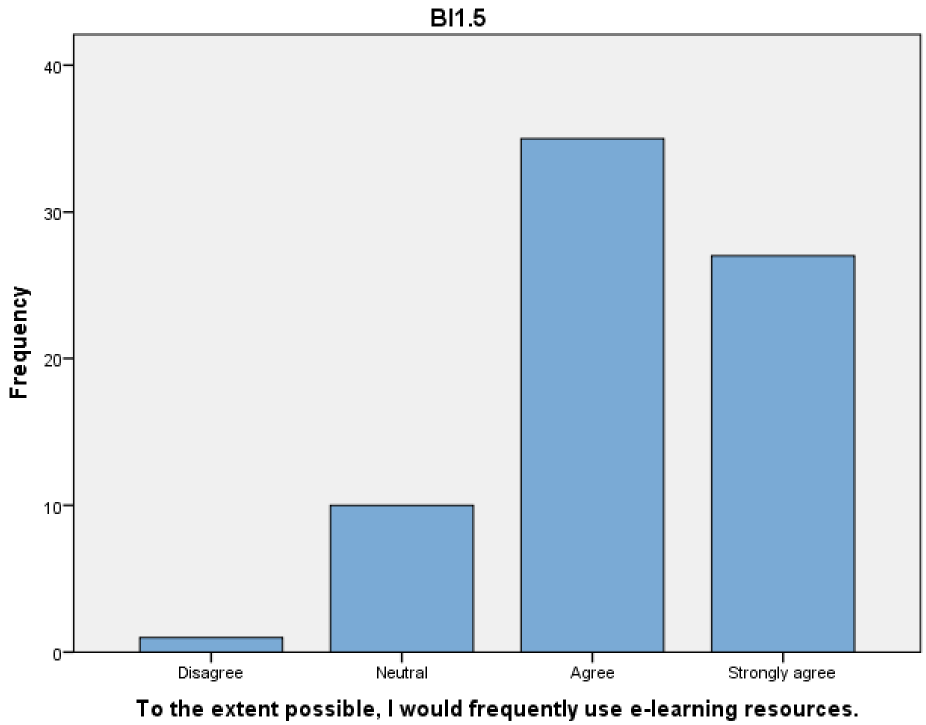

Figure 5.35: Academic Staff's Intentions to Frequently Use E-learning Resources

The descriptive statistics of the five individual indicator statements, that were used to collect a measure of the behavioural intention of academic staff to using e-learning resources, are summarised in Table 5.8 below.

Table 5.8: Descriptive Statistics of Academic Staff's Behavioural Intention Indicators

*Used in SEM		*BI1.1	BI1.2	*BI1.3	*BI1.4	*BI1.5
N	Valid	73	73	73	72	73
	Missing	0	0	0	1	0
Mean		4.15	3.60	4.15	4.29	4.21
Mode		4	4	4	4	4
Std. Deviation		.739	.893	.681	.659	.726
Skewness		-1.097	-.199	-.196	-.697	-.561
Std. Error of Skewness		.281	.281	.281	.283	.281
Kurtosis		3.257	-.642	-.804	.826	-.103
Std. Error of Kurtosis		.555	.555	.555	.559	.555

Table 5.8 above shows the trend of a negative skewness in the distribution of all behavioural intention data of academics using e-learning resources, which indicates that there are relatively few small values and the left histogram tail is long compared to the right histogram tail. Two behavioural intention indicators statements (BI1.1 and BI1.4), but especially BI1.1, have a positive kurtosis with a high peak near the mean (see Figure 5.36 below), and a heavy tail in the left direction; the others have a negative kurtosis with these data distributions having flat tops near the mean (see Figure 5.37 below).

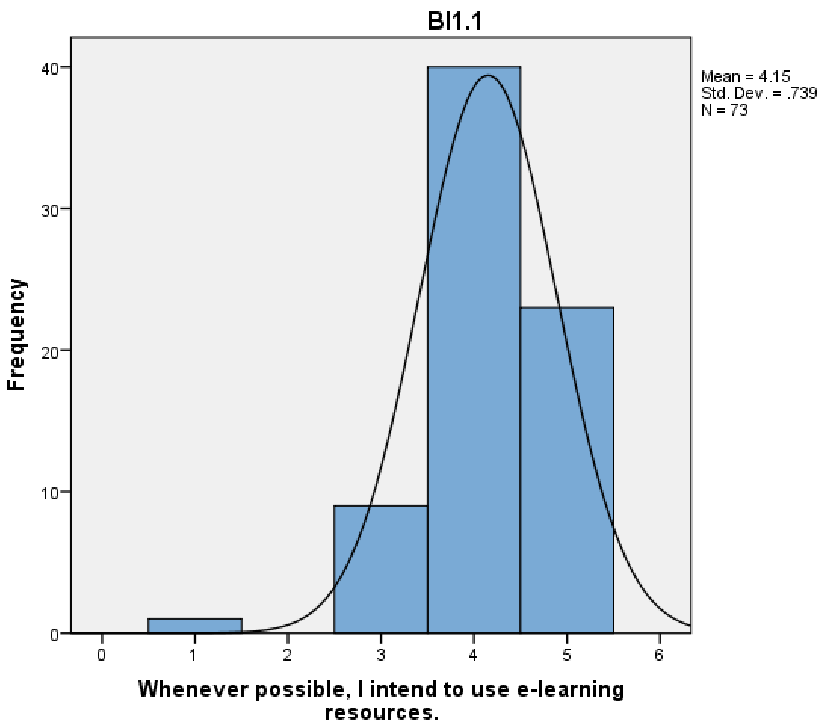

Figure 5.36: Academic Staff's Histogram Showing a Negative Skewness and Positive Kurtosis in BI1.1 Data

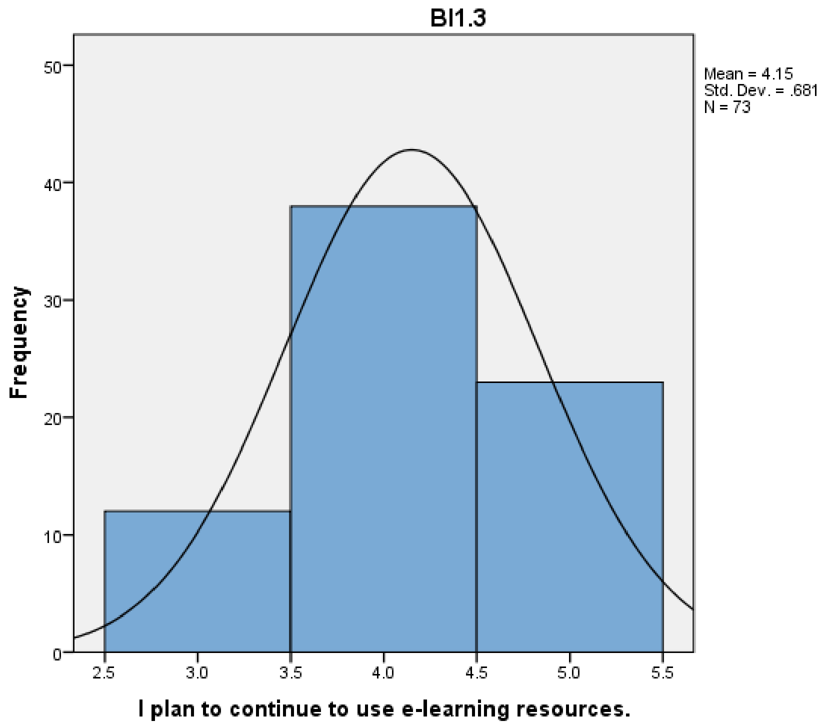

Figure 5.37: Academic Staff's Histogram Showing a Negative Skewness and Negative Kurtosis in BI1.3 Data

5.4.3 Performance Expectancies

5.4.3.1 Students

Figures 5.38 to 5.42 graphically summarise the student responses to the performance expectancy indicator statements. The mode for most indicators is four (4), which indicates that most students agree that the use of e-learning resources were useful in obtaining performance gains in academic tasks. However, the majority of students are neutral about their marks improving through the use of e-learning resources.

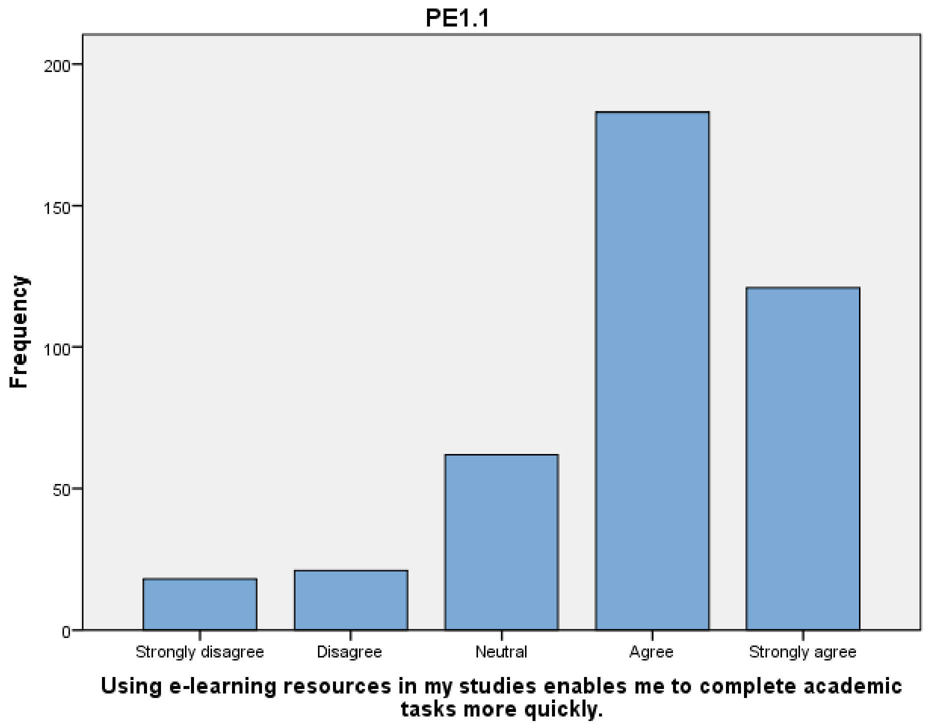

Figure 5.38: Student's Perceptions that Using E-learning Resources Speeds up the Completion of Academic Tasks

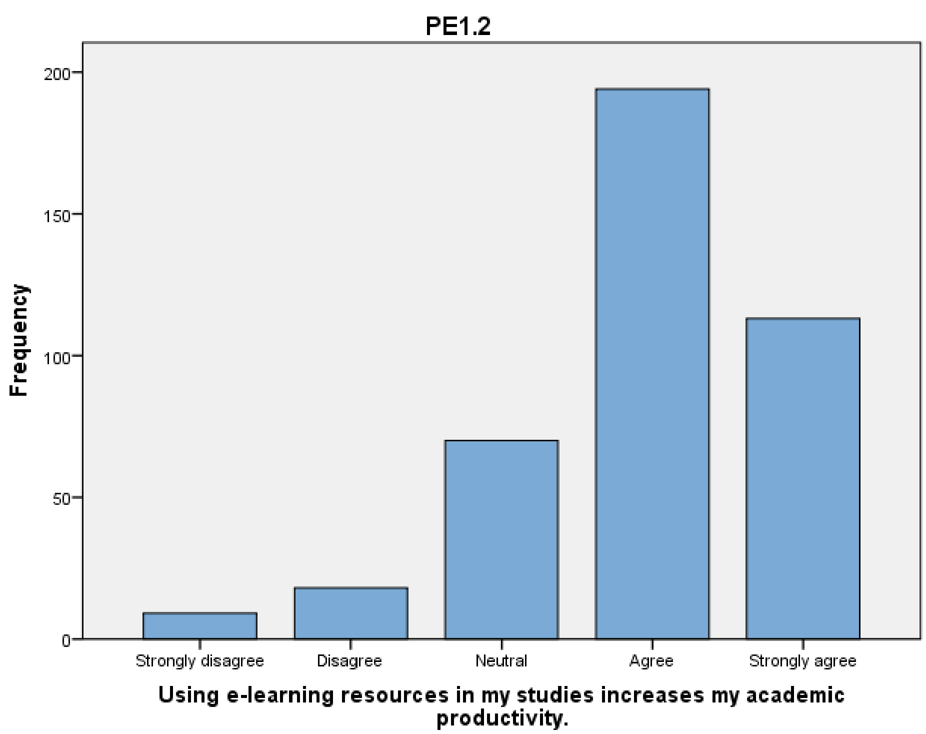

Figure 5.39: Students' Perceptions that Using E-learning Resources Increases Academic Productivity

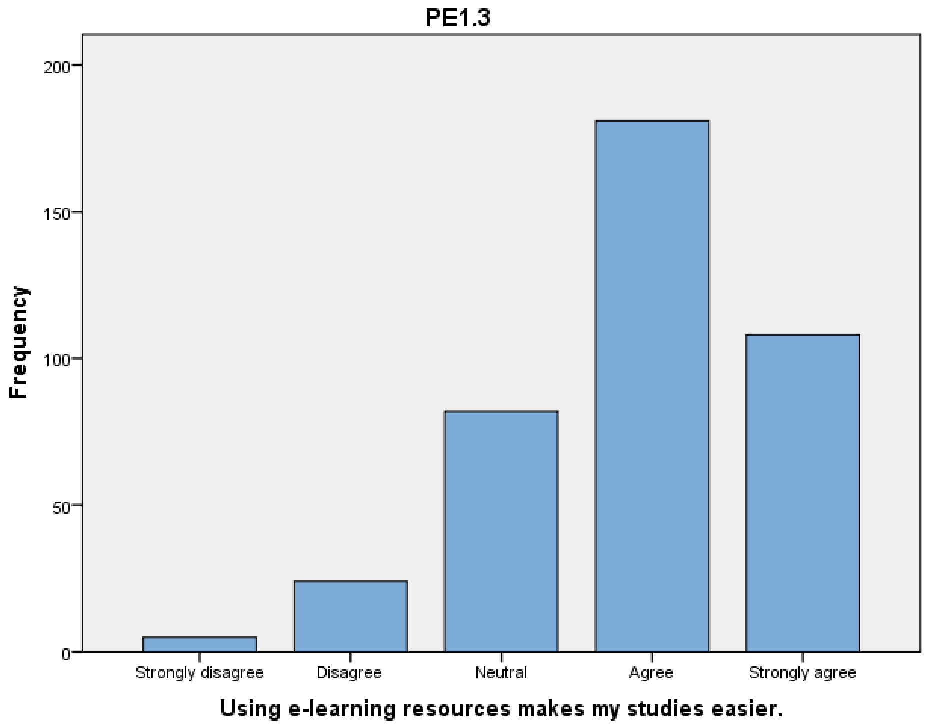

Figure 5.40: Students' Perceptions that Using E-learning Resources Makes their Studies Easier

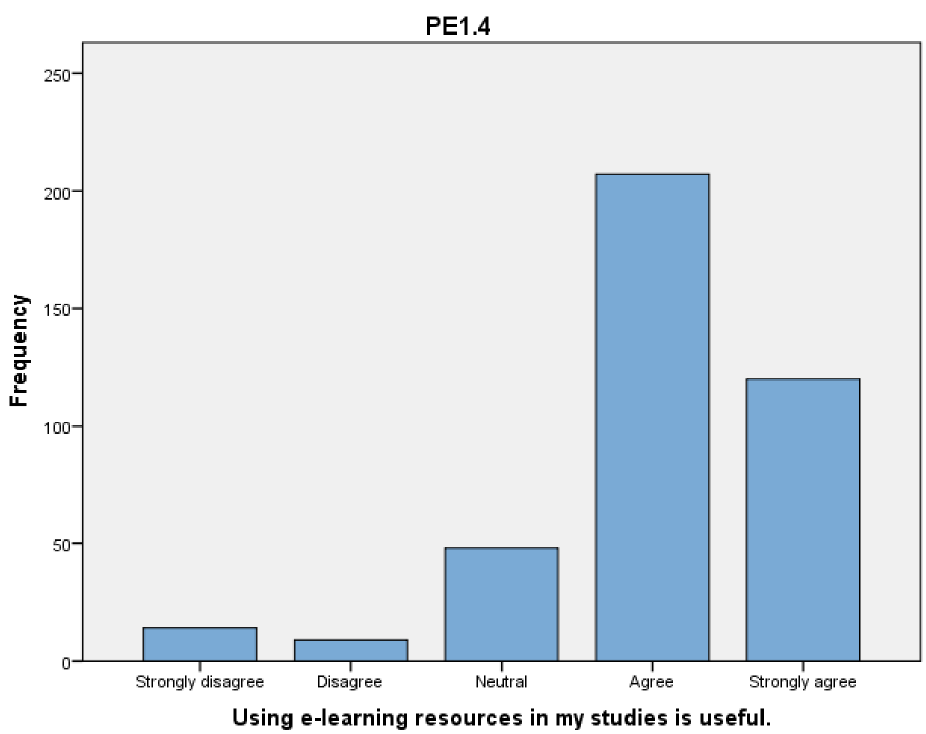

Figure 5.41: Students' Perceptions of E-learning Resources being Useful in their Studies

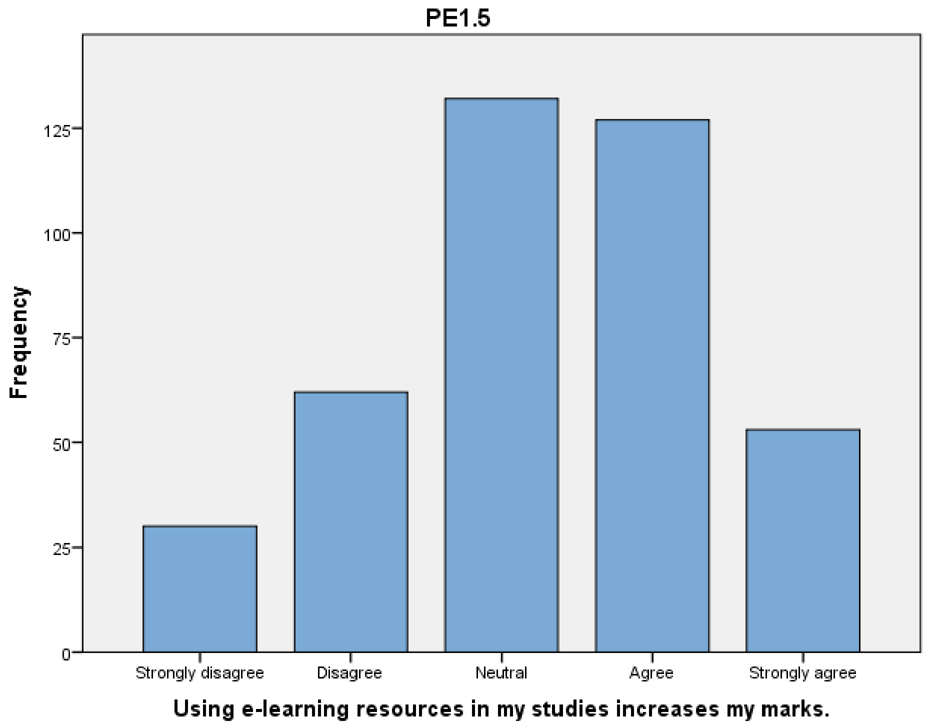

Figure 5.42: Students' Perceptions that Using E-learning Resources Improves their Marks

The descriptive statistics of the five (5) individual indicator statements, that were used to collect a self-reported measure of the performance expectancy of students when using e-learning resources, are summarised in Table 5.9 below.

Table 5.9: Descriptive statistics of Students' Performance Expectancy Indicators

*Used in SEM		PE1.1	*PE1.2	*PE1.3	*PE1.4	PE1.5
N	Valid	405	404	400	398	404
	Missing	0	1	5	7	1
Mean		3.91	3.95	3.91	4.03	3.27
Mode		4	4	4	4	3
Std. Deviation		1.026	.912	.906	.911	1.103
Skewness		-1.100	-.968	-.710	-1.365	-.304
Std. Error of Skewness		.121	.121	.122	.122	.121
Kurtosis		1.009	1.121	.316	2.516	-.519
Std. Error of Kurtosis		.242	.242	.243	.244	.242

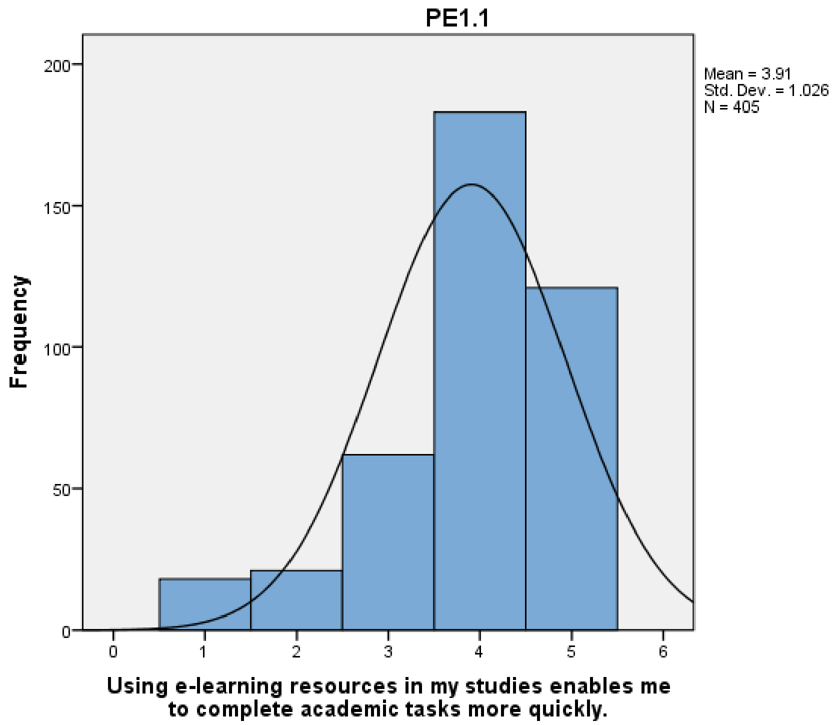

Figure 5.43: Student's Histogram Showing a Large Negative Skewness and Positive Kurtosis in PE 1.1 Data

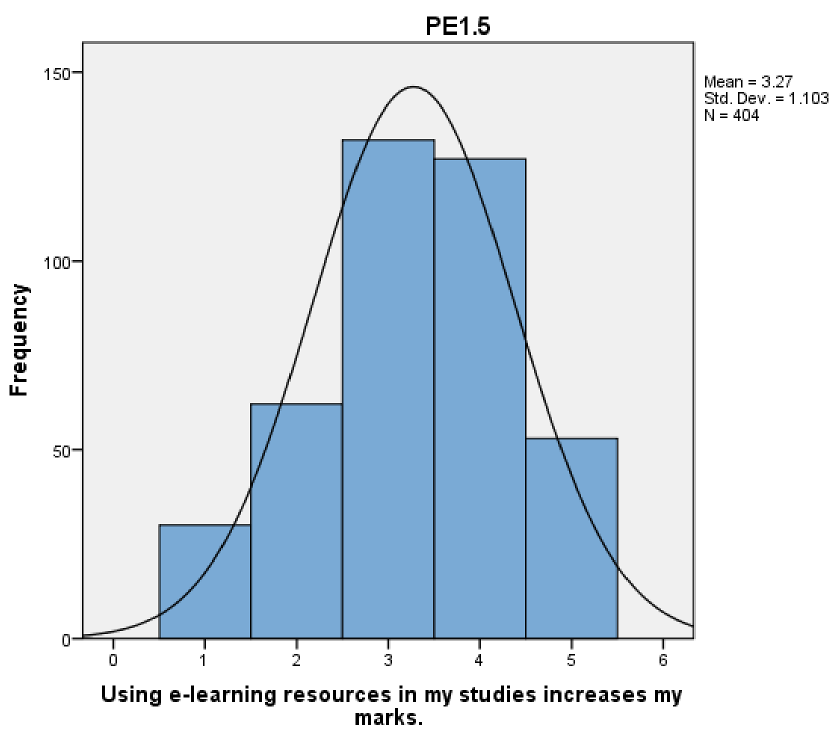

Figure 5.44: Student's Histogram Showing a Negative Skewness and Negative Kurtosis in PE 1.5 Data

Figure 5.43 above shows the trend that can also be seen in Table 5.9 (page 160) of a negative skewness in the distribution of all performance expectancy data of students using e-learning resources. PE1.1 and PE1.4 have the most extreme values over -1. Most performance expectancy indicators statements have a positive kurtosis with a high peak near the mean (see Figure 5.43 above) and a heavy tail in the left direction. However, the last indicator (BI 1.5) has a negative kurtosis with this data distribution having a flat top near the mean (see Figure 5.44 above).

5.4.3.2 Academic Staff

Figures 5.45 to 5.49 below graphically show the academic responses to their performance expectancy indicator statements. The mode for most indicators is four (4), which indicates that most academic staff agrees that the use of e-learning resources were beneficial to obtain performance gains in their academic endeavours. Most academic staff strongly agrees that e-learning resources are, in general useful.

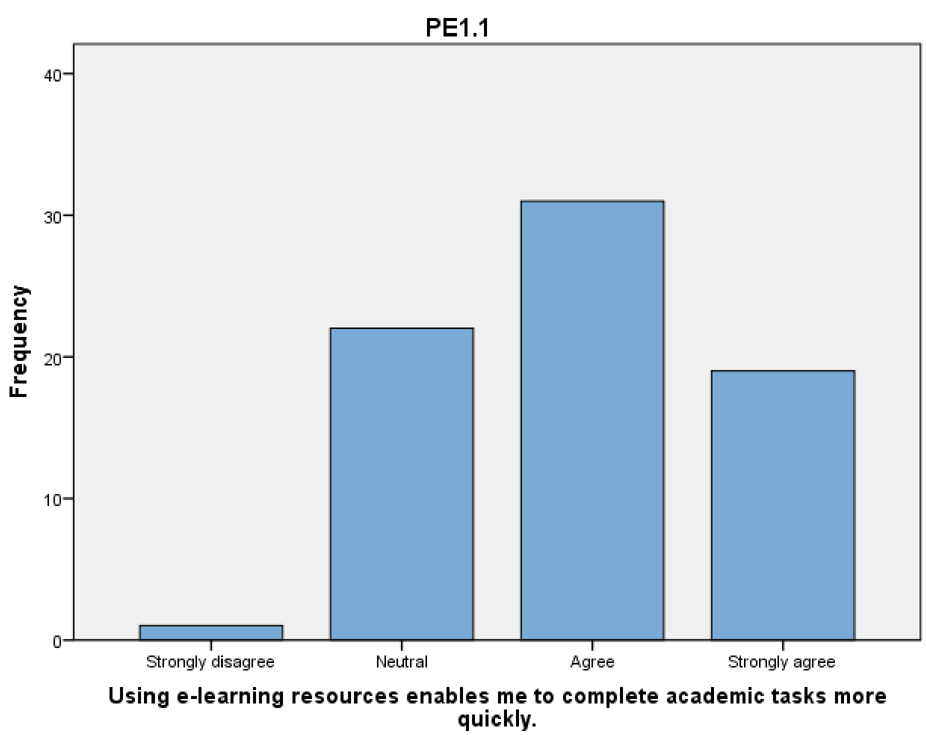

Figure 5.45: Academic Staff's Perceptions that Using E-learning Resources Speeds up the Completion of Academic Tasks

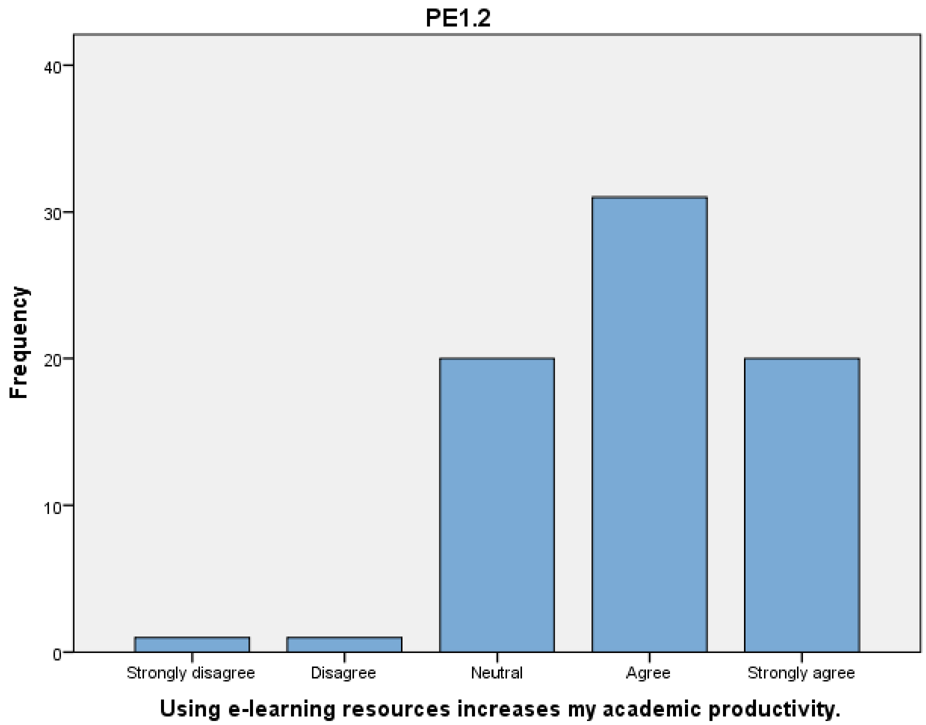

Figure 5.46: Academic Staff's Perceptions that Using E-learning Resources Increases their Academic Productivity

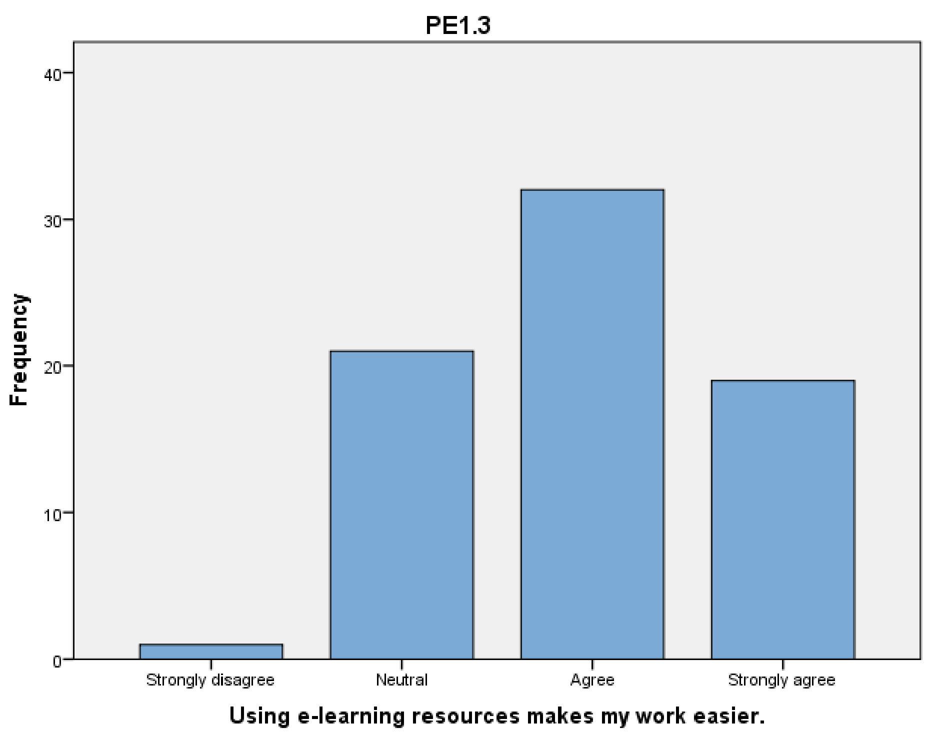

Figure 5.47: Academic Staff's Perceptions that Using E-learning Resources Makes their Work Easier

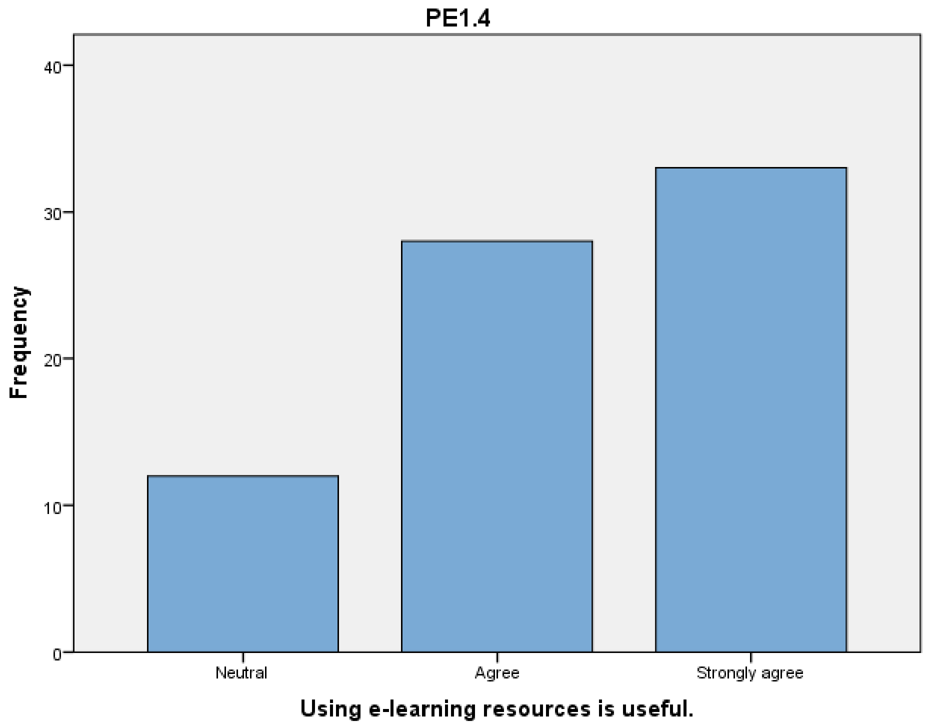

Figure 5.48: Academic Staff's Perceptions of E-learning Resources being Useful

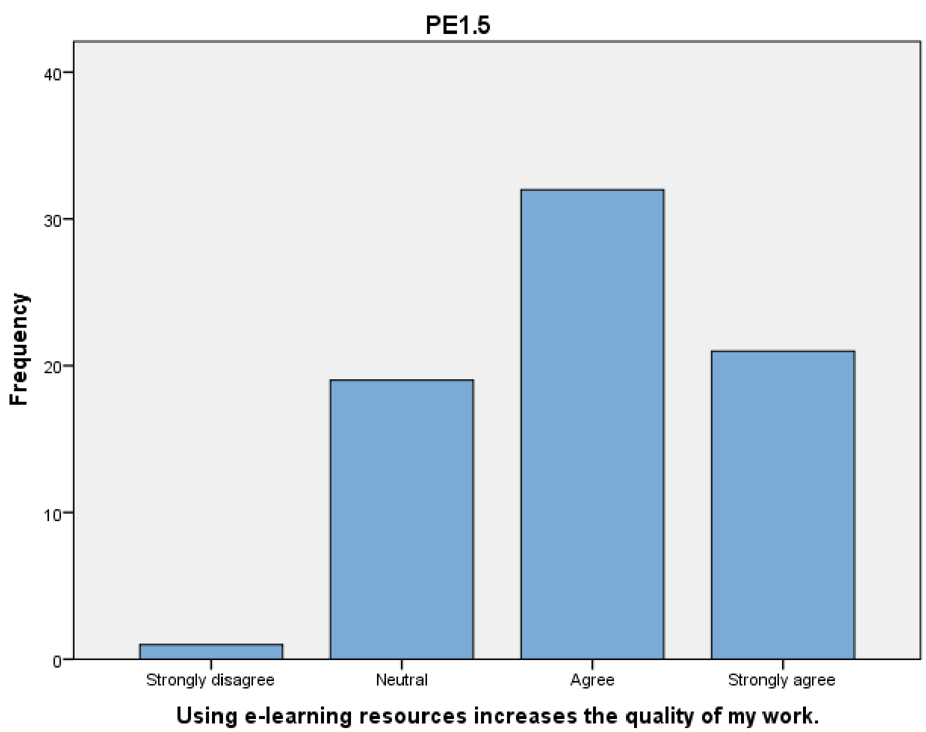

Figure 5.49: Academic Staff's Perceptions that Using E-learning Resources Increases the Quality of their Work

A summary of the descriptive statistics of the five (5) individual indicator statements, that were used to collect a measure of the performance expectancy of academic staff when using e-learning resources, are shown in Table 5.10 below.

