Investigating the Impact of Digital Technologies on the Performance of Learning in Higher Education

A thesis submitted in fulfilment of the requirements for the degree of

Doctor of Philosophy

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Declaration

I certify that except where due acknowledgement has been made, the work is that of the author alone; the work has not been submitted previously, in whole or in part, to qualify for any other academic award; the content of the project is the result of work which has been carried out since the official commencement date of the approved research program; any editorial work, paid or unpaid, carried out by a third party is acknowledged; and, ethics procedures and guidelines have been followed.

I acknowledge the support I have received for my research through the provision of an Australian Government Research Training Program Scholarship.

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List of Publications

International Conferences

Bere A and Mckay E (2017). Investigating the Impact of ICT Tutorial Strategies to Promote Improved Database Knowledge Acquisition. *Proceedings of the 28th Australasian Conference on Information Systems,* 4-6 December 2017. Hobart, Australia.

Bere A and Mckay E (2018). An Investigation of the Impact of ICT Tutorials in Transforming South African Higher Education: Application of the Rasch Model. *Proceedings of the 7th International Conference on Probabilistic Models for Measurement,* 17-19 January 2018. Perth, Australia.

Bere A, Deng H and Tay R (2018). Investigating the Impact of eLearning Using LMS on the Performance of Teaching and Learning in Higher Education. *Proceedings of the IEEE Conference on e-Learning, e-Management and e-Services*, 21 – 22 November 2018. Langkawi, Malaysia.

Bere A, Deng H and Tay R (2018). Assessing the Impact of Using Instant Messaging in eLearning on the Performance of Teaching and Learning in Higher Education. *Proceedings of the 29th Australasian Conference on Information Systems,* 3-5 December 2018. Sydney, Australia.

Declaration of Co-Authorship and Contribution

Bere A and Mckay E (2017). Investigating the Impact of ICT Tutorial Strategies to Promote Improved Database Knowledge Acquisition. *Proceedings of the 28th Australasian Conference on Information Systems,* 4-6 December 2017. Hobart, Australia.

Nature of the Candidate's Contribution Including the Percentage of the Total

The candidate has involved in designing the research through conducting a review of the related literature, designing the research instrument, collecting the data and analysing the data and writing up the paper for publication. The percentage of the total contribution is at 70%

Nature of the Co-Authors' Contribution Including the Percentage of the Total

The co-author is my supervisor. Her contribution is on guiding the implementation of the research through discussion and rewriting the draft in preparing the paper for publication. Their percentage contribution is at 30%.

Candidate's Declaration

I declare that the publication above meets the requirements to be included in the thesis as outlined in the Research Higher Degree Thesis Policy and Procedure.

	15-10-2019
Candidate Signature	Date

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Bere A and Mckay E (2018). An Investigation of the Impact of ICT Tutorials in Transforming South African Higher Education: Application of the Rasch Model. *Proceedings of the 7th International Conference on Probabilistic Models for Measurement*, 17-19 January 2018. Perth, Australia.

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Nature of the Candidate's Contribution Including the Percentage of the Total

The candidate has involved in designing the research through conducting a review of the related literature, designing the research instrument, collecting the data and analysing the data and writing up the paper for publication. The percentage of the total contribution is at 60%

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The two co-authors are my supervisors. Their contribution is on guiding the implementation of the research through discussion and rewriting the draft in preparing the paper for publication. Their percentage contribution is at 40%.

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Nature of the Candidate's Contribution Including the Percentage of the Total

The candidate has involved in designing the research through conducting a review of the related literature, designing the research instrument, collecting the data and analysing the data and writing up the paper for publication. The percentage of the total contribution is at 60%

Nature of the Co-Authors' Contribution Including the Percentage of the Total

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List of Abbreviations

ANOVA	Analysis of variance
BI	Behavioural intentions
CPUT	Cape Peninsula University of Technology
CUT	Central University of Technology
CSA	Cognitive skills analysis
F2F	Face-to-face
GDP	Gross domestic products
HTML	HyperText Markup language
IRT	Rasch item response
ICT	Information communications technologies
IM	Instant messaging
IT	Information technology
LMS	Learner management system
Obs	Observation
PEOU	Perceived ease of use
PU	Perceived usefulness
SEM	Structural equation modelling
SN	Social norm
SQL	Structured query language
TELI	Technology-enhanced learning investigation
TV	Television
Tx	Experiment treatment

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Abstract

The central theme of blended learning is to draw from the best practices of digital learning and face-to-face (F2F) learning to create a cohesive learning experience for improving the performance of learning. Blended learning is becoming increasingly popular across the world because of the benefits it can bring including easy and quick access to learning resources, timely feedback to students, better collaboration, and improved flexible and personalised learning. As a result, many higher education institutions across the world have introduced blended learning.

Following the global trend, South Africa has been actively pursuing the development of blended learning in higher education. This leads to the passing of the e-Education policy with specific objectives for improving the development of digital learning in higher education. Despite these efforts, the adoption of digital technologies in higher education in South Africa is unsatisfactory. The performance of individual students in teaching and learning in higher education is deteriorating. This shows the need for better understanding the impact of specific digital technologies in blended learning on the performance of learning in South African higher education.

The objective of this research is to investigate the adoption of specific digital technologies in South African higher education for better understanding the effectiveness of these technologies on the performance of learning. Specifically, this research aims to (a) investigate the impact of learning management system (LMS) on the performance of learning, (b) explore the impact of using instant messaging (IM)

on the performance of learning, and (c) examine the relative effectiveness of LMS and IM on the performance of learning in higher education in South Africa.

A quantitative research methodology is adopted in this study. It employs a pre-test and post-test method for assessing the performance of learning. The study uses a ‘treatment’ group of LMS + F2F and IM + F2F and a comparison group of F2F design for investigating the relationship between the use of specific digital technologies and the performance of learning in higher education. The data is collected in higher education in South Africa using paper-based surveys. Various statistical analysis techniques including descriptive statistics, *t*-test, and regression analysis have been used for analysing the data in the study.

The study shows that the adoption of LMS and IM has a positive impact on the performance of learning in higher education. The comparative analysis study shows that (a) digital learning using LMS and F2F teaching is more effective than traditional F2F teaching, (b) digital learning using IM and F2F is more effective than traditional F2F teaching, and (c) digital learning using LMS is slightly more effective than blended digital learning using IM on the performance of learning in higher education. Such findings can help to better understand the adoption of specific digital technologies in higher education in South Africa.

This study contributes to the digital learning research from both theoretical and practical perspectives. Theoretically, this study (a) explores the impact of specific digital technologies including LMS and IM on the performance of learning, (b) investigates the effect of student characteristics on the performance of learning using specific digital technologies, and (c) conducts a comparative analysis of specific digital technologies in blended learning on the performance of learning in higher education. This study is the first of its kind that conducts a comparative analysis of specific digital technologies on the performance of learning in higher education.

Practically, this study provides empirical evidence on the effectiveness of LMS and IM for improving learning. Based on the results of this study, existing policies to encourage the adoption of digital technologies should be supported and strengthened. This study can thus (a) help government departments develop specific policies and strategies for adopting specific digital technologies in order to improve the performance of learning, (b) provide South African higher education institutions with guidelines for facilitating the adoption of digital technologies, and (c) challenges LMS and IM instructional developers and software developers for the continuous development of effective digital technologies for teaching and learning.

Chapter 1

Introduction

1.1 Research Background

Advancements in digital technologies have been transforming education and training from the traditional model to the electronic mode in higher education across the world (Dias et al., 2014, Sek et al., 2016). This is due to the benefits that digital technologies can bring to teaching and learning, including the provision of opportunities to support easy and quick access to learning resources, the availability of timely feedback to students, the support of anywhere and anytime learning, and the enhancement of students' participation in teaching and learning through improved interaction (Sridharan et al., 2011, Sridharan and Deng, 2014, Carter et al., 2017, Mokiwa, 2017). As a result, digital learning is becoming increasingly popular across the world (Niemi and Multisilta, 2016, Pombo et al., 2016).

There are many countries that have invested a large amount of money on digital learning through the integration of digital technologies into their education systems (Karunasena et al., 2013a, Bai et al., 2016). The Turkish government, for instance, has spent 11.7% of the national education budget on the development of various digital learning programs in higher education (Bai et al., 2016). The countries in the Gulf Cooperation Council, including Saudi Arabia, United Arab Emirates, and Qatar, have channelled an unprecedented amount of financial resources into developing world-class digital learning systems in their higher education. In 2013, the Saudi Arabian government committed US$54 billion in the development of digital learning in higher education (UAE Government News, 2013). In the same year, the United Arab Emirates spent almost 20% of its entire budget in digital learning development in higher education. Qatar spent over US$6 billion on education, more than double its education spending between 2007 and 2012 (UAE Government News, 2013). Such investments have demonstrated the commitment of individual countries across the world at the development of digital learning in their respective higher education sectors.

In line with the global trend, the South African government has invested tremendous efforts in the development of digital learning in higher education through the implementation of specific strategies and policies (Bere et al., 2018a; 2018b). Such strategies and policies were formulated as early as in 1995 in South Africa (Vandeyar, 2015). It was followed by the adoption of the National Information communications technologies Strategy in 2001. This leads to the passing of the e-Education policy with the specific objective for improving the development of digital learning in higher education including ensuring the digital competence of all course facilitators and students by 2013 and enhancing the learning outcome of individual students through the utilisation of digital learning (Department of Education, 2004, Vandeyar, 2015, Bere et al., 2018a).

The adoption of the e-Education policy in higher education in South Africa has fundamentally transformed teaching and learning in the sector. This results in the high proliferation of digital learning technologies and the implementation of various initiatives for the acquisition of specific skills in utilising ICT in higher education in South Africa. As a result, each public university in the country has adopted specific digital learning programs for improving their teaching and learning under various circumstances (Bagarukayo and Kalema, 2015). University staffs have been trained through attending various workshops and training courses for better integrating digital learning into teaching and learning. University curriculums have been revised for improving the adoption of digital learning in higher education (Mostert and Quinn, 2009).

Despite the widespread adoption of digital learning and the optimism about its potential for improving teaching and learning in higher education, the effectiveness of adopting digital technologies through the implementation of the e-Education policy is not impressive (Bagarukayo and Kalema, 2015, Ng'ambi et al., 2016). High rates of dropouts and failures are still common in higher education in South Africa (Council on Higher Education, 2013a, Department of Higher Education and Training, 2013). There are some studies that recognise the reasons for such poor performance, including the lack of skills in many academics in the use of digital technologies and the presence of resistance to the adoption of digital learning technologies in higher education (Awidi and Cooper, 2015, Bagarukayo and Kalema, 2015). Furthermore, there is a lack of comprehensive studies on the effectiveness of adopting digital learning technologies in higher education in South Africa (Ng'ambi et al., 2016).

The availability of emerging technologies, including mobile technologies and mobile broadband access, has further complicated the process of adopting digital technologies in higher education in South Africa. There are specific alternatives in digital learning, including learning management systems (LMS) and instant messaging (IM), that make the development of digital learning more challenging and complicated (Kim et al., 2014, Yoon et al., 2015, Bere et al., 2018a). Specific questions have been raised about the use of these technologies in digital learning in the context of higher education in South Africa, including which technologies are more effective for improving the performance of learning in higher education. To adequately address these concerns, this study aims to investigate the adoption of specific digital learning technologies in higher education in South Africa for better understanding the effectiveness of these technologies on the performance of learning.

1.2 Motivation for the Research

The motivation to undertake this research is due to three reasons. Firstly, there is a lack of studies that investigate the effectiveness of digital technologies on the performance of learning in higher education (Islam, 2016). Existing studies try to address this issue primarily from the perspective of user perceptions through behavioural intentions to accept and use digital learning technologies in higher education (Sridharan et al., 2010, Alsabawy et al., 2016, Sek et al., 2016, Yakubu and Dasuki, 2018b). These studies explore various user perceptions that influence student behavioural intentions with respect to specific theoretical backgrounds under various circumstances. The effectiveness of digital technologies on the performance of learning has been ignored.

Secondly, there is a lack of comparative studies in investigating the impact of specific digital technologies, including LMS and IM, on the performance of learning in higher education. Existing studies attempt to explore the performance of learning by investigating the effectiveness of a single digital learning technology under specific situations (Parkes et al., 2013, Hwang et al., 2015). Such studies do not provide sufficient understanding of the effectiveness of alternative digital learning technologies in teaching and learning in higher education.

Thirdly, there is a lack of studies focusing on the effectiveness of specific digital technologies including LMS and IM in higher education in South Africa (Ng'ambi et al., 2016). Existing studies investigate the effectiveness of digital learning in general rather than focusing on specific technologies (Huang et al., 2011, Mohammadi, 2015). Since digital learning is evolving, studies that attempt to address the opportunities associated with the use of specific technologies should be encouraged (Ng'ambi et al., 2016).

1.3 Research Objectives and Research Questions

The objective of this research is to investigate the adoption of specific digital technologies in higher education in South Africa for better understanding the effectiveness of these technologies on the performance of learning. Specifically, the research aims to (a) investigate the impact of LMS on the performance of learning, (b) explore the impact of IM on the performance of learning, and (c) examine the relative effectiveness of LMS and IM on the performance of learning in higher education in South Africa.

To achieve these research objectives, the main research question for the study is formulated as follows:

How effective are specific digital technologies including LMS and IM on the performance of learning in higher education in South Africa?

To answer this research question, several subsidiary questions are developed as follows:

(a) How effective is LMS on the performance of learning in higher education in South Africa?

(b) How effective is IM on the performance of learning in higher education in South Africa? and

(c) *What is the relative effectiveness of LMS and IM on the performance of learning in higher education in South Africa?*

1.4 Research Methodologies

The objective of this research is to investigate the impact of digital technologies including LMS and IM on the performance of learning in higher education in South Africa. To achieve the objective of the study, a quantitative research methodology is adopted (Williamson and Johanson, 2013, Leedy and Ormrod, 2015, Chen et al., 2019). A quantitative research methodology is usually used for examining a research problem by deductively forming specific hypotheses based on relevant theories in a given situation. Such hypotheses are then tested and validated for answering the research question (Creswell and Creswell, 2017, Leedy and Ormrod, 2019). Specifically, a quantitative research methodology helps to determine whether a specific hypothesis should be rejected or not based on the numeric data collected (Deng et al., 2018; Cui et al., 2019).

A quantitative research methodology is suitable for meeting the objective of this research due to three reasons. First, each step for collecting and analysing data in the adoption of a quantitative methodology in a study is standardised. Such standardisation reduces bias in a study (Leavy, 2017). Second, the findings obtained from the use of a quantitative research methodology can be generalised to a large population (AlKalbani et al., 2016, Creswell and Creswell, 2017). Third, the adoption of a quantitative research methodology allows the relationship between various variables to be examined in a quantitative manner. This facilitates determining the cause and effect relationship between these variables in the study. Such relationships can then be used to make predictions on the impact of specific digital technologies including LMS and IM on the performance of learning in higher education.

A quantitative research methodology for this study employs a pre-test and post-test 'treatment' and comparison group true experimental design. True experimental design is suitable for investigating the cause and effect relationship between the use of specific digital technologies and the performance of learning in higher education

(Williamson and Johanson, 2013). This is because a pre-test and post-test ‘treatment’ and comparison group true-experimental design can help determine whether an improvement in the performance of learning has taken place or not due to the adoption of specific digital technologies including LMS and IM. Such an experimental design can control confounding variables. As a result, there is a reasonable basis for drawing a conclusion about the cause and effect relationship in this study (Leedy and Ormrod, 2019).

As shown in Figure 1.1, this study follows eight stages to fulfil the objective of the study using a quantitative research methodology. The study commences with the formulation of the research objective and the research question in the first stage. This is followed by a review of the related literature in stage two, leading to a better understanding of the relevant study in exploring the performance of learning using specific digital technologies including LMS and IM. Such understanding leads to the development of the research hypotheses for the study in stage three.

During the fourth stage, the research methodology for the research is presented. In this stage, a quantitative methodology is selected for investigating the impact of specific digital technologies on the performance of learning in higher education. This leads to the implementation of the pre-test and post-test ‘treatment’ and comparison group true experimental design in the research study.

In the fifth stage, the research survey instruments including pre-test and post-test are developed and validated for facilitating the collection of data from undergraduate students in higher education in South Africa in the database management course. This is followed by the collection of data in stage six. The data for the study is collected from undergraduate students in South African higher education in the database management course using the developed research survey instrument.

The seventh stage presents four data analysis techniques adopted for addressing the research question in this study. First, descriptive statistics for examining whether there is an improvement in the performance of learning or not in higher education through (a) the adoption of LMS, (b) the adoption of IM, and (c) the impact of specific attributes of participants including gender, language, race, and age. This is achieved using two measures including the measure of central tendency and the measure of dispersion. Such descriptive statistics provide the initial findings with regards to the impact of specific digital technologies including LMS and IM on the performance of learning in higher education. Second, a *t*-test is applied for examining individual hypotheses for exploring whether the adoption of specific digital technologies including LMS and IM influences the performance of learning in higher education. The *t*-test is adopted because it provides a more reliable indication of the impact of specific digital technologies including LMS and IM on the performance of learning. Specifically, the paired-sample *t*-test is adopted. It examines the pre-test and post-test for determining the impact of specific digital technologies. Third, regression analysis is conducted for examining the impact of specific attributes of individual participants including gender, language, race, and age on the performance of learning using specific digital technologies. Fourth, the independent-sample *t*-test is carried out for conducting the comparative analysis in the study. Finally, the results of the data analysis are interpreted for drawing specific conclusions in order to adequately answer the research question in stage eight.

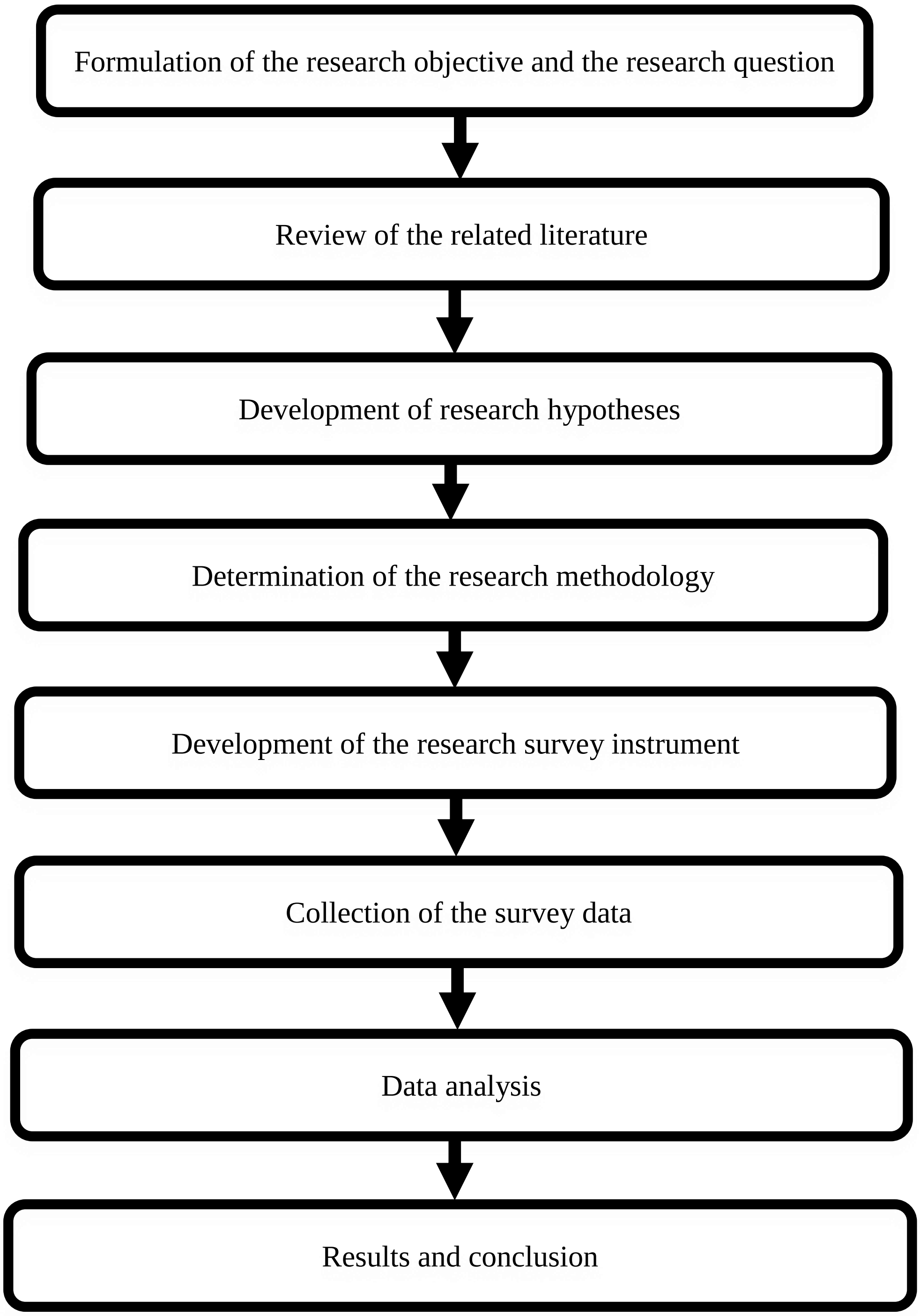

Figure 1.1 An Overview of the Research Process

1.5 Structure of the Thesis

There are nine chapters in this thesis shown as in Figure 1.2. **Chapter 1** presents an introduction to the study. This introduction covers various aspects including the background of the study, the motivation of the research, the research objective, the research question, and the research methodology. This provides the basis for the presentation of the entire thesis.

Chapter 2 presents a comprehensive review of the literature. Such literature is related to the development of various aspects including digital technologies in education, existing literature on digital technologies in higher education, existing literature on the performance of learning using digital technologies, the development of digital learning in South African higher education, and the adoption of specific digital technologies including LMS and IM in higher education. This leads to the identification of the limitation of existing research. As a result, the review of the related literature justifies the need for this research.

Chapter 3 provides the theoretical framework of the study. The hypotheses for investigating the impact of specific digital technologies including LMS and IM on the performance of learning in higher education in South Africa are formulated in this chapter. The formulated hypotheses pave the way for the development of the survey instrument in examining the impact of digital technologies on the performance of learning in higher education.