Table 5.10: Descriptive Statistics of Academic Staff's Performance Expectancy Indicators

*Used in SEM		*PE1.1	*PE1.2	*PE1.3	*PE1.4	*PE1.5
N	Valid	73	73	73	73	73
	Missing	0	0	0	0	0
Mean		3.92	3.93	3.93	4.29	3.99
Mode		4	4	4	5	4
Std. Deviation		.829	.855	.822	.736	.825
Skewness		-.445	-.552	-.488	-.515	-.585
Std. Error of Skewness		.281	.281	.281	.281	.281
Kurtosis		.516	.509	.653	-.980	.774
Std. Error of Kurtosis		.555	.555	.555	.555	.555

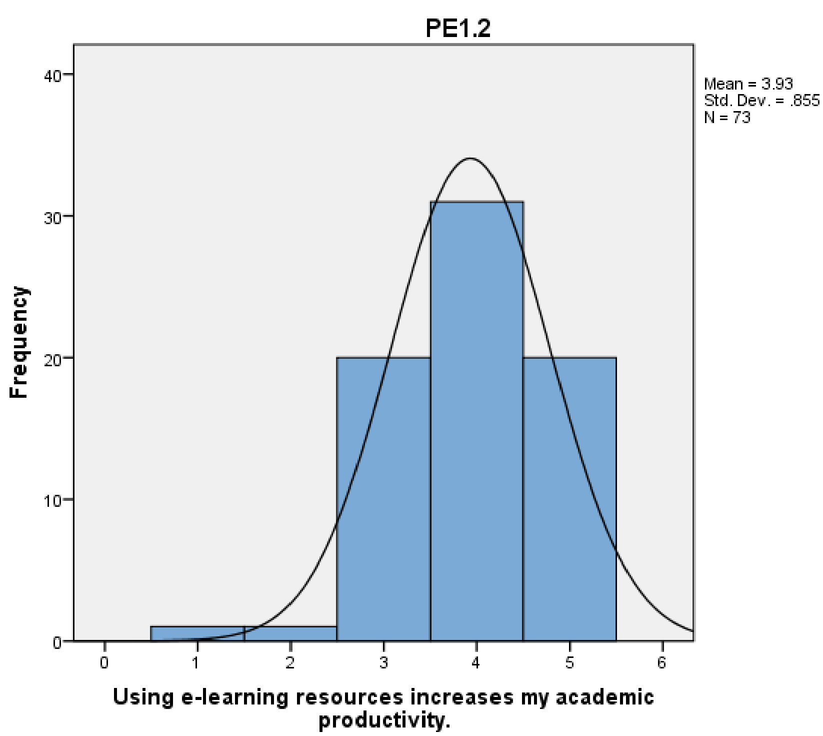

Figure 5.50: Academic Staff's Histogram Showing a Negative Skewness and Positive Kurtosis in PE 1.2 Data

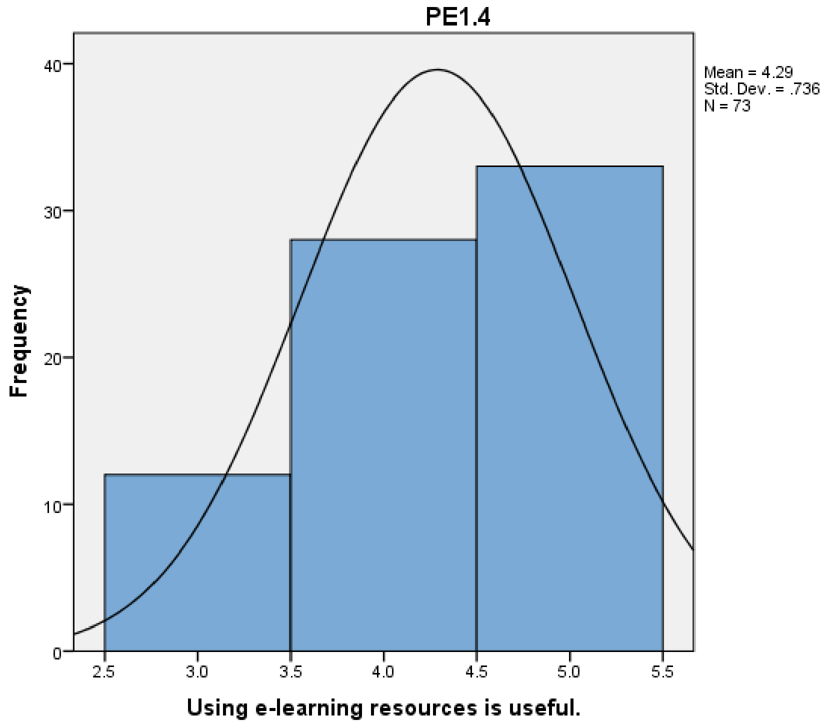

Figure 5.51: Academic Staff's Histogram Showing a Negative Skewness and Negative Kurtosis in PE 1.4 data

Figure 5.50 above shows the trend that can be also be seen in Table 5.10 (page 165) of a negative skewness in the distribution of all performance expectancy data of academic staff using e-learning resources. This indicates that there are relatively few small values, and the left histogram tail is long compared to the right histogram tail. Most performance expectancy indicators statements have a positive kurtosis, with a relatively high peak near the mean (see Figure 5.50 above), and a heavy tail in the left direction. One indicator, however (BI 1.4), has a negative kurtosis with this data distribution having a flat top near the mean (see Figure 5.51 above).

5.4.4 Effort Expectancies

5.4.4.1 Students

Figures 5.52 to 5.55 below represent the student responses to the effort expectancy indicator statements. As can be seen, the mode for all indicators is four (4), which indicates that most students agree that it does not require much effort to use e-learning resources.

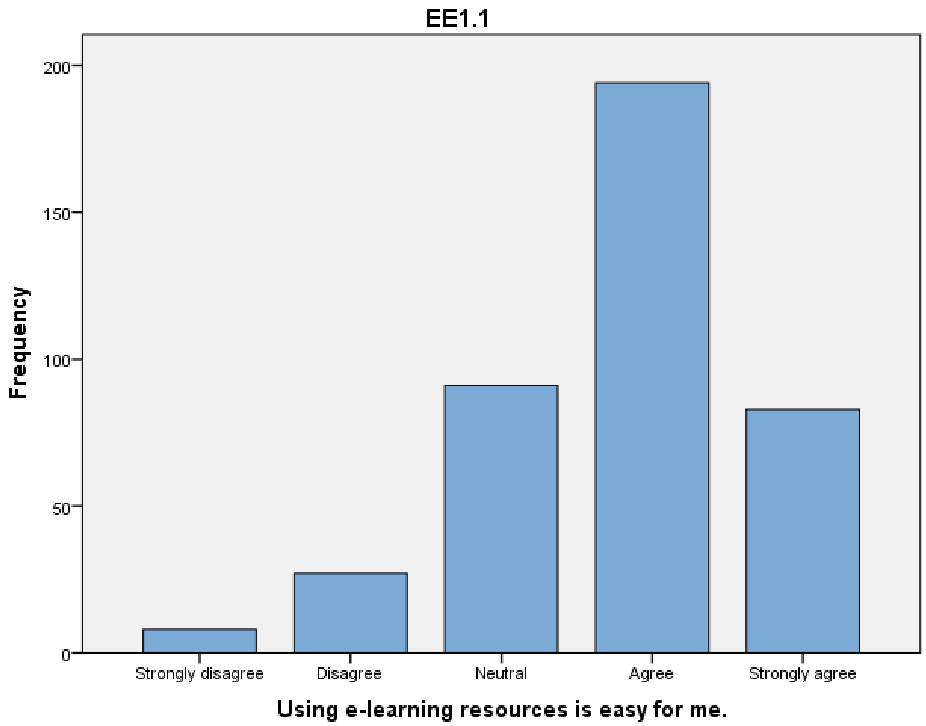

Figure 5.52: Students' Perceptions of E-learning Resources being Easy to Use

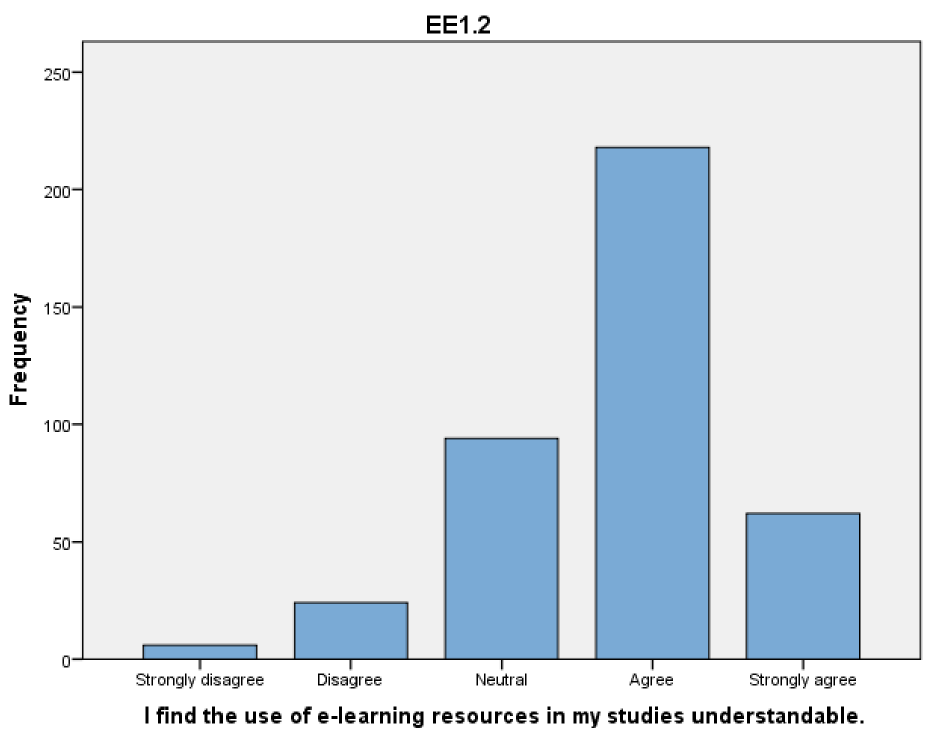

Figure 5.53: Students' Understanding of Using E-learning Resources

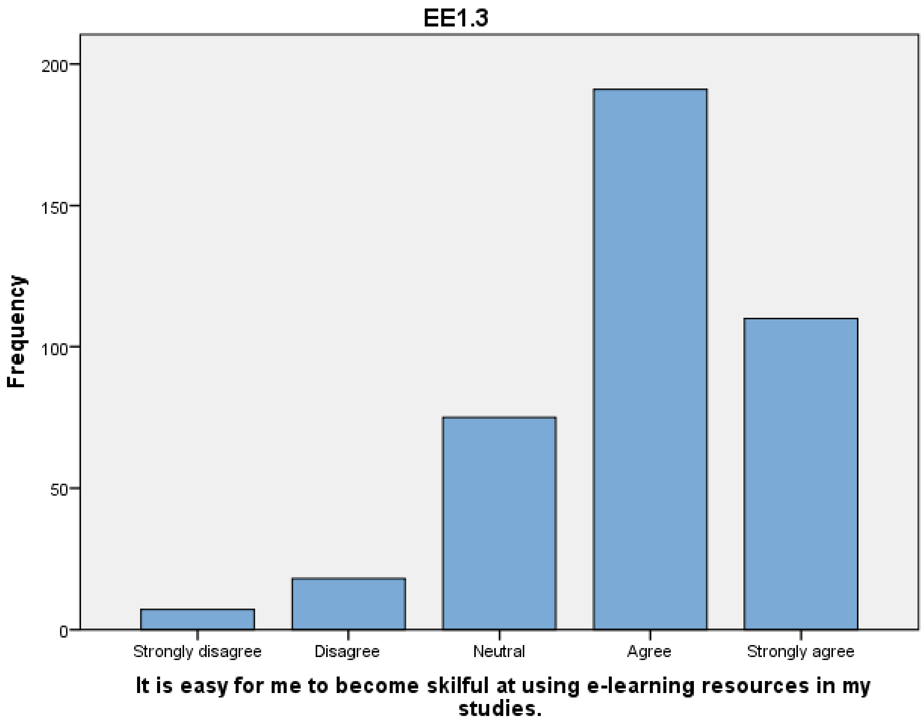

Figure 5.54: Students' Perceptions of Easily Becoming Skilful in Using E-learning Resources

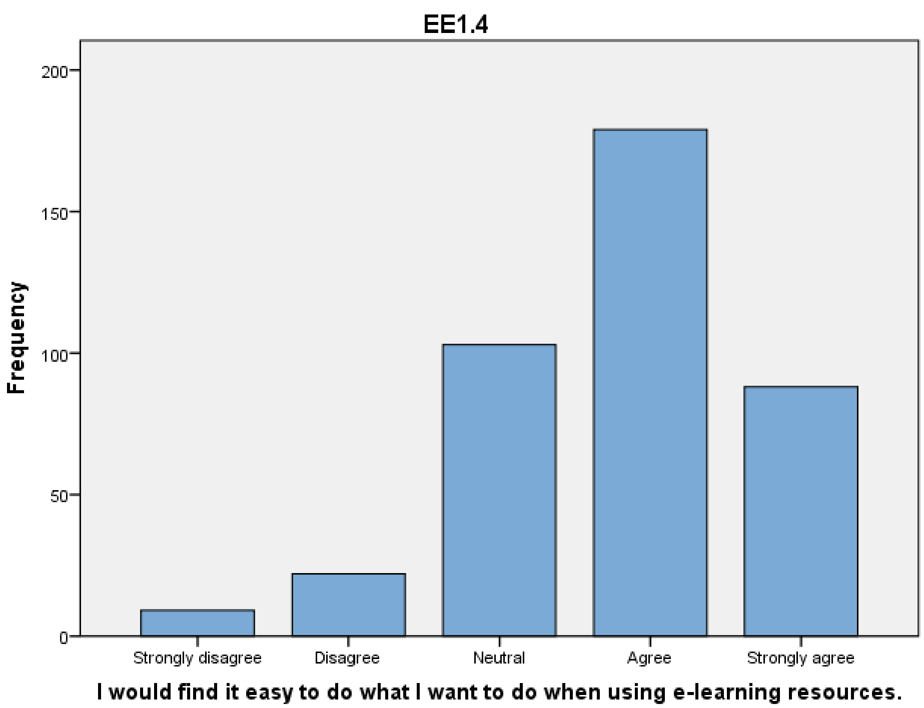

Figure 5.55: Students' Perceptions of Easily Doing What they Want to Do When Using E-learning Resources

The descriptive statistics of the four (4) individual indicator statements, that were used to collect a self-reported measure of the effort expectancy of students when using e-learning resources, are summarised in Table 5.11 below.

Table 5.11: Descriptive Statistics of Students' Effort Expectancy Indicators

*Used in SEM		*EE1.1	*EE1.2	*EE1.3	*EE1.4
N	Valid *Used in SEM	403	404	401	401
	Missing	2	1	4	4
Mean		3.79	3.76	3.95	3.79
Mode		4	4	4	4
Std. Deviation		.914	.837	.893	.924
Skewness		-.725	-.744	-.867	-.670
Std. Error of Skewness		.122	.121	.122	.122
Kurtosis		.500	.856	.894	.446
Std. Error of Kurtosis		.243	.242	.243	.243

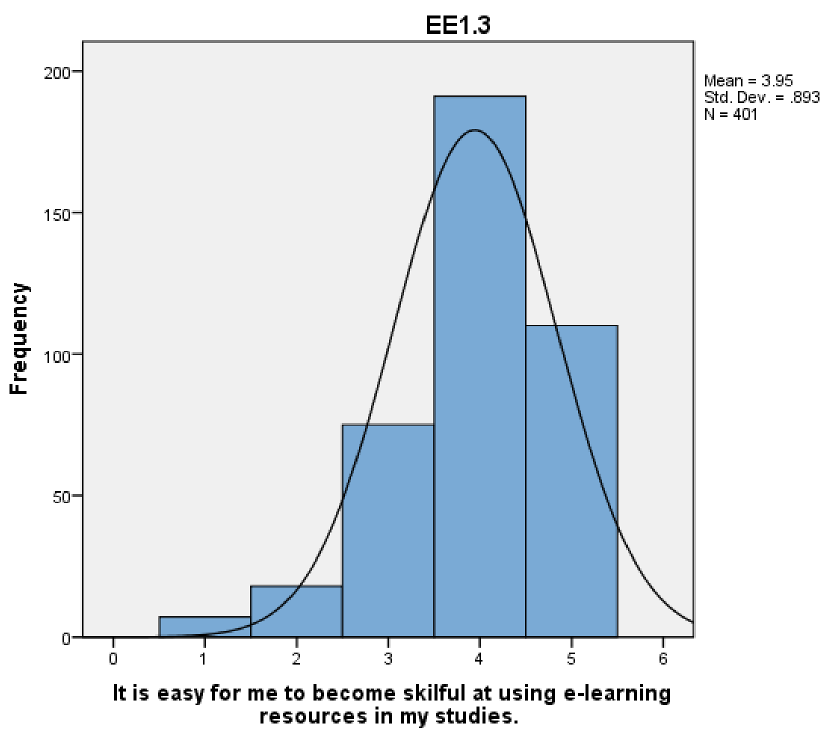

Figure 5.56: Students' Histogram Showing Negative Skewness and Positive Kurtosis in EE1.3 Data

Figure 5.56 above shows the trend that can also be seen in Table 5.11 (page 169) of a negative skewness in the distribution of all effort expectancy data of students using e-learning resources. All indicators statements also have a positive kurtosis with a relatively high peak near the mean (see Figure 5.56 above) and a heavy tail in the left direction.

5.4.4.2 Academic Staff

Figures 5.57 to 5.60 below graphically represent the academic staff's responses to their effort expectancy indicator statements. The mode for most indicators is four (4), indicating that most academic staff agrees that it does not take much effort to use e-learning resources at the University of Zululand.

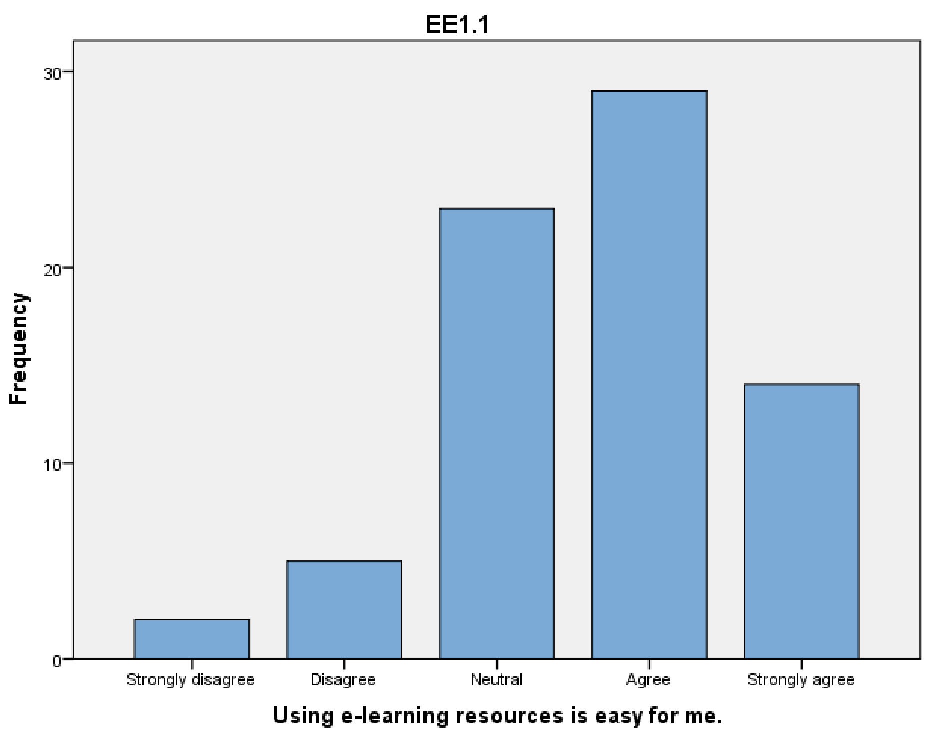

Figure 5.57: Academic staff's Perceptions that E-learning Resources are Easy to Use

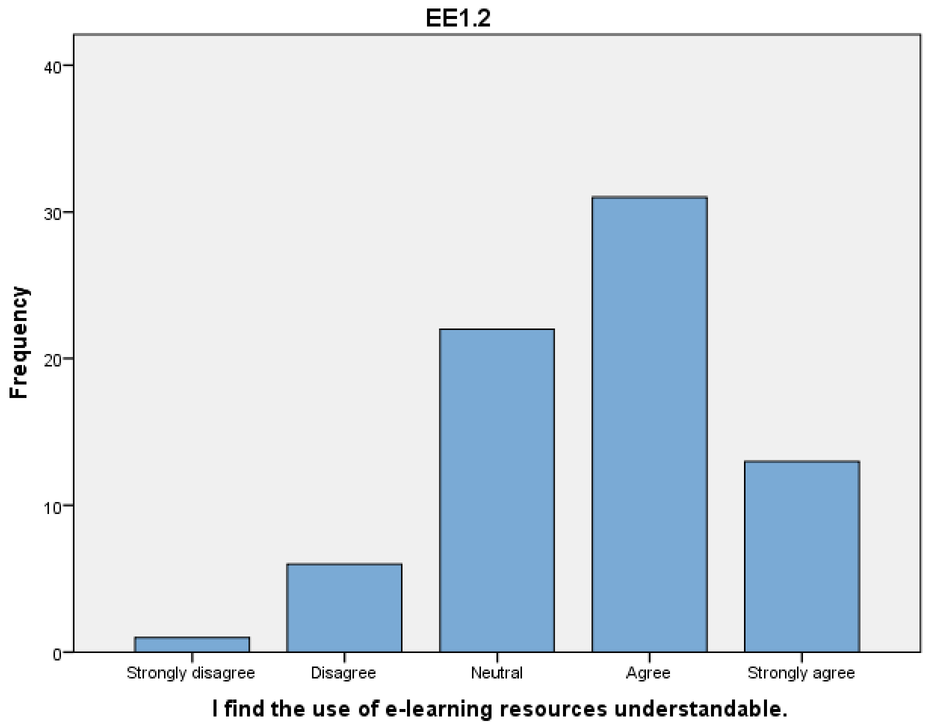

Figure 5.58: Academic Staffs' Understanding of Using E-learning Resources

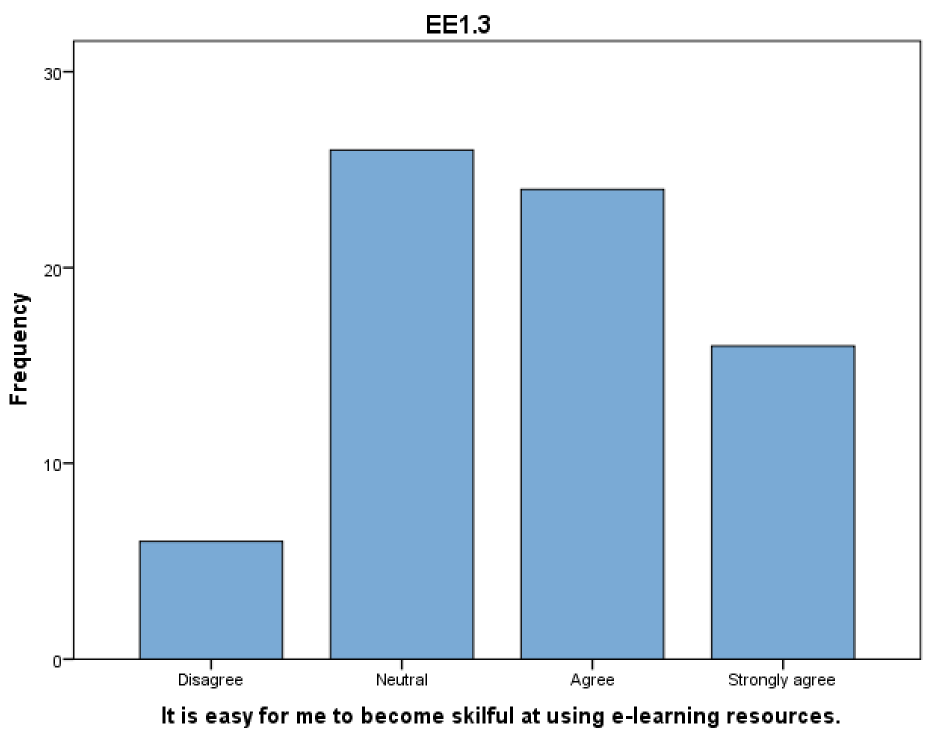

Figure 5.59: Academic Staffs' Perceptions of Easily Becoming Skilful in Using E-learning Resources

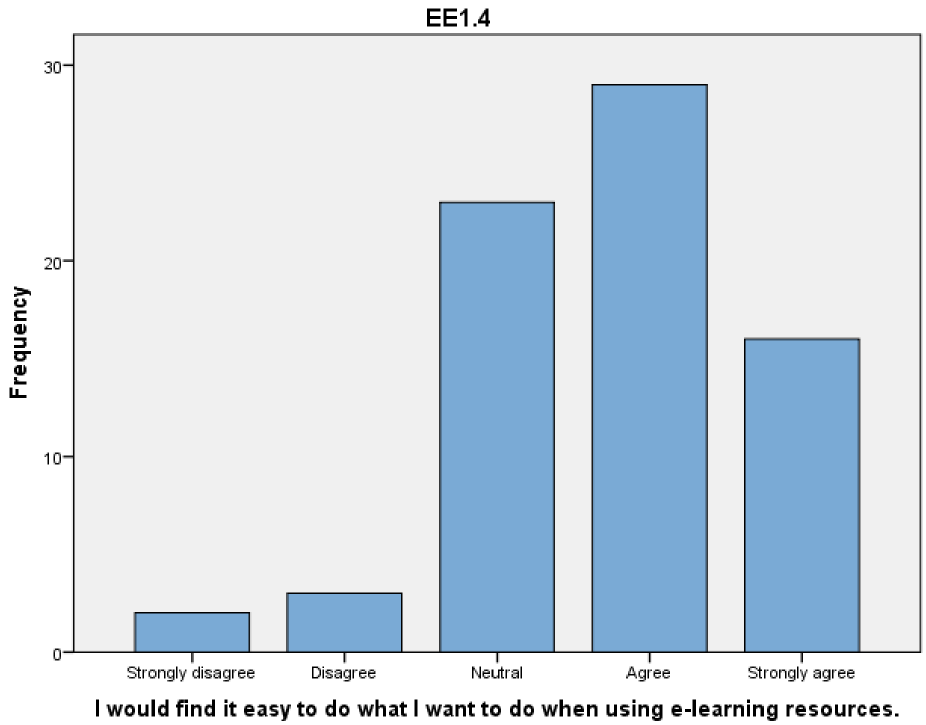

Figure 5.60: Academic Staff's Perceptions of Easily Doing What they Want to Do when Using E-learning Resources

A summary of the descriptive statistics of the four (4) individual indicator statements, that were used to collect a measure of the effort expectancy of academic staff when using e-learning resources, are shown in Table 5.12 below.