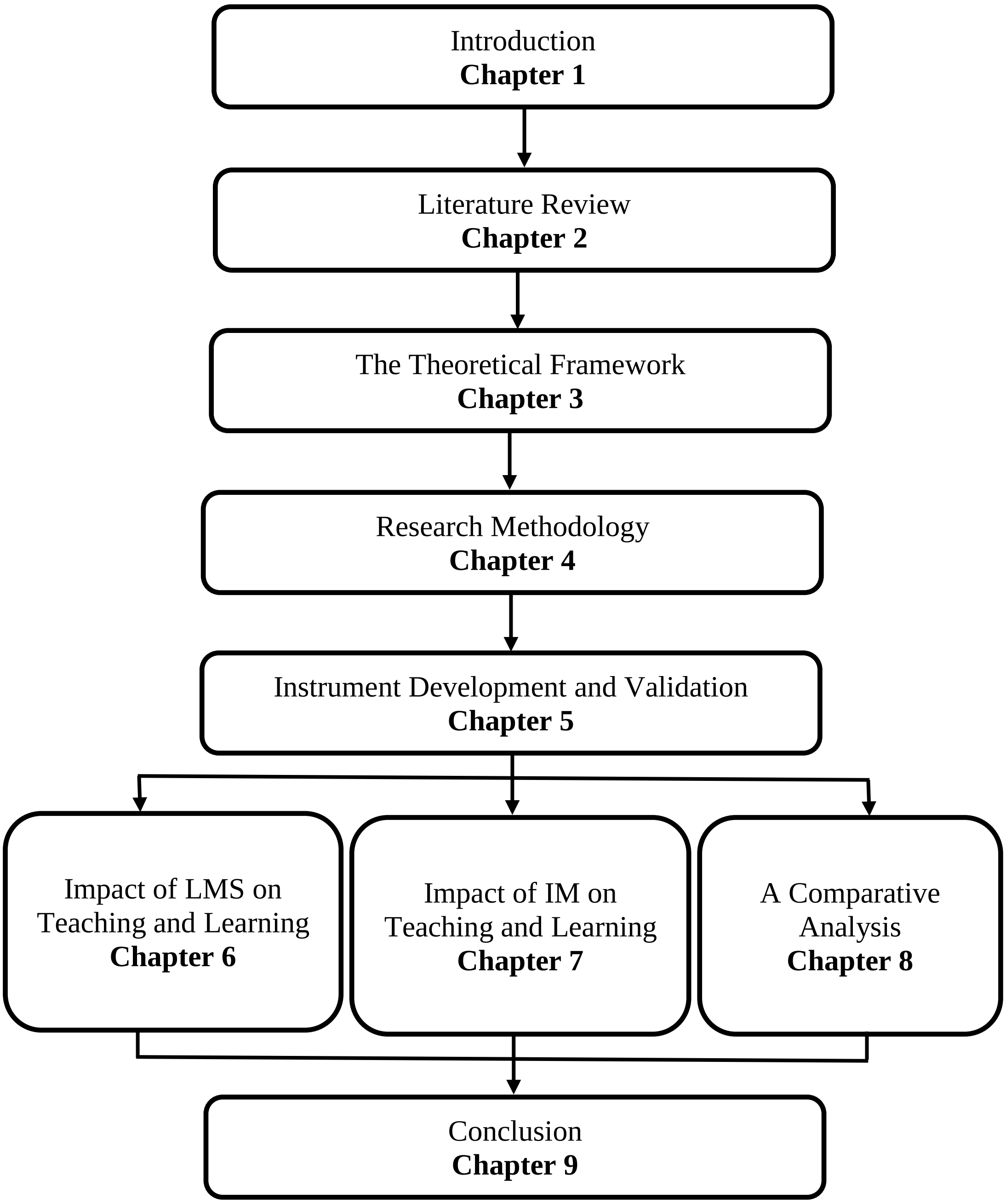

Figure 1.2 An Overview of the Thesis

Chapter 4 provides a description of the research methodology that this study adopts. An outline of different research methodologies under various research paradigms is presented. How suitable a research methodology for meeting the objective of this research project is discussed. This leads to the presentation of the various quantitative data analysis techniques adopted in this research. The implementation of the data analysis process is explained. The demographics of the participant in this research is addressed in this chapter.

Chapter 5 describes the research instruments that the study develops. How these research instruments are designed to meet the objective of this study using the selected experimental design is explained. In particular, the development of the pre-test and post-test survey instruments, the process of collecting data, and the procedures for enhancing the reliability and the validity of the research instruments are explained in this chapter.

Chapter 6 presents the results from the surveys for investigating the impact of LMS on the performance of learning in higher education in South Africa. The chapter reveals how the data is analysed using descriptive statistics, regression analysis, and paired-sample *t*-test to better understand the impact of LMS on the performance of learning in higher education. The discussion of the research findings with regards to the impact of LMS on the performance of learning is provided.

Chapter 7 presents the results from the surveys for investigating the impact of IM on the performance of learning in higher education in South Africa. The chapter reveals how the data is analysed using descriptive statistics, regression analysis, and paired-sample *t*-test is to better understand the impact of IM on the performance of learning in higher education. The discussion of the research findings with respect to the impact of IM on the performance of learning is provided.

Chapter 8 presents the results of a comparative study. Three comparative analyses for investigating the impact of LMS and IM on the performance of learning in higher education in South Africa are conducted in this chapter. Such a comparative analysis is conducted using two data analysis statistics including the descriptive statistics and the independent-sample *t*-test statistics.

Chapter 9 provides a conclusion for this study. It revisits the research question to confirm what has been achieved in the study. The chapter presents a summary of the research findings and the contribution of the research. It discusses the limitation of the research. Furthermore, the chapter presents some suggestions for further research in the related area.

Chapter 2

Literature Review

2.1 Introduction

The rapid development of information communications technology (ICT) is transforming the delivery of teaching and learning through the adoption of digital learning in higher education (Sridharan et al., 2010, Bhuasiri et al., 2012, Sek et al., 2015, Sek et al., 2016). This is due to the numerous benefits that digital learning offers including acquired lifelong skills, improved knowledge creation abilities, enhanced collaboration skills, improved independent learning capabilities, increased geographical reach, and reduced costs in the delivery of teaching and learning (Hu and Hui, 2012, Al-Gahtani, 2016, Niemi and Multisilta, 2016). As a result, the adoption of digital learning in higher education worldwide has been becoming increasingly popular (Sridharan et al., 2009, Bhuasiri et al., 2012, Al-Gahtani, 2016, Sek et al., 2018).

South Africa is no exception to the global trend in the rapid adoption of digital learning in higher education (Bere et al., 2018a). The South African government initiated the implementation of digital learning in higher education two decades ago. The implemented digital learning facilities at higher education institutions in South Africa, however, are underutilised (Ng'ambi and Rambe, 2008, Bagarukayo and Kalema, 2015, Ramoroka, 2019). As a result, digital learning has failed to meet the expectation of transforming higher education through the provision of better teaching and learning (Ng'ambi et al., 2016, Ramoroka, 2019). This shows the need for better understanding the impact of digital learning in higher education in South Africa.

There is lack of empirical research in Africa for better understanding the impact of digital technologies in teaching and learning in higher education (Ng'ambi et al., 2016, Yakubu and Dasuki, 2018b). This is because the adoption of digital technologies for teaching and learning in higher education is at its infancy stage in Africa including South Africa (Yakubu and Dasuki, 2018a). Most African countries embrace traditional F2F teaching due to numerous factors including the paucity of financial resources, the shortage of trained higher education practitioners in the use of digital technologies for improving learning outcomes, the resistance to changes among higher education stakeholders including academics, campus managers, and instructional designers, and the existence of institutional barriers preventing broader uptake of digital technologies for teaching and learning (Ng'ambi et al., 2016, Yakubu and Dasuki, 2018b). As a result, there is lack of knowledge in higher education in Africa about the impact of digital technologies on the performance of learning (Bere et al., 2018a, Yakubu and Dasuki, 2018b). This study responds to this need for more digital learning-based research in developing countries including South Africa by investigating the impact of specific digital technologies including LMS and IM on the performance of learning in higher education in South Africa.

This chapter presents a comprehensive review of the related literature with respect to the development of digital learning in South Africa. Existing research on the use of digital technologies in higher education is critically examined. The effect of digital technologies on the performance of learning has been deliberated. This justifies the need for undertaking this research and leads to the development of specific hypotheses for investigating the impact of LMS and IM on the performance of learning in higher education in South Africa.

To achieve this objective, the rest of the Chapter is organised as follows. Section 2.2 presents an overview of digital learning and its developments. Section 2.3 provides a comprehensive review of digital learning developments in South African higher education. This is followed by a discussion of specific digital learning technology adoption in Section 2.4. Section 2.5 offers concluding remarks for this Chapter.

2.2 An Overview of Digital Learning

Digital learning is a complex phenomenon that has no single agreed definition in the literature (Nicholson, 2007, Sridharan et al., 2009, Hung and Zhang, 2012, Sek et al., 2016). It can be approached from different viewpoints including the educational paradigm, the delivery system, and the technology (Lee et al., 2009, Aparicio et al., 2016). Educational philosophers view digital learning as a self-regulated knowledge acquisition practice through various active learning processes including interaction and individual experiences using digital technologies (Lee and Lee, 2008). The delivery system-orientation view considers digital learning as the distribution of teaching and learning materials in various formats including documents, texts, audios, and videos through the application of ICT (Lee et al., 2009, Sek et al., 2016). The technology-oriented view accepts that digital learning is the application of various digital technologies including Internet, data storage and management facilities like the cloud and database systems, data access technologies such handheld devices, laptops, and personal computers for providing a wide range of solutions that improve knowledge acquisition, leading to better performance in teaching and learning (Hung and Zhang, 2012, Abdullah and Ward, 2016). The common theme across these views is that digital learning is about the use of ICT for improving resource sharing to enhance the performance of learning with the emphasis on students playing an active role (Hung and Zhang, 2012, Sek et al., 2014).

Digital learning can be classified in various ways based on how it is offered (Waththage, 2015). It, for example, can be classified as blended learning and pure learning (Sridharan et al., 2010). Digital learning can also be categorized as asynchronous learning and synchronous learning (Waththage, 2015, Perveen, 2016, Hadullo et al., 2018). Blended learning combines digital learning and F2F teaching to creating a cohesive learning experience (Tshabalala et al., 2014). It is the most popular digital learning modality in higher education. This is because blended learning utilises the benefits of both F2F teaching and digital learning for improving the performance of learning in higher education (Olivier, 2013, Tshabalala et al., 2014).

Pure learning is the delivery of teaching and learning using digital technologies only (Waththage, 2015). It is commonly used in distance-based education. The adoption of pure learning in higher education has been becoming increasingly popular. This is because the adoption of pure learning increases learning opportunities for students who cannot attend F2F offerings, improves knowledge sharing between geographically dispersed students, and assembles and disseminates teaching and learning content in a cost-effective manner (Tuckman, 2007, Iqbal et al., 2011).

Digital learning can be classified as asynchronous learning and synchronous learning (Perveen, 2016). Asynchronous learning is the delivery of teaching and learning without a simultaneous online presence of facilitators and students. It encourages self-pacing in teaching and learning. This is because students can engage with learning resources at their convenience (Waththage, 2015, Perveen, 2016). Synchronous learning is the delivery of teaching and learning in real-time. It involves a simultaneous online presence of facilitators and students. Synchronous learning encourages collaborative interaction between and among students and facilitators, leading to the development of a community of enquiry (Perveen, 2016, Hadullo et al., 2018). Table 2.1 presents a summary of the discussion above.

There are numerous benefits that digital learning can offer in higher education (Karunasena et al., 2013a, Schoonenboom, 2014, Sek et al., 2016). Digital learning, for example, provides flexibility with respect to teaching and learning content, place and time of learning, and pace (Donnelly and Benson, 2008, Dlodlo, 2009, Njenga and Fourie, 2011, Murphy and Stewart, 2017). The teaching and learning content is easy to update. Such content can be transformed into different formats easily and quickly (Donnelly and Benson, 2008, Njenga and Fourie, 2011). The content can be translated using electronic translators into different languages (Donnelly and Benson, 2008). The content can be accessed and distributed at low costs. It can be available to the intended audience electronically without undue delays (Njenga and Fourie, 2011).

Table 2:1 An Overview of Digital Learning

Digital Learning	**Description**
Blended learning	• Combination of F2F teaching and digital learning • Presence of students and instructors at the same time
Pure learning	• Digital interaction • No physical class attendance
Synchronous learning	• Real-time interaction • Synchronous interaction
Asynchronous learning	• Off-line learning • Asynchronous interaction

The use of digital technologies in teaching and learning enables better management of student learning progresses (Hamuy and Galaz, 2010, Njenga and Fourie, 2011). This is because students can access their course grades and evaluate their performance in a timely manner. They can tell the status of teaching and learning content (Hamuy and Galaz, 2010). Course facilitators can easily identify low performing students and provide them with appropriate support (Hamuy and Galaz, 2010, Njenga and Fourie, 2011). As a result, course facilitators can administer extra and frequent assessments to underperforming students. Such students can improve their understanding and build their confidence through constantly revisiting teaching and learning content (Hamuy and Galaz, 2010, Njenga and Fourie, 2011). This shows that digital learning can improve the performance of learning in higher education.

The adoption of digital learning can help create a community of practice (Boven, 2014, Bere and Rambe, 2016). Such a community can help students to interact with their peers and facilitators in a stimulating learning environment. As a result, students can develop numerous skills including communication, problem-solving, critical thinking, and teamwork (Kim et al., 2014, Amara et al., 2016).

The pervasiveness of digital learning benefits students who cannot constantly attend classes due to various reasons (Sridharan et al., 2010, Bere, 2012, Waththage, 2015). Such students can conveniently access teaching and learning materials anywhere and at anytime (Waththage, 2015) This shows that digital learning provides the flexibility required in teaching and learning in higher education.

There are other benefits of digital learning including reducing costs, providing solutions for lack of classroom space, connectedness, better teaching and learning approaches, and assisting students to acquire skills and preparing students for the knowledge economy (Dlodlo, 2009, Njenga and Fourie, 2011, Murphy and Stewart, 2017). As a result, the adoption of digital learning in higher education worldwide has been becoming increasingly popular (Bhuasiri et al., 2012, Al-Gahtani, 2016).

There are many challenges to designing and implementing digital learning in teaching and learning in higher education (Waththage, 2015, Ng'ambi et al., 2016). Such challenges include lack of adequate training of higher education practitioners in the appropriate use of digital technologies for enhancing the performance of learning, the availability of institutional barriers to a broader uptake of digital technologies in teaching and learning, the increasing need for more effective practices to encourage the persistent resistance to change from F2F teaching to digital learning of higher education practitioners, and the lack of ICT infrastructure to support digital learning (Waththage, 2015, Ng'ambi et al., 2016).

There are various digital learning hindrances including the cost of digital learning application licenses, the presence of rigid institutional policies, and the adoption of nonuniform digital technologies (Sanchez-Franco, 2010, Wang et al., 2012). Some digital learning technologies require costly licenses. Some institutions may not afford or maintain using these technologies in the long term. Various higher education institutions offer different digital learning technologies. As a result, a student has to learn how to use the new digital learning technology when this student moves from one institution to another (Sanchez-Franco, 2010, Wang et al., 2012). A summary of the benefits and challenges of digital learning is presented in Table 2.2.

Table 2:2 An Overview of the Benefits and Challenges of Digital Learning

Benefits	Challenges
• Reduce costs • Easy management of student progresses • Solutions for lack of classroom space • Flexibility • Better teaching and learning approaches • Community of practice • Preparation for the knowledge economy	• Lack of adequate staff training • Resistance to the use of digital technologies • Lack of ICT infrastructure • Institutional barriers

There are four phases in the development of digital learning as shown in Figure 2.1. The first phase involves the broadcasting of teaching and learning using radio and television (TV). The second phase is related to the use of information seeking based teaching and learning. The third phase focuses on interactive learning through contributing and sharing of teaching and learning resources using Web 2.0 digital technologies including social media. The fourth phase is the use of IM digital technologies for facilitating interactive teaching and learning.

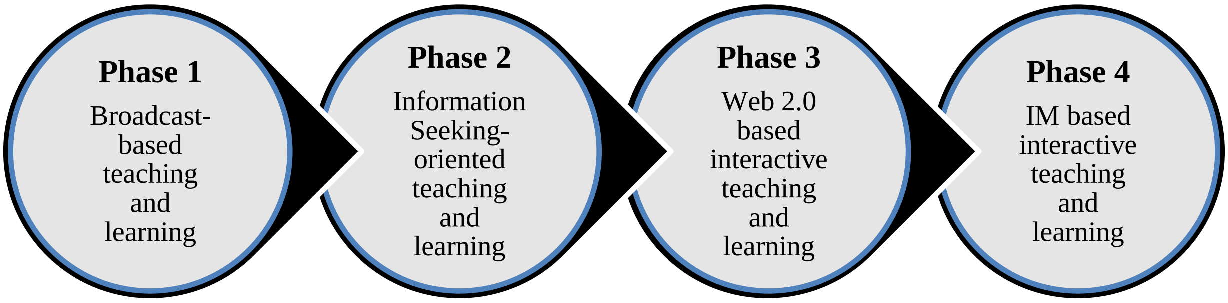

Figure 2. 1 An Overview of Digital Learning Development

Broadcasting-based teaching and learning

The earliest digital learning technique involves broadcasting using digital technologies including radio and TV (Duby, 1990, Forsslund, 1991, Kwape, 2000). It is about the use of radio and TV programmes for distributing learning resources to a dispersed audience (Duby, 1990, Cruse, 2006, The Canadian Encyclopedia, 2013). Its purpose is to enlighten, inform, and provide intellectual stimulation to its audience (The Canadian Encyclopedia, 2013). It emerged in the 1920s as a convenient teaching and learning technique. Such a technique facilitates the receiving of learning resources both in homes and in classrooms (The Canadian Encyclopedia, 2013). As a result, the adoption of radio and TV broadcasting in higher education has transformed teaching and learning worldwide (Duby, 1990, Kwape, 2000, Cruse, 2006).

Radio broadcasting has been increasingly becoming popular in formal and informal teaching and learning (Duby, 1990, Kenyaplex, 2017). This is because of the benefits it offers including improving the listening skill of students, provoking the imagination capacity of students, encouraging the engagement between instructors and students, improving the access to teaching and learning resources, and providing students with quality teaching and learning resources (Duby, 1990, Kenyaplex, 2017).

The proliferation of TV has transformed digital learning from radio broadcasting to TV broadcasting (Cruse, 2006). The adoption of TV in teaching and learning has led to numerous benefits in higher education. The combination of visuals and audio in teaching and learning, for example, reinforces student learning. It improves student comprehension. This provides mass teaching and learning opportunities in higher education. It further reduces the dependency of the delivery of teaching and learning on verbal teaching and learning. This stimulates teaching and learning enthusiasm in higher education (Cruse, 2006, Leado, 2016). Overall TV broadcasting in higher education has a positive impact on the performance of learning.

There are several challenges for delivering teaching and learning using radio and TV broadcasting. These digital technologies involve one-way communication (Cruse, 2006). The content is developed by subject experts including instructors and instructional designers without the involvement of students (Cruse, 2006). Students cannot interact with other users using these digital technologies. This shows that teaching and learning using broadcasting encourages passive learning (Cruse, 2006).

Teaching and learning resources in radio and TV broadcasting based higher education can be recorded and replayed (Duby, 1990, Cruse, 2006). Sharing such recorded teaching and learning materials among students and instructors, however, is inflexible. As a result, students and higher education staff prefer the use of Internet digital technologies over radio and TV broadcasting in teaching and learning. This is because the use of the Internet including Web 1.0 allows the storage of teaching and learning resources in one location for facilitating their ease access. This means that the use of Internet digital technologies offers flexible sharing of teaching and learning resources from a central repository.

Information seeking oriented teaching and learning

Web 1.0 is the first generation of the World Wide Web (Cormode and Krishnamurthy, 2008, Greenhow et al., 2009, Aghaei et al., 2012). It was invented in 1991 by Tim Berners-Lee (Wu and Ackland, 2014). Its core protocols are the Hypertext Transfer Protocol, the HyperText Markup Language (HTML) and the Uniform Resource identifier (Aghaei et al., 2012). Web 1.0 is made up of statistic mono-directional web pages connected by hyperlinks (Robson and Freeman, 2005, Greenhow et al., 2009, Aghaei et al., 2012). The content of Web 1.0 is defined by individuals with programming or web design technical skills. Most users are consumers of the content (Cormode and Krishnamurthy, 2008, Brown, 2012). As a result, Web 1.0 is characterised by centralised one-way communication (Cifuentes et al., 2011).

There are various characteristics of Web 1.0 including static pages, website content stored in files, presence of content and web page layout in tables, proprietary HTML tags, guestbooks, and emailing of forms (Robson and Freeman, 2005, Website Builders, 2019). Static pages contain fixed content. Each page is coded in HTML. It displays the same content each time it is loaded (Website Builders, 2019). Web 1.0

does not allow interaction between users (Aghaei et al., 2012). Users of websites are information seekers who cannot make any contributions to the content (Aghaei et al., 2012, Brown, 2012). The goal of websites is to establish an online presence through delivering information anywhere and at anytime (Aghaei et al., 2012).

Web 1.0 technologies store website content in files, unlike modern websites which stores website content in databases (Website Builders, 2019). The use of file systems in websites creates numerous challenges including data redundancy, data inconsistency, data isolation, dependence on application programs, and data security (Coronel and Morris, 2016). Web 1.0 digital technologies combine the content and webpage layout in the web page markup using HTML elements including tables (Website Builders, 2019). The best practice for web design encourages the separation of webpage markup and styling using external style sheets. Such styles determine the look and layout of the webpages (Coronel and Morris, 2016, Website Builders, 2019).

The use of proprietary tags in Web 1.0 creates significant incompatibility problems between websites and users using unsupported browsers (Website Builders, 2019). As a result, the efficiency of Web 1.0 is reduced due to the use of proprietary tags. In Web 1.0, the comments of users are added to the guestbook. The use of guestbook allows the loading of a page with a long list of user comments without slowing down the performance of a website particularly when a dial-up Internet connection is used (Robson and Freeman, 2005, Website Builders, 2019). The website hosting severs for Web 1.0 does not support server-side scripting. Server-side scripting allows a web server to submit a form in a website. When a submit button is clicked in Web 1.0, the user's email is launched to allow him/her to email the form to an email address provided on the website (Website Builders, 2019).

The adoption of Web 1.0 in higher education has transformed the teaching and learning practices in the 1990s. This is because of the benefits that Web 1.0 offers including better sharing of teaching and learning resources, increasing access to education, and better self-paced learning opportunities. As a result, the adoption of Web 1.0 in teaching and learning has been increasingly popular globally.

Web 2.0 based interactive teaching and learning

Web 2.0 emerged in 2003 as a solution for moving beyond content delivery to individual publishing in teaching and learning in higher education while trying to improving the easiness of use, customisation, collaboration, interactivity, and sharing of information (Sigala and learning, 2007). Users with no technical skills can update content. This allows users to focus on specific information and collaborative tasks in the delivery of teaching and learning (Sigala and learning, 2007). As a result, Web 2.0 technologies improve the delivery of teaching and learning in higher education.

Web 2.0 is a user-generated, read-write, social, and interactive web (AlJeraisy et al., 2015). It is a user-centric and participative web. Such a web allows gathering and managing large crowds of people with a common interest in social interaction (Aghaei et al., 2012). Web 2.0 technologies are bi-directional. Users can access information on websites and participate in content development (Sigala and learning, 2007, Aghaei et al., 2012, AlJeraisy et al., 2015). As a result, the adoption of Web 2.0 in business, health, agriculture and education has been becoming increasingly popular (Allen et al., 2010, Berthon et al., 2012, Rambe, 2012, Moorhead et al., 2013).

The use of Web 2.0 in higher education allows students to seek, contribute and share information in teaching and learning (Sigala and learning, 2007). Consequently, students are co-producers of teaching and learning content rather than passive information consumers. The characteristics of Web 2.0 support for both synchronous and asynchronous communication (Sigala and learning, 2007, Su et al., 2010). Such characteristics provide students with more opportunities for accessing, sharing, and interacting with peers and facilitators (Su et al., 2010). As a result, teaching and learning using Web 2.0 has become highly autonomous, informal, self-motivated. It forms an integral part of the higher education experience of students (Su et al., 2010, Dabbagh and Kitsantas, 2012).

There are various social media applications that are Web 2.0 enabled (Sigala and learning, 2007). The development of Web 2.0 has facilitated the integration of social media into LMS for improving the performance of formal and informal teaching and learning in higher education (Sigala and learning, 2007, Dabbagh and Kitsantas, 2012). This is because various types of social media including Twitter, Facebook, YouTube, wikis, and blogging offers numerous benefits to teaching and learning. Such benefits include advanced collaboration among students and course facilitators, improved social presence, capacity to offer student-centred personalised learning, ability to learn from user-generated content leading to collective wisdom (Sigala and learning, 2007, Dabbagh and Kitsantas, 2012). As a result, the adoption of Web 2.0 empowers students to take charge of their own learning, facilitates knowledge creation, enhances critical thinking, improves motivation to learn, and promotes active learning (Dabbagh and Kitsantas, 2012). This shows that Web 2.0 affords the development of student-focused teaching and learning contexts consisting of socially engaging tasks that encourage students to take an active role in the creation and application of knowledge rather than simply memorising it (Sigala and learning, 2007). A comparative analysis of web 1.0 and web 2.0 is presented in Table 2.3.