Table 5.12: Descriptive Statistics of Academic Staff's Effort Expectancy Indicators

*Used in SEM		*EE1.1	*EE1.2	*EE1.3	*EE1.4
N	Valid	73	73	72	73
	Missing	0	0	1	0
Mean		3.66	3.67	3.69	3.74
Mode		4	4	3	4
Std. Deviation		.961	.914	.914	.943
Skewness		-.512	-.414	-.031	-.573
Std. Error of Skewness		.281	.281	.283	.281
Kurtosis		.198	-.030	-.884	.448
Std. Error of Kurtosis		.555	.555	.559	.555

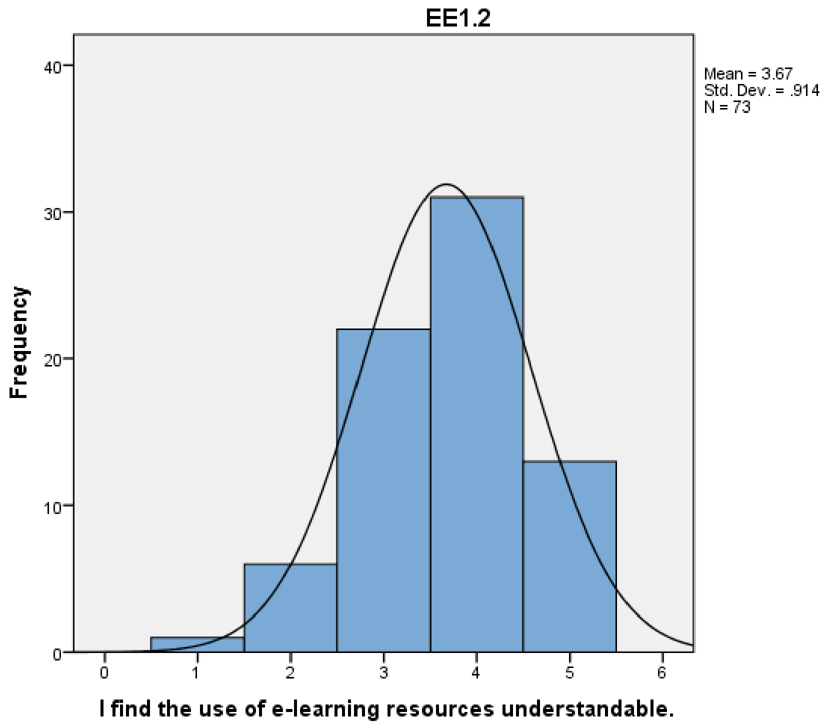

Figure 5.61: Academic Staff's Histogram Showing a Negative Skewness and Negative Kurtosis in EE 1.2 Data

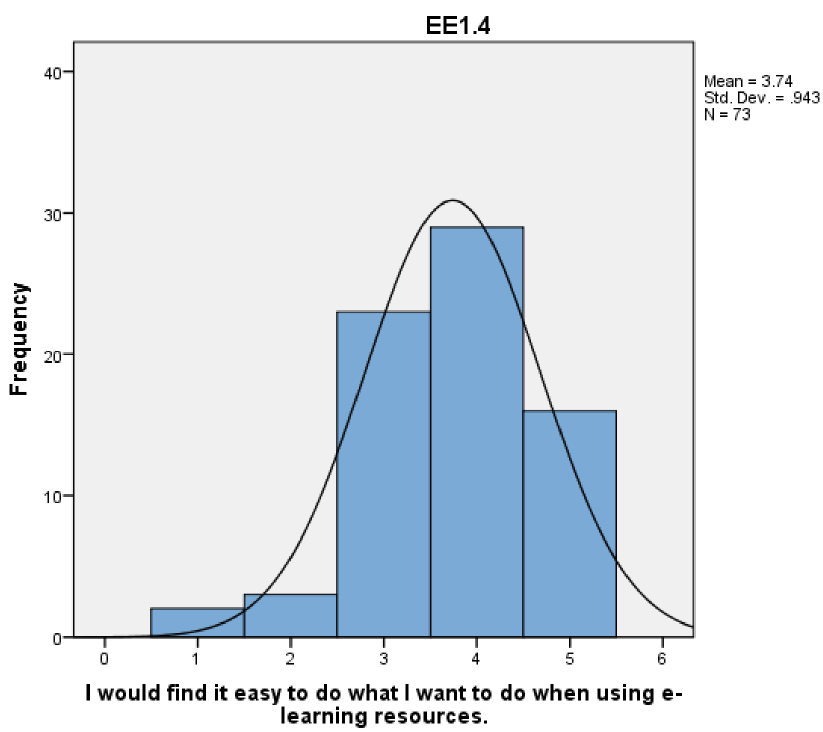

Figure 5.62: Academic Staff's Histogram Showing a Negative Skewness and Positive Kurtosis in EE 1.4 Data

Figure 5.61 above shows the trend that can be also be seen in Table 5.12 (page 172) of a negative skewness in the distribution of all effort expectancy data of academic staff using e-learning resources. This indicates that there are relatively few small values and the left histogram tail is long compared to the right histogram tail. Two indicators statements (EE1.1 and EE1.4) have a positive kurtosis, with a relatively high peak near the mean (see Figure 5.62 above), and a heavy tail in the left direction. The other two (EE1.2 and EE1.3) have a negative kurtosis with their data distributions having flat tops near the mean (see Figure 5.61 above).

5.4.5 Social Influences

5.4.5.1 Students

Figures 5.63 to 5.66 below graphically represent the student responses to the social influence indicator statements. The mode for the four (4) social influence indicators was 3, 4, 4 and 2, which seem to indicate that students have mixed opinions about social influences on their use of e-learning resources.

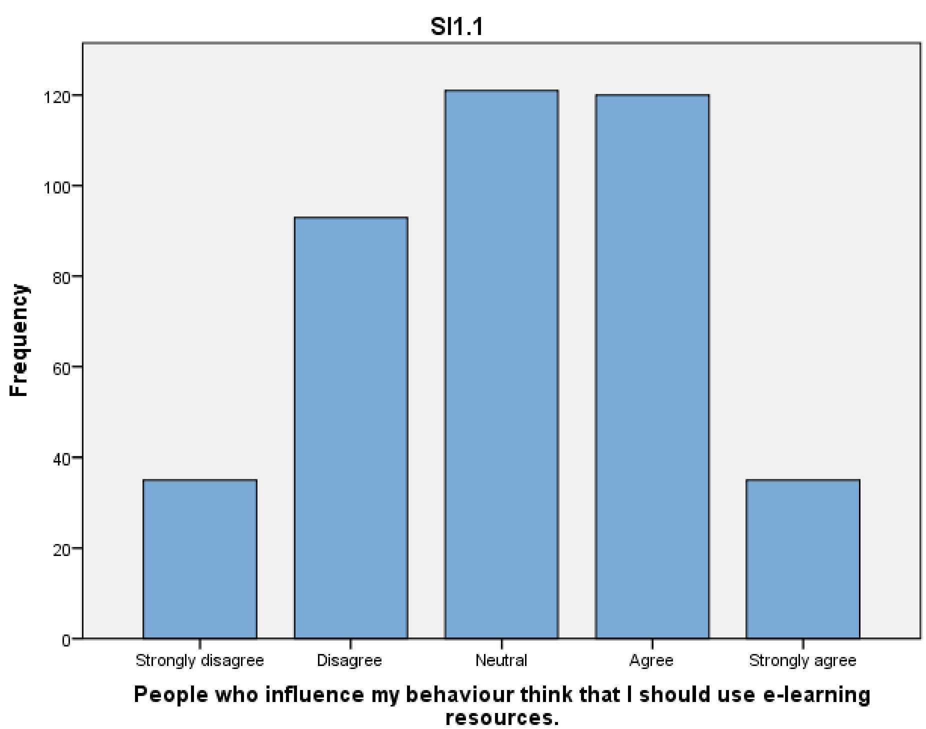

Figure 5.63: Students' Perceptions of Whether People who Influence their Behaviour Think they Should Use E-learning Resources

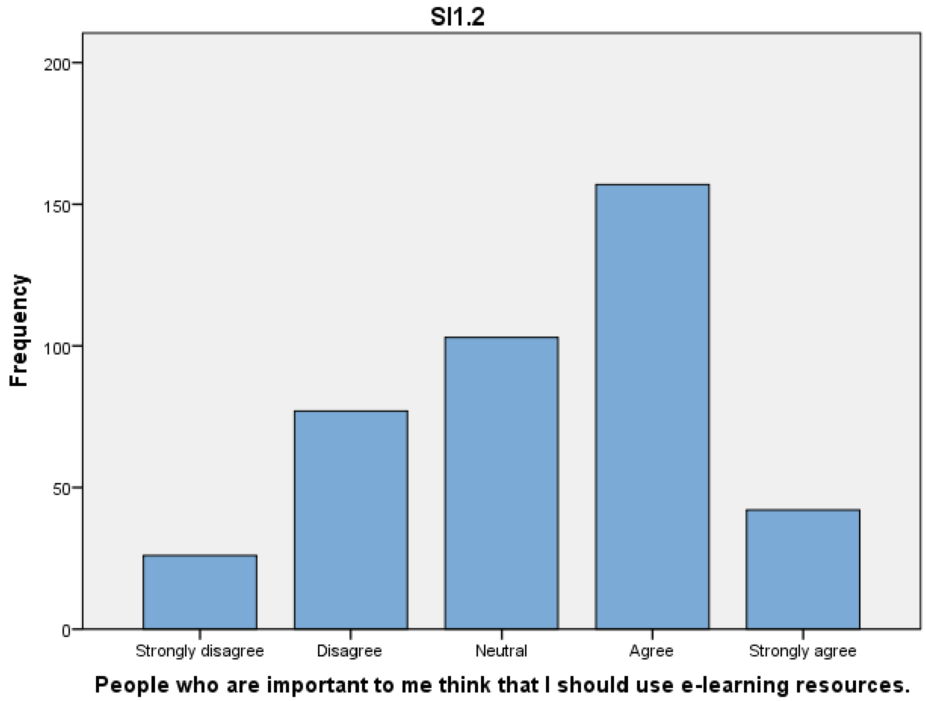

Figure 5.64: Students' Perceptions of Whether People Who are Important to Them Think they Should Use E-learning Resources

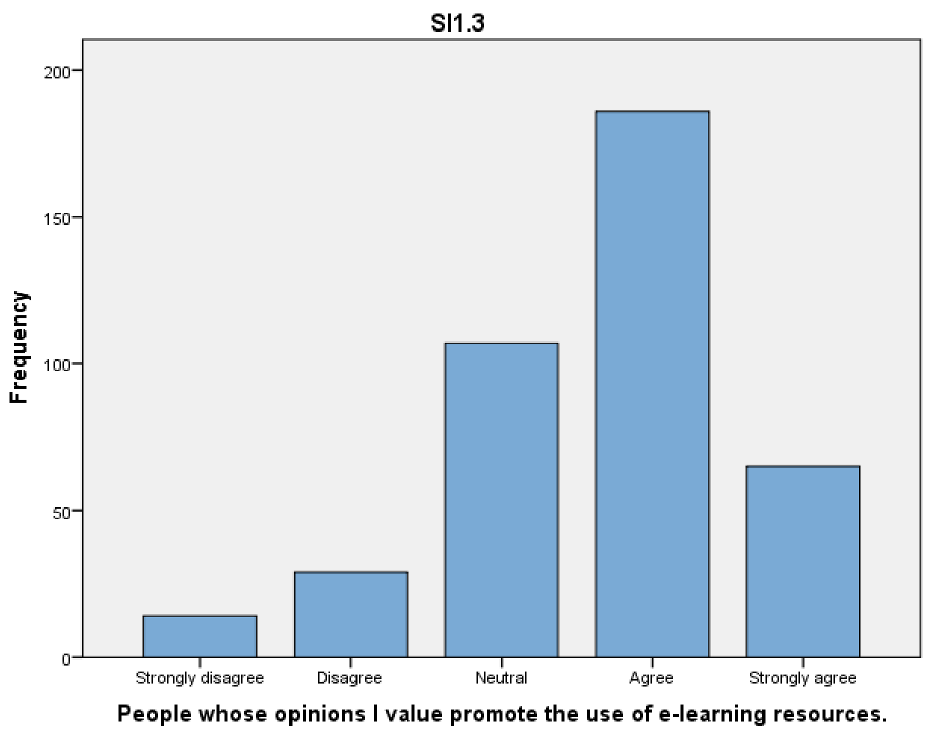

Figure 5.65: Students' Perceptions of Whether People Whose Opinions they Value Promote the Use of E-learning Resources

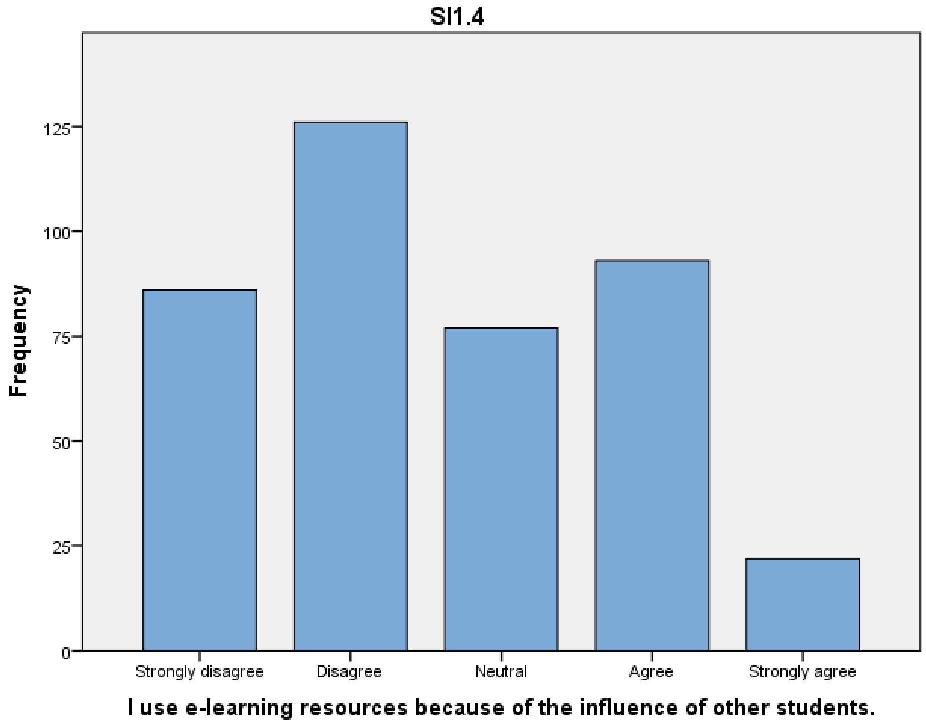

Figure 5.66: Students' Perceptions of Whether Other Students Influence their Use of E-learning Resources

The descriptive statistics of the four (4) individual indicator statements, that were used to collect a self-reported measure of the social influences on students' behavioural intentions to use e-learning resources, are summarised in Table 5.13 below.

Table 5.13: Descriptive Statistics of Students' Social Influence Indicators

*Used in SEM		*SI1.1	*SI1.2	*SI1.3	SI1.4
N	Valid	404	405	401	404
	Missing	1	0	4	1
Mean		3.07	3.28	3.65	2.60
Mode		3	4	4	2
Std. Deviation		1.104	1.084	.954	1.207
Skewness		-.133	-.380	-.718	.259
Std. Error of Skewness		.121	.121	.122	.121
Kurtosis		-.752	-.629	.474	-1.041
Std. Error of Kurtosis		.242	.242	.243	.242

Figure 5.67: Student Histogram Showing a Very Slight Negative Skewness and Negative Kurtosis in SI1.1 Data

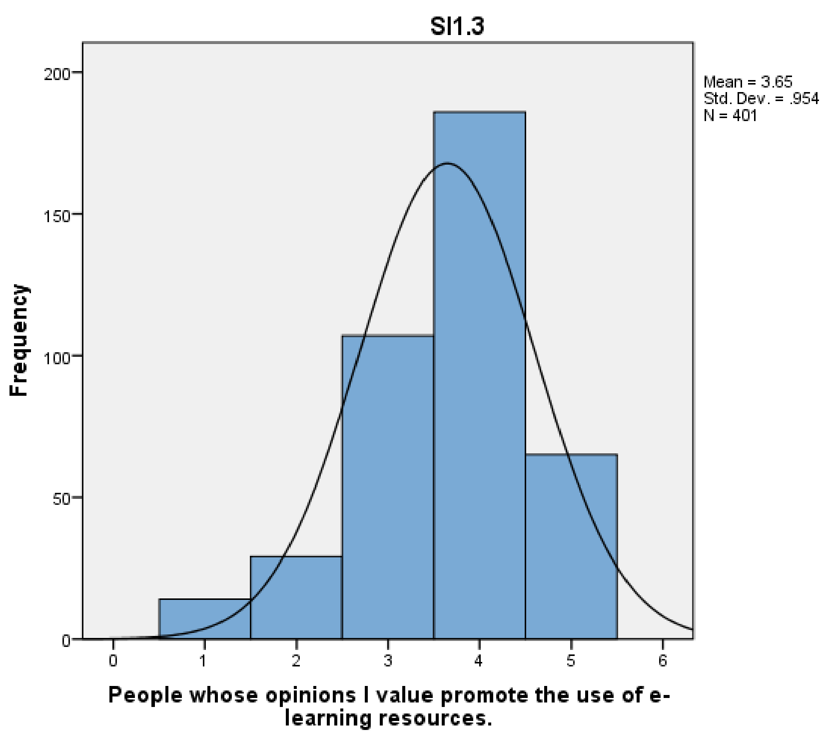

Figure 5.68: Students' Histogram Showing a Negative Skewness and Positive Kurtosis in SI1.3 Data

Figure 5.67 above shows the trend that can be also be seen in Table 5.13 (page 176) of a negative skewness in the distribution of most social influence data of students, except SI1.4, which has a positive skewness. Most performance expectancy indicators statements have a negative kurtosis, with these data distributions having flat tops near the mean (see Figure 5.67 above), while SI1.3 has a positive kurtosis with a relatively high peak near the mean (see Figure 5.68 above), and a heavy tail in the left direction.

5.4.5.2 Academic Staff

Figures 5.69 to 5.72 below show the responses of academic staff to the social influence indicator statements. The modes for indicators is three (3), three (3), four (4) and three (3), which suggests that most academic staff at the University of Zululand have neutral feelings about whether there are social influences in their decisions or behavioural intentions to usage e-learning resources or not.

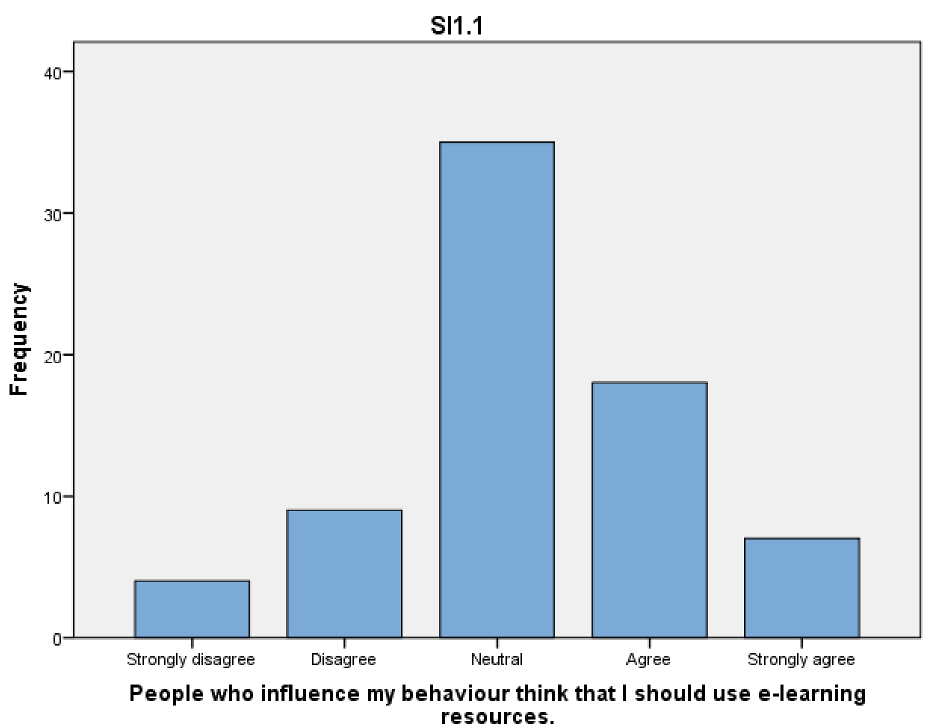

Figure 5.69: Academic Staff's Perceptions of Whether People Who Influence their Behaviour Think they Should Use E-learning Resources

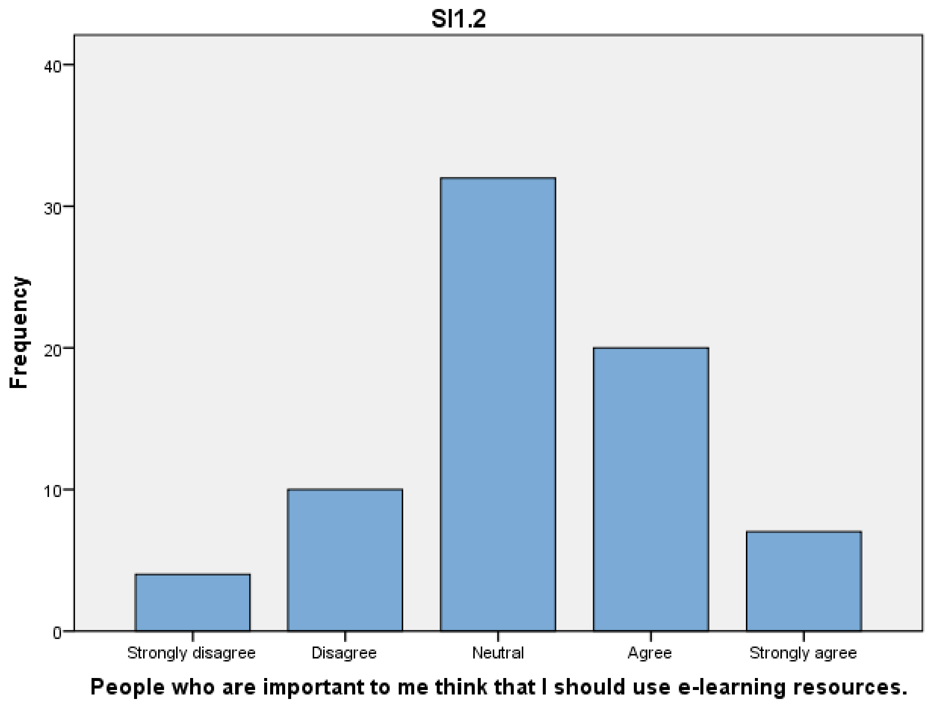

Figure 5.70: Academic Staff's Perceptions of Whether People Who are Important to Them Think They Should Use E-learning Resources

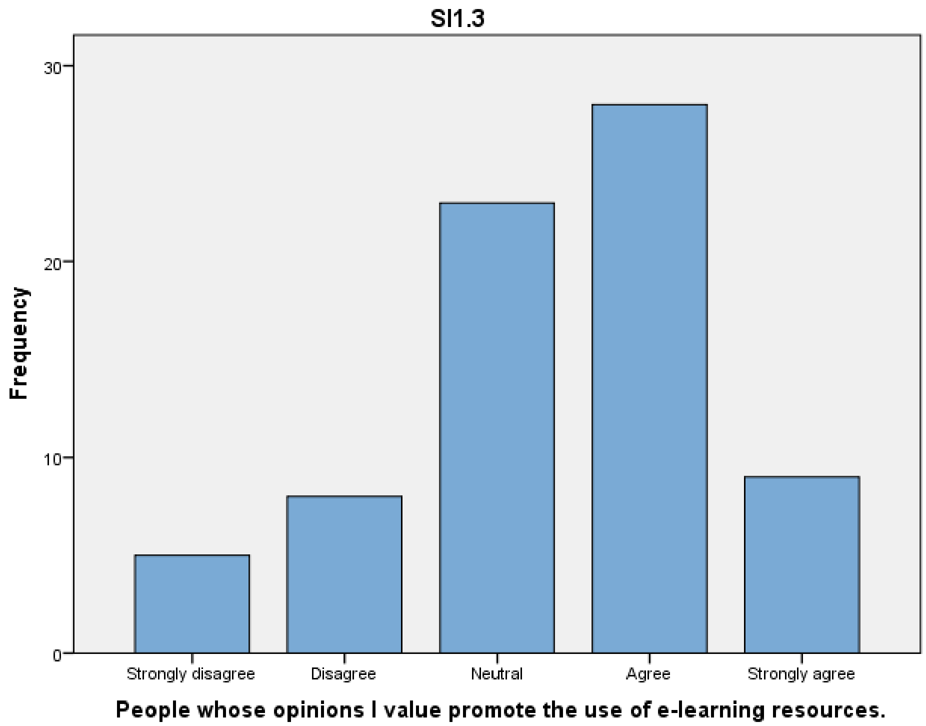

Figure 5.71: Academic Staff's Perceptions of Whether People Whose Opinions they Value Promote the Use of E-learning Resources

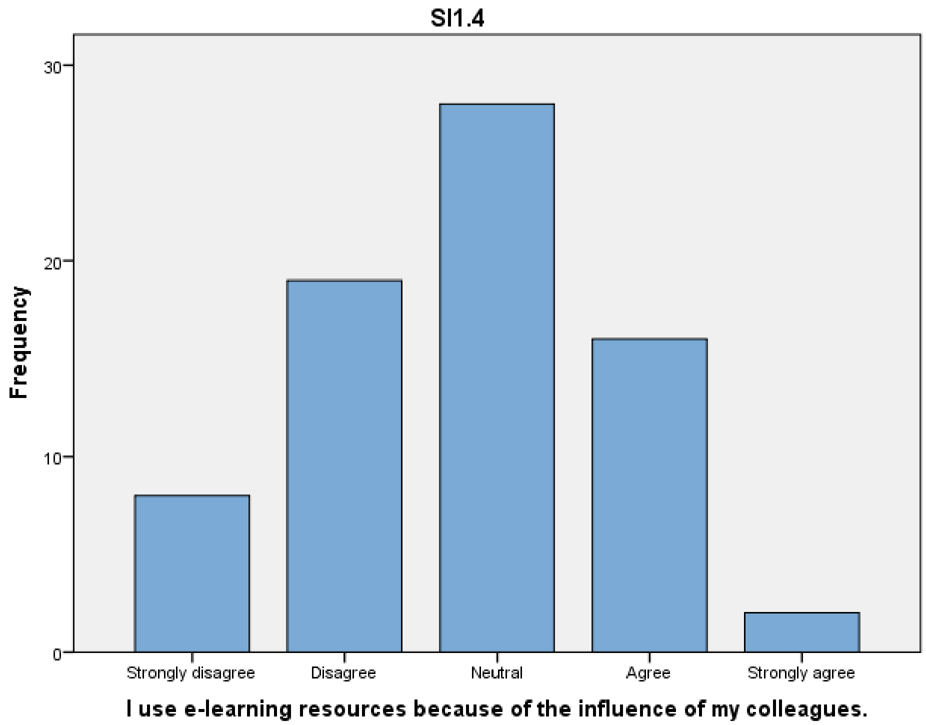

Figure 5.72: Academic Staff's Perceptions of Whether Colleagues Influence their Use of E-learning Resources

The summary of the descriptive statistics of the four (4) individual indicator statements, that were used to collect a self-reported measure of the social influences on academic staff to use e-learning resources, are show in Table 5.14 below.

Table 5.14: Descriptive statistics of Academic Staff's Social Influence Indicators

*Used in SEM		*SI1.1	*SI1.2	*SI1.3	SI1.4
N	Valid	73	73	73	73
	Missing	0	0	0	0
Mean		3.21	3.22	3.38	2.79
Mode		3	3	4	3
Std. Deviation		.971	.989	1.062	.999
Skewness		-.148	-.193	-.543	-.086
Std. Error of Skewness		.281	.281	.281	.281
Kurtosis		.153	-.026	-.087	-.531
Std. Error of Kurtosis		.555	.555	.555	.555

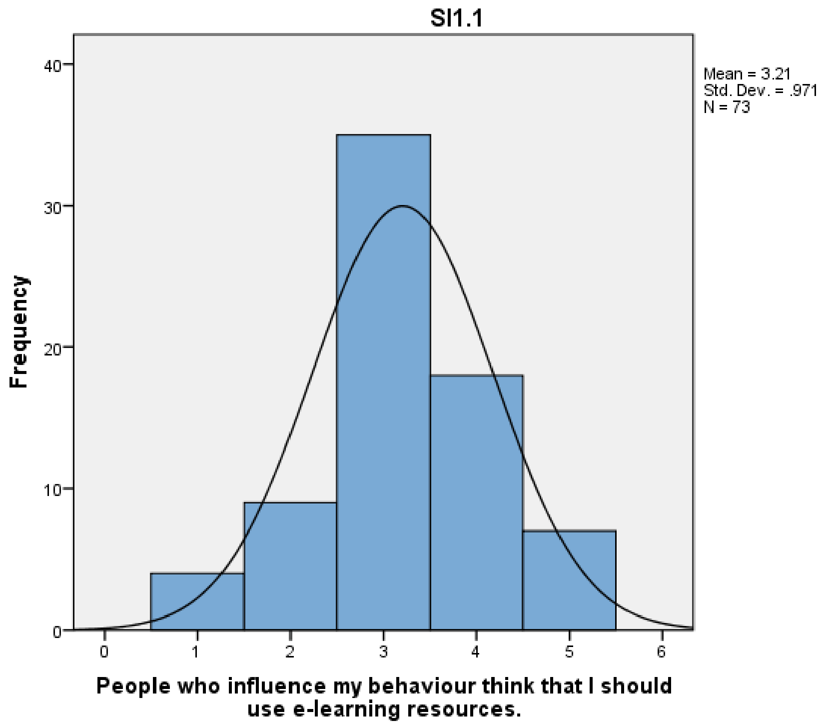

Figure 5.73: Academic Staff's Histogram Showing a Negative Skewness and Positive Kurtosis in SI1.1 Data

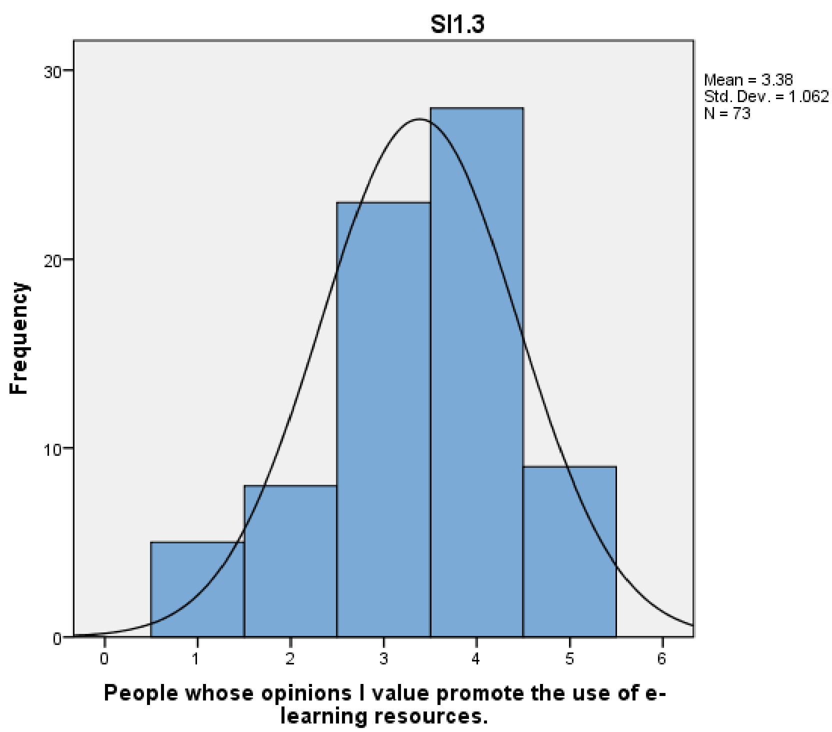

Figure 5.74: Academic Staff's Histogram Showing a Negative Skewness and Negative Kurtosis in SI1.3 Data

Figures 5.73 and 5.74 above show the trend that can also be seen in Table 5.14 (page 180) of a negative skewness in the distribution of all social influence data of academic staff, which indicates that there are relatively few small values and the left histogram tail is long compared to the right histogram tail. Most social influence indicator statements have a negative kurtosis, with these data distributions having flat tops near the mean (see Figure 5.74 above), while SI1.1 has a positive kurtosis with a relatively high peak near the mean (see Figure 5.73 above), and a heavier tail in the left direction.

5.4.6 Facilitating Conditions

5.4.6.1 Students

Figures 5.75 to 5.79 below represent the student responses to the facilitating conditions indicator statements. The mode for all indicators is four (4), which seem to suggest that students agree that the conditions at the University of Zululand do facilitate their use of e-learning resources.