Table 2.3 A Comparative Analysis between Web 1.0 and Web 2.0

Criteria	**Web 1.0**	**Web 2.0**
Mode of usage	Read	Read and write
Unit of content	File	Record
State	Static	Dynamic
How content is viewed	Web browser	Web browsers, RSS and mobile devices
Creation of content	Web authors	Everyone
Data storage	File system	Relational databases
Unique protocols	HTML	XML, RSS
Content ownership	Owing	Sharing
architecture model	Client-Server	Peer-to-peer
Software	Web forms	Web application
Internet type	Dialup	Broadband
Costs	Hardware costs	Bandwidth costs
Interaction	Lectures	Conversations
Category	Information portals	Platforms

IM based interactive teaching and learning

IM is a free downloadable cross-platform online chat application that offers real-time text transmission over the Internet (Hsieh and Tseng, 2017). It runs on various devices including smartphones, tablets, iPads, and desktops (Tang and Hew, 2017). There are many IM applications including WhatsApp, Facebook massager, WeChat, Snapchat, and Viber (Hsieh and Tseng, 2017, Tang and Hew, 2017). WhatsApp is the most popular IM worldwide with approximately 1.5 billion users by February 2018 (Tang and Hew, 2017, Investopedia, 2019)

There are numerous benefits for communicating using IM including cross-platform accessibility, multi-modality, easy formation of group chats, and free charge. IM shares a variety of media including text, audio, video, graphics, documents, location, and emoticons either in groups or individually at very low costs (Hsieh and Tseng, 2017, Tang and Hew, 2017). The device’s built-in camera can be used to capture real-time events which can be shared immediately in IM (Tang and Hew, 2017). As a result, the adoption of IM has been becoming increasingly popular.

The adoption of IM in higher education has been becoming increasingly popular (So, 2016, Tang and Hew, 2017). This because of the numerous benefits IM can offer to teaching and learning. The adoption of IM promotes active learning in higher education (Rambe and Bere, 2013, So, 2016, Nkhoma et al., 2018). Students can contribute to the development of teaching and learning resources. They can share teaching and learning content and receive timely feedback from peers and facilitators

(Rambe and Bere, 2013, So, 2016, Nkhoma et al., 2018). The use of IM in teaching and learning is common particularly in resource-constrained environments like higher education in South Africa (Rambe and Bere, 2013, Murire and Cilliers, 2017). This is because interaction using IM is less costly compared to the cost of communicating using other digital technologies (Rambe and Bere, 2013, So, 2016).

The development of digital learning is complex and challenging (Tarus et al., 2015, Sek et al., 2016). Such complexity and challenges in the development of digital learning come from various perspectives including (a) the performance of learning perspective, (b) the technological perspective, and (c) the user perspective (Bagarukayo and Kalema, 2015, Tarus et al., 2015, Yakubu and Dasuki, 2018a). Better understanding such complexity and challenges has a fundamental impact on the development of digital learning across the world (Bagarukayo and Kalema, 2015, Tarus et al., 2015, Yakubu and Dasuki, 2018a). As a result, how to adequately address such complexity and challenges is becoming critical for the effective development of digital learning in individual countries (Bagarukayo and Kalema, 2015, Bere et al., 2018b). Table 2.4 presents a summary of digital learning development.

Table 2:4 A Summary of Digital Learning Development

Dimensions	Broadcasting	Web 1.0	Web 2.0	IM
Mass access	√	√	√	√
Flexible content sharing	χ	χ	√	√
Interactivity	χ	χ	√	√
Cross-platforms	χ	χ	√	√
Formal and informal learning	√	√	√	√
Emoticons	χ	χ	√	√
Anytime and anywhere learning	χ	√	√	√
Controlled learning	√	√	X	χ
Requirement of technical skills	√	√	X	χ
Bi-directional communication	χ	χ	√	√

Use of specific digital technologies in teaching and learning

Most LMS applications in higher education including popular platforms such as Blackboard and Moodle run on Web 1.0 (Sclater, 2008, VetED, 2019). Web 1.0 enabled LMS has a low impact with respect to the performance of learning (Sclater, 2008, VetED, 2019). This is because these digital technologies promote a culture of dependency rather than the autonomy of students. A Web 1.0 enabled LMS provides a structured environment in which the facilitator decide on how, when, and what students learn (Sclater, 2008, VetED, 2019). Activities in such LMS are monitored and controlled (Sclater, 2008, VetED, 2019). The Web 1.0 enabled LMS is commonly used as storage services for lecture notes and PowerPoint presentations. It is used as a medium for conveying course announcements to students (Sclater, 2008). Higher education institutions lack an understanding of how LMS can be effectively utilised (Sclater, 2008, Louw et al., 2016b). As a result, the features of most LMS are underutilised (Sclater, 2008, Louw et al., 2016b).

Discussion forums are the primary source for interaction in LMS (Green et al., 2014, AlJeraisy et al., 2015, Louw et al., 2016b). They facilitate asynchronous text discussion among users. Contributions are organised in discussion threads (Bower, 2015). This shows that discussion forums are useful for more reflective text conversations. They do not require real-time interaction (Bower, 2015). To enhance the functionality of LMS, Web 2.0 technologies are integrated into LMS particularly to the discussion forums (AlJeraisy et al., 2015, Bower, 2015).

There is a need for better understanding the impact of digital technologies on the performance of learning in higher education (Bere et al., 2018a, b). Such research can help to show whether LMS is intended to continue as the primary means for providing a digital learning experience in higher education (Sclater, 2008). Research in digital learning should help higher education managers, instructional designers, and higher education institution IT staff to decide if:

(a) *Web 2.0 particularly social media and other applications appealing to most students should be integrated into LMS.*
(b) *Digital technology tools hosted on the Internet by third-party organisations can be implemented for formal teaching and learning?*
(c) *Students can be allowed to decide on the choice of digital technologies to be adopted by higher education institutions for formal teaching and learning?*
(d) *It is worth for a higher education institution to incur expenses for licensing of LMS than adopting open source and freeware digital technologies for teaching and learning (Sclater, 2008).*

Most students enter higher education with increasing digital experience and competence in using Web 2.0 digital technologies and IM for social interaction (Rambe, 2012, Liu and Shi, 2016, Bere, 2018). Such students find LMS inferior in terms of performance and usability (Sclater, 2008, Bere, 2012). Higher education institutions are pressurised to integrate Web 2.0 emerging technologies to LMS for enhancing the performance of learning (Sclater, 2008, AlJeraisy et al., 2015, Bere, 2018). As a result, many higher education institutions worldwide who are technically literate, visionary, and influential have already initiated the implementation of Web 2.0 (Sclater, 2008). This shows that the development of LMS is still evolving.

The popularity of Web 2.0 in higher education is growing (Sclater, 2008). This is because of the numerous opportunities Web 2.0 technologies can offer in teaching and learning including helping students engage with learning, encouraging social interaction, allowing students to work at the conceptual level of understanding, enabling students to develop critical thinking skills, allowing students to collaboratively create knowledge, and enabling students to construct knowledge, enabling students to customise teaching and learning (Sclater, 2008, den Exter et al., 2012, Bere and Rambe, 2019). As a result, students can develop a sense of ownership currently not possible in traditional discussion forums (Sclater, 2008).

The adoption of IM in higher education has led to the development of effective student-instructor communication (Rambe and Bere, 2013, So, 2016, Nkhoma et al., 2018). The digital skills for using IM are transferable between the classroom setting and the workplace environment when graduates are employed (Nkhoma et al., 2018). Students develop a better sense of belonging to their IM communities (Rambe and Bere, 2013, Nkhoma et al., 2018). As a result, they can use such communities as additional spaces for social and informal interaction for teaching and learning related activities.

The adoption of IM in higher education creates opportunities for direct communication between students and their facilitators anytime and anywhere (So, 2016, Nkhoma et al., 2018). Such interactions encourage the development of personal rapport between students and facilitators (Rambe and Bere, 2013, Nkhoma et al., 2018). The use of IM in teaching and learning reduces the distance between students and their facilitators. This makes students feel more comfortable to share ideas and knowledge (Rambe and Bere, 2013, Nkhoma et al., 2018). Students and instructors can take advantage of IM's easy and inexpensive means of communication to improve teaching and learning using asynchronous and synchronous interaction (Rambe and Bere, 2013, So, 2016, Nkhoma et al., 2018).

There are many digital technologies with the potential for improving the performance of learning (AlJeraisy et al., 2015, Bere and Rambe, 2019). The availability of such digital technologies with relatively similar functionality can confuse students, academics, and higher education managers about which one they should use (AlJeraisy et al., 2015). This confusion can be solved by conducting research that investigates the impact of such specific digital technologies on the performance of learning in higher education (Bere et al., 2018a, b).

There are several similarities and differences between LMS and IM in their adoption in higher education. To better understand these similarities and differences, Table 2.5 presents a summary of these digital technologies.

Table 2:5 A Summary of LMS and IM Comparison

Dimensions	LMS	IM
Negligible bandwidth cost to users	χ	√
Highly ubiquitous	χ	√
Multiple-modality	√	√
High personalisation levels	χ	√
Easy group formation	χ	√
Communication is controlled and monitored	√	χ
Easy conversational interaction	χ	√
Easy content organisation	√	χ
Easy content sharing	√	√
High privacy level	√	√

2.3 Digital Learning Developments in Higher Education in South Africa

South Africa has the highest gross domestic products (GDP) in Southern Africa and second in the continent (The World Bank, 2011). It is projected to be approximately 412.00 Billion USD in 2020 (Brand South Africa, 2019). The economy of South Africa is shifting from mining and agriculture to a knowledge economy (The World Bank, 2011, Brand South Africa, 2019). As a result, higher education is encouraged to nature its graduates with skills that align with a modern economy including proficiency in the use of digital technologies.

The government of South Africa has recognised the potential of utilising emerging digital technologies for improving the efficiency of higher education (Ng'ambi et al., 2016). This is demonstrated by various strategies, policies and initiatives that the higher education section has adopted over the years (ICT strategy, 2001, Ng'ambi et al., 2016). The higher education, for example, has introduced the Internet and LMS in all public higher education institutions (Ng'ambi et al., 2016). The government has developed strategies and policies for addressing the numerous challenges it faced including the rising cost of higher education, declining government funding, the pressure to increase access of students in higher education, the redressing of the racial inequalities introduced by the Apartheid regime, and the pressure to improve the performance of learning (ICT strategy, 2001, Czerniewicz et al., 2006, Ng'ambi et al., 2016). As a result, the utilisation of digital technologies in higher education has been evolving.

Although the South African higher education lacks a coherent national policy framework for managing the implementation and utilisation of digital technologies in higher education, several ICT frameworks for basic education and further education and training have been developed in guiding the implementation and utilisation of digital technologies in higher education (Czerniewicz et al., 2006, Cross and Adam, 2007). The technology-enhanced learning investigation (TELI) strategy of 1997, for example, provides the first set of guidelines for the utilisation of ICT in higher education. Its purpose is to create awareness of the benefits of adopting digital technologies in teaching and learning.

There are numerous of such benefits identified in TELI including the adoption of digital technologies in teaching and learning offer an effective participation in the information society, has the potential to better the performance of learning, promote access to teaching and learning content, and create new opportunities for students and academics for transforming teaching and learning (Cross and Adam, 2007). As a result, TELI encourages the integration of digital technologies in teaching and learning. It suggests that the utilisation of digital technologies should be guided by teaching and learning principles (ICT strategy, 2001).

To meet the objectives of TELI, there are several specific objectives that the South African higher education institutions are trying to achieve including (a) improving access to desktop computers for higher education staff, (b) offering opportunities to develop digital technologies skills of the staff, and (c) growing digital technologies network infrastructure. At this stage, the role of digital technologies in higher education is to enhance the productivity of staff and to enable ICT skill development of staff (ICT strategy, 2001, Cross and Adam, 2007).

The national plan for higher education was developed in 2001. The objective of this strategy is to provide a blueprint for describing how digital technologies can potentially transform the higher education landscape in the twenty-first century (Ng'ambi et al., 2016). It encourages South African higher education to use ICT infrastructure to better teaching and learning performance (Ng'ambi et al., 2016). The national plan for higher education focuses on improving the performance of learning through better access to digital learning resources (Ng'ambi et al., 2016).

In 2004, the e-education policy was passed. The policy stipulates the need for all higher education students and academics to adopt ICT in education (Ng'ambi et al., 2016). Its objective is to improve the development of digital learning in higher education including ensuring the digital competence of all course facilitators and students by 2013 and enhancing students' outcomes through the utilisation of digital learning (Department of Education, 2004, Vandeyar, 2015). This leads to the implementation of various initiatives including (a) the development of workshops and ICT refresher courses for academics and (b) the introduction of end-user computing courses in the first year for students in higher education (Ng'ambi et al., 2016). This shows the government's commitment to the efficient utilisation of digital technologies in higher education.

The implementation of the e-education policy has facilitated a better utilisation of digital technologies in higher education across different higher education institutions. LMS users, for example, have exhibited varied basic system usage competencies in higher education. The utilisation of LMS by academics is mainly for uploading teaching and learning resources and publishing announcements to students in specific courses (Ng'ambi et al., 2016). The role of students in the utilisation of LMS includes downloading course-related content for offline study and accessing course announcements. Students and staff have demonstrated their capabilities in the use of emails (Czerniewicz and Ng’ambi, 2004). The government and higher education institutions have prioritised ICT skill development for academics to facilitate efficient teaching and learning through the use of LMS (Czerniewicz and Ng’ambi, 2004). As a result, the adoption of LMS in higher education in South Africa has been increasingly popular.

The South African government has invested intensively in digital learning (Ssekakubo et al., 2011, Bozalek et al., 2014, Ramdeyal, 2014, Ng'ambi et al., 2016, Bere et al., 2018b). Several public higher education institutions have provided their students and staff with digital technologies to pursue the benefits of digital learning (Makura, 2014, Ng'ambi et al., 2016). Despite these efforts, the adoption of digital learning in South Africa is not encouraging (Czerniewicz and Ng’ambi, 2004, Makura, 2014, Ng'ambi et al., 2016). This is demonstrated by dwindling student performance in teaching and learning. Also, numerous studies have indicated the underutilisation of digital technologies in higher education in South Africa (Czerniewicz and Ng’ambi, 2004, Makura, 2014, Louw et al., 2016a, Ng'ambi et al., 2016, Ramoroka, 2019). This shows there is a need to investigate the impact of specific digital technologies on the performance of learning in higher education in South Africa.

2.4 Adoption of LMS and IM in digital learning

The rapid development of digital learning has created an urgent need for understanding the effectiveness of specific digital technologies on the efficient delivery of teaching and learning in higher education (Sek et al., 2016, So, 2016, Tang and Hew, 2017, Yakubu and Dasuki, 2018b). This leads to the investigation of the impact of specific digital technologies on the performance of learning in higher education from different perspectives (Glass and Li, 2010, Allagui, 2014, Lwoga, 2014, Salem and Salem, 2015, Awada, 2016, Sek et al., 2016, Bere et al., 2018a, b). As a result, numerous studies have been conducted in this regard. These studies can be grouped into four categories including user perceptions, teaching and learning affordances, technology affordances, and performance of learning.

User perception perspective

User perceptions are about the beliefs of individuals with respect to the acceptance and use of new digital technologies (Agarwal and Prasad, 1998). Such beliefs are crucial in the development of attitudes of specific stakeholders including students that influence the adoption of digital technologies (Agarwal and Prasad, 1998). There are numerous antecedents of user perceptions in the adoption of digital technologies based on different technology adoption theories including the technology acceptance model (Duan et al., 2019), the theory of diffusion of innovation (Tran et al., 2018), and the unified theory of acceptance and use of technology (Agarwal and Prasad, 1998). This leads to a wide investigation of user perceptions for better understanding the adoption of digital technologies in higher education.

The importance of user perceptions for better understanding the adoption of specific digital technologies attracts much attention in digital learning research in various circumstances (Bhuasiri et al., 2012, Lwoga, 2014, Callister and Love, 2016, Sun et al., 2018). This is because user perceptions can help measure the performance of learning using digital technologies (McGill and Klobas, 2009, Richardson et al., 2017). Since the adoption of digital technologies in teaching and learning is evolving, user perceptions can help gain a better understanding of the determinants for improving the adoption of these digital technologies (Agarwal and Prasad, 1998, Bere and Rambe, 2016). As a result, the use of user perceptions has been becoming increasingly popular in digital learning studies (Park, 2009, Lwoga, 2014, Salem and Salem, 2015, Bere and Rambe, 2016, Louw et al., 2016b).

There are various studies which have investigated the various user perceptions in the adoption of specific digital technologies in teaching and learning in higher education. McGill and Klobas (2009), for example, examine the user perception that influences the adoption of LMS in higher education in Australia. The data is collected from a total of 267 participants using a survey instrument. The data is analysed using structural equation modelling (SEM). The results show that user perceptions for teaching and learning using LMS are influenced by task-technology fit and social norms (SN).

Park (2009) investigates the adoption of LMS in higher education in South Korea. The data is collected from a total of 628 participants using a survey instrument. SEM is used for analysing the data. This study shows that self-efficacy and SN are the determinants for behavioural intentions (BI) and attitude towards the use of LMS in higher education. It reveals that perceived usefulness (PU) and perceived ease of use (PEOU) have no significant effect on BI. The study shows that system accessibility has a positive impact on PEOU of LMS in its adoption in higher education.

Reio Jr and Crim (2013) explore user perception in the adoption of LMS for teaching and learning in higher education in the United States of America. The data is collected from a total of 280 participants using a survey instrument. SEM is used for testing and validating a specific conceptual framework developed in the study. The results show the presence of a statistically significant relationship between social presence and student satisfaction. The results also reveal that perceived convenience, perceived enjoyment, and curiosity are the predictors for continual LMS usage intentions. This study demonstrates the importance of user perceptions for better understanding user's beliefs in the adoption of LMS in higher education.

Bere (2014) investigates the factors that influence the adoption of IM in teaching and learning in South African higher education. The data is collected from a total of 196 participants using a survey instrument. The data is analysed using SEM. The results show that performance expectancy, effort expectancy, social influence, student-centric learning and hedonic motivation have a positive effect on BI in the adoption of IM in South African higher education.

Alsadoon (2018) investigates the factors that influence the perceived satisfaction of students in teaching and learning with respect to the adoption of IM in higher education in Saudi Arabia. The data is collected from a total of 73 participants using a survey instrument. Correlational analysis and multiple regression have been used for analysing the data. The study reveals the presence of a statistically significant relationship between social presence and student satisfaction. The study also shows that females have better satisfaction than males in the adoption of IM for teaching and learning in higher education. The study reveals that the relationship between student age and student satisfaction is statistically insignificant.

Table 2.6 presents an overview of the studies related to the user perception of the adoption of LMS and IM in higher education discussed above.

Table 2.6 An Overview of the Studies from the User Perception

Reference	**Participants**	**Data Analysis Methods**	**Main Findings**
McGill and Klobas (2009)	263	SEM	• User perceptions influence task-technology fit • User perceptions influence SN
Park (2009)	628	SEM	• Self-efficacy and SN are the determinants for BI • SN determines attitude towards the use of LMS • PU and PEOU has no significant effect on BI

			• System accessibility has a positive impact on PEOU of LMS
Reio Jr and Crim (2013)	280	SEM	• There is a significant relationship between social presence and student satisfaction. • perceived convenience predicts BI to use LMS in future • , perceived enjoyment predicts BI to use LMS in future • Curiosity predicts BI to use LMS in future
Bere (2014)	196	SEM	• Performance expectancy has a positive effect on BI • Effort expectancy has a positive effect on BI • Social influence has a positive effect on BI • Student-centric learning has a positive effect on BI

			• Hedonic motivation has a positive effect on BI on the adoption of IM
Alsadoon (2018)	73	Correlational analysis Regression analysis	• There is a significant relationship between social presence and student satisfaction. • Females are more satisfied with the use of IM than males • There is a significant relationship between age and satisfaction

Digital technology affordance perspective

Digital technology affordances are the inherent properties of digital technologies in which these digital technologies are used (Day and Lloyd, 2007, Meredith, 2017). They are related to understanding the properties of digital technologies for improving teaching and learning in higher education (Tang and Hew (2017).

There are various studies that have explored the digital technology affordance of specific digital technologies in teaching and learning in higher education (Allagui, 2014, Kim et al., 2014, Robinson et al., 2015, Tang and Hew, 2017). Green et al. (2014), for example, examine how students utilise LMS for participating in teaching and learning in higher education. The data is collected from a total of 608 LMS discussion forum posts. Content analysis is adopted for analysing the data. The results reveal that the asynchronous discussion forums improve the efficiency of teaching and learning. This is because the discussion forum has the technical capabilities to offer interactivity, allows every student to participate in teaching and learning anytime and anywhere (Sek et al., 2016).

Tang and Hew (2017) conduct a systematic literature review for better understanding how IM can be used for teaching and learning in higher education. The data is collected from a total of 39 empirical studies. The data is analysed using content analysis. The results show six properties of digital technology affordances including temporal, user-friendly, minimal cost, multi-modal, presence awareness and compatible are critical in the adoption of IM in higher education.

Klein et al. (2018) investigate the technology affordance of IM that influences the performance of learning in the adoption of IM in Brazil. The data is collected from a total of 140 participants using a survey. Descriptive statistics and content analysis are applied for analysing the data. The study shows various IM technology affordance properties including interactivity, knowledge sharing, sense of presence, collaboration, ubiquity, asynchronous, and synchronous interaction that are critical in the adoption of IM for improving teaching and learning in higher education.

Table 2.7 presents an overview of the studies from the digital technology affordances perspective discussed above.

Table 2.7 An Overview of the Studies from the Digital Technology Affordance Perspectives

Reference	Participants	Data Analysis Methods	Main Findings
Green et al. (2014),	608	Content	• Asynchronous communication • Digital connectivity • Ubiquitous learning
Tang and Hew (2017)	39	Content analysis	• Temporal • User-friendly • Minimal cost • Multi-modal • Presence awareness • Compatible
Klein et al. (2018)	140	Descriptive statistics Content analysis	• Interactivity • Knowledge sharing • Sense of presence • Collaboration • Ubiquitous • Asynchronous • Synchronous

Teaching and learning affordance perspective

Teaching and learning affordances are about the actions that have been carried out by students and facilitators in turning pedagogical inputs into outputs in teaching and learning in higher education (Goodhue and Thompson, 1995, Lu and Yang, 2014). In digital learning, teaching and learning affordances are the pieces of work that students perform through a sequence of actions using specific digital technologies for reaching the goals of teaching and learning (Lu and Yang, 2014). Teaching and learning affordances are extremely important in explaining how student outcomes can be improved through the adoption of specific digital technologies in higher education.

There are numerous studies that have been done for better understanding the impact of teaching and learning affordances on improving teaching and learning outcomes using specific digital technologies (Day and Lloyd, 2007). Rambe and Bere (2013), for example, investigate the impact of student participation using IM for better understanding the usefulness of this specific digital technology in teaching and learning. The study adopts a mixed-methods approach. The data is collected from a total of 95 participants using a survey instrument. Descriptive statistics are used for exploring the data with respect to the specific research questions. Furthermore, qualitative data have been collected from 15 participants using interviews. This data is analysed using content analysis. The study shows that the use of IM facilitates teaching and learning affordances including student participation, collaborative problem solving, deep reflection, collaborative creation of knowledge, and instant feedback.

Robinson et al. (2015) conduct a study in the United Kingdom for better understanding the impact of social presence on the performance of learning using IM in higher education. The data is collected from a total of 6,118 postings from 11 participants. Thematic analysis is used for analysing the data. The study shows that social presence in the adoption of IM is useful for improving the performance of learning in higher education. It identifies the characteristics of social presence in the adoption of IM including instant feedback, convenience, immediacy and flexibility learning which are critical for the adoption of IM.

Richardson et al. (2017) investigate the relationship between interactions using LMS and student outcomes in teaching and learning in higher education. The data is collected from related literature of 25 empirical studies published between 1992 and May 2015. A meta-analysis technique is applied for analysing the data. The study shows numerous teaching and learning affordances including social presence, collaborative learning, student perceptions, course length, and the quality of students.

Tang and Hew (2017) conduct a systematic literature review for better understanding how IM can be used for teaching and learning in higher education. The data is collected from a total of 39 empirical studies. Content analysis is used for analysing the data. The study shows various teaching and learning affordances including journaling, dialogic, transmissive, constructionist with peer feedback, helpline, and assessment.

Table 2.8 presents an overview of the studies from the teaching and learning affordance perspective discussed above.