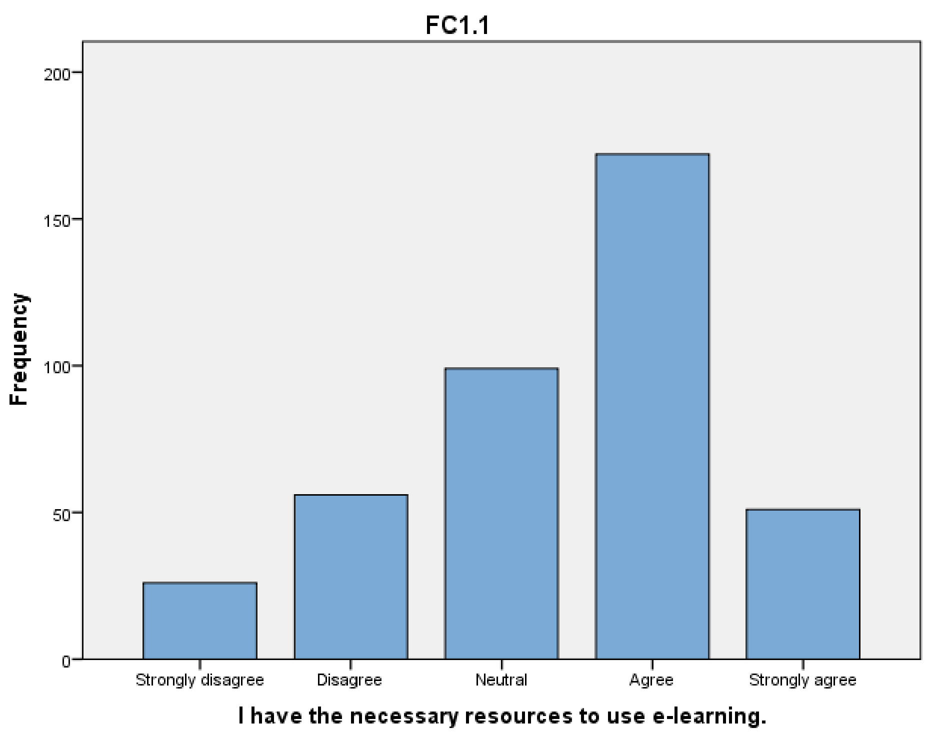

Figure 5.75: Students' Perceptions of Whether They Have the Necessary E-learning Resources

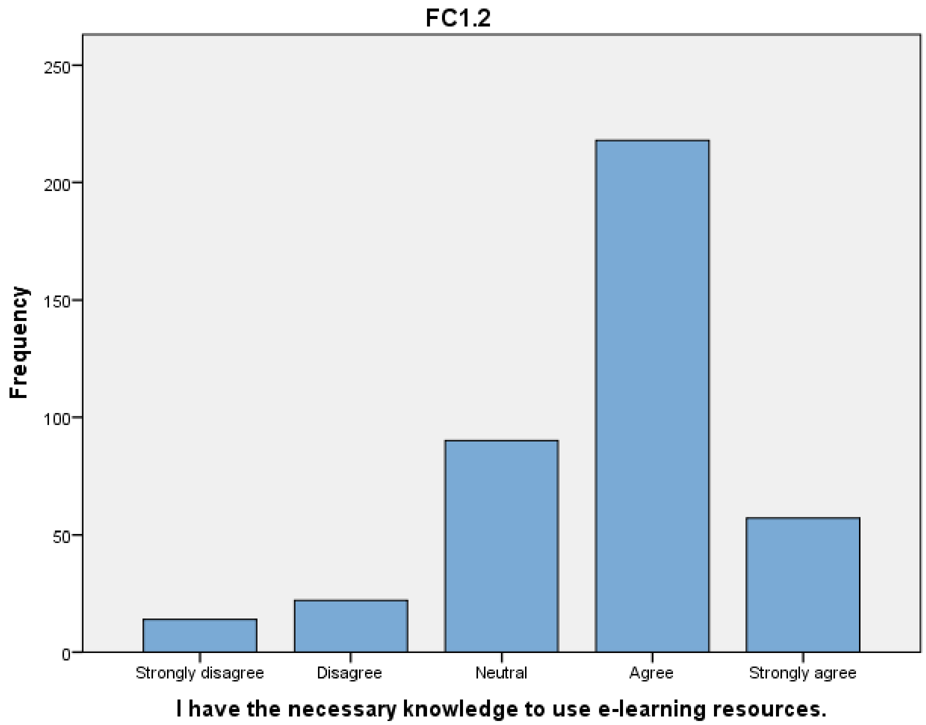

Figure 5.76: Students' Perceptions of Whether They Have the Necessary Knowledge to Use E-learning Resources

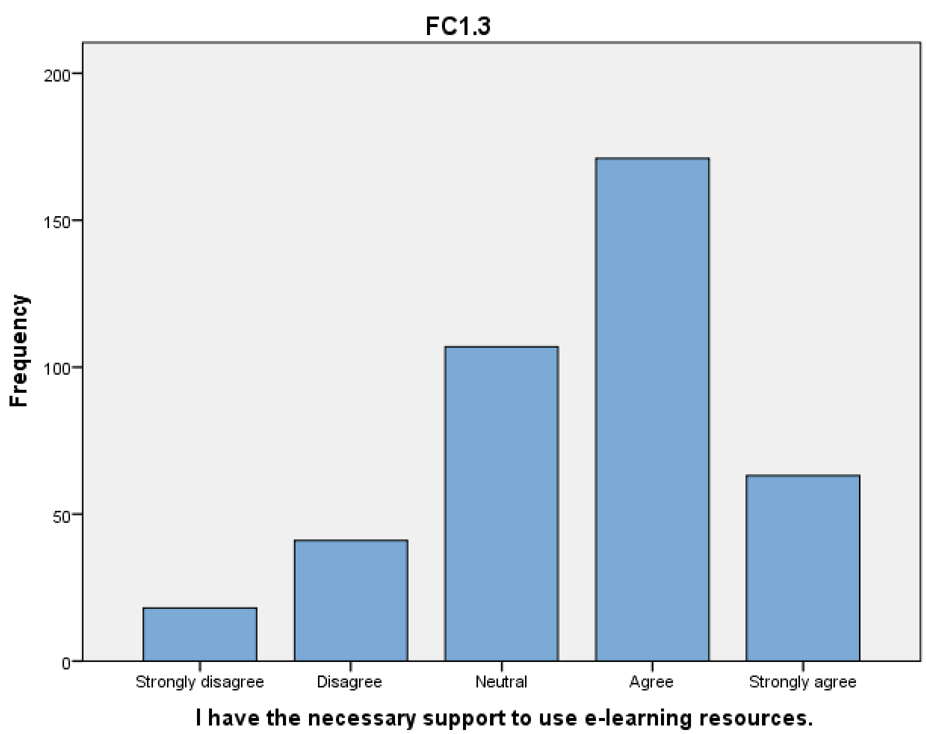

Figure 5.77: Students' Perceptions of Whether They Have the Necessary Support to Use E-learning Resources

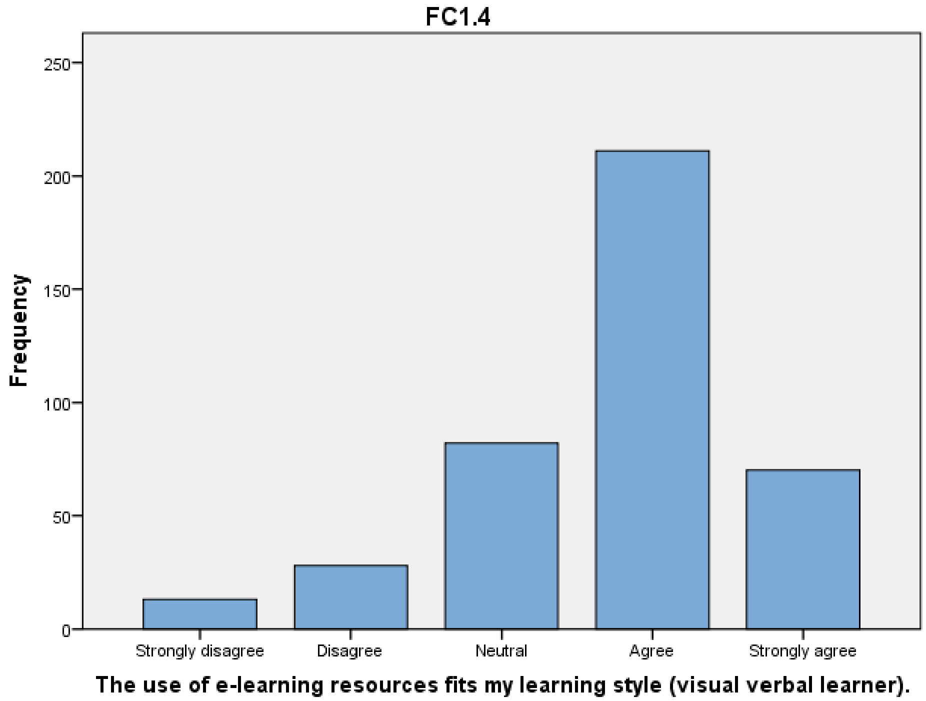

Figure 5.78: Students' Perceptions of Whether Using E-learning Resources Fit their Learning Style

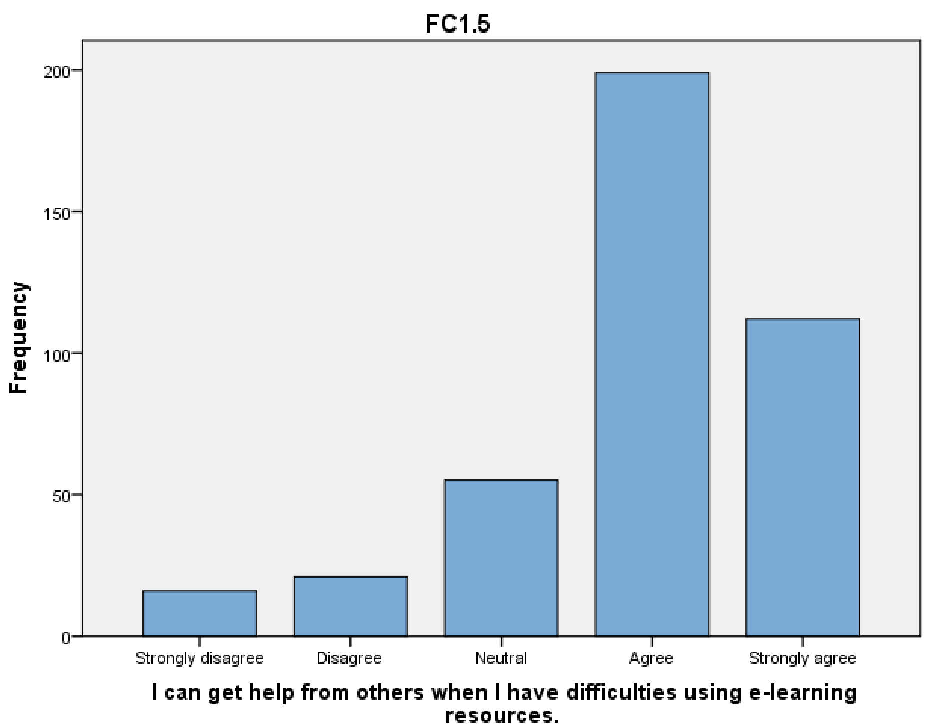

Figure 5.79: Students' Perceptions of Whether They Can Get Help from Others When they Experience Difficulties Using E-learning Resources

The descriptive statistics of the five (5) individual indicator statements, that were used to collect a self-reported measure of the facilitating conditions for students to use e-learning resources, are summarised in Table 5.15 below.

Table 5.15: Descriptive statistics of Students' Facilitating Conditions Indicators

*Used in SEM		*FC1.1	*FC1.2	*FC1.3	FC1.4	FC1.5
N	Valid	404	401	400	404	403
	Missing	1	4	5	1	2
Mean		3.41	3.70	3.55	3.74	3.92
Mode		4	4	4	4	4
Std. Deviation		1.077	.902	1.020	.935	.988
Skewness		-.576	-.980	-.620	-.912	-1.158
Std. Error of Skewness		.121	.122	.122	.121	.122
Kurtosis		-.314	1.256	.018	.877	1.318
Std. Error of Kurtosis		.242	.243	.243	.242	.243

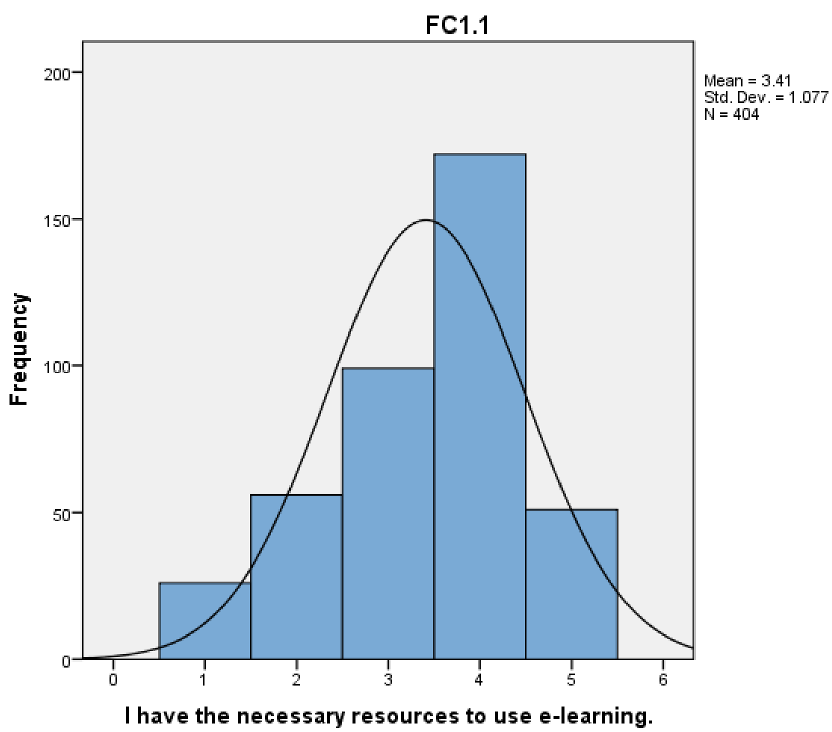

Figure 5.80: Students' Histogram Showing a Negative Skewness and Negative Kurtosis in FC1.1 Data

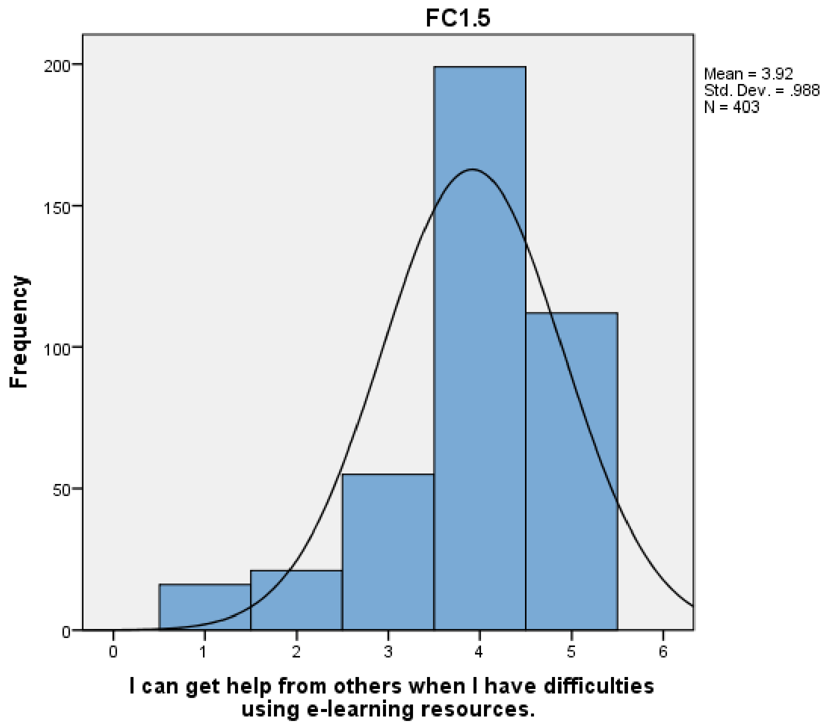

Figure 5.81: Students' Histogram Showing Large Negative Skewness and Positive kurtosis in FC1.5 Data

Figures 5.80 and 5.81 above show the trend that can be also be seen in Table 5.15 (page 185) of a negative skewness in the distribution of most facilitating conditions data of students, with FC1.5 having the most extreme value over -1. Most facilitating conditions indicator statements have a positive kurtosis with a relatively high peak near the mean (see Figure 5.81 above) and a heavy tail in the left direction. FC1.1 has a negative kurtosis, with this data distribution having a flatter top near the mean (see Figure 5.80 above).

5.4.6.2 Academic Staff

Figures 5.82 to 5.86 below graphically represent the academics staff's responses to the facilitating conditions indicator statements. The mode for most indicators is four (4), which indicates that most academic staff agrees that the conditions at the University of Zululand facilitate their usage of e-learning resources. It should be noted, however, that most academic staff were neutral about whether or not they got the necessary support to use e-learning resources at the University of Zululand (see Figure 5.84 below).

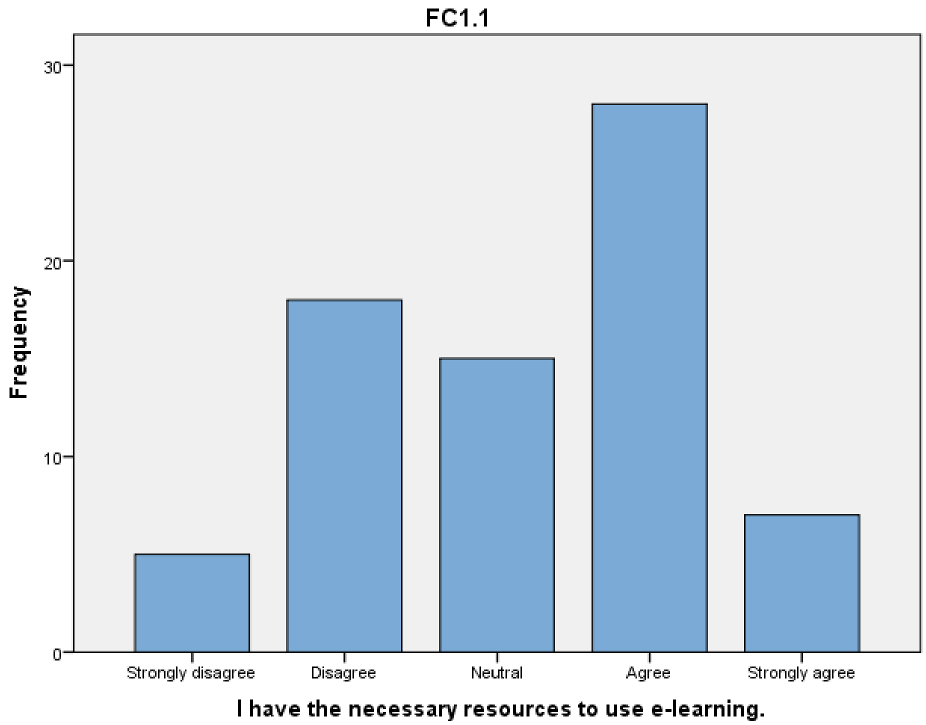

Figure 5.82: Academic Staff's Perceptions of Whether They Have the Necessary E-learning Resources

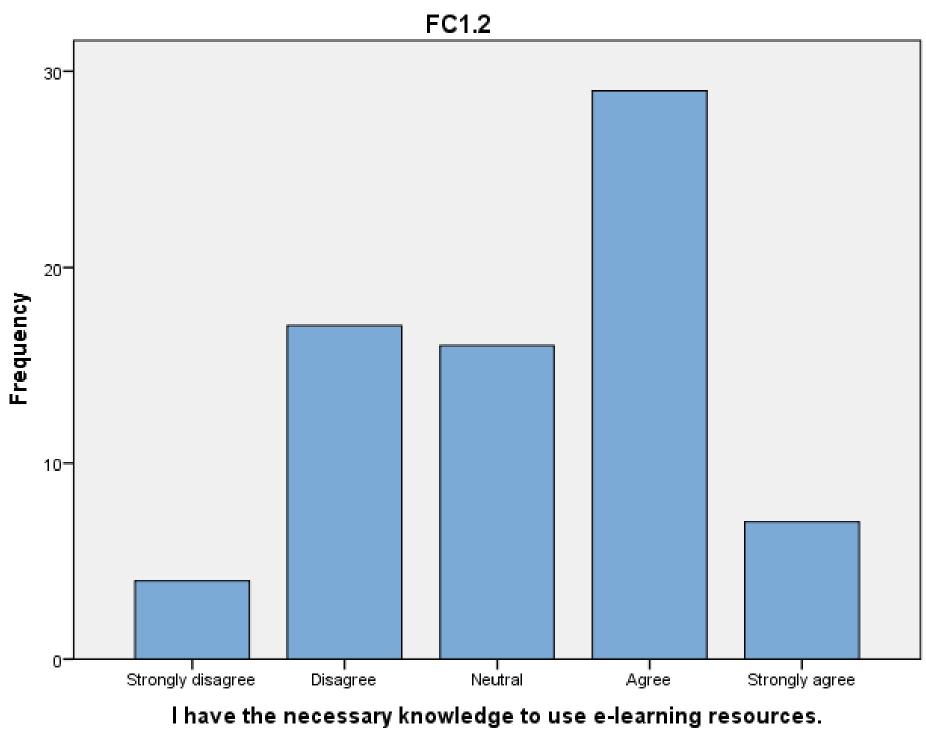

Figure 5.83: Academic Staff's Perceptions of Whether They Have the Necessary Knowledge to Use E-learning Resources

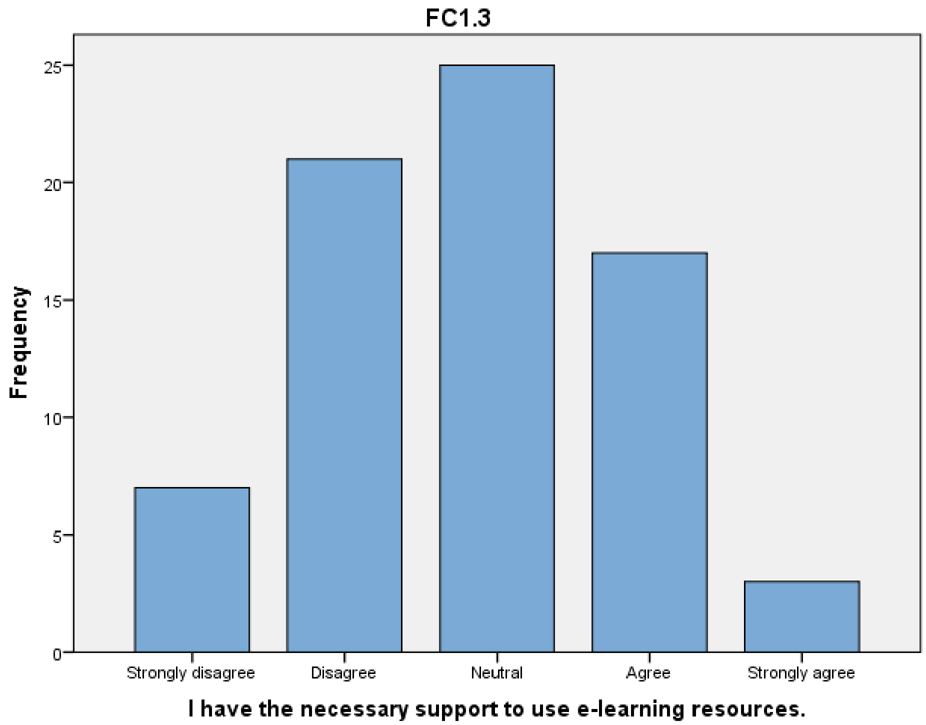

Figure 5.84: Academic Staff's Perceptions of Whether They Have the Necessary Support to Use E-learning Resources

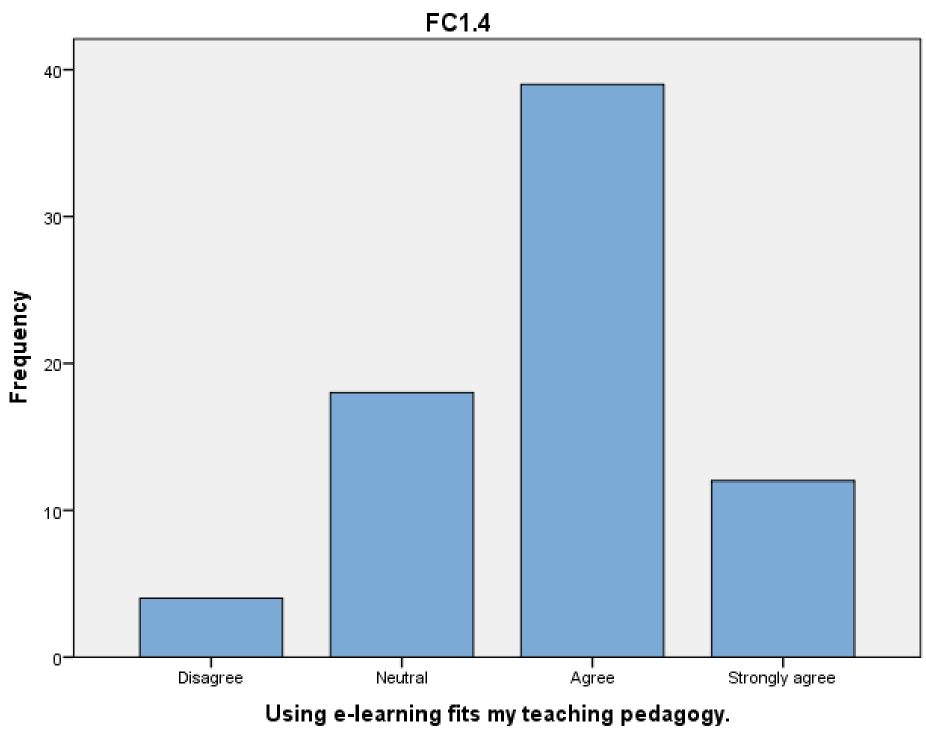

Figure 5.85: Academic Staff's Perceptions of Whether Using E-learning Resources Fit their Teaching Pedagogy

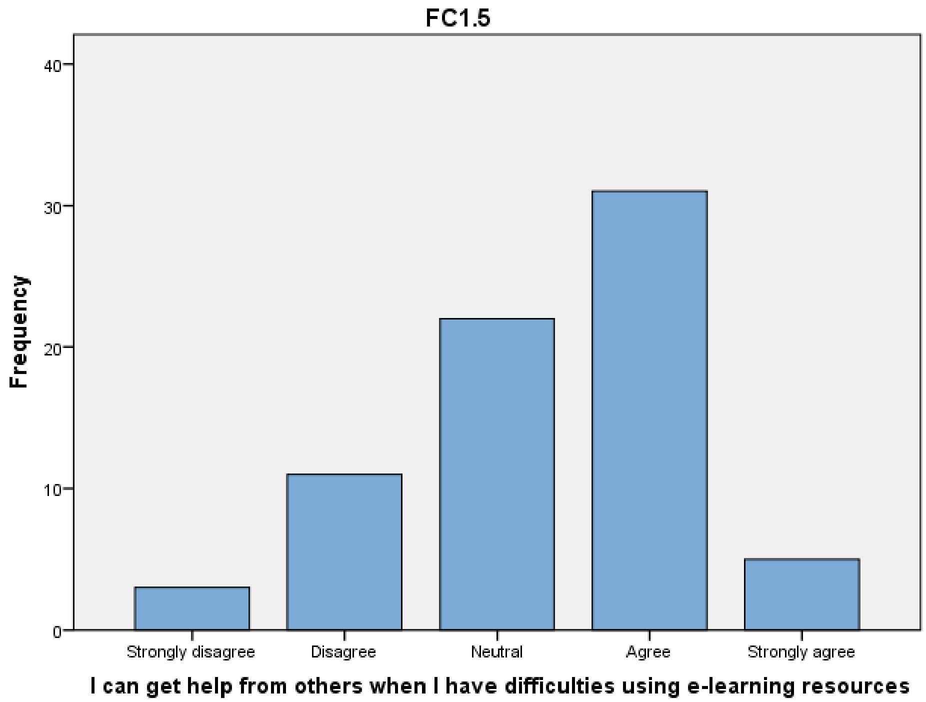

Figure 5.86: Academic Staff's Perceptions of Whether They Can Get Help from Others When they Experience Difficulties Using E-learning Resources

The descriptive statistics of the five (5) individual indicator statements, that were used to collect a self-reported measure of the facilitating conditions for academic staff to use e-learning resources at the University of Zululand, are summarised in Table 5.16 below.

Table 5.16: Descriptive Statistics of the Five Facilitating Conditions Indicators for Academic Staff

		FC1.1	FC1.2	FC1.3	FC1.4	FC1.5
N	Valid	73	73	73	73	72
	Missing	0	0	0	0	1
Mean		3.19	3.25	2.84	3.81	3.33
Mode		4	4	3	4	4
Std. Deviation		1.126	1.090	1.028	.776	.964
Skewness		-.270	-.313	.024	-.385	-.528
Std. Error of Skewness		.281	.281	.281	.281	.283
Kurtosis		-.891	-.793	-.600	-.013	-.139
Std. Error of Kurtosis		.555	.555	.555	.555	.559

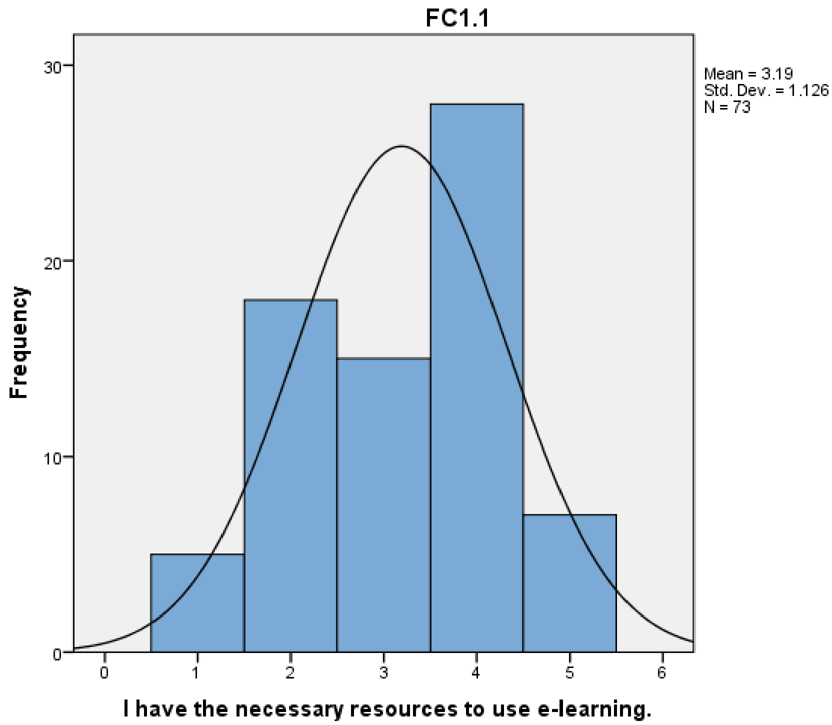

Figure 5.87: Academic staff's Histogram Showing a Negative Skewness and Negative Kurtosis in the FC1.1 Data

Figure 5.87 above shows the trend that can be also be seen in Table 5.16 (page 189) of a negative skewness in the distribution of all facilitating conditions data of academic staff. Most facilitating conditions indicator statements have a negative kurtosis, with this data distribution having a flat top near the mean (see Figure 5.87 above). FC1.3 has a slightly positive kurtosis, with a relatively high peak near the mean, and a heavy tail in the left direction.

5.5 Measurement Models

5.5.1 Students

The Partial Least Squares - Structural Equation Model's (PLS-SEM) algorithm converged in six (6) iterations in the first PLS algorithm run, and five (5) in the last, showing that the algorithm could find a stable solution in one less iteration after the unreliable indicators were removed from the measurement model.

The outer reflective measurement model will be validated by following the guidelines suggested by Straub *et al.* (2004) and Lewis *et al.* (2005) in Urbach and Ahlemann (2010:18), Hair *et al.* (2011) and Hair *et al.* (2014). To start the approximations for the relationships between the reflective latent variables and their indicators, the indicator's outer loadings are investigated. Table 5.17 (page 192) contains the statistics that led to the removal of unreliable indicator items (see bolded items in Table 5.17 on page 192). The offending items, in the order that they were removed, included:

1. SI1.4 (I use e-learning resources because of the influence of other students).
2. FC1.5 (I can get help from others when I have difficulties using e-learning resources), BI1.2 (I perceive using e-learning resources as natural for me).
3. Use3 (I never use, almost never use, sometimes use, often use or always use e-learning resources in my residence).
4. PE1.5 (Using e-learning resources in my studies increases my marks).
5. FC1.4 (The use of e-learning resources fits my learning style - visual verbal learner).

All these items were below the recommended loading value of 0.70 and, because they do not adequately explain their associated latent variables, were considered unreliable for the purposes of the student data analysis. A weaker behavioural intention indicator below this value (0.64) was however retained for content validity (BI1.1 - Whenever possible, I intend to use e-learning resources) as observed by Hair *et al* (2011:146). The significance of the indicator loadings were also tested using the resampling method bootstrapping (Efron 1979; Efron and Tibshirani 1993 in Urbach and Ahlemann, 2010:18) and all proved significant.

Table 5.17: Analysing Indicator Reliability, Internal Consistency Reliability and Convergent Validity in Students' Outer Measurement Model

Latent Variable (LV)	LV Indicator Item	Indicator Outer Loading		Indicator Reliability		Bootstrap t Value		Composite Reliability (CR)		Average Variance Extracted (AVE)	
		*1st	Final	1st	Final	1st	Final	1st	Final	1st	Final
Use	Use1	0.76	0.83	0.58	0.69	16.02	16.81	0.74	0.79	0.49	0.65
	Use2	0.71	0.79	0.50	0.62	11.48	16.66				
	Use3	**0.63**	4th	0.40	**-**	9.59	-				
Behavioural Intention	BI1.1	0.65	0.64	0.42	0.41	14.10	14.46	0.84	0.84	0.51	0.57
	BI1.2	**0.60**	3rd	0.36	**-**	13.35	-				
	BI1.3	0.80	0.82	0.64	0.67	33.07	41.70				
	BI1.4	0.81	0.83	0.66	0.69	32.77	40.89				
	BI1.5	0.70	0.73	0.49	0.53	15.16	19.48				
Performance Expectancy	PE1.1	0.68	0.70	0.46	0.49	14.07	12.41	0.84	0.84	0.52	0.57
	PE1.2	0.76	0.78	0.58	0.61	27.06	24.53				
	PE1.3	0.78	0.79	0.61	0.62	30.29	31.93				
	PE1.4	0.72	0.75	0.52	0.56	15.78	25.63				
	PE1.5	**0.64**	5th	0.41	**-**	13.80	-				
Effort Expectancy	EE1.1	0.71	0.71	0.50	0.50	15.14	14.20	0.83	0.83	0.56	0.56
	EE1.2	0.73	0.72	0.53	0.52	18.88	17.06				
	EE1.3	0.81	0.82	0.66	0.67	37.56	35.75				
	EE1.4	0.73	0.73	0.53	0.53	23.18	21.49				
Social Influence	SI1.1	0.77	0.77	0.59	0.59	18.09	18.55	0.79	0.86	0.52	0.67
	SI1.2	0.86	0.86	0.74	0.74	37.97	43.39				
	SI1.3	0.83	0.83	0.69	0.69	28.81	29.88				
	SI1.4	**0.24**	**1st	0.06	**-**	2.54	-				
Facilitating Conditions	FC1.1	0.70	0.75	0.49	0.56	15.83	13.32	0.83	0.85	0.49	0.66
	FC1.2	0.79	0.86	0.62	0.74	27.35	43.11				
	FC1.3	0.76	0.81	0.58	0.66	23.11	23.79				
	FC1.4	**0.65**	6th	0.42	**-**	11.20	-				
	FC1.5	**0.58**	2nd	0.34	**-**	9.23	-				

* Horizontal - PLS algorithm run
* Vertical - bold items removed
** Order in which the items were removed

Table 5.18 below contains the summary of the retained indicators' loadings reliability (loading value squared), internal consistency reliability (composite reliability values above 0.7), and convergent validity (average variance extracted values above 0.5).