Table 2.8 An Overview of the Studies from the Teaching and Learning Affordance Perspective

Reference	Participants	Data Analysis Methods	Main Findings
Rambe and Bere (2013)	95	Content analysis Descriptive statistics	• Student participation • Collaborative problem solving, deep • Reflection • Collaborative creation of knowledge • Timely feedback.
Robinson et al. (2015)	11	Thematic analysis	• Social presence • Collaborative learning • Student perceptions • Course length • Quality of students.
Tang and Hew (2017)	39	Content analysis	• Journaling • dialogic • Transmissive • Peer feedback • Helpline • Assessment.

Teaching and learning performance perspective

The performance of learning is commonly measured using student grades in higher education particularly in developing countries (Bere et al., 2018a). This is because student grades are a standardised measurement of the achievement in a course (Ladyshewsky, 2004, Callister and Love, 2016, Bere et al., 2018b). It is important because such grades provide an unbiased and quantifiable indication of student learning under specific situations (Sek et al., 2015). As a result, there is an increasing interest for better understanding the performance of learning based on student grades (Ladyshewsky, 2004, Callister and Love, 2016, So, 2016, Salehi, 2017, Bere et al., 2018a, b).

There are various studies which have investigated the performance of learning in higher education using grades (Anstine and Skidmore, 2005, Callister and Love, 2016, So, 2016, Salehi, 2017). Anstine and Skidmore (2005), for example, conduct a comparative study between the use of LMS and F2F teaching on the performance of learning in the United States of America. The data is collected from 78 participants using student grades from class tests. Descriptive statistics and regression analysis using least squares and ordinary least squares (OLS) are used for data analysis. The descriptive statistics results reveal that the impact between the use using LMS and F2F is similar with respect to the performance of learning. The regression analysis results show that F2F has a higher impact than the use of LMS with respect to the performance of learning.

Xu and Jaggars (2013) investigate the impact of LMS on the performance of learning in the United State of America. The data is collected from 1165 participants using a LMS administrative dataset. Ordinary least squares technique is used for data analysis. The study shows that the use of LMS has a negative impact on student grades and course persistence.

Callister and Love (2016), for example, conduct a comparative analysis between the use of LMS and F2F on the performance of learning in higher education in the United States of America. The data is collected from a total of 60 participants based on their final examination scores. Descriptive statistics and ANOVA have been used for analysing the data. The study shows no significant difference between LMS and F2F teaching with respect to the performance of learning.

So (2016) evaluate the use of IM in teaching and learning in higher education in Hong Kong. The data is collected from a total of 60 participants using pre-test and post-test surveys. Descriptive statistics and the Analysis of variance (ANOVA) are used for data analysis. The study reveals that the use of IM improves the performance of learning in higher education. The study also shows that the use of IM is more effective that F2F teaching with respect to the performance of learning.

Halabi and Larkins (2016) examine the effectiveness of LMS on the performance of learning in Australia. The data is collected from 132 participants using a LMS administrative dataset. Descriptive statistics and multiple regression have been used for data analysis. The study reveals the use of LMS has a positive impact on the performance of learning. Students with previous course knowledge benefit more than students with no prior course experience with respect to the performance of learning using LMS in higher education. International students benefit more than local students with respect to the performance of learning using LMS. Females benefit more than males with respect to the performance of learning using LMS.

Salehi (2017) investigate the impact of the adoption of IM on the performance of learning between male students and female students in higher education. The data is collected from 60 participants using pre-test and post-test surveys. Descriptive statistics and independent sample *t*-test have been used for data analysis. The study reveals that the use of IM improves the performance of learning in higher education. It also shows no significant difference between males and females with respect to the performance of learning using IM.

Cetinkaya (2017) investigate the impact of the adoption of IM on the performance of learning in higher education in Turkey. The data is collected from 60 participants using a survey instrument. Descriptive statistics and ANOVA have been used for data analysis. The study shows that LMS improves the performance of learning in higher education. Table 2.9 presents an overview of the studies from the teaching and learning performance perspective discussed above.

Table 2.9 An Overview of the Studies from the Teaching and Learning Performance Perspective

Reference	Participants	Data Analysis Methods	Main Findings
Anstine and Skidmore (2005)	78	Descriptive statistics Regression analysis	• Descriptive statistics show a similar impact between the use of LMS and F2F • F2F is more effective than LMS
Xu and Jaggars (2013)	1165	Regression analysis	• LMS has a negative impact on student grades • LMS has a negative impact on course retention.
Callister and Love (2016),	60	Descriptive statistics ANOVA	• LMS improves performance in teaching and learning • No significant difference between LMS and F2F with respect to student grades
So (2016)	60	Descriptive statistics ANOVA	• IM improves the student grades • IM is more effective that F2F
Halabi and Larkins (2016)	132	Descriptive statistics Regression analysis	• LMS improves student grades • Students with previous course experience perform better than

			students with no previous course experience • Females have a higher impact than males • LMS has a higher impact on international students than local students
Salehi (2017)	60	Descriptive statistics Independent sample *t*-test	• IM improves student grades • No significant difference between males and females with respect to student grades.

Empirical studies for investigating the performance of learning using student grades is growing. This is because researchers have realised the importance of assessing the impact of digital learning using student grades (Halabi and Larkins, 2016). Studies for better understanding the performance of learning provides inconsistent results. Xu and Jaggars (2013), for example, show that digital learning has a negative impact of teaching and learning while Halabi and Larkins (2016) indicate the adoption of digital technologies is beneficiary in teaching and learning. Callister and Love (2016) reveal that there is no significant difference between digital learning and F2F with respect to the performance of learning. This shows that an understanding of the impact of specific digital technologies for teaching and learning in higher education is blurry. As result, there is a needy to for more research of this nature to be conducted particularly from different contexts.

Adoption of LMS and IM in in South African higher education

There is an urgent need to improve the performance of learning in higher education in higher education in South Africa. This is due to the critical role that the South African higher education plays in transforming the country through the adoption of the latest digital technologies. South Africa, for example, has a 35% throughput in higher education (Council on Higher Education, 2013b, Bere and McKay, 2017a). Approximately 55% of the students particularly indigenous South Africans have never finished their degrees in higher education. Specifically, the throughput of indigenous people is only at 5% in higher education in South Africa (Council on Higher Education, 2013b, Bere and McKay, 2017a). This shows the urgency for improving the performance of learning in South African higher education through the adoption of digital technologies.

There is a common recognition in South Africa that the adoption of digital technologies can improve the performance of learning (Ng'ambi et al., 2016). As a result, several initiatives including installation of digital technologies infrastructure, adoption of specific digital technologies including LMS and IM, and development of digital technology policies and strategies have been implemented at different institutions (Ng'ambi et al., 2016). The adoption of specific digital technologies including LMS and IM in higher education for improving the performance of learning has been explored (Halabi et al., 2014, Bere and McKay, 2017a, Nkhoma et al., 2018).

Halabi et al. (2010) conduct a comparative analysis between the use of LMS and F2F on the performance of learning in higher education in South Africa. The data is collected from 84 participants using surveys. Descriptive statistics and samples *t*-test have been used for data analysis. The study shows that LMS improves performance of learning. LMS users with no prior course experience perform slightly better than F2F with respect to teaching and learning. There is no significant difference between LMS users and F2F for participants with course experience. The gender of a participant has no effect on the performance of teaching using LMS.

Halabi et al. (2014) examine the relationship between the adoption of LMS and performance in teaching and learning in higher education in South Africa. The data is collected from 1253 using a LMS administrative dataset descriptive statistics and ANOVA have been used for data analysis. The study shows that the amount of time spent using LMS influences the performance of learning.

Bere et al. (2018a) investigate the impact of using IM on the performance of learning in higher education in South Africa. The data is collected from 134 participants using pre-test and post-test surveys. Descriptive statistics, linear regression and ANOVA have been used for data analysis. The study reveals that the use of IM is beneficiary on the performance of learning. It also shows that IM is more effective than F2F teaching with regards to the performance of learning.

There is lack of comparative studies for better understanding the impact of specific digital technologies including LMS and IM on the performance of learning in higher education (Halabi et al., 2014, Bere and McKay, 2017a). Such studies can help the government and higher education institutions to encourage adoption of a specific digital technology that offers the highest teaching and learning returns. This study is the first to compare the impact of specific digital technologies including LMS and IM on the performance of learning in South African higher education. The study also explores the impact of various student characteristics including gender, language, race, and age on the performance of learning using specific digital technologies. Such an investigation can help the government and higher education managers to better understand whether the adoption of specific digital technologies improves the performance of indigenous South Africans irrespective of their unique characteristics.

Table 2.10 An Overview of the Studies from the Performance of Teaching and in South Africa

Reference	Participants	Data Analysis Methods	Main Findings
Halabi et al. (2010)	84	Descriptive statistics Samples *t*-test	• LMS influences grades of new students in a course • LMS has no influence on the grades of students with previous course experience • No significant relationship between gender and student grades.
Halabi et al. (2014)	1253	Descriptive statistics ANOVA	• High online presence leads to high grades • LMS improves student grades
Bere et al. (2018a)	134	Descriptive statistics Regression analysis ANOVA	• IM improves student grades • IM has a higher impact than F2F

2.5 Concluding Remarks

This chapter presents a comprehensive review of the literature related to digital learning development and its adoption across the world. It first provides an overview of the digital learning development process. It then presents an overview of digital learning in South Africa. It reviews digital learning adoption studies from different perspectives to justify the need for developing suitable hypotheses to investigate the impact of specific digital technologies on the performance of learning.

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Chapter 3

A Conceptual Framework

3.1 Introduction

A hypothesis is a set of clearly formulated and empirically testable propositions (Williamson and Johnson, 2017). It is used to show a presumed relationship between two variables in a manner that can be tested with empirical data (Williamson and Johnson, 2017, Leedy and Ormrod, 2019). Hypotheses are useful for guiding (a) the identification of suitable variables that can help to resolve a research problem, (b) the selection of relevant research designs, the selection of appropriate types of data to be collected, and the selection of pertinent data analysis techniques, and (c) the development of reliable research findings (Leedy and Ormrod, 2019). As a result, hypotheses are commonly developed in various studies for adequately achieving their specific purposes.

There are two major orientations in developing specific hypotheses including the null hypothesis and the alternative hypothesis (Leedy and Ormrod, 2019). A null hypothesis suggests that a statistically significant result is due entirely to chance. An alternative hypothesis is a position which indicates that a new belief is true instead of an old belief (Leedy and Ormrod, 2019). In this study, hypotheses are developed and tested for facilitating the investigation of the impact of specific digital technologies including LMS and IM on the performance of learning in higher education. This leads to the answering of the research question of the study.

The objective of this chapter is to develop a set of hypotheses for investigating the adoption of specific digital technologies in higher education in South Africa for better understanding the effectiveness of these technologies on the performance of learning. This leads to the formulation of thirteen hypotheses using related literature. Such hypotheses are tested quantitatively for better understanding the impact of specific digital technologies including LMS and IM on the performance of learning in higher education in South Africa.

The content in this chapter is organised into three sections. Section 3.2 addresses the development of the hypotheses in this study using the related literature. Section 3.3 ends the chapter with some concluding remarks.

3.2 Research Hypotheses

The performance of learning in digital learning can be measured from different views, including social presence, level of interaction, student satisfaction, and student grade (Rambe and Bere, 2013, Robinson et al., 2015, So, 2016). Short et al. (1976), for example, use social presence to measure the performance of learning in which the social presence is referred to as "the degree of salience of the other person in the interaction and the consequent salience of the interpersonal relationships" in learning. Extending this concept to digital learning, Alsadoon (2018) treat social presence in measuring the performance of learning as the degree at which a communication medium mimics the characteristics of F2F interaction. This is because social presence developed through digital learning encourages active learning which in turn improves the performance of learning (Rambe and Bere, 2013, Richardson et al., 2017).

Interactions are two-way communication between individuals, either on an individual or group basis. Jesus and Moreira (2009), for example, use interactions to measure the performance of learning. Johnson and Cooke (2016) view interactions in measuring the performance of learning in digital learning as consisting of either synchronous or asynchronous communication in various forms including talking and listening using digital technologies, emailing, texting, and posting on discussion boards. Interaction through digital learning enables collaborative learning which often gives individual students a voice. This leads to the development of various teaching and learning skills including critical thinking through listening and debating with peers, higher-level thinking and communication, independent learning strategies, and teamwork. As a result, individual students can gain a deep understanding of the content which results in better teaching and learning performance (Bere and Rambe, 2019).