Table 5.18: Summary of Internal Consistency Reliability, Indicator Reliability and Convergent Validity in Students' Outer Measurement Model

Latent Variable (LV)	LV Indicator Item	Indicator Outer Loading	Indicator Reliability	Composite Reliability (CR)	Cronbachs Alpha	Average Variance Extracted (AVE)
Use	Use1 Use2	0.83 0.79	0.69 0.62	0.74	0.46	0.65
Behavioural Intention	BI1.1 BI1.3 BI1.4 BI1.5	0.64 0.82 0.83 0.73	0.41 0.67 0.69 0.53	0.84	0.75	0.57
Performance Expectancy	PE1.1 PE1.2 PE1.3 PE1.4	0.70 0.78 0.79 0.75	0.49 0.61 0.62 0.56	0.84	0.75	0.57
Effort Expectancy	EE1.1 EE1.2 EE1.3 EE1.4	0.71 0.72 0.82 0.73	0.50 0.52 0.67 0.53	0.83	0.74	0.56
Social Influence	SI1.1 SI1.2 SI1.3	0.77 0.86 0.83	0.59 0.74 0.69	0.79	0.76	0.67
Facilitating Conditions	FC1.1 FC1.2 FC1.3	0.75 0.86 0.81	0.56 0.74 0.66	0.83	0.75	0.66

Cross loadings shown in Table 5.19 (page 194) show that the loadings of each indicator is higher for its designated construct than for any of the other constructs, and each of the constructs loads highest with its own items, and therefore, it can be concluded that the models' constructs differ sufficiently from one another.

Table 5.20 (page 194) shows Fornell-Larcker criterion evidence of discriminant validity between each reflective construct and their remaining reliable indicators. The AVE of each LV should be greater than the LV's highest squared correlation with any other LV, which is the same as comparing the correlation with the square root of the AVE.

Table 5.19: Cross Loadings Showing Discriminant Validity in Different Construct's Indicators in the Students' Outer Measurement Model

	Discriminant Validity	BI	EE	FC	PE	SI	USE
BI1.1	Yes	0.64	0.41	0.19	0.36	0.19	0.21
BI1.3		0.82	0.45	0.30	0.48	0.27	0.27
BI1.4		0.83	0.48	0.27	0.51	0.30	0.24
BI1.5		0.73	0.30	0.22	0.31	0.28	0.20
EE1.1	Yes	0.31	0.71	0.47	0.37	0.13	0.33
EE1.2		0.37	0.72	0.40	0.44	0.23	0.29
EE1.3		0.48	0.82	0.35	0.51	0.34	0.24
EE1.4		0.44	0.73	0.27	0.46	0.28	0.17
FC1.1	Yes	0.21	0.29	0.75	0.20	0.19	0.18
FC1.2		0.33	0.50	0.86	0.27	0.25	0.34
FC1.3		0.24	0.35	0.81	0.24	0.26	0.28
PE1.1	Yes	0.37	0.48	0.21	0.70	0.25	0.29
PE1.2		0.45	0.45	0.19	0.78	0.27	0.27
PE1.3		0.44	0.44	0.23	0.79	0.39	0.26
PE1.4		0.44	0.46	0.26	0.75	0.29	0.25
SI1.1	Yes	0.22	0.27	0.24	0.30	0.77	0.13
SI1.2		0.29	0.28	0.24	0.33	0.86	0.16
SI1.3		0.32	0.29	0.24	0.35	0.83	0.16
Use1	Yes	0.22	0.27	0.32	0.26	0.16	0.83
Use2		0.28	0.26	0.23	0.31	0.13	0.79

Table 5.20: Fornell-Larcker Criterion Showing Discriminant Validity between Different Constructs for Students

	BI	EE	FC	PE	SI	USE
BI	1.00					
EE	0.55	1.00				
FC	0.33	0.49	1.00			
PE	0.57	0.60	0.30	1.00		
SI	0.35	0.34	0.29	0.40	1.00	
USE	0.31	0.33	0.34	0.35	0.18	1.00
sqrt (AVE)	0.75	0.75	0.81	0.75	0.82	0.81

5.5.2 Academic staff

PLS-SEM algorithm converged in six (6) iterations in both the first PLS algorithm run and the last, showing that the algorithm could find a stable solution relatively easily.

Table 5.21 (page 196) contains the statistics that 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 do 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 were 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 (see Table 5.21 on page 196).

Table 5.21: Analysing Indicator Reliability, Internal Consistency Reliability and Convergent Validity in Academic Staff's Outer Measurement Model

Latent Variable (LV)	Construct Indicator Item	Indicator Outer loading		Indicator Reliability		Bootstrap t Value		Composite Reliability (CR)		Average Variance Extracted (AVE)	
		*1st	Final	1st	Final	1st	Final	1st	Final	1st	Final
Use	Use1	0.93	0.93	0.86	0.87	72.91	69.76	0.90	0.90	0.76	0.76
	Use2	0.91	0.91	0.82	0.82	40.08	40.62				
	Use3	0.77	0.77	0.59	0.59	10.71	11.17				
Behavioural Intention	BI1.1	0.77	0.77	0.59	0.59	20.11	20.88	0.91	0.91	0.68	0.68
	BI1.2	0.68	0.68	0.46	0.46	8.54	8.71				
	BI1.3	0.89	0.89	0.79	0.79	20.91	20.93				
	BI1.4	0.88	0.88	0.77	0.77	27.50	27.13				
	BI1.5	0.87	0.87	0.76	0.76	17.30	17.36				
Performance Expectancy	PE1.1	0.92	0.92	0.85	0.85	33.47	31.63	0.96	0.96	0.82	0.82
	PE1.2	0.92	0.92	0.85	0.85	31.91	31.65				
	PE1.3	0.93	0.93	0.86	0.86	33.35	31.23				
	PE1.4	0.86	0.86	0.74	0.74	31.08	31.63				
	PE1.5	0.90	0.90	0.81	0.81	34.33	33.17				
Effort Expectancy	EE1.1	0.90	0.90	0.81	0.81	51.48	51.33	0.94	0.94	0.79	0.79
	EE1.2	0.92	0.92	0.85	0.85	32.02	30.00				
	EE1.3	0.87	0.87	0.75	0.75	17.92	17.75				
	EE1.4	0.86	0.86	0.74	0.74	23.10	20.94				
Social Influence	SI1.1	0.91	0.91	0.83	0.82	4.39	6.79	0.92	0.97	0.76	0.91
	SI1.2	0.97	0.97	0.93	0.94	4.49	7.61				
	SI1.3	0.98	0.98	0.96	0.96	4.47	7.23				
	SI1.4	**0.57**	2nd	0.33	-	1.89	-				
Facilitating Conditions	FC1.1	0.75	0.74	0.56	0.55	6.96	6.25	0.82	0.82	0.48	0.54
	FC1.2	0.86	0.87	0.75	0.75	13.84	16.69				
	FC1.3	0.66	0.65	0.44	0.42	3.79	3.57				
	FC1.4	0.64	0.65	0.41	0.43	5.02	5.36				
	FC1.5	**0.50**	**1st	0.25	-	2.79	-				

* Horizontal – PLS algorithm run
* Vertical - bold items removed
** Order in which the items were removed

Table 5.22 below contains the summary of the retained indicators' loadings reliability (loading value squared), internal consistency reliability (composite reliability values above 0.7), and convergent validity (average variance extracted values above 0.5). There are two indicators above .950, indicating potential common method bias (Straub *et al.* 2004:401 in Urbach and Ahlemann, 2010:18).

Table 5.22: Summary of Indicator Reliability, Internal Consistency Reliability and Convergent Validity in Academic Staff's Outer Measurement Model

Latent Variable (LV)	LV Indicator Item	Indicator Outer Loading	Indicator Reliability	Composite Reliability (CR)	Cronbachs Alpha	Average Variance Extracted (AVE)
Use	Use1 Use2 Use3	0.93 0.91 0.77	0.87 0.82 0.59	0.90	0.85	0.76
Behavioural Intention	BI1.1 BI1.2 BI1.3 BI1.4 BI1.5	0.77 0.68 0.89 0.88 0.87	0.59 0.46 0.79 0.77 0.76	0.91	0.88	0.68
Performance Expectancy	PE1.1 PE1.2 PE1.3 PE1.4 PE1.5	0.92 0.92 0.93 0.86 0.90	0.85 0.85 0.86 0.74 0.81	0.96	0.95	0.82
Effort Expectancy	EE1.1 EE1.2 EE1.3 EE1.4	0.90 0.92 0.87 0.86	0.81 0.85 0.75 0.74	0.94	0.91	0.79
Social Influence	SI1.1 SI1.2 SI1.3	0.91 0.97 0.98	0.82 0.94 0.96	0.97	0.96	0.91
Facilitating Conditions	FC1.1 FC1.2 FC1.3 FC1.4	0.74 0.87 0.65 0.65	0.55 0.75 0.42 0.43	0.82	0.72	0.54

Cross loadings contained in Table 5.23 (page 198) show that the loadings of each indicator is higher for its designated construct than for any of the other constructs, and each of the constructs loads highest with its own items, and therefore, it can be concluded that the models' constructs differ sufficiently from one another showing discriminant validity.

Table 5.23: Cross Loadings Showing Discriminant Validity in Different Construct's Indicators within the Academic Staff's Outer Measurement Model

	Discriminant Validity	BI	EE	FC	PE	SI	USE
BI1.1	Yes	0.77	0.34	0.39	0.54	0.23	0.44
BI1.2		0.68	0.54	0.55	0.48	-0.02	0.38
BI1.3		0.89	0.47	0.59	0.62	0.12	0.58
BI1.4		0.88	0.42	0.43	0.50	0.00	0.38
BI1.5		0.87	0.39	0.39	0.50	0.05	0.43
EE1.1	Yes	0.51	0.90	0.59	0.68	-0.02	0.54
EE1.2		0.50	0.92	0.57	0.70	-0.06	0.53
EE1.3		0.37	0.87	0.61	0.51	-0.17	0.36
EE1.4		0.47	0.86	0.57	0.65	0.05	0.41
FC1.1	Yes	0.32	0.40	0.74	0.24	0.16	0.28
FC1.2		0.49	0.69	0.87	0.47	0.04	0.46
FC1.3		0.21	0.25	0.65	0.10	0.14	0.19
FC1.4		0.58	0.44	0.65	0.44	-0.09	0.34
PE1.1	Yes	0.54	0.73	0.42	0.92	0.12	0.61
PE1.2		0.52	0.63	0.34	0.92	0.09	0.66
PE1.3		0.51	0.75	0.45	0.93	0.04	0.61
PE1.4		0.59	0.54	0.41	0.86	0.12	0.63
PE1.5		0.72	0.63	0.52	0.90	0.05	0.68
SI1.1	Yes	0.02	-0.12	-0.05	0.07	0.91	-0.04
SI1.2		0.08	-0.05	0.04	0.11	0.97	0.04
SI1.3		0.12	-0.03	0.09	0.08	0.98	0.00
Use1	Yes	0.43	0.53	0.46	0.69	-0.03	0.93
Use2		0.60	0.46	0.47	0.59	-0.02	0.91
Use3		0.32	0.38	0.20	0.59	0.12	0.77

Table 5.24 (page 199) shows Fornell-Larcker criterion evidence of discriminant validity between each reflective construct and their remaining reliable indicators. The AVE of each LV should be greater than the LV's highest squared correlation with any other LV, which is the same as comparing the correlation with the square root of the AVE.

Table 5.24: Fornell-Larcker Criterion Showing Discriminant Validity between Different Constructs for Academic Staff

	BI	EE	FC	PE	SI	USE
BI	1.00					
EE	0.53	1.00				
FC	0.58	0.66	1.00			
PE	0.65	0.72	0.48	1.00		
SI	0.10	-0.05	0.06	0.09	1.00	
USE	0.54	0.53	0.46	0.71	0.01	1.00
sqrt (AVE)	0.82	0.89	0.73	0.91	0.95	0.87

5.6 Structural Models

Urbach and Ahlemann (2010:21), Hair *et al.* (2011:147) and Hair *et al.* (2014:169) give the essential criteria for the assessment of the PLS structural equation model. Firstly, assess the structural model for collinearity; secondly, assess the significance and relevance of the path coefficients; thirdly, assess each endogenous Latent Variable's (LV) coefficient of determination (R^2); fourthly, assess the effect sizes (f^2), and lastly the predictive relevance Q^2 and the q^2 effect sizes (Hair *et al*., 2014:169). The coefficient of determination (R^2) in this study measures the relationships of a user's behavioural intentions to use, and use of e-learning resources, explained variance to its total variance, giving an indication of the model's predictive accuracy for these relationships. Values should be sufficiently high for the model to have a minimum level of explanatory power, with Chin (1998b) in Urbach and Ahlemann (2010:20) considering values of approximately .670 as substantial, and values around .333 as average, with values of .190 and lower as weak.

According to Hair *et al.* (2011:147), the individual path coefficients of the PLS structural model can be interpreted as standardised beta coefficients of ordinary least squares regressions. Urbach and Ahlemann (2010:21) state that a path coefficient's magnitude indicates the strength of the relationship between two LVs, and some authors contend that path coefficients should exceed .100 to account for a certain impact within the model (e.g., Huber *et al.* 2007 in Urbach and Ahlemann, 2010:21). As with the indicators' loadings, each path coefficient's significance can be assessed by means of a bootstrapping procedure (Urbach and Ahlemann, 2010:21), and paths that are non-significant, or show signs contrary to the hypothesized direction do not support the alternate hypothesis, whereas significant paths showing the alternate hypothesised direction empirically support the proposed causal relationship.

5.6.1 Students

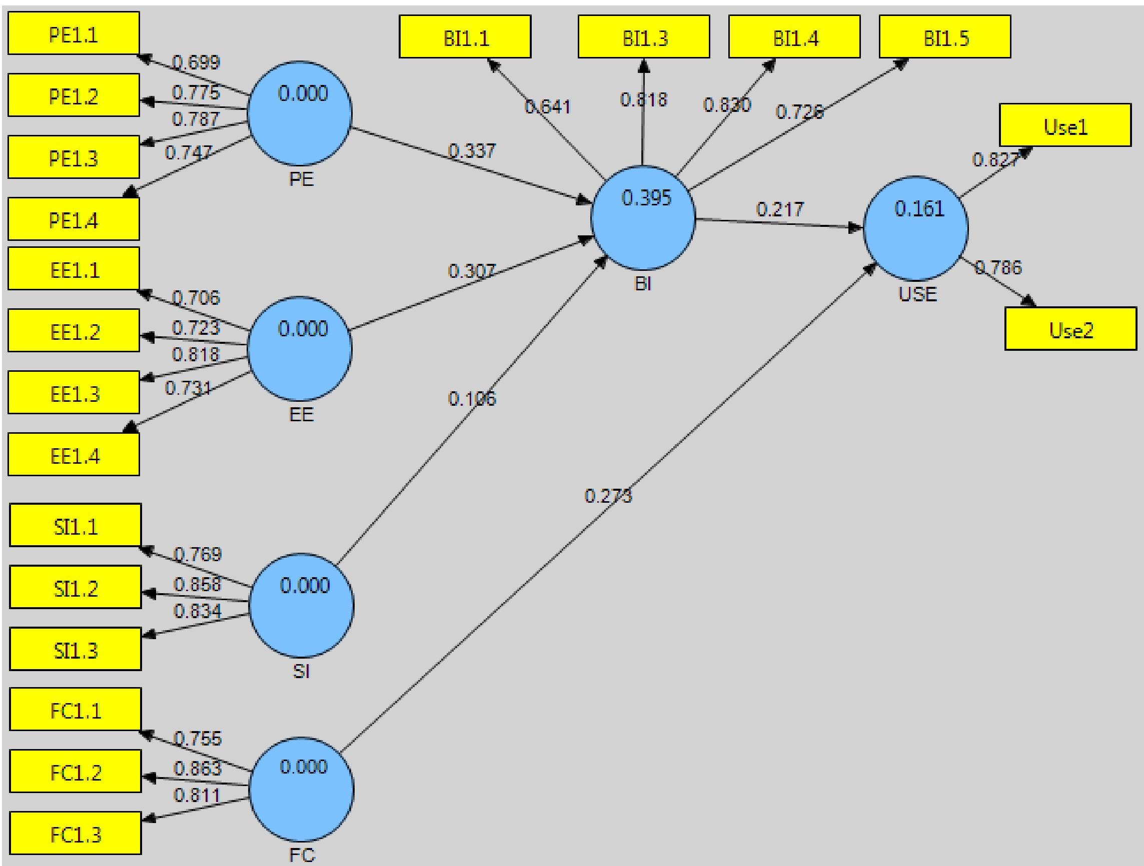

Figure 5.88: The Students' UTAUT Model Depicted in SmartPLS (Ringle *et al.*, 2004) after PLS Algorithm Calculation

The first step in assessing the PLS-SEM structural model is to run the collinearity assessments for the two sets of predictor constructs (Hair *et al.,* 2014:168) ((BI and FC for Use and PE, EE and SI for BI), which were run in IBM SPSS Statistics and can be seen in Tables 5.25 and 5.26 (page 201). Note, VIF values above 5 and tolerance values below 0.20 are indicative of unwanted collinearity (Hair *et al.,* 2014:170).

Table 5.25: Collinearity Assessment for Student's Use Predictor Constructs

Coefficients [a]

Model		Unstandardised Coefficients		Standardised Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	1.67	.26		6.45	.00		
	FC	.30	.05	.28	5.89	.00	.91	1.10
	BI	.26	.07	.19	3.95	.00	.91	1.10

a. Dependent Variable: Use

Table 5.26: Collinearity Assessment for Students' Behavioural Intentions Predictor Constructs

Coefficients [a]

Model		Unstandardised Coefficients		Standardised Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	1.32	.17		7.61	.00		
	PE	.28	.05	.30	5.77	.00	.59	1.70
	EE	.28	.05	.30	5.79	.00	.63	1.60
	SI	.08	.03	.10	2.38	.02	.86	1.16

a. Dependent Variable: BI

The second step in assessing the PLS-SEM structural model is to examine the path coefficients, after running the PLS-SEM algorithm, as these represent the hypothesized relationships between the independent and dependent constructs (Hair *et al.,* 2014:170).

The significance of the path coefficients depends on its standard error, which was obtained by bootstrapping in SmartPLS (Hair *et al.,* 2014:171). For the student sample (n=405), the empirical t value has to be larger than the critical t value (1.96) at a significance level of five percent (5%), and the p value should therefore be less than 0.05 for the hypothesized relationships to be significant, as seen in Table 5.27 (page 202).

Table 5.27: Significance Testing of the Path Coefficients for the Structural Model of Students

	Path Coefficients	t Value	Significance Level	p Value	95% Confidence Intervals LLCI	ULCI
BI -> USE	0.22	4.50	***	0.00	0.13	0.32
EE -> BI	0.31	4.35	***	0.00	0.16	0.42
FC -> USE	0.27	5.86	***	0.00	0.17	0.34
PE -> BI	0.34	5.77	***	0.00	0.24	0.48
SI -> BI	0.11	2.12	**	0.04	0.01	0.19

Note: NS = not significant

**p < .05. ***p < 0.01

The significance of the total effects, including the direct (PE, EE, SI on BI and BI and FC on Use), and indirect (PE, EE and SI on Use) effects, was obtained by bootstrapping in SmartPLS and summarised in Table 5.28 below.

Table 5.28: Significance Testing of the Total Effects for the Structural Model of Students

	Total Effect	t Value	Significance Level	p Value	95% Confidence Intervals LLCI	ULCI
BI -> USE	0.22	4.50	***	0.00	0.13	0.32
EE -> BI	0.31	4.35	***	0.00	0.16	0.42
EE -> USE	0.07	3.01	***	0.00	0.02	0.11
FC -> USE	0.27	5.86	***	0.00	0.17	0.34
PE -> BI	0.34	5.77	***	0.00	0.24	0.48
PE -> USE	0.07	3.33	***	0.00	0.03	0.13
SI -> BI	0.11	2.07	**	0.05	0.00	0.19
SI -> USE	0.02	1.88	NS	0.07	0.00	0.04

Note: NS = not significant

**p < .05. ***p < 0.01

The coefficient of determination (R^2), which is a measure of the model's predictive accuracy (Hair *et al*., 2014:174), adjusted R^2 and the Stone-Geisser's

(Q^2) value, which indicates the model's predictive relevance (Hair *et al.,* 2014:178) can be seen in Table 5.29 (page 203).

Table 5.29: Endogenous LV's R^2, R^2_{adj} and Q^2 Values for the Students' Structural Model

	R Square	Adjusted R Square	Q Square
BI	0.40	0.39	0.22
EE			
FC			
PE			
SI			
USE	0.16	0.16	0.11

In addition the endogenous latent variables R^2 values, the change in its R^2 value, when a selected exogenous latent variable is included or excluded in the model, is estimated in by running the PLS-SEM algorithm twice to calculate the f^2 effect sizes (Hair *et al.,* 2014:177) shown in Table 5.30 below.

Table 5.30: f^2 Effect Size of Exogenous Constructs Explaining Endogenous constructs for Students

	Effect size explaining BI	Effect size explaining Use
PE	0.11	
EE	0.10	
SI	0.01	
FC		0.08
BI		0.05

Similar to the f^2 effect sizes approach to assessing R^2 values, the relative impact of predictive relevance of the exogenous latent variables explaining endogenous ones can be compared by the measure of the q^2 effect size (Hair *et al,* 2014:183) shown in Table 5.31 below.

Table 5.31: q^2 Effect Size of Exogenous Constructs Explaining Endogenous Constructs for Students

	Effect size explaining BI	Effect size explaining Use
PE	0.05	
EE	0.04	
SI	0.01	
FC		0.05
BI		0.03

5.6.2 Academic staff

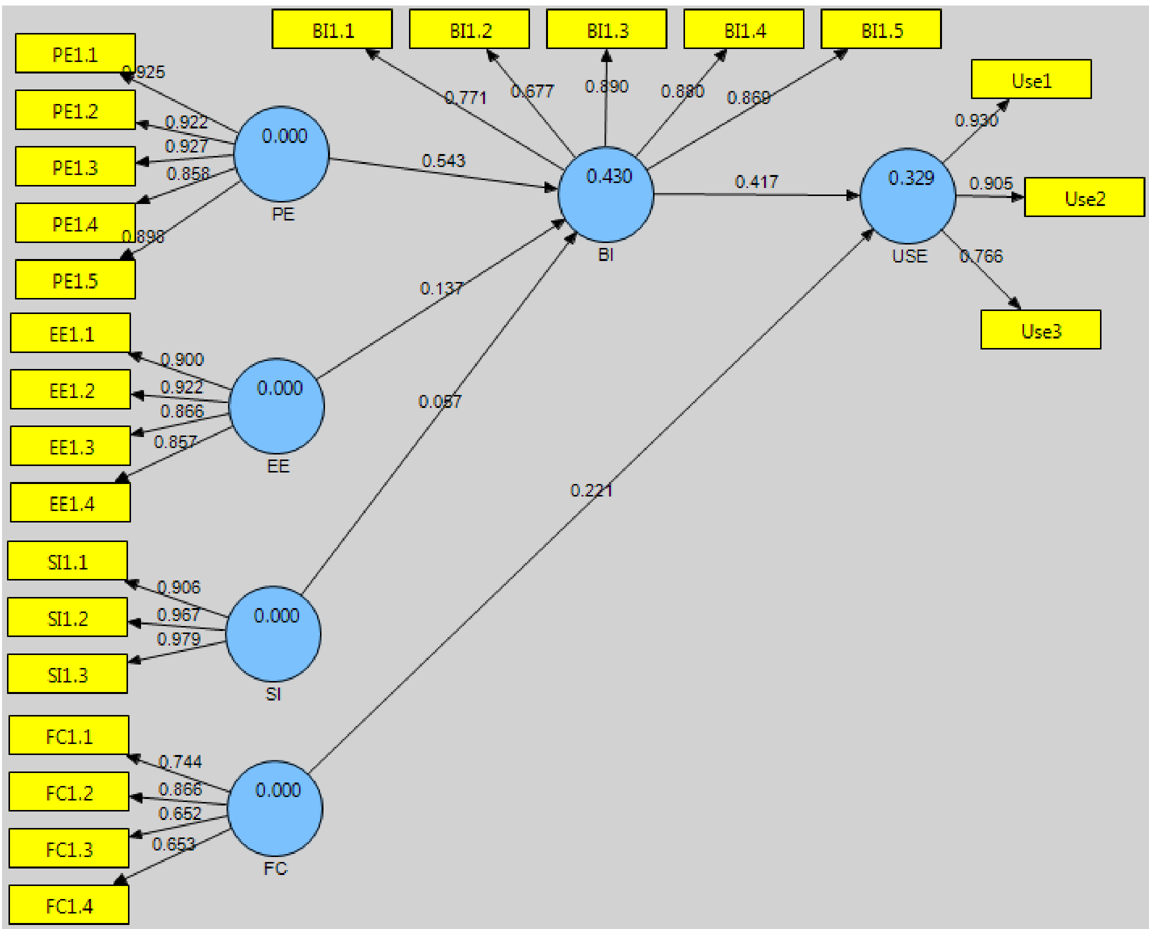

Figure 5.89: The Academic Staff's UTAUT Model Depicted in SmartPLS (Ringle *et al.*, 2004) after PLS Algorithm Calculation

The collinearity assessments (Hair *et al*., 2014:168) for the two sets of predictor constructs (BI and FC for Use and PE, EE and SI for BI), which were run in IBM SPSS Statistics and can be seen in Tables 5.32 and 5.33 (page 205), show no unwanted collinearity. Note, VIF values above 5 and tolerance values below 0.20 are indicative of unwanted collinearity (Hair *et al.,* 2014:170).

Table 5.32: Collinearity Assessment for Academic Staff's Use Predictor Constructs

Coefficients [a]

Model		Unstandardised Coefficients		Standardised Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	-1.42	.93		-1.52	.13		
	FC	.40	.21	.22	1.89	.06	.73	1.36
	BI	.82	.26	.37	3.15	.00	.73	1.36

a. Dependent Variable: Use

Table 5.33: Collinearity Assessment for Academic Staff's Behavioural Intentions Predictor Constructs

Coefficients [a]

Model		Unstandardised Coefficients		Standardised Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	1.80	.36		4.97	.00		
	PE	.34	.11	.40	3.02	.00	.48	2.11
	EE	.29	.10	.29	2.19	.03	.48	2.10
	SI	.04	.06	.06	.60	.54	.94	1.06

a. Dependent Variable: BI

The path coefficients representing the hypothesized relationships between the independent and dependent constructs can be seen in Table 5.34 (page 206). 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 five percent (5%), and the p value should be less than 0.05 for the hypothesized relationships to be significant, as seen in Table 5.34 (page 206)

Table 5.34: Significance Testing of the Path Coefficients for the Structural Model of Academic Staff

	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

The significance testing of the total effects include 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 5.35 below was obtained by bootstrapping

Table 5.35: Significance Testing of the Total Effects Coefficients for the Structural Model of Academic Staff

	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
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 5.36 below.

Table 5.36: Endogenous LV's R^2 and Q^2 Values for the Academic Staff's 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 5.37 below.

Table 5.37: 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 5.38 below.

Table 5.38: 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

5.7 Moderation

Having described the relationships of the UTAUT constructs for the primary users of e-learning resources at the University of Zululand, 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 depends 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 (Morris and Venkatesh 2000 in Venkatesh *et al.,* 2003:439). Experience was operationalised via a dummy variable that took ordinal values of one, two, three, four and five (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).

5.7.1 Moderating Effects for Students

H_{a15}: The effect of performance expectancy on behavioural intention of students to use e-learning resources will be moderated by (a) gender and (b) age, such that the effect will be stronger for men and particularly for younger men.

Running the individual moderating analyses in PROCESS using model 1 gives the following results (see Table 5.39, page 209) for the moderating effect of gender and its significance on the performance expectancy effect of students' behavioural intentions to use e-learning resources, i.e. Y = BI, X = PE and M = Gender (coded 0 = Female and 1 = Male). The moderating effect of gender (int_1 in Table 5.39, page 209) has a low path coefficient with a negative sign, indicating that the measured performance expectancy effect of females (0.54) is slightly higher than that of males (0.44). The moderating effect is insignificant because the t value is less than 1.96 and the p value is greater than 0.05 at the ninety-five percent (95%) confidence interval.

Table 5.39: Moderator Analysis of Gender on Students' Performance Expectancy

Outcome: BI						
Model Summary						
R	R-sq	F	df1	df2	p	
.53	.28	28.55	3.00	401.00	.00	
Model						
	coeff	se	t	p	LLCI	ULCI
constant	1.70	.28	6.12	.00	1.16	2.25
Gender	.35	.45	.78	.43	-.53	1.24
PE	.52	.07	7.64	.00	.38	.65
int_1	-.07	.11	-.68	.50	-.29	.14

* Bolded line shows moderating effect and its significance

Table 5.40 below indicates the moderating effect of age and its significance on the performance expectancy effect of students' behavioural intentions to use e-learning resources i.e. Y = BI, X = PE and M = Age. The path coefficient shows a very small positive moderating effect and is not significant at the ninety-five percent (95%) confidence interval.

Table 5.40: Moderator Analysis of Age on Performance Expectancy for Students

Outcome: BI						
Model Summary						
R	R-sq	F	df1	df2	p	
.53	.28	27.64	3.00	401.00	.00	
Model						
	coeff	se	t	p	LLCI	ULCI
constant	3.77	.03	125.16	.00	3.71	3.83
Age	.00	.00	.35	.72	-.01	.01
PE	.45	.06	6.91	.00	.32	.57
int_1	.01	.01	1.04	.30	-.01	.04

* Bolded line shows moderating effect and its significance

H_{a17}: The effect of social influence on behavioural intention of students to use e-learning resources will be moderated by (a) gender, (b) age, and (c) experience, such that the effect will be stronger for women, particularly older women, in the early stages of experience.

Table 5.41 below indicates the moderating effect of gender and its significance on the social influence of students' behavioural intentions to use e-learning resources, i.e. Y = BI, X = SI and M = Gender (coded 0 = Female and 1 = Male). The path coefficient shows a very small negative value that supports the theory that social influence effects in females (0.25) is higher than that of males (0.19), but the moderating effect is not significant at the ninety-five percent (95%) confidence interval.

Table 5.41: Moderator Analysis of Gender on Students' Social Influences

Outcome: BI						
Model Summary						
R	**R-sq**	**F**	**df1**	**df2**	**p**	
.31	**.10**	**7.27**	**3.00**	**401.00**	**.00**	
Model						
	coeff	**se**	**t**	**p**	**LLCI**	**ULCI**
constant	**2.91**	**.23**	**12.69**	**.00**	**2.46**	**3.36**
Gender	**.30**	**.37**	**.82**	**.41**	**-.42**	**1.02**
SI	**.25**	**.06**	**4.04**	**.00**	**.13**	**.38**
int_1	**-.07**	**.10**	**-.63**	**.53**	**-.27**	**.14**

* Bolded line shows moderating effect and its significance

Table 5.42 (page 211) indicates the moderating effect of age and its significance on the social influence effect of students' behavioural intentions to use e-learning resources i.e. Y = BI, X = SI and M = Age. The path coefficient shows virtually no effect and is not significant at the ninety-five percent (95%) confidence interval.

Table 5.42: Moderator Analysis of Age on Students' Social Influences

Outcome: BI						
Model Summary						
R	R-sq	F	df1	df2	p	
.31	.10	7.90	3.00	401.00	.00	
Model						
	coeff	se	t	p	LLCI	ULCI
constant	3.77	.04	103.13	.00	3.70	3.84
Age	.00	.01	.22	.83	-.01	.02
SI	.23	.05	4.55	.00	.13	.34
int_1	.00	.00	.38	.71	-.01	.01

* Bolded line shows moderating effect and its significance

Table 5.43 below shows the moderating effect of experience and its significance on the social influence effect of students' behavioural intentions to use e-learning resources, i.e. Y = BI, X = SI and M = Exper. The path coefficient shows virtually no effect and is not significant at the ninety-five percent (95%) confidence interval.

Table 5.43: Moderator Analysis of Experience on Students' Social Influences

Outcome: BI						
Model Summary						
R	R-sq	F	df1	df2	p	
.31	.09	7.28	3.00	401.00	.00	
Model						
	coeff	se	t	p	LLCI	ULCI
constant	3.78	.04	105.95	.00	3.71	3.85
Exper	.00	.00	.18	.86	.00	.00
SI	.23	.05	4.21	.00	.12	.34
int_1	.00	.00	.05	.96	-.01	.01

* Bolded line shows moderating effect and its significance

H_{a19}: The effect of effort expectancy on behavioural intention of students to use e-learning resources will be moderated by (a) gender, (b) age and

(c) experience, such that the effect will be stronger for women, particularly for younger women, and particularly at early stages of experience.

Table 5.44 below indicates the moderating effect of gender and its significance on the effort expectancy effect of students' behavioural intentions to use e-learning resources, i.e. Y = BI, X = EE and M = Gender (coded 0 = Female and 1 = Male). The path coefficient shows a moderate negative value that supports the theory that effort expectancy effects in females (0.61) is higher than that of males (0.35), the moderating effect is significant at the ninety-five percent (95%) confidence interval.

Table 5.44: Moderator Analysis of Gender on Students' Effort Expectancy

Outcome: BI

Model Summary

R	R-sq	F	df1	df2	p
.53	.28	27.72	3.00	401.00	.00

Model

	coeff	se	t	p	LLCI	ULCI
constant	1.44	.28	5.08	.00	.88	1.99
Gender	1.05	.52	2.02	.04	.03	2.07
EE	.61	.07	8.45	.00	.47	.76
int_1	-.27	.13	-2.03	.04	-.52	-.01

* Bolded line shows moderating effect and its significance

Table 5.45 (page 213) shows the moderating effect of age and its significance on the effort expectancy effect of students' behavioural intentions to use e-learning resources, i.e. Y = BI, X = EE and M = Age. The path coefficient shows virtually no effect and is not significant at the ninety-five percent (95%) confidence interval.

Table 5.45: Moderator Analysis of Age on Students' Effort expectancy

Outcome: BI						
Model Summary						
R	**R-sq**	**F**	**df1**	**df2**	**p**	
.52	**.27**	**15.82**	**3.00**	**401.00**	**.00**	
Model						
	coeff	**se**	**t**	**p**	**LLCI**	**ULCI**
constant	**3.78**	**.03**	**128.29**	**.00**	**3.72**	**3.84**
Age	**.00**	**.00**	**-.15**	**.88**	**-.01**	**.00**
EE	**.46**	**.08**	**5.58**	**.00**	**.30**	**.63**
int_1	**.01**	**.02**	**.50**	**.62**	**-.02**	**.04**

* Bolded line shows moderating effect and its significance

Table 5.46 below indicates the moderating effect of experience and its significance on the effort expectancy effect of students' behavioural intentions to use e-learning resources, i.e. Y = BI, X = EE and M = Exper. The path coefficient shows no effect and is not significant at the ninety-five percent (95%) confidence interval.

Table 5.46: Moderator Analysis of Experience on Students' Effort Expectancy

Outcome: BI						
Model Summary						
R	**R-sq**	**F**	**df1**	**df2**	**p**	
.52	**.27**	**16.18**	**3.00**	**401.00**	**.00**	
Model						
	coeff	**se**	**t**	**p**	**LLCI**	**ULCI**
constant	**3.78**	**.03**	**132.16**	**.00**	**3.73**	**3.84**
Exper	**.00**	**.00**	**.12**	**.91**	**.00**	**.00**
EE	**.47**	**.08**	**5.76**	**.00**	**.31**	**.63**
int_1	**.00**	**.01**	**.57**	**.57**	**-.01**	**.01**

* Bolded line shows moderating effect and its significance

H_{a21}: The effect of facilitating conditions on students' usage of e-learning resources will be moderated by (a) age and (b) experience, such that the effect will be stronger for older users, particularly in the early stages of experience.

Table 5.47 below specifies the moderating effect of age and its significance on the facilitating conditions of students' to use e-learning resources, i.e. Y = Use, X = FC and M = Age. The path coefficient shows virtually no effect and is not significant at the ninety-five percent (95%) confidence interval.

Table 5.47: Moderator Analysis of Age on Facilitating Conditions of Students

Outcome: Use

Model Summary

R	R-sq	F	df1	df2	p
.35	.12	15.49	3.00	401.00	.00

Model

	coeff	se	t	p	LLCI	ULCI
constant	3.67	.05	74.81	.00	3.57	3.77
Age	.01	.01	1.13	.26	-.01	.03
FC	.33	.06	5.14	.00	.20	.46
int_1	.01	.01	1.12	.26	-.01	.04

* Bolded line shows moderating effect and its significance

Table 5.48 (page 215) shows the moderating effect of experience and its significance on the facilitating conditions of students' to use e-learning resources, i.e. Y = Use, X = FC and M = Age. The path coefficient shows no effect and is not significant at the ninety-five percent (95%) confidence interval.

Table 5.48: Moderator Analysis of Experience on Facilitating Conditions of Students

Outcome: Use

Model Summary

R	R-sq	F	df1	df2	p
.34	.12	15.35	3.00	401.00	.00

Model

	coeff	se	t	p	LLCI	ULCI
constant	3.69	.07	56.36	.00	3.56	3.82
Exper	.00	.01	.08	.93	-.01	.01
FC	.36	.07	5.54	.00	.24	.49
int_1	.00	.01	-.14	.89	-.01	.01

* Bolded line shows moderating effect and its significance

While conducting the moderation analysis in SmartPLS (Ringle *et al.*, 2004), the PLS algorithm calculation showed slightly different results when all the moderating effects were run together, as seen in Figure 5.90 (page 216). A positive correlation between experience and use of e-learning resources increased R^2 of use in the students' UTAUT model (0.29).

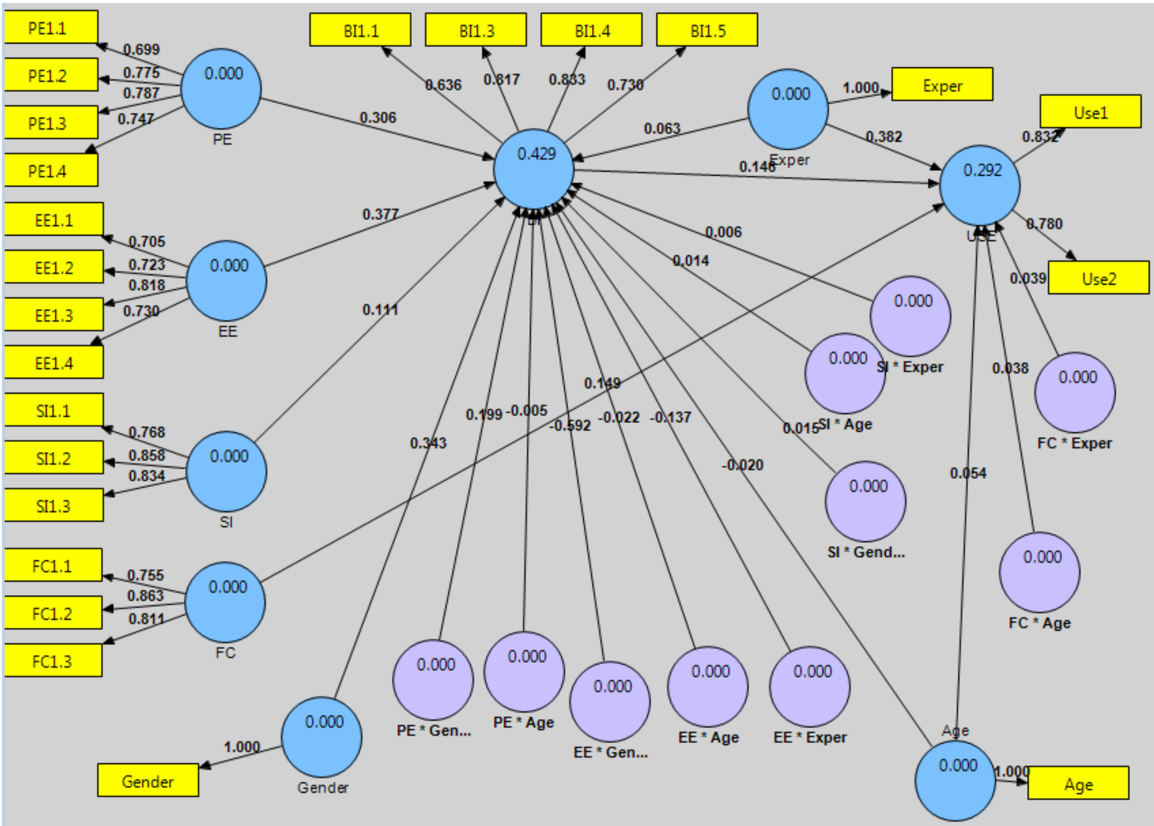

Figure 5.90: Moderation Analysis in Student Model Using SmartPLS (Ringle *et al.*, 2004) - PLS Algorithm Calculation

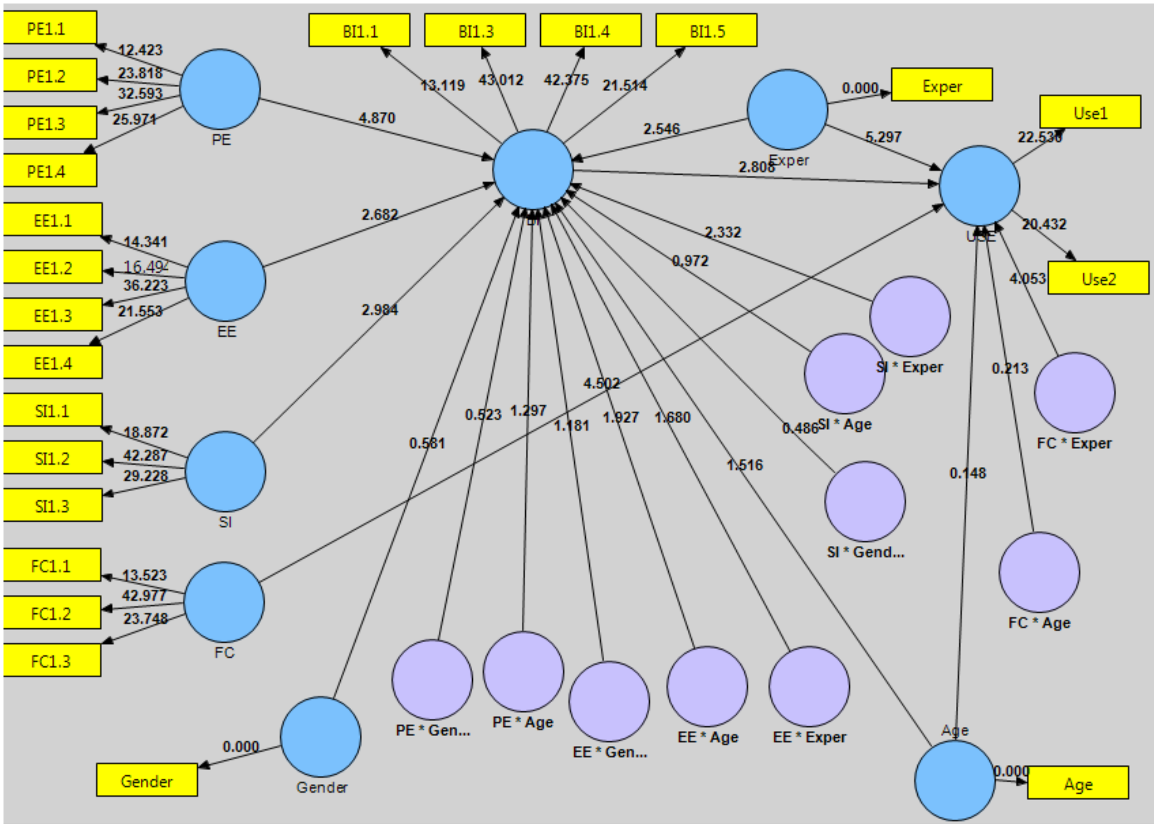

Figure 5.91: Bootstrapping the Student Model's Moderation Analysis in SmartPLS (Ringle *et al.*, 2004)

Bootstrapping resulted in two of the moderating effects in the model being significant at the ninety-five percent (95%) confidence level, that of experience moderating social influence towards behavioural intention - SI*Exper (t Value = 2.33), and of experience moderating facilitating conditions towards use - FC*Exper (t Value = 4.05), as seen in Figure 5.91 above. However, on close inspection the convergent validity (AVE) and composite reliability values did not meet the required criterion to be included in the model.

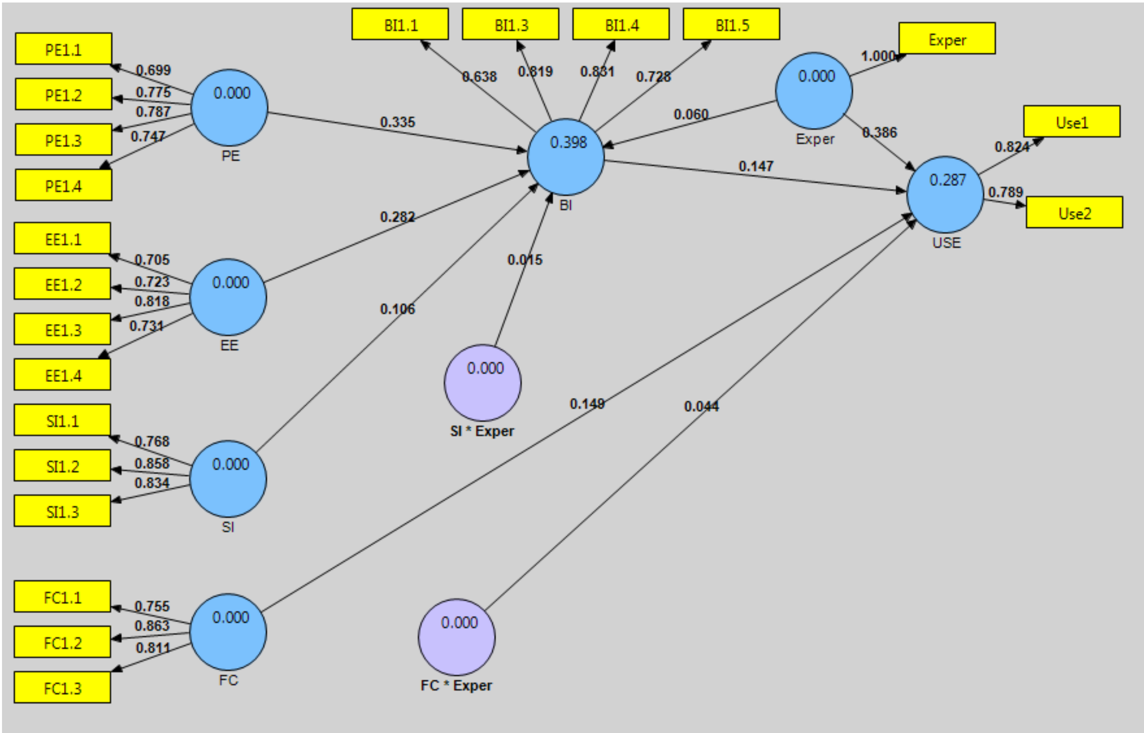

Figure 5.92: Final Moderation Analysis in Student Model Using SmartPLS (Ringle *et al.*, 2004) - PLS Algorithm Calculation

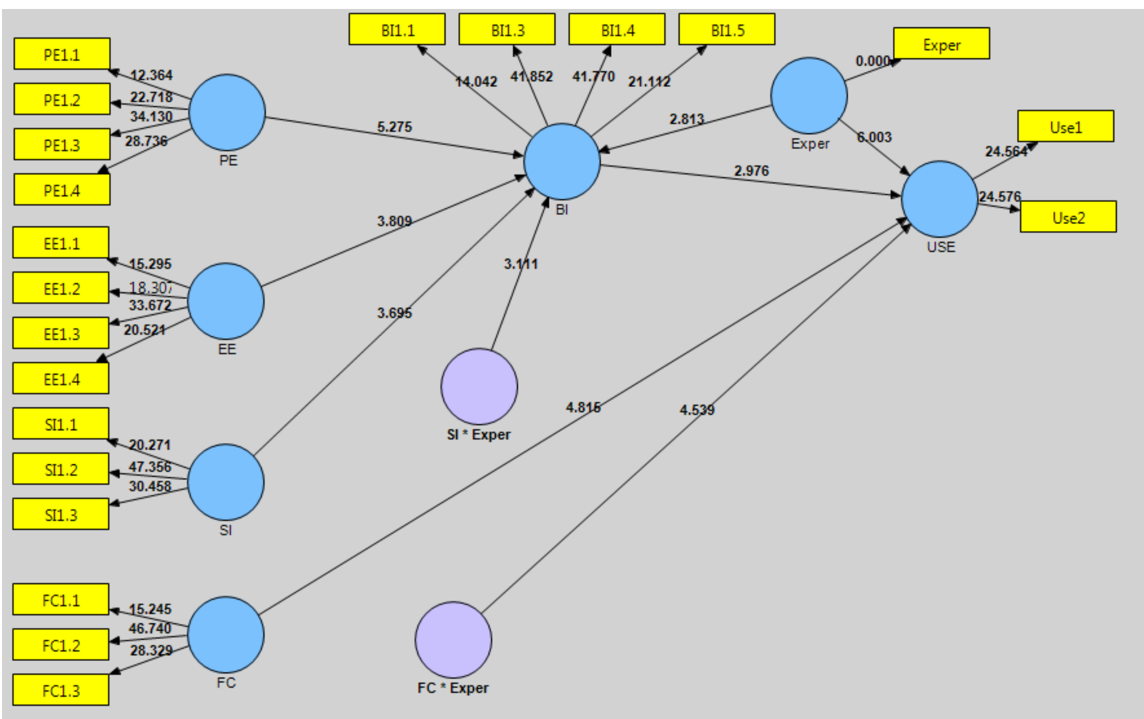

Figure 5. 93: Final bootstrapping of the student model's moderation analysis in SmartPLS (Ringle *et al.*, 2004)

5.7.2 Moderating Effects for Academic staff

H_{a16}: The effect of performance expectancy on behavioural intention of academic staff to use e-learning resources will be moderated by (a) gender and (b) age, such that the effect will be stronger for men and particularly for younger men.

The moderating effect of gender and its significance on the performance expectancy effect of academic staff's behavioural intentions to use e-learning resources, i.e. Y = BI, X = PE and M = Gender (coded 0 = Female and 1 = Male) can be seen in Table 5.49 below. The path coefficient has a low positive value, indicating that the measured performance expectancy effect of males (0.60) is higher than that of females (0.42). The effect is not significant at the ninety-five percent (95%) confidence interval (t Value must be greater than 1.99, and p Value less than 0.05).

Table 5.49: Moderator Analysis of Gender on Academic Staff's Performance Expectancy

Outcome: BI

Model Summary

R	R-sq	F	df1	df2	p
.63	.40	16.87	3.00	69.00	.00

Model

	coeff	se	t	p	LLCI	ULCI
constant	2.31	.34	6.80	.00	1.63	2.98
Gender	-.60	.60	-1.00	.32	-1.81	.60
PE	.42	.08	5.02	.00	.25	.59
int_1	.18	.15	1.19	.24	-.12	.48

* Bolded line shows moderating effect and its significance

Table 5.50 (page 220) indicates the moderating effect of age and its significance on the performance expectancy effect of academic staff's behavioural intentions to use e-learning resources, i.e. Y = BI, X = PE and M = Age. The path coefficient shows no moderating effect and is not significant at the ninety-five percent (95%) confidence interval.

Table 5.50: Moderator Analysis of Age on Performance Expectancy for Academic Staff

Outcome: BI

Model Summary

R	R-sq	F	df1	df2	p
.62	.38	22.82	3.00	69.00	.00

Model

	coeff	se	t	p	LLCI	ULCI
constant	4.07	.06	68.35	.00	3.95	4.19
Age	.00	.01	-.73	.47	-.02	.01
PE	.51	.07	7.12	.00	.37	.65
int_1	.00	.01	-.43	.67	-.02	.01

* Bolded line shows moderating effect and its significance

> **H_{a18}:** The effect of social influence on behavioural intention of academic staff to use e-learning resources will be moderated by (a) gender, (b) age, and (c) experience, such that the effect will be stronger for women, particularly older women, in the early stages of experience.

Table 5.51 (page 221) shows the moderating effect of gender and its significance on the social influence of academic staff's behavioural intentions to use e-learning resources, i.e. Y = BI, X = SI and M = Gender (coded 0 = Female and 1 = Male). The path coefficient shows a very small negative value that indicates that social influence effects in females (0.05) are slightly higher than those of males (0.04), the moderating effect is, however, not significant at the ninety-five percent (95%) confidence interval.

Table 5.51: Moderator Analysis of Gender on Academic Staff's Social Influences

Outcome: BI						
Model Summary						
R	**R-sq**	**F**	**df1**	**df2**	**p**	
.11	**.01**	**.18**	**3.00**	**69.00**	**.91**	
Model						
	coeff	**se**	**t**	**p**	**LLCI**	**ULCI**
constant	**3.85**	**.75**	**5.14**	**.00**	**2.35**	**5.34**
Gender	**.13**	**.85**	**.15**	**.88**	**-1.57**	**1.82**
SI	**.05**	**.21**	**.24**	**.81**	**-.36**	**.46**
int_1	**-.01**	**.24**	**-.03**	**.98**	**-.48**	**.47**

* Bolded line shows moderating effect and its significance

Table 5.52 below shows the moderating effect of age and its significance on the social influence effect of academic staff's behavioural intentions to use e-learning resources, i.e. Y = BI, X = SI and M = Age. The path coefficient shows no effect, which is not significant at the ninety-five percent (95%) confidence interval.

Table 5.52: Moderator Analysis of Age on Academic Staff's Social Influences

Outcome: BI						
Model Summary						
R	**R-sq**	**F**	**df1**	**df2**	**p**	
.16	**.02**	**.56**	**3.00**	**69.00**	**.64**	
Model						
	coeff	**se**	**t**	**p**	**LLCI**	**ULCI**
constant	**4.07**	**.08**	**52.93**	**.00**	**3.92**	**4.23**
Age	**-.01**	**.01**	**-1.10**	**.27**	**-.02**	**.01**
SI	**.05**	**.11**	**.51**	**.61**	**-.16**	**.27**
int_1	**.00**	**.01**	**-.26**	**.79**	**-.02**	**.02**

* Bolded line shows moderating effect and its significance

Table 5.53 (page 222) indicates the moderating effect of experience and its significance on the social influence effect of academic staff's behavioural intentions to use e-learning resources, i.e. Y = BI, X = SI and M = Exper. The path coefficient shows a small negative effect and is not significant at the ninety-five percent (95%) confidence interval.

Table 5.53: Moderator Analysis of Experience on Academic Staff's Social Influences

Outcome: BI

Model Summary

R	R-sq	F	df1	df2	p
.50	.25	10.16	3.00	69.00	.00

Model

	coeff	se	t	p	LLCI	ULCI
constant	4.06	.07	60.89	.00	3.93	4.20
Exper	.22	.07	3.17	.00	.08	.36
SI	.07	.07	.95	.35	-.07	.21
int_1	-.09	.05	-1.79	.08	-.19	.01

* Bolded line shows moderating effect and its significance

> **H_{a20}:** The effect of effort expectancy on behavioural intention of academic staff to use e-learning resources will be moderated by (a) gender, (b) age and (c) experience, such that the effect will be stronger for women, particularly for younger women, and particularly at early stages of experience.

Table 5.54 (page 223) shows the moderating effect of gender and its significance on the effort expectancy effect of academic staff's behavioural intentions to use e-learning resources, i.e. Y = BI, X = EE and M = Gender (coded 0 = Female and 1 = Male). The path coefficient shows a small positive value that indicates that effort expectancy effects in females (0.31) is actually lower than that of males (0.50), the moderating effect is however not significant at the ninety-five percent (95%) confidence interval.

Table 5.54: Moderator Analysis of Gender on Academic Staff's Effort Expectancy

Outcome: BI

Model Summary

R	R-sq	F	df1	df2	p
.58	.34	15.39	3.00	69.00	.00

Model

	coeff	se	t	p	LLCI	ULCI
constant	2.89	.47	6.18	.00	1.96	3.82
Gender	-.65	.59	-1.11	.27	-1.82	.52
EE	.31	.12	2.52	.01	.07	.56
int_1	.18	.15	1.22	.23	-.12	.48

* Bolded line shows moderating effect and its significance

Table 5.55 below indicates the moderating effect of age and its significance on the effort expectancy effect of academic staff's behavioural intentions to use e-learning resources, i.e. Y = BI, X = EE and M = Age. The path coefficient shows no effect and is not significant at the ninety-five percent (95%) confidence interval.

Table 5.55: Moderator Analysis of Age on Academic Staff's Effort Expectancy

Outcome: BI

Model Summary

R	R-sq	F	df1	df2	p
.57	.33	14.68	3.00	69.00	.00

Model

	coeff	se	t	p	LLCI	ULCI
constant	4.07	.06	64.68	.00	3.95	4.20
Age	.00	.01	-.26	.80	-.02	.01
EE	.43	.07	6.16	.00	.29	.57
int_1	.00	.01	.41	.68	-.01	.02

* Bolded line shows moderating effect and its significance

Table 5.56 below indicates the moderating effect of experience and its significance on the effort expectancy effect of academic staff's behavioural intentions to use e-learning resources, i.e. Y = BI, X = EE and M = Exper. The path coefficient shows a small negative effect and is not significant at the ninety-five percent (95%) confidence interval.

Table 5.56: Moderator Analysis of Experience on Academic Staff's Effort Expectancy

Outcome: BI

Model Summary

R	R-sq	F	df1	df2	p
.58	.34	17.69	3.00	69.00	.00

Model

	coeff	se	t	p	LLCI	ULCI
constant	4.09	.08	49.28	.00	3.92	4.25
Exper	.06	.11	.55	.58	-.15	.27
EE	.37	.13	2.79	.01	.11	.63
int_1	-.03	.06	-.53	.60	-.14	.08

* Bolded line shows moderating effect and its significance

H_{a22}: The effect of facilitating conditions on academic staff's usage of e-learning resources will be moderated by (a) age and (b) experience, such that the effect will be stronger for older users, particularly in the early stages of experience.

Table 5.57 (page 225) shows the moderating effect of age and its significance on the facilitating conditions of academic staff to use e-learning resources, i.e. Y = Use, X = FC and M = Age. The path coefficient shows virtually no effect and is not significant at the ninety-five percent (95%) confidence interval.

Table 5.57: Moderator Analysis of Age on Facilitating Conditions Effect of Academic Staff

Outcome: Use

Model Summary

R	R-sq	F	df1	df2	p
.45	.21	6.50	3.00	69.00	.00

Model

	coeff	se	t	p	LLCI	ULCI
constant	3.30	.15	21.37	.00	2.99	3.61
Age	.00	.02	.01	.99	-.03	.03
FC	.71	.18	3.85	.00	.34	1.08
int_1	.04	.02	1.60	.11	-.01	.09

* Bolded line shows moderating effect and its significance

Table 5.58 below specifies the moderating effect of experience and its significance on the facilitating conditions of academic staff to use e-learning resources, i.e. Y = Use, X = FC and M = Age. The path coefficient shows a small negative effect and is not significant at the ninety-five percent (95%) confidence interval.

Table 5.58: Moderator Analysis of Experience on Facilitating Conditions of Academic Staff

Outcome: Use

Model Summary

R	R-sq	F	df1	df2	p
.81	.66	44.07	3.00	69.00	.00

Model

	coeff	se	t	p	LLCI	ULCI
constant	3.27	.12	26.80	.00	3.03	3.51
Exper	.91	.12	7.87	.00	.68	1.14
FC	-.02	.17	-.13	.90	-.37	.33
int_1	-.08	.12	-.68	.50	-.31	.15

* Bolded line shows moderating effect and its significance

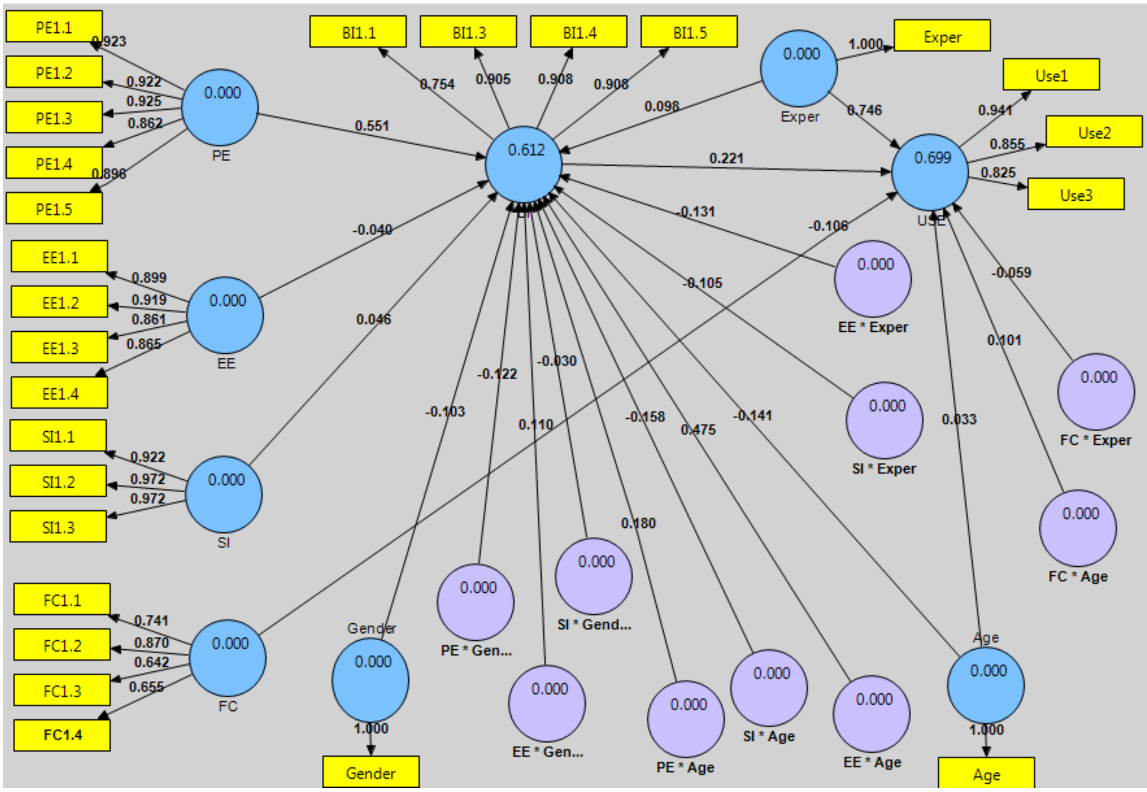

Figure 5.94: Moderation Analysis in Academic Staff Model Using SmartPLS (Ringle *et al.*, 2004) – PLS algorithm Calculation

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, as seen in Figure 5.94 above. The study observed a strong correlation between experience and use of e-learning resources, with Use's R^2 (0.70) almost doubling.

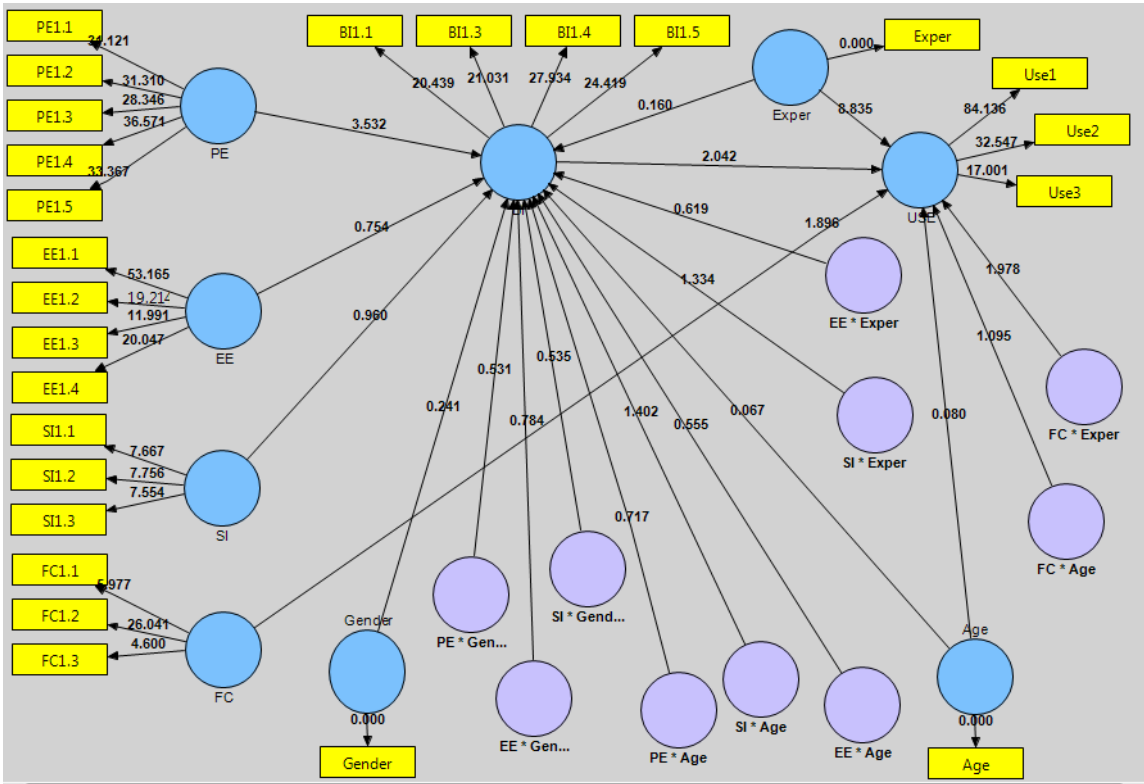

Figure 5.95: Bootstrapping the academic staff model's moderation analysis in SmartPLS (Ringle *et al.*, 2004)

Bootstrapping shown in Figure 5.95 above indicates only one moderating effect to be significant within the constructs of the academic staff's UTAUT model, which was that of experience on facilitating conditions of academic staff – FC*Exper (t = 1.98). However, on close inspection the convergent validity (AVE) values did not meet the required criterion to be included in the model.

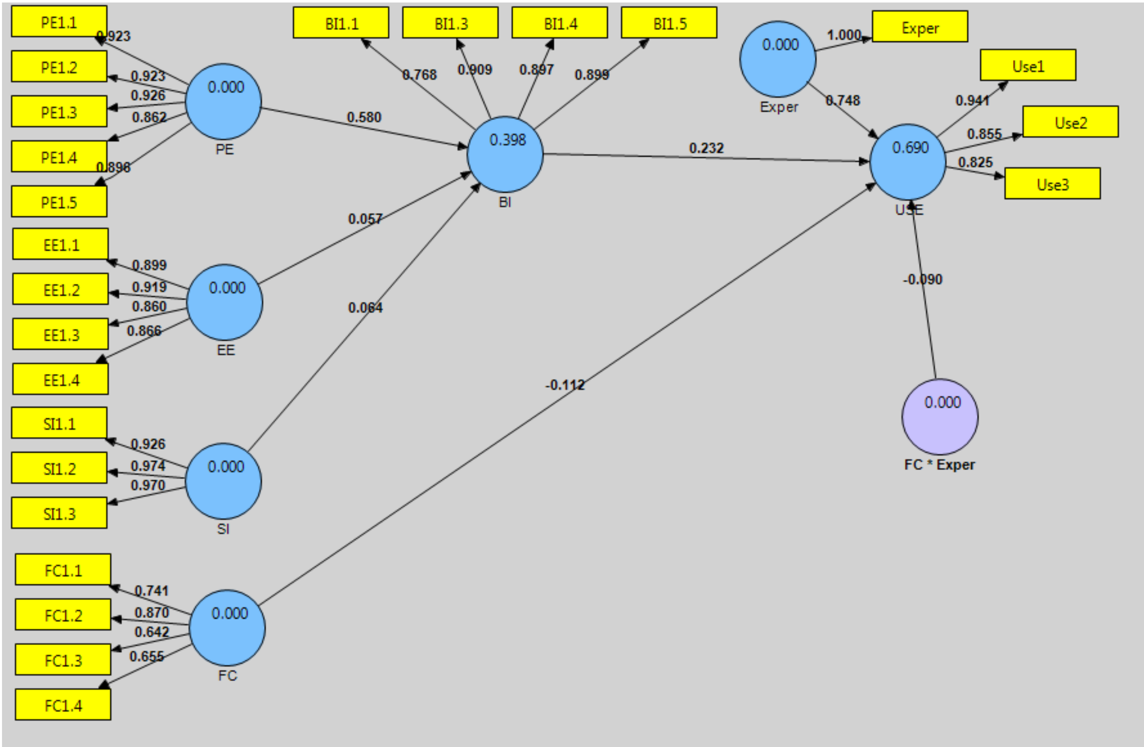

Figure 5.96: Final Moderation Analysis in Academic Staff Model Using SmartPLS (Ringle *et al.*, 2004) – PLS Algorithm Calculation

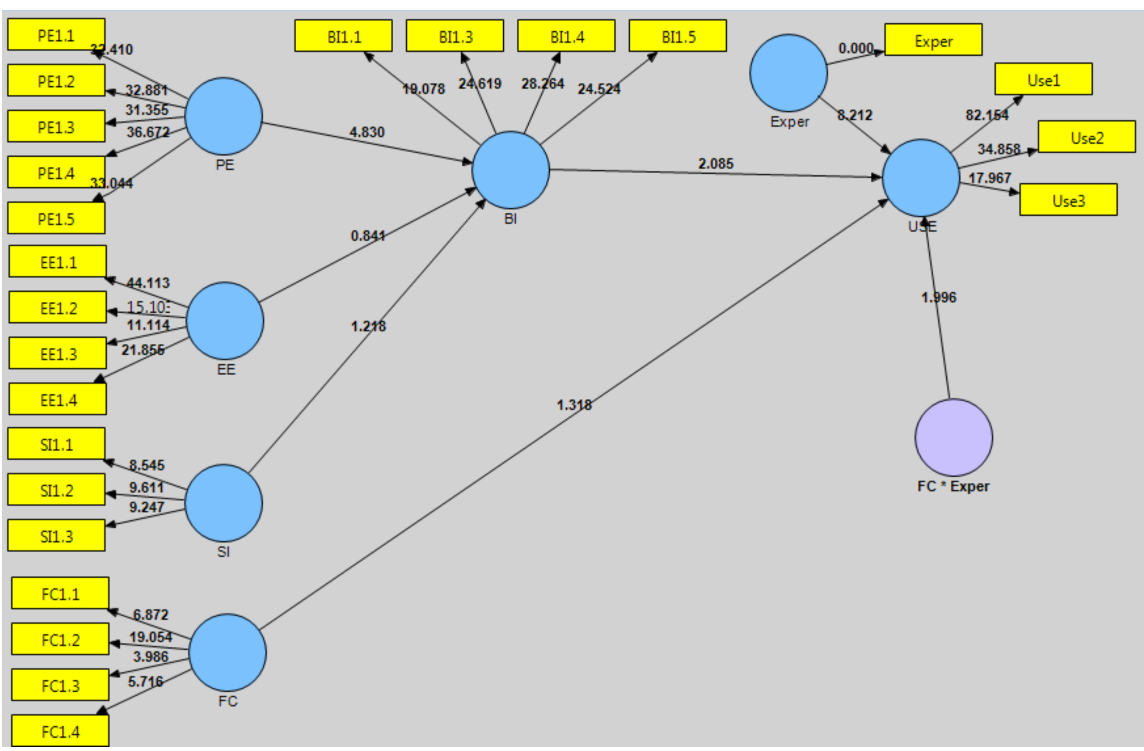

Figure 5.97: Final Bootstrapping of the Academic Staff Model's Moderation Analysis in SmartPLS (Ringle *et al.*, 2004)

5.8 Summary

This chapter begins by describing the sample sizes and biographical details of the primary users of e-learning resources at the University of Zululand and follows with the summative information and descriptive statistics of their survey responses. Thereafter, the regression analysis of the outer measurement model and inner structural model of the UTAUT was conducted using SmartPLS (Ringle *et al.,* 2004) and presented together with the required validity and reliability checks. Finally, moderation analysis was conducted to understand under what conditions the constructs of the UTAUT model operate, by exploring the theorised moderating effects using model one (1) of the PROCESS (Hayes, 2013) procedure for IMB SPSS statistics and SmartPLS (Ringle *et al.*, 2004).

Chapter 6: DISCUSSION OF FINDINGS

6.1 Introduction

The data produced by the statistical analysis in chapter five (5) provides the basis for answering the individual research questions and hypotheses of the study. Bearing in mind that the main aim of the study was to measure whether primary users (academic staff and students) at the University of Zululand will accept e-learning within a blended learning environment, another question was to what extent the UTAUT model can be efficiently utilised to predict the acceptance of e-learning by these users. The third aim addressed by this study was to determine the impact of the various UTAUT variables or constructs on the primary user's behavioural intentions and their use of e-learning at the University of Zululand. Lastly the study investigates the hypothesised moderating effects of these constructs in order to better understand the conditions under which they operate.

6.2 The Sample Sizes and Biographical Representation

Both primary user sample sizes met the minimum sample size of the often cited ten (10) times rule, which in the UTAUT model's case was thirty (30) (Barclay *et al.*, 1995 in Hair *et al.,* 2014:20), but the study takes 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 (3) (PE, EE, SI predicting BI). According to Cohen (1992) in Hair *et al.* (2014:20), for three independent variables, the study would either need a sample size of 124, 59, 38 or 30 observations to achieve a statistical power of eighty percent (80%) for detecting coefficients of determinations (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 0.40 for students and 0.43 for academic staff, this would roughly translate to around fifty-nine (59) necessary observations to obtain a statistical power of eighty percent (80%).

The student sample (n = 405) consisted of around twenty percent (85; 20%) more females than males (see Figure 5.1, page 129), which might have introduced bias when conducting the gender moderating effect analysis discussed later in the chapter. The stratification of the student sample according to academic levels indicates that almost fifty percent (50%) of respondents were first year students (see Figure 5.2, page 130). This means that half the student sample only have two semesters of experience using e-learning resources, which will also be discussed later in the chapter when the study discusses the low coefficient of determination for predicting the use of e-learning. The stratification of the student sample according to faculty (see Table 5.1 page 126) was slightly offset by two modules namely: CBIS102 (Business Information Systems 1B), which together with students from the Faculty of Commerce, Administration and Law also had students from the Faculty of Education enrolled and SCPS122 (Computer literacy II), which together with students from the Faculty of Science and Agriculture also had students from all other faculties enrolled. Overall however, the student sample had some representation from all faculties (see Figure 5.3, page 131). Demographically most of the students reported being Black South Africans (99%) (see Figure 5.4 page 131) between the ages of eighteen (18) to twenty-nine (29) (93%) (see Table 5.3, page 129). The response rate for the student survey was fifty-nine percent (59%), which is acceptable; the missing forty percent (40%) can be partly explained by lower class attendance during the revision period before the exams and network problems, which prevented some respondents moving from the first to the second page on the survey instrument. The latter problem could have arisen from multiple responses coming from the same student proxy server and the same public internet protocol address, which could have caused verification problems on the hosting site.

A limitation of selecting the academic staff sample (n=73) was that the email address book, which was used as the study's sample frame, was not completely up-to-date and this led to the disqualification of six (6) participants, however this number may have been more. The academic staff sample consisted of around twenty percent (15; 20%) more males than females (see Figure 5.6, page 133), which might have also introduced bias when conducting the gender moderating effect analysis in academic staff, which is discussed later in the chapter. There was the larger age range (21–69 years) amongst the academic staff sample, which was more conducive to testing the age moderating effect than in the student sample (16–41 years). The stratification of the staff, according to their positions, seems to be dominated by lecturers (45%) (see Figure 5.7, page 134), however all faculties of the institution were represented in the academic staff sample (see Figure 5.8 page 134). The response rate for the academic staff's survey was fifty-two percent (52%), which could lead to some response bias.

The determination of skewness, and kurtosis of all survey responses, was included in the data analysis of this study because of previous findings of non-normal data in psychometric studies (Hair, Tatham, Anderson, and Black, 1998 in Moran, 2006:59). The skewness results for a number of responses to indicator statements used in the structural equation models for students (BI1.3, BI1.4, BI1.5, PE1.1 and PE1.4) and academic staff (BI1.1) confirm some non-normal data, whose skewness values were less than minus one (-1) (indicate substantially negatively skewed distributions in these cases) (Hair *et al.,* 2010:36). The choice to use Partial Least Squares - Structural Equation Modelling (PLS-SEM) in this study is appropriate because of the non-normality of some of the data used and because of the relatively small academic staff sample size, which suites PLS‑SEM's ability to work efficiently with smaller sample sizes (Hair *et al.*, 2011:140).

6.3 Acceptance of E-learning Resources

To answer the main research question, on whether students and academic staff accept e-learning resources at the University of Zululand, the study must look at both the descriptive and inferential statistics presented in the previous chapter. The mode for students' and academic staff's behavioural intention to use e-learning resources was both four (4), which indicates that both primary users agree that it is their intention to use e-learning resources at the University of Zululand. Also both primary users' UTAUT models' path coefficients from exogenous Latent Variables (LVs) to endogenous LVs were positive and both models had LV index values greater than three (3), which indicate positive relationships between primary users and the UTAUT constructs. The study's empirical results suggest the acceptance / adoption of e-learning resources by most students and academic staff at the University of Zululand. 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 latent variables i.e. Behavioural Intention (BI) to use, and Use Behaviour (UB), of e-learning resources.

6.4 UTAUT Predicting Behavioural Intention (BI)

In order to respond to the second research question, of how efficiently the UTAUT model was able to predict the acceptance of e-learning resources at the University of Zululand, the study will compare its results with those found in seminal studies and literature. It will specifically look at the primary users behavioural intention's coefficient of determinations (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 indicates 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 we use the R^2 value to compare models that are specified differently, i.e. 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 value 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. This was noticed when adding the constructs age, gender and experience to the UTAUT model for the moderation analysis of academic staff. The original

Behavioural Intention (BI) 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 behavioural intention now become six (see Figures 5.89, page 204 and 5.92, page 218), all of which proved non-significant in this study, but significant in Venkatesh *et al.'s* (2003) original study. Hair *et al.* (2014:176) therefore recommend the adjusted R^2 value (R^2_{adj}), as represented in the formula below, to 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, k the number of exogenous LVs.

- For the significant UTAUT staff model with 3 (PE, EE and SI) exogenous constructs $R^2_{adj} = 0.40$
- For the non-significant moderated UTAUT staff model with 6 (PE, EE, SI, age, gender and experience) exogenous constructs $R^2_{adj} = 0.57$
- For the significant but unreliable moderated staff model with 4 (PE, EE, SI and experience) exogenous constructs $R^2_{adj} = 0.36$

The first and last listed R^2_{adj} values demonstrates that, although when adding experience, which proved highly correlated to use behaviour, when it increased the coefficient of determination for Use Behaviour (UB), the more complex model, with a lower R^2_{adj} for Behavioural Intentions (BI), proved less successful in predicting behavioural intentions to use e-learning resources.

So while the UTAUT model was not able to match the high (70 %) predictive accuracy of behavioural intentions as in Venkatesh *et al.'s* (2003) study, the explained variance in behavioural intention was thirty-nine percent (39%) for students and forty-one percent (41%) for academic staff (see adjusted *R* square values in Table 5.29, page 203 and Table 5.36, page 207). Both adjusted coefficients of determination demonstrate moderate efficiencies in predicting behavioural intentions to use e-learning resources at the University of Zululand,

and compares with the predictive strength of the eight models used to make up the UTAUT model, with the variance in behavioural intention explained ranging from seventeen percent (17%) to forty-two percent (42%) (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 behavioural intention, the Q^2 values for the student and academic staff models were 0.22 and 0.28 respectively, which shows that the UTAUT model has predictive relevance for this dependent variable for both primary users at the University of Zululand.

Based on these empirical results, the study rejects $\mathbf{H_{01}}$ and $\mathbf{H_{02}}$ in favour of:

> $\mathbf{H_{a1}}$**:** UTAUT will account for some percent of variance (adjusted R^2) in students' behavioural intention to use e-learning resources; and
>
> $\mathbf{H_{a2}}$**:** UTAUT will account for some percent of variance (adjusted R^2) in academic staff's behavioural intention to use e-learning resources.

6.5 Other UTAUT Constructs and Hypotheses

The third question dealt with by this study is the impact of the various UTAUT constructs (endogenous and exogenous) on primary user's behavioural intentions to use and their use behaviour of e-learning at the University of Zululand, as well as, under what conditions these constructs operate.

6.5.1 Use Behaviour (UB)

The UTAUT ultimately theorises that behavioural intention and facilitating conditions predict use behaviour. The relationship between facilitating conditions and use behaviour will be discussed later in the chapter, the BI-UB relationship together with the use behaviour coefficient of determinations (R^2) and the Stone-Geisser (Q^2) values will be discussed below. Legris *et al.'s* (2001:196) critical review of the technology acceptance model found that in eleven (11) of twenty-two (22) studies, use behaviour was measured through self-reporting, normally consisting of two or three questions questioning users about the frequency of use or the amount of time spent using the resources. Only in one study, was use behaviour measured by an automatic measuring tools, while in the ten (10) remaining studies, use behaviour was not measured as it was either compulsory to use or this variable was simply ignored (Legris *et al.,* 2001:196). Taiwo and Downe's (2013:48) meta-analysis of thirty-seven (37) UTAUT studies found that the correlations between Behavioural Intention and Usage Behaviour (BI-UB) were reported from thirteen (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%) actually investigate the effect of behavioural intentions on use behaviour, rather relying on the premise that a strong relationship existed between intentions and usage, which Venkatesh *et al.* (2003) had originally postulated and found to be significant. In Venkatesh *et al.'s* (2003) study, usage behaviour was measured as actual duration of use via system logs, while usage behaviour was self-measured in Moran's (2006) and Brand's (2006) studies. This study also adopted the self-measurement approach by asking the primary users how frequently they used e-learning resources.

From the descriptive statistics (see Figure 5.11, page 137) forty-five percent (45%) of the students consider the use of e-learning resources at the University of Zululand as both voluntary and compulsory, while forty percent (40%) consider their usage as compulsory, the minority of fifteen percent (15%) regard their usage as purely voluntary. This means that almost sixty percent (60%) of students will voluntarily use these resources outside of their scheduled classes. The majority of seventy-six percent (76%) of the staff on the other hand perceives their usage as purely voluntary (see Figure 5.18, page 143), which reflects the lack of a usage policy for e-learning resources at the University of Zululand. The forty-four percent (44%) of students and thirty-four (34%) of academic staff consider themselves moderately experienced; this measurement item was highly correlated to usage behaviour when inserted into the UTAUT model for moderation analysis (see Figures 5.92, page 218 and 5.96, page 228). It increases the amount of explained variances for usage behaviour in the UTAUT model by thirteen percent (13%) in students and thirty-six (36%) for academic staff and therefore should be recommended for further mediation / moderation analysis. The modes three, three and one (3, 3 and 1) for the indicator statements of student use behaviour reflect that most students only sometimes use e-learning resources in their formal lectures and sometimes during open-time for academic tasks, while the majority never used these resources within their residences. The modes five, one and three, and five (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 show that the student UTAUT model explained only sixteen percent (16%) variance in usage behaviour, while the academic staff UTAUT model was able to explain thirty one percent (31%) variance in this dependent variable (see *R* and adjusted *R* square values in Table 5.29, page 203 and 5.36, page 207). These values indicate a low predictive accuracy to explain use behaviour in students and a moderate predictive accuracy for academic staff. The Q^2 values for the student and academic staff models were 0.11 and 0.22 respectively, which shows that the UTAUT model has twice the predictive relevance for this dependent variable for academic staff than for students at the University of Zululand.

The path coefficients between Behavioural Intentions and Use Behaviour (BI-UB) of students (0.22, t = 4.50) and academic staff (0.42, t = 3.46), are both positive and significant, with the latter relationship having twice the strength of the first. Cohen's f^2 effect size for the students BI-UB relationship is weak (0.05), while for academic staff it is moderate (0.16). The Stone-Geisser's q^2 effect size value, which indicates the relative impact of predictive relevance, is weak (0.03) for the students BI-UB relationship, while for academic staff it is moderately weak (0.09).

Based on these empirical results, the study rejects $\mathbf{H_{03}}$, $\mathbf{H_{04}}$, $\mathbf{H_{013}}$ and $\mathbf{H_{014}}$ in favour of:

> $\mathbf{H_{a3}}$**:** UTAUT will account for some percent of variance (adjusted R^2) in students' use of e-learning resources.

H_{a4}: UTAUT will account for some percent of variance (adjusted R^2) in academic staff's use of e-learning resources.

H_{a13}: Behavioural intention will have a significant relationship on students' use of e-learning resources.

H_{a14}: Behavioural intention will have a significant relationship on academic staff's use of e-learning resources.

6.5.2 Performance Expectancy (PE)

Performance expectancy in this study is defined as the degree to which an individual believes that using e-learning resources will help them attain gains in their academic performances. It has been postulated to have the most significant positive relationship with behavioural intentions to use technologies in the UTAUT (Venkatesh *et al.,* 2003). Taiwo and Downe's (2013:52) obtained forty-three (43) correlations between users' performance expectancy and their behavioural intentions (PE-BI) from thirty-seven (37) studies and confirmed that this relationship was reported to have the highest positive significant correlations within the UTAUT.

Descriptive statistics show that four out of the five performance expectancy indicators for students (see Table 5.9 page 160) show a mode of four (4), which reflect general agreement amongst the students that using e-learning resources will result in some gains in academic performance. The academic staff responses to PE indicator statements had modes of four (4) and five (5) (see Table 5.10 page 165), which confirms their agreement and strong agreement to expecting performance gains in their behavioural intentions to use e-learning resources at the University of Zululand.

The relationship between performance expectancy and behavioural intentions to use e-learning resources proved both positive and significant as reflected in the study's PE-BI path coefficients for the students (0.34, t = 5.77) and academic staff (0.54, t = 4.42), with the latter relationship proving stronger than the first.

With students, the indirect effect of performance expectancy on their usage behaviour was small compared to direct effects of behavioural intentions and facilitating conditions. With academic staff, the indirect effect of performance expectancy on their usage behaviour was similar to the direct effects of facilitating conditions, but half the direct effect of an individual's behavioural intentions on usage behaviour. Cohen's f^2 effect size for the students' PE-BI relationship is moderately small (0.11), while for academic staff, the effect size for this relationship is medium (0.23). The Stone-Geisser's q^2 effect size value, which indicates the relative impact of predictive relevance of the PE-BI relationship, is small (0.05) for the students, while medium (0.13) for the academic staff.

Based on these empirical results, the study rejects $\mathbf{H_{05}}$ and $\mathbf{H_{06}}$ in favour of:

> $\mathbf{H_{a5}}$**:** Performance expectancy will have a significant relationship on students' behavioural intention to use e-learning resources.
>
> $\mathbf{H_{a6}}$**:** 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 a users' Performance Expectancy (PE), a negative correlation between PE and Behavioural Intentions (BI) to use e-learning resources was found in students, indicating that contrary to Venkatesh *et al.'s* (2003) initial hypothesis, there was actually a higher PE-BI effect in female students (X dummy coded 0) than male students (X dummy coded 1). The small effect was however found to be insignificant at the ninety-five percent (95%) confidence interval because the t value is less than 1.96 and the p value greater than 0.05 (see Table 5.39, page 209). Venkatesh *et al.* (2003:449) based this premise on gender differences in research conducted by Minton and Schneider (1980), which indicated that men tend to be highly task-oriented and, therefore, performance expectancies, which focus on task achievement, are likely to be particularly noticeable in men. Venkatesh *et al.* (2003:449) did take note of other gender schema theories suggesting that such differences arise from gender roles and socialisation processes strengthened from birth, rather than biological gender as such (Bem and Allen 1974:506; Lubinski et al. 1983:428; Lynott and

McCandless 2000:8; Kirchmeyer 2002:929). The moderation analysis of the students' age, and the performance expectancy effect on their behavioural intentions to use e-learning resources, showed a very small positive value for the path coefficient, but is not significant at the ninety-five percent (95%) confidence interval (see Table 5.40, page 209), i.e. contrary to Venkatesh *et al.* (2003) study, an increase in students age increased their PE-BI relationship. In academic staff, the gender-PE interaction was found to be consistent with gender theory but not significant at the ninety-five percent (95%) confidence interval (t Value must be greater than 1.99, and p Value less than 0.05), i.e. the measured performance expectancy effect of males (0.60) was higher than that of females (0.42) (see Table 5.49 page 219). Age, however, had no moderating effect on the performance expectancy effect of academic staff's behavioural intentions to use e-learning resources, and was not significant at the ninety-five percent (95%) confidence interval (see Table 5.50, page 220).

Based on these empirical results, the study does not reject $\mathbf{H_{015}}$ and $\mathbf{H_{016}}$:

> $\mathbf{H_{015}}$**:** The effect of performance expectancy on behavioural intention of students 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.
>
> $\mathbf{H_{016}}$**:** 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.

6.5.3 Effort Expectancy (EE)

In this study, effort expectancy is defined as the degree of ease or straightforwardness associated with the use of the e-learning resources at the University of Zululand. Taiwo and Downe's (2013:52) obtained forty-two (42) reported correlations between Effort Expectancy and Behavioural Intentions (EE-BI) from thirty-six (36) studies, which is very similar to the number of Performance Expectancy-Behavioural Intentions (PE-BI) relationships studied

(43). The authors' meta-analysis showed a significant positive relationship between EE-BI, although weaker than the PE-BI, and Behavioural Intentions-Use Behaviour (BI-UB) relationships, roughly the same strength as the Social Influence-Behavioural Intentions (SI-BI) relationships but stronger than the Facilitating Conditions-Use Behaviour (FC-UB) relationships. These findings confirm that the straightforwardness of technologies support individuals behavioural intentions 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 shown in Table 5.11 (page 169), it can be seen that the mode for all students' effort expectancy indicators is four (4), revealing that most students agree that they do not need to exercise much effort to use e-learning resources at the University of Zululand. For academic staff, the mode for three out of four of their effort expectancy indicators was also four (4) (see Table 5.12, page 172); the exception was where most staff were neutral about the idea of becoming skilful at using e-learning resources.

The inferential statistics show that the students' Effort Expectancy-Behavioural Intention (EE-BI) path coefficient is positive and significant (0.31, t = 4.35) (see Table 5.27, page 202), however, for academic staff the EE-BI relationship is considerably weaker and not significant (0.14, t = 1.51) (see Table 5.34, page 206), which could suggest that the academic staff's greater experience diminishes the EE effect on BI as postulated by Agarwal and Prasad (1997:570), (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. With students, the indirect effect of effort expectancy on their usage behaviour was small compared to those of the direct effects of behavioural intentions and facilitating conditions but significant (see Tables 5.28, page 202). With academic staff, the indirect effect of effort expectancy on their usage behaviour was small and insignificant (see Tables 5.35 page 206) .Cohen's f^2 effect size for the students EE-BI relationship is moderately small (0.10), while for academic staff the effect size for this relationship is small (0.02). The Stone-Geisser's q^2 effect size value, which indicates the relative impact of predictive relevance for the EE-BI relationship, is small for the students (0.04) and for academic staff (0.01) at the University of Zululand.

Based on these empirical results, the study rejects $\mathbf{H_{07}}$ in favour of:

> $\mathbf{H_{a7}}$**:** Effort expectancy will have a significant relationship on students' behavioural intention to use e-learning resources.

However, the study does not reject $\mathbf{H_{08:}}$

> $\mathbf{H_{08}}$**:** Effort expectancy will not have a significant relationship on academic staff's behavioural intention to use e-learning resources.

The PROCESS (Hayes, 2013) moderation analysis of the effort expectancy construct indicated that gender yielded a significant (t = 2.04) moderating effect on the effort expectancy effect of students' behavioural intentions to use e-learning resources (see Table 5.44, page 212), i.e. Y = BI, X = EE and M = Gender (coded 0 = Female and 1 = Male). The path coefficient shows a moderate negative (-0.27) value that supports the theory that effort expectancy relationships towards behavioural intention are stronger in females (0.61) than males (0.35). SmartPLS (Ringle *et al.*, 2004) confirmed this moderating effect (-0.59) within the whole model, however, bootstrapping resulted in a non-significant *t* value (1.18), which leads to the study's first inconclusive result. Another two PROCESS (Hayes, 2013) analyses show no moderating effects of age or experience (see Table 5.45 and Table 5.46, page 213) on the effort expectancy relationship of students' behavioural intentions to use e-learning resources at the University of Zululand and both are non-significant at the ninety-five percent (95%) confidence interval.

For the academic staff, a PROCESS (Hayes, 2013) analysis of the moderating effect of gender on the effort expectancy effect of academic staff's behavioural intentions to use e-learning shows a small positive value, which indicates that effort expectancy effects in females (0.31) is actually lower than that of males (0.50). The moderating effect is however not significant at the ninety-five percent (95%) confidence interval (see Table 5.54, page 223). Another analysis of the moderating effect of age on the effort expectancy effect of academic staff's behavioural intentions to use e-learning resources shows no effect and is not significant at the ninety-five percent (95%) confidence interval (see Table 5.55, page 223). The analysis of the moderating effect of experience and its significance on the effort expectancy effect of academic staff's behavioural intentions to use e-learning yielded a small negative relationship and is not significant at the ninety-five percent (95%) confidence interval (see Table 5.56, page 224).

Based on the above empirical results, the study does not reject $\mathbf{H_{019}}$ and $\mathbf{H_{020}}$:

> $\mathbf{H_{019}}$**:** The effect of effort expectancy on behavioural intention of students 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.
>
> $\mathbf{H_{020}}$**:** 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.

6.5.4 Social Influence (SI)

The social influences on students' or academic staff's behavioural intentions to use e-learning resources refer to colleagues, or those who the individual perceives as being important, influences at the University of Zululand. Taiwo and Downe's (2013:52) obtained thirty-six (36) correlations between Social Influence and Behavioural Intentions to use technologies (SI-BI) from thirty-one (31) studies, which the authors noted is 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 social influence in technology acceptance decisions is multifaceted and subject to a wide range of dependent effects, which impact on an individual's behaviour through three mechanisms: 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 achievements, while the compliance mechanism causes an individual to simply alter their intentions in response to the social pressure (Venkatesh *et al.* 2003:452).

The students' descriptive statistics of the four indicator statements used to measure the effect of social influences on students' behavioural intentions to use e-learning resources at the University of Zululand (see Table 5.13, page 176) show mixed modes (3, 4, 4, 2), reflecting that students were neutral (3), or agree (4, 4), that social influences, other than fellow students (2), did affect their behavioural intentions. The academic staff's responses showed a more neutral perspective on any social influences on their behavioural intentions towards using e-learning resources, with modes for their four indicators being (3, 3, 4, 3) (see Table 5.14, page 180). 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 at the University of Zululand.

From the inferential statistics, the relationship between Social Influences (SI) and Behavioural Intentions (BI) can be observed through the SI-BI path coefficient, which for students is a small positive value (0.11) that is significant (t = 2.12), while for academic staff, the SI-BI relationship is considerably weaker (0.06) and not significant (t = 1.11) at the ninety-five percent (95%) confidence interval. With students and academic staff, the indirect effects of social influence on their usage behaviour are both small and non-significant (see Tables 5.28, page 202 and 5.35, page 206). Cohen's f^2 effect size for both the students' and academic staff's SI-BI relationship is small (0.01) (see Tables 5.30 page 203 and 5.37 page 207). The Stone-Geisser's q^2 effect size value is small for the students (0.01) and non-existent for academic staff (0.00) at the University of Zululand, which indicates the little predictive relevance of the primary users' SI-BI relationship.

Based on these empirical results, the study rejects $\mathbf{H_{09}}$ in favour of:

> $\mathbf{H_{a9}}$**:** Social influence will have a significant relationship on students' behavioural intention to use e-learning resources.

However, the study does not reject $\mathbf{H_{010}}$:

> $\mathbf{H_{010}}$**:** 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 social influence construct in students shows that the moderating effect of gender (coded 0 = Female and 1 = Male) (see Table 5.45, page 213) has a path coefficient with a very small negative value that supports the theory that social influence effects in females (0.25) are greater than those of males (0.19), however, this effect is not significant at the ninety-five percent (95%) confidence interval. The moderating effects of age and experience, on the social influence effect of students' behavioural intentions to use e-learning resources, both have path coefficients that show virtually no effect and that are not significant at the ninety-five percent (95%) confidence interval (see Tables 5.46, page 213 and 5.47, page 214). The results of the PROCESS (Hayes, 2013) moderation analysis of the social influence construct in academic staff shows 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 social influence effects in females (0.05) are slightly higher than those of males (0.04); the moderating effect is, however, not significant at the ninety-five percent (95%) confidence interval (see Table 5.56, page 224). 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 ninety-five percent (95%) confidence interval (see Table 5.57, page 225). Another PROCESS (Hayes, 2013) moderation analysis of experience on the social influence effect of academic staff's behavioural intentions to use e-learning resources (see Table 5.58, page 225) results in path coefficient with a small negative value; the effect is not significant at the ninety-five percent (95%) confidence interval.

Based on the above empirical results, the study does not reject $\mathbf{H_{017}}$ and $\mathbf{H_{018}}$:

> $\mathbf{H_{017}}$**:** The effect of social influence on behavioural intention of students 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.
>
> $\mathbf{H_{018}}$**:** 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.

6.5.5 Facilitating Conditions (FC)

In this study, the facilitating conditions are defined as the amount of technical and organisational resources, support and knowledge, which students and academic staff believe exists at the University of Zululand to facilitate the use of e-learning resources. Taiwo and Downe's (2013:52) obtained only sixteen (16) correlations between Facilitating Conditions (FC), and Use Behaviour (UB) (FC-UB) from thirteen (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 performance expectancy constructs and effort expectancy constructs are present, facilitating conditions becomes non-significant in predicting behavioural intention, however, when moderated by age and experience facilitating conditions will have a significant influence on usage behaviour, such that the effect will be stronger for older users, particularly with increasing experience.

The students' descriptive statistics of the five facilitating conditions indicator statements (see Table 5.15, page 185) show modes of four (4), which reflects that most students agree that they do have the necessary knowledge, learning style, resources and support to use the e-learning resources at the University of Zululand. The academic staff also agree to having sufficient knowledge, a suitable teaching pedagogy and necessary resources, each having modes of four (4), however, academic staff are neutral (mode = 3) to whether they receive enough support to use the e-learning resources.

The inferential statistics show that the primary users' relationships between Facilitating Conditions (FC) and Use Behaviour (FC-UB) are both positive and significant. For students, the path coefficient (0.27) is larger than that of the academic staff (0.22), and more significant (t = 5.86 and t = 2.15), indicating a stronger and more significant relationship between facilitating conditions and use of e-learning resources for students at the University of Zululand. Cohen's f^2 effect size for the students' FC-UB relationship is moderately small (0.08), while for academic staff, the effect size is small (0.05). The Stone-Geisser's q^2 effect size value for the students and academic staff is moderately small and small respectively (0.05, 0.01), indicating low predictive relevance of the primary users' FC-UB relationship at the University of Zululand.

Based on these empirical results, the study rejects $\mathbf{H_{011}}$ and $\mathbf{H_{012}}$ in favour of:

> $\mathbf{H_{a11}}$**:** Facilitating conditions will have a significant relationship on students' use of e-learning resources.
>
> $\mathbf{H_{a12}}$**:** 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 facilitating conditions construct in students indicate that the moderating effects of age and experience have virtually no effect on usage behaviour and are not significant at the ninety-five percent (95%) confidence interval (see Tables 5.47, page 214 and 5.48, page 215). The same PROCESS (Hayes, 2013) moderation analysis of age of academic staff and facilitating conditions shows virtually no effect on usage behaviour, and this effect is also not significant at the ninety-five percent (95%) confidence interval (see Table 5.57, page 225). The moderation analysis of experience of academic staff and facilitating conditions shows a small negative effect on usage behaviour and is not significant at the ninety-five percent (95%) confidence interval (see Table 5.58 page 225). SmartPLS (Ringle *et al.*, 2004) found the same negative relationship (-0.09), but bootstrapping found this to be significant (t = 1.97) (see Figures 5.96 and 5.97, page 228), leading to the study's second inconclusive result, however, the convergent validity (AVE) values did not meet the required convergent validity criterion to be included in the model.

Based on the above empirical results, the study does not reject $\mathbf{H_{021}}$ and $\mathbf{H_{022}}$:

> $\mathbf{H_{021}}$**:** The effect of facilitating conditions on students' 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.

H_{022}: 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.

6.6 Limitations in the Results

The concept of e-learning at the University of Zululand 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 usage or intentions to use different resources within different contexts.

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

Although the study attempted to identify multivariate outliers by calculating Mahalanobis D^2 values in IBM SPSS Statistics for both primary user samples, their subsequent removal from the samples did not improve the predictive accuracy of the UTAUT models and therefore these responses were not excluded.

Chapter 7: SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

7.1 Introduction

This chapter provides a summary of the previous chapters' empirical findings and then draws conclusions on these. In the tradition of the study's Positivism research paradigm, the study finally provides recommendations for future research, with the aim of constructing suggestions for social change around the use of e-learning resources at the University of Zululand.

7.2 Summary of Findings

The unique contextual setting and dataset of the study provides empirical findings that can't be generalised to in different tertiary education settings, but can be used to better understand the behavioural intentions to use, and the use of, e-learning resources by students and academic staff at the University of Zululand. The results do contribute to UTAUT's theoretical validity and empirical applicability to the management of e-learning based initiatives.

7.2.1 Acceptance of E-learning Resources by Primary Users

The main aim of the study was to statistically predict the acceptance of e-learning resources by the primary users at the University of Zululand, which the study can empirically confirm through the examination of the results of modes, percentages, frequencies and inferential statistics of both students and academic staff. The extent of this acceptance by students and academic staff will depend on nurturing the positive relationships that will influence their behavioural intentions to use, and usage behaviour, of these resources. The empirical results show that for students the acceptance of these resources will strengthen if they boost their academic performances and are user friendly or easy to use. While for academic staff, results indicate that these resources mainly need to improve staff's academic performances, to increase the level of adoption by these users. Another finding that most academic staff consider the use of e-learning resources at the University of Zululand voluntary, could also provide an opportunity to improve adoption, i.e. by drafting policies that make the use of these resources mandatory rather than voluntary under certain circumstances.

7.2.2 UTAUT's Predictive Accuracy and Relevance at the University of Zululand

Another aim of the study was to investigate the UTAUT's efficiency to predict behavioural intentions of the primary users to use e-learning resources at the University of Zululand, as well as their use behaviour of these resources. Empirical results demonstrate moderate predictive accuracies (adjusted R^2) for students' and academic staff's behavioural intentions to use e-learning resources and that both UTAUT SEM's have some predictive relevance (Q^2) in this respect. While UTAUT had a low predictive accuracy (adjusted R^2) for students' usage behaviour of e-learning resources, the theory was twice as accurate in predicting the academic staff's usage behaviour, which was almost accurate enough to demonstrate a moderate accuracy.

A further aim was to validate the individual relationships between UTAUT's four exogenous and two endogenous latent variables (LVs), while also investigating under what conditions these LVs are moderated by the primary users' gender, age and experience at using e-learning resources.

7.2.3 Performance Expectancy (PE)

Descriptive statistics reflect general agreement, amongst the students and academic staff, to expecting performance gains when using e-learning resources at the University of Zululand.

The relationship between the expected academic performance gains in primary users, and their behavioural intentions to use e-learning resources at the University of Zululand proved to be significant and the strongest direct effect on the primary users. The magnitude of the path coefficient (PE-BI) was almost twice as large for academic staff as that found in the students' structural model. The indirect effect of performance expectancy on students' usage behaviour was small, while in academic staff, this indirect effect was similar in magnitude to the direct effect of facilitating conditions and was half the direct effect of an individual's behavioural intentions on their usage behaviour. Cohen's effect size (f^2) for performance expectancy on student's behavioural intentions was close to a medium effect, while academic staff's performance expectancy had a medium to large effect on their behavioural intentions to use e-learning resources. The Stone-Geisser's (Q^2) effect size value for students indicates a moderately small impact of predictive relevance for the PE-BI relationship, while for the academic staff a medium impact was observed. Gender and age were found not to influence the students' or academic staff's performance expectancy effect on their behavioural intentions to use e-learning resources at the University of Zululand.

7.2.4 Effort Expectancy (EE)

It can be seen from the mode for all students' effort expectancy indicators that most students agree that they do not need to exercise much effort to use e-learning resources at the University of Zululand. The same can be said for academic staff, however, the exception was where most staffs were neutral about the idea of becoming skilful at using e-learning resources.

The ease of use, or the amount of effort, that students associated with using e-learning resources at the University of Zululand proved to be significant and the second strongest positive relationship with their behavioural intentions to use these resources. While for academic staff, the path coefficient between effort expectancy and behavioural intentions to use e-learning resources showed a weak relationship that was non-significant, which possibly demonstrates the theory found in literature that the effect of this construct on an individuals' behavioural intentions becomes insignificant with increased experience or sustained usage (Agarwal and Prasad 1997:570, 1998; Thompson, Higgins and Howell, 1991:140). For students, the indirect effect of effort expectancy on their usage behaviour was small compared to the direct effects of behavioural intentions and facilitating conditions, but the relationship was significant. With academic staff, the indirect effect of effort expectancy on their usage behaviour was also small but non-significant. Cohen's effect size (f^2) for effort expectancy on the student's behavioural intentions was less than a medium effect but greater than a small effect, while for academic staff this LV had a small effect size on their behavioural intentions to use e-learning resources. The Stone-Geisser's (Q^2) effect size value for students indicates a small impact of predictive relevance for their relationship between effort expectancy and behavioural intentions (EE-BI) to use e-learning resources, while for the academic staff an even smaller impact was observed. Results of the moderating effect of gender on the students' relationship between effort expectancy and their behavioural intentions to use e-learning resources support the theory that this effect is stronger in females, however, the first inconclusive result of the study was encountered, with a significant interaction found through Hayes' (2013) PROCESS analysis, but insignificant moderating effect observed through bootstrapping in SmartPLS (Ringle *et al.* 2004). In academic staff, the moderating effect of gender on their relationship between effort expectancy and their behavioural intentions to use e-learning resources did not support the UTAUT theory and was non-significant. Age and experience were both found not to influence students' or academic staff's relationships between their effort expectancy and behavioural intentions, with both sets of moderating effects being non-significant.

7.2.5 Social Influence (SI)

The students' descriptive statistics reflect that students are neutral, or agree that social influences, other than fellow students, did somehow affect their behavioural intentions to use e-learning resources at the University of Zululand, while the academic staff's responses show a more neutral perspective on any social influences on their behavioural intentions towards using e-learning resources.

Social influences on students proved to be the weakest positive relationship towards their behavioural intentions to use e-learning resources at the University of Zululand, however, it did prove to be a significant relationship. For academic staff, this also proved to be the weakest effect towards their intentions to use e-learning resources, although even weaker than that of the students, the relationship also proved to be non-significant. In students and academic staff, the indirect effect of social influences on their usage behaviour is small and non-significant. Cohen's effect size (f^2) for social influence on the student's and academic staff's behavioural intentions was small. The Stone-Geisser's (Q^2) effect size value for students indicates a small impact of predictive relevance for the relationship between social influences and their behavioural intentions to use e-learning resources, while for the academic staff there was no impact of predictive relevance observed. The moderating effect of gender on the relationship between social influences of students and their behavioural intentions to use e-learning resources was found to be greater in females than in males, as hypothesised by Venkatesh *et al.* (2003:452), however, the moderating effect is non-significant. Age and experience were found not to influence the relationship between social influences of students and academic staff and their behavioural intentions to use e-learning resources, with the moderating effects being non-significant. In academic staff, the social influence effects on females' behavioural intentions to use e-learning resources are slightly higher than those of male staff, however, the moderating effect is non-significant.

7.2.6 Facilitating Conditions (FC)

The students' modes for the five facilitating conditions indicator statements reflects that most students agree that they do have the necessary knowledge, learning style, resources and support to use the e-learning resources at the University of Zululand. Academic staffs also agree to having sufficient knowledge, a suitable teaching pedagogy and necessary resources to use e-learning resources, however, academic staff are neutral to whether they receive enough support at the University of Zululand.

The relationship between the facilitating conditions and usage behaviour proved to be the strongest direct effect on students to use e-learning resources at the

University of Zululand, as well as the most significant. For academic staff, this relationship proved to be a less salient direct effect on their usage behaviour and is just significant at the ninety-five percent (95%) confidence interval. Cohen's effect size (f^2) for facilitating conditions on the student's usage behaviour was moderately small, while for academic staff it was small. The Stone-Geisser's (Q^2) effect size value for students indicates a moderately small impact of predictive relevance for their relationship between facilitating conditions and their usage behaviour, while for the academic staff, a very small impact of predictive relevance was observed. Moderation analyses of the facilitating conditions construct in students indicated that the moderating effect of age and experience have virtually no effect on usage behaviour and are non-significant. The moderation analysis of age of academic staff and facilitating conditions, meanwhile, shows virtually no effect on usage behaviour and this effect is also non-significant. However, the moderation analysis of the experience of academic staff and facilitating conditions shows a small negative effect on usage behaviour, and is not significant in Hayes' (2013) PROCESS analysis, but bootstrapping in SmartPLS (Ringle et al., 2004) found the same negative relationship to be significant ($t = 1.97$) leading to the study's second inconclusive result.

7.2.7 Behavioural Intentions (BI)

The modes for students' and academic staff's behavioural intention to use e-learning resources indicate that both primary users agree that it is their intention to use e-learning resources at the University of Zululand.

The behavioural intentions of students to use e-learning resources have a moderately weak positive relationship with their usage behaviour, however, this effect is significant. The exogenous LVs performance expectancy and effort expectancy have the greatest effects on students' behavioural intentions to use e-learning resources respectively, while facilitating conditions has a greater direct effect on students' usage behaviour than their behavioural intentions do. For academic staff, the relationship between their behavioural intentions and use behaviour was roughly twice as strong as that found in students and also significant. The exogenous LV performance expectancy has the greatest effect on academic staff's behavioural intentions to use e-learning resources, followed by the smaller effects of effort expectancy and social influences. The academic staff's behavioural intentions are the largest effect on their use behaviour, almost twice the direct effect of facilitating conditions and indirect effect of performance expectancy, which both had comparable values.

7.2.8 Usage Behaviour (UB)

The modes for the indicator statements of student use behaviour reflect that most students only sometimes use e-learning resources in their formal lectures and sometimes during open-time for academic tasks, while the majority never used these resources within their residences. The modes 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 students' use behaviour of e-learning resources is most influenced by the direct effect of the facilitating conditions, then by their behavioural intentions, while the most influential indirect effects were performance and effort expectancies and lastly social influences. For academic staff, the direct effect of their behavioural intentions to use e-learning resources is the most influential on their usage behaviour, followed by the indirect and direct effects of performance expectancy and facilitating conditions respectively, then lastly the indirect effects of effort expectancy and social influences.

7.3 Conclusions

The Unified Theory of Acceptance and Use of Technology (UTAUT) was partially validated by the primary users of e-learning resources at the University of Zululand. The theory showed moderate predictive accuracies and predictive relevance towards their behavioural intentions to using these resources within this contextual setting. UTAUT demonstrated a weak accuracy and relevance in successfully predicting students' usage behaviour, possibly because almost half of the student sample represented first year candidates who in their early stages of their academic careers possibly only used e-learning resources because their academic programmes required their enrolment in two semesters of computer literacy. UTAUT proved more successful in its predictive accuracy and relevance towards academic staff's usage behaviour of e-learning resources. Results of the academic staff usage behaviour indicates that most staff only used e-learning resources for administration and research, while only a few use these resources for formal teaching. This trend needs to be addressed by firstly, providing useful resources that will improve both teaching and learning, and secondly providing appropriate skills development and support for these resources to both academic staff and students. The moderating effects hypothesised by Venkatesh *et al.* (2003) were found not to have any significant effects in this tertiary education environment and the study postulates that the acceptance of technologies in different settings (industrial, financial and educational sectors) requires their own contextualised socio-economic moderators for these to be significant. Cognisance of maintaining a parsimonious structural equation model should be taken into consideration in the moderation analysis before adding too many insignificant exogenous LV's that are correlated to the endogenous LVs of the model.

The most significant effect on both primary users' behavioural intentions to use e-learning resources at the University of Zululand was their performance expectancies from the resources, with the relationship being twice as strong in academic staff as in students. This result possibly indicates that the importance of this relationship is more salient for individuals who are employed, rather than tertiary education students. The study's results questions Venkatesh *et al.'s* (2003) hypothesis that the relationship between users' performance expectancies and their behavioural intentions will be moderated by gender and age so that the effect will be stronger for males, and particularly younger males, in all contextual settings, especially within the tertiary education sector. The acquisition of quality e-learning resources at the University of Zululand, combined with relevant skills development, should support performance gains, and hence the behavioural intentions of both students and academic staff to use e-learning resources at the institution.

The relationship between effort expectancy and individuals' behavioural intentions to use e-learning resources only proved significant for students at the University of Zululand, but not for academic staff. 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 results could also indicate that many first year students, which made up almost half the student sample, found the two computer literacy modules relatively easy. The study's moderation analysis of gender, age and experience on an individuals' relationship between effort expectancy with their behavioural intentions to use e-learning resources again questions Venkatesh *et al.'s* (2003) hypothesis that the effect will be stronger for women, particularly for younger women, and particularly at the early stages of experience. It seems inconsistent that it is postulated that young task orientated males have more performance expectancies, while young inexperienced women will find it easier to use technologies. It could mean that they put more emphasis on using "user friendly" technologies, however, when using the same technologies, under the same contextual settings, the study would not expect a stronger ease of use relationship as postulated by Venkatesh *et al.* (2003). The study takes cognisance of the finding that although the majority of students and academic staff agree that they find it easy using e-learning resources, there was a minority who said they don't, 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 for the primary users of e-learning resources at the University of Zululand.

The effect of social influences on the primary users' behavioural intentions to use e-learning at the University of Zululand resources is found to be more significant in situations where use of the resources are mandatory. For example the relationship between social influences of academic staff on students' behavioural intentions to use e-learning resources was significant for the students' who had scheduled classes that were compulsory to attend. While for most academic staff who considered the use of these resources as being voluntary, the relationship was insignificant. The introduction of user policies and facilitating conditions to instill mandatory use of these resources by academic staff might strengthen this effect as relevant skills development and support become more salient. This will increase the interactions and relationships between management, academic and support staff. Although the study did find gender to moderate the relationships between social influences and their behavioural intentions in both primary users, such that social influences were greater in females than males, both were found to be insignificant. Age and experiences of students and academic staff had virtually no effect on their social influences to use e-learning resources at the University of Zululand and were both non-significant.

Facilitating conditions had the strongest, and most significant, direct effect on students' use behaviour of e-learning resources, while for academic staff, their behavioural intentions had twice the effect that facilitating conditions had on their use behaviour. These results indicate the importance of creating conducive facilitating conditions for students and positive behavioural intentions in academic staff to facilitate the use of e-learning resources at the University of Zululand. 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 get at using e-learning resources, the less content they are in terms of the facilities and support at the University of Zululand.

7.4 Recommendations for Future Research

Recommendations for future research include:

1. Extend the scope of the UTAUT for predicting the acceptance and use of specific e-learning resources at the University of Zululand, for example, the Learning Management System (LMS), the library's e-resources including research databases and the Institutional Repository (IR) and the lecture theatre and computer laboratory resources such as electronic (e) - boards.
2. Integrate both interpretive and critical research paradigms to the study's positivist results to investigate policy development, future implementation and support of e-learning resources at the University of Zululand.
3. Investigate how to incorporate the instrument and data analysis methods of the study into quality assurance and support of e-learning resources at a departmental and modular level at the University of Zululand.
4. Extend and improve the static, one shot cross-sectional measurement method of primary users by using dynamic longitudinal and multiple time period measurements that do not rely on self-reporting methods if possible.
5. Increase the number of reliable and validated indicators for the UTAUT constructs, especially for the endogenous LV of use behaviour together with the moderating effect of users' experience.
6. Undertake a broad mediation and moderation analysis of the UTAUT to identify some significant contextual socio-economic moderators and or mediators on the theory's four exogenous LVs' (PE, EE, SI and FC) relationships with the two endogenous LVs (BI and UB).

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APPENDIX A. LETTER REQUESTING PARTICIPATION (ACADEMIC STAFF)

Dear [First and Last name of academic staff]

RE: Request to respond to my survey on e-learning at the University of Zululand

For the purposes of this study e-learning is broadly defined as the use of Information and Communication Technologies (ICTs) and Information Systems (IS) in teaching and learning. At the University of Zululand this normally occurs within a blended learning environment, where traditional face-to-face teaching and learning is combined with e-learning, experiential learning, research and community engagement. E-learning resources can include office ICT, portable presentation tools for lectures, intranet, internet and wireless network services, Moodle Learning Management System (LMS), computer labs, the library's e-resources, research databases and institutional repository etc.

The purpose of this study is to empirically validate the Unified Theory of Acceptance and Use of Technology (UTAUT) model's ability to predict user acceptance of e-learning by lecturers and students within the context of the University of Zululand's blended learning environment.

Please take a few minutes to complete this survey, it will be greatly appreciated! All your information will be treated confidentially and you can view the results of this study later @ http://elearn.uzulu.ac.za/survey.

If you have any queries, don't hesitate to contact me.
Kind regards

Neil Evans

APPENDIX B. QUESTIONNAIRES

Student Survey

For the purposes of this study e-learning is broadly defined as the use of Information and Communication Technologies (ICTs) and Information Systems (IS) in teaching and learning. At the University of Zululand this normally occurs within a blended learning environment, where traditional face-to-face teaching and learning is combined with e-learning, experiential learning, research and community engagement. E-learning resources can include using the computer labs, email, World Wide Web (WWW), intranet, internet and wireless network services, Moodle Learning Management System (LMS), the library's e-resources, research databases and institutional repository.

The purpose of this study is to empirically validate the Unified Theory of Acceptance and Use of Technology (UTAUT) model's ability to predict user acceptance of e-learning by lecturers and students within the context of the University of Zululand's blended learning environment.

Please take a few minutes to complete this survey, it will be greatly appreciated! All your information will be treated confidentially and you can view the results of this study later @ http://elearn.uzulu.ac.za/survey.

If you have any queries, don't hesitate to contact me.
Kind regards
Neil Evans

1. Biographical information

1. Please choose your Gender*

○ Female
○ Male

2. Please select your race

○ Asian
○ Black
○ Coloured
○ Indian
○ White

3. What is your age?*

[ ]

4. What is your nationality?

○ South African
○ Other (please specify)
[ ]

5. Please select your level of study at the University of Zululand:*

○ 1st Year
○ 2nd Year
○ 3rd Year
○ 4th Year
○ PostGrad
○ Other (please specify)
[ ]

6. Please indicate which faculty you are in at the University of Zululand: *

○ Faculty of Arts
○ Faculty of Commerce, Administration and Law
○ Faculty of Education
○ Faculty of Science and Agriculture
○ Other (please specify)
[ ]

2. Measuring UTAUT constructs and moderators

7. Please indicate your usage of e-learning resources by completing the sentences below:*

	never use	almost never use	sometimes use	often use	always use
I _______ e-learning resources during my formal lectures.	○	○	○	○	○
I _______ e-learning resources for academic tasks during open time in the computer labs.	○	○	○	○	○
I _______ e-learning resources in my residence.	○	○	○	○	○

8. How would you describe your usage of e-learning resources at the University of Zululand?*

○ Voluntary
○ Compulsory
○ Both

9. How experienced are you at using e-learning resources*

	Not at all experienced	Slightly experienced	Somewhat experienced	Moderately experienced	Extremely experienced
Please choose:	○	○	○	○	○

10. Please indicate your response to the following statements using the 5 point likert scale: *

	strongly disagree	disagree	neutral	agree	strongly agree
1. Using e-learning resources in my studies enables me to complete academic tasks more quickly.	○	○	○	○	○
2. Using e-learning resources in my studies increases my academic productivity.	○	○	○	○	○
3. Using e-learning resources makes my studies easier.	○	○	○	○	○
4. Using e-learning resources in my studies is useful.	○	○	○	○	○
5. Using e-learning resources in my studies increases my marks.	○	○	○	○	○

11. Please indicate your response to the following statements using the 5 point likert scale:*

	strongly disagree	disagree	neutral	agree	strongly agree
1. Using e-learning resources is easy for me.	○	○	○	○	○
2. I find the use of e-learning resources in my studies understandable.	○	○	○	○	○
3. It is easy for me to become skilful at using e-learning resources in my studies.	○	○	○	○	○
4. I would find it easy to do what I want to do when using e-learning resources.	○	○	○	○	○

12. Please indicate your response to the following statements using the 5 point likert scale:*

	strongly disagree	disagree	neutral	agree	strongly agree
1. People who influence my behaviour think that I should use e-learning resources.	○	○	○	○	○
2. People who are important to me think that I should use e-learning resources.	○	○	○	○	○
3. People whose opinions I value promote the use of e-learning resources.	○	○	○	○	○
4. I use e-learning resources because of the influence of other students.	○	○	○	○	○

13. Please indicate your response to the following statements using the 5 point likert scale:*

	strongly disagree	disagree	neutral	agree	strongly agree
1. I have the necessary resources to use e-learning.	○	○	○	○	○
2. I have the necessary knowledge to use e-learning resources.	○	○	○	○	○
3. I have the necessary support to use e-learning resources.	○	○	○	○	○
4. The use of e-learning resources fits my learning style (visual verbal learner).	○	○	○	○	○
5. I can get help from others when I have difficulties using e-learning resources.	○	○	○	○	○

14. Please indicate your response to the following statements using the 5 point likert scale:*

	strongly disagree	disagree	neutral	agree	strongly agree
1. Whenever possible, I intend to use e-learning resources.	○	○	○	○	○
2. I perceive using e-learning resources as natural for me.	○	○	○	○	○
3. I plan to continue to use e-learning resources.	○	○	○	○	○
4. To the extent possible, I would use e-learning resources to learn.	○	○	○	○	○
5. To the extent possible, I would frequently use e-learning resources.	○	○	○	○	○

15. If you have any additional comments please submit them in the text box below (optional):

16. Name (Optional):

17. Email (Optional):

Please contact evansn@unizulu.ac.za if you have any questions regarding this survey

Lecturer Survey

For the purposes of this study e-learning is broadly defined as the use of Information and Communication Technologies (ICTs) and Information Systems (IS) in teaching and learning. At the University of Zululand this normally occurs within a blended learning environment, where traditional face-to-face teaching and learning is combined with e-learning, experiential learning, research and community engagement. E-learning resources can include office ICT, portable presentation tools for lectures, intranet, internet and wireless network services, Moodle Learning Management System (LMS), computer labs, the library's e-resources, research databases and institutional repository etc.

The purpose of this study is to empirically validate the Unified Theory of Acceptance and Use of Technology (UTAUT) model's ability to predict user acceptance of e-learning by lecturers and students within the context of the University of Zululand's blended learning environment.

Please take a few minutes to complete this survey, it will be greatly appreciated! All your information will be treated confidentially and you can view the results of this study later @ http://elearn.uzulu.ac.za/survey.

If you have any queries, don't hesitate to contact me.
Kind regards
Neil Evans

1. Biographical information

1. Please choose your Gender*

○ Male
○ Female

2. Please select your race

○ Asian
○ Black
○ Coloured
○ Indian
○ White

3. What is your age?*

[ ]

4. What is your nationality?

○ South African
○ Other (please specify)

[ ]

5. Please select your position at the University of Zululand:

○ Junior Lecturer
○ Lecturer
○ Senior Lecturer
○ Associate Professor
○ Professor
○ Other (please specify)

[ ]

6. Please indicate which faculty you are in at the University of Zululand:

○ Faculty of Arts
○ Faculty of Commerce, Administration and Law
○ Faculty of Education
○ Faculty of Science and Agriculture
○ Other (please specify)

[ ]

2. Measuring UTAUT constructs and moderators

7. Please indicate your usage of e-learning resources by completing the sentences below:*

	never use	almost never use	sometimes use	often use	always use
I _______ e-learning resources for communication and administration in my office.	○	○	○	○	○
I _______ e-learning resources during my lectures.	○	○	○	○	○
I _______ e-learning resources for research in my office	○	○	○	○	○

8. How would you describe your usage of e-learning resources at the University of Zululand?*

○ Voluntary
○ Compulsory
○ Both

9. How experienced are you at using e-learning resources*

	Not at all experienced	Slightly experienced	Somewhat experienced	Moderately experienced	Extremely experienced
Please choose:	○	○	○	○	○

10. Please indicate your response to the following statements using the 5 point likert scale: *

	strongly disagree	disagree	neutral	agree	strongly agree
1. Using e-learning resources enables me to complete academic tasks more quickly.	○	○	○	○	○
2. Using e-learning resources increases my academic productivity.	○	○	○	○	○
3. Using e-learning resources makes my work easier.	○	○	○	○	○
4. Using e-learning resources is useful.	○	○	○	○	○
5. Using e-learning resources increases the quality of my work.	○	○	○	○	○

11. Please indicate your response to the following statements using the 5 point likert scale:*

	strongly disagree	disagree	neutral	agree	strongly agree
1. Using e-learning resources is easy for me.	○	○	○	○	○
2. I find the use of e-learning resources understandable.	○	○	○	○	○
3. It is easy for me to become skilful at using e-learning resources.	○	○	○	○	○
4. I would find it easy to do what I want to do when using e-learning resources.	○	○	○	○	○

12. Please indicate your response to the following statements using the 5 point likert scale:*

	strongly disagree	disagree	neutral	agree	strongly agree
1. People who influence my behaviour think that I should use e-learning resources.	○	○	○	○	○
2. People who are important to me think that I should use e-learning resources.	○	○	○	○	○
3. People whose opinions I value promote the use of e-learning resources.	○	○	○	○	○
4. I use e-learning resources because of the influence of my colleagues.	○	○	○	○	○

13. Please indicate your response to the following statements using the 5 point likert scale:*

	strongly disagree	disagree	neutral	agree	strongly agree
1. I have the necessary resources to use e-learning.	○	○	○	○	○
2. I have the necessary knowledge to use e-learning resources.	○	○	○	○	○
3. I have the necessary support to use e-learning resources.	○	○	○	○	○
4. Using e-learning fits my teaching pedagogy.	○	○	○	○	○
5. I can get help from others when I have difficulties using e-learning resources.	○	○	○	○	○

14. Please indicate your response to the following statements using the 5 point likert scale:*

	strongly disagree	disagree	neutral	agree	strongly agree
1. Whenever possible, I intend to use e-learning resources.	○	○	○	○	○
2. I perceive using e-learning resources as natural for me.	○	○	○	○	○
3. I plan to continue to use e-learning resources.	○	○	○	○	○
4. To the extent possible, I would use e-learning resources to teach.	○	○	○	○	○
5. To the extent possible, I would frequently use e-learning resources.	○	○	○	○	○

15. If you have any additional comments please submit them below (optional):

16. Name (Optional):

17. Email (Optional):

Please contact evansn@unizulu.ac.za if you have any questions regarding this survey

APPENDIX C. CODING OF INSTRUMENT

Indicator	Description	Coding
Gender	Gender	0/1 Dummy variable
N/A	Race	1–5 Dummy variable
Age	Age	Continuous dummy variable
N/A	Nationality	1/2 Dummy variable
N/A	Position at University of Zululand	1–6 Dummy variable
N/A	Level of study at University of Zululand	1–6 Dummy variable
N/A	Faculty at University of Zululand	1–5 Dummy variable
Use1	Usage behaviour	1–5 Likert scale
Use2	Usage behaviour	1–5 Likert scale
Use3	Usage behaviour	1–5 Likert scale
VolCom	Voluntary or compulsory usage	1–3 Dummy variable
Exper	Experience using e-learning	1–5 Dummy variable
PE1.1	Performance expectancy	1–5 Likert scale
PE1.2	Performance expectancy	1–5 Likert scale
PE1.3	Performance expectancy	1–5 Likert scale
PE1.4	Performance expectancy	1–5 Likert scale
PE1.5	Performance expectancy	1–5 Likert scale
EE1.1	Effort expectancy	1–5 Likert scale
EE1.2	Effort expectancy	1–5 Likert scale
EE1.3	Effort expectancy	1–5 Likert scale
EE1.4	Effort expectancy	1–5 Likert scale
SI1.1	Social influence	1–5 Likert scale
SI1.2	Social influence	1–5 Likert scale
SI1.3	Social influence	1–5 Likert scale
SI1.4	Social influence	1–5 Likert scale
FC1.1	Facilitating conditions	1–5 Likert scale
FC1.2	Facilitating conditions	1–5 Likert scale
FC1.3	Facilitating conditions	1–5 Likert scale
FC1.4	Facilitating conditions	1–5 Likert scale
FC1.5	Facilitating conditions	1–5 Likert scale
BI1.1	Behavioural intention	1–5 Likert scale
BI1.2	Behavioural intention	1–5 Likert scale
BI1.3	Behavioural intention	1–5 Likert scale
BI1.4	Behavioural intention	1–5 Likert scale
BI1.5	Behavioural intention	1–5 Likert scale
N/A	Missing data	-999

APPENDIX D. MODULE CODES, NAMES, LEVELS AND DESCRIPTIONS

Module Code	Module Name	Academic Level	Description
AINF132	Computer Literacy for Information Studies 2	1	Introduction to Microsoft Excel and Access
AINF242	Multimedia II	2	This module aims to equip students with knowledge and skills in video and sound editing and webpage design of Content Management System (CMS)
ACOM342	Media Studies 2	3	Media Studies
CBIS102	Business Information Systems 1B	1	Essential functions and knowledge required to prepare financial, information in spreadsheet format. A wide variety of topics that make up the essential skills of an administrative assistant will be taught.
CMIS302	Information Systems Management 3B	3	First part of project - Design and build of an information system. To combine all previous gained knowledge, during the previous courses, to design, develop and implement a working model of an Information System. Second part of project - Implementation and management of an information system. To combine all previous gained knowledge, during the previous courses, to design, develop and implement a working model of an Information System.

Module Code	Module Name	Academic Level	Description
ESCL01B	Academic Computer Literacy	1	Academic computer literacy.
EACA04B	Computer Assisted Language Learning	4	Computer assisted language learning.
SCPS122	Computer Literacy II	1	This course is designed to introduce a student to spreadsheet skills, such as excel, and presentation creation and usage, as in PowerPoint.
SCPS212	Introduction to Software Engineering	2	The aim of this course is to provide an introduction to the basic principles of software engineering.
SHYD312	Hydrological Fieldwork and Hydrological Research Project	3	The purpose of this module is to give learners exposure to field techniques and practices in all aspects of hydrology followed by providing an introduction to hydrological research through an individual project covering some aspect of hydrology.