User satisfaction is the individual user's feelings with regards to various use factors of information systems in line with the task performance (Delone and McLean, 2003). Extending this concept to digital learning, Vasileva-Stojanovska et al. (2015) view user satisfaction as a student's opinion about the potential of digital learning to improve his or her performance of learning. This shows that user satisfaction strongly predicts the performance of learning in higher education (Vasileva-Stojanovska et al., 2015).

Student grades are a standardised measurement of achievements in a course (Warne et al., 2014). They are commonly used in measuring the performance of learning, in particular in developing countries like South Africa. Achievements of higher grades are an indication of higher performance of learning (López-Pérez et al., 2011, Stricker et al., 2011). Previous research including Rudman (2017) and (Bere and McKay, 2017b) uses student grades to examine the impact of digital learning on the performance of learning in South African higher education. These studies use the grade in the final examination to operationalise the teaching and learning outcome (Stricker et al., 2011). This leads to the understanding that student grades are the major benchmark for measuring the performance of learning in a digital learning environment.

There is a common recognition that the performance of learning is positively associated with the adoption of specific digital technologies including LMS and IM. Jaggars and Xu (2016), for instance, reveal the various factors that enhance the impact of specific digital technologies, including LMS and IM, on the performance of learning. Performance is measured using the quality of interpersonal interaction, the frequency and effective student-instructor interaction, flexible learning options, and improved access and efficiency on teaching and learning. Such factors create a digital technology environment which encourages students to commit themselves to teaching and learning, and influences the attainment of better academic outcomes (Jaggars and

Xu, 2016). McGill and Klobas (2009) show that the positive attitude of students and instructors towards the adoption of specific digital technologies influences the performance of learning. Such attitudes can help influence active interaction with peers using digital technologies (Bere and Rambe, 2019). Previous research reveals numerous benefits of adopting digital technologies in teaching and learning including the formation of communities of practices, timely feedback, non-threatening learning environment due to peer interaction, and anywhere and anytime collaborative learning (Bere and Rambe, 2016, Bere, 2018, Sun et al., 2018). This leads to better knowledge sharing, critical thinking, and knowledge construction (Sun et al., 2018). As a result, the adoption of digital technologies can help improve the performance of learning.

The adoption of LMS improves performance of learning (Ladyshewsky, 2004, Bere, 2012, Bhuasiri et al., 2012, Bere et al., 2018b). This is because LMS offers numerous benefits to teaching and learning including personalised instruction, content standardisation, interactivity, on-demand availability, self-pacing, confidence, and increased convenience (Bhuasiri et al., 2012). As a result, LMS create opportunities for active participation which can help improve student outcomes. This leads to the understanding that the adoption of LMS in higher education particularly in developing countries including South Africa improves the performance of learning (Bere, 2012, Bhuasiri et al., 2012). Based on this background the following hypothesis is developed.

***H1**: Digital learning using LMS influences the performance of learning in South African higher education.*

In statistical terms, the above conceptual hypothesis can be written as statistical hypotheses as follow:

Ho1: Digital learning using LMS has no effect on the performance of learning in South African higher education.

Ha1: Digital learning using LMS has a positive effect on the performance of learning in South African higher education.

Since the performance of learning is measured using the test score of students, or more specifically, the difference in the test score (post-test score – pre-test score), the above hypotheses are equivalent to:

Ho1: Test score difference = 0 (for students using LMS)

Ha1: Test score difference > 0 (for students using LMS)

In this study, the conceptual hypothesis is tested using a standard one-tail *t*-test and applied to a sample of students who have used LMS in teaching and learning in higher education in South Africa.

The adoption of IM is beneficial with respect to the performance of learning (So, 2016, Bere et al., 2018a). This is due to the technological and pedagogical affordances that IM offers to students. Such technological affordances of IM include temporal, user-friendly, minimal cost, social presence, and multi-modality (Rambe and Bere, 2013, Tang and Hew, 2017). The pedagogical affordances of IM in higher education include journaling, dialogic, transmissive, constructionist with peer feedback, helpline, and assessment (Tang and Hew, 2017). As a result, the technological and pedagogical affordances of IM can help improve student outcomes in higher education. This leads to the understanding that the adoption of IM is expected to improve the performance of learning in higher education. Based on this background, the following hypothesis is developed.

> ***H2****:* *Digital learning using IM influence the performance of learning in South African higher education.*

In statistical terms, the above conceptual hypothesis can be written as statistical hypotheses as follow:

> *Ho2:* *Digital learning using IM has no effect on the performance of learning in South African higher education.*
>
> *Ha2:* *Digital learning using IM has a positive effect on the performance of learning in South African higher education.*

Since the performance of learning is measured using students' test scores, the above hypothesis is equivalent to:

> *Ho2:* *Test score difference = 0 (for students using IM)*
>
> *Ha2***:** *Test score difference > 0 (for students using IM)*

Similarly, the conceptual hypothesis (H2) is tested using a standard one-tail *t*-test and applied to a sample of students who have adopted IM in teaching and learning in South African higher education.

Traditional F2F teaching in higher education is the most commonly used instructional method in developing countries like South Africa (Bere and McKay, 2017b). Various teaching and learning strategies including small group work, instructor body language, and structured curriculum contribute to the popularity of traditional F2F teaching. This is due to numerous benefits including the capacity to empower students on how to interact, the provision of opportunities to develop productive dispositions and intellectual autonomy, and the ability to facilitate interpersonal skills development and the appreciation for engaging in democratic processes in teaching and learning in higher education (Jansen, 2012).

Contrarily, traditional F2F teaching and learning has numerous challenges including restrictions to learning constrained by space and time, the reduction of students' attention in teaching and learning, the cost of delivery, and the use of large amounts of paper which has implications on the environment (Bere and McKay, 2017b). As a result, F2F teaching and learning is losing its popularity in higher education. This is due to the numerous benefits digital technologies offer including the ability to support anywhere and anytime learning, provision of authentic collaborative learning, quick provision of feedback, cost-effective, and environment-friendly (So, 2016, Sun et al., 2018). This leads to the development of the understandings that the adoption of specific digital technologies including LMS and IM is an effective alternative to traditional F2F teaching and learning.

The use of LMS has a higher impact than F2F teaching with respect to the performance of learning in higher education (Means et al., 2013, Bernard et al., 2014, Gross et al., 2015). This is because LMS students get access to rich teaching resources which helps them deepen their understanding of the course content (Li et al., 2019). In LMS, students can use their previous learning experience to enhance their current learning through self-paced learning (Li et al., 2019). This shows that the adoption of LMS is expected to improve the performance of learning. As a result, more teachers are integrating LMS into their regular F2F teaching to enhance student knowledge acquisition (Li et al., 2019). Based on this background the following hypothesis is developed.

***H3**:* *LMS based digital learning LMS + F2F has better performance of learning than F2F teaching alone in South African higher education.*

In statistical terms, the above conceptual hypothesis can be written as statistical hypotheses. Since the performance of learning is measured using students' test scores, the above hypothesis is equivalent to:

Ho3: Test score difference LMS + F2F = test score difference F2F

Ha3: Test score difference LMS + F2F > test score difference F2F

In this study, the conceptual hypothesis (H3) is tested using a standard one-tail *t*-test and applied to two samples of students who have adopted LMS + F2F and F2F in teaching and learning in higher education in South Africa.

The use of IM has a higher impact than F2F teaching with respect to the performance of learning in higher education (So, 2016, Bere et al., 2018a, Sun et al., 2018). This is because of the several benefits that IM offers including edutainment, ease of use, very low communication costs, effective social presence (Rambe and Bere, 2013, Tang and Hew, 2017). As a result, IM offers effective collaborative learning. This, in turn, leads to the generation of new knowledge, effective knowledge sharing, improved critical thinking, increases their ability to transfer learning to new contexts and to create new meanings, increased transfer of learning to new contexts, and increased creation of new meanings (So, 2016, Baguma et al., 2019). This leads to deeper and long-lasting learning. Based on this background, the following hypothesis is developed.

> ***H4***: *IM based digital learning IM + F2F has better performance of learning than F2F teaching in South African higher education.*

In statistical terms, the above conceptual hypothesis can be written as statistical hypotheses. Since the performance of learning is measured using students' test scores, the above hypothesis is equivalent to:

> *Ho4: Test score difference IM + F2F = test score difference F2F*
>
> *Ha4: Test score difference IM + F2F > test score difference F2F*

In this study, the conceptual hypothesis (H4) is tested using a standard one-tail *t*-test and applied to two samples of students who have adopted IM + F2F and F2F in teaching and learning.

The gender of a student is a crucial demographic characteristic for investigating the performance of learning using digital technologies (Kimbrough et al., 2013). There is a longstanding belief that male students are more productive than females with respect to the performance of learning using digital technologies (Dholakia and Dholakia, 1994, Joiner et al., 1996, Huffman et al., 2013). This is because females underestimate their digital skills, and they possess higher digital technology anxiety (Shashaani, 1994). As a result, females lack confidence in the use of digital technologies in teaching and learning. This shows that the gender of a student influences the performance of learning in higher education.

Existing studies investigating the impact of gender on the performance of learning using digital technologies, however, have produced conflicting findings (Sang et al., 2010). Padilla-MeléNdez et al. (2013), for example, show no significant difference between male and female students on the performance of learning using digital technologies. Chou et al. (2011), on the other hand, reveal that males perform better in teaching and learning using digital technologies compared to females. Contrary to the findings of Padilla-MeléNdez et al. (2013) and Chou et al. (2011), Terzis and Economides (2011) show that females have higher perceptions with regards to the perceived ease of use and the perceived usefulness of digital technologies. To improve the successful adoption of digital technologies including LMS and IM in South African higher education, it is crucial to better understand the impact of student gender differences on the performance of learning using such specific digital technologies. Based on this background, the following hypotheses are developed.

H5: *The performance of learning using LMS is influenced by the gender of students in South African higher education.*

In statistical terms, the above conceptual hypothesis can be written as the following statistical hypotheses for students in the LMS + F2F group. Since the performance of learning is measured using students' test scores, the above hypothesis is equivalent to:

Ho5: Test score difference (male) = test score difference (female)

Ha5: Test score difference (male) ≠ test score difference female)

The conceptual hypothesis (H5) can be tested using a standard two-tail *t*-test and applied to two samples of students who are in the LMS + F2F group: one sample with male students and the other with female students. Alternatively, it can be tested using a standard regression model of gender on the test score difference. The regression method is used in this study.

***H6**: The performance of learning using IM is influenced by the gender of students in South African higher education*

Similarly, the above conceptual hypothesis can be written as the following statistical hypotheses for students in the IM + F2F group:

Ho6: Test score difference (male) = test score difference (female)

Ha6: Test score difference (male) ≠ test score difference female)

The above conceptual hypothesis can be tested using a standard two-tail *t*-test and applied to two samples of students who are using IM + F2F: one with male students and the other with female students. Alternatively, it can be tested using a standard regression model of gender on the test score difference. The regression method is used in this study.

The language of instruction has effects on the performance of learning in digital learning (Taylor and von Fintel, 2016, Bere and McKay, 2017b). Language disadvantages significantly contribute to poor teaching and learning outcomes particularly in developing countries like South Africa where teaching and learning are offered in a non-native language (Taylor and von Fintel, 2016). This means that there is a direct relationship between the language of instruction and the student performance of learning (Awopetu, 2016). This leads to the understanding that the language of instruction is a crucial contributor to the performance of learning in South Africa (Taylor and von Fintel, 2016). This is because the use of native language in teaching and learning increases the confidence and motivation of students. This, in turn, increases the performance of learning (Taylor and von Fintel, 2016). Based on this background, the following hypotheses are developed.

***H7**:* *The performance of learning using LMS is influenced by the language of students in South African higher education.*

Similarly, the above conceptual hypothesis can be written as the following statistical hypotheses for students in the LMS + F2F group:

Ho7: *There is no test-score difference between the different language groups in South Africa.*

Ha7: *Test score differences among the different language groups are present in South African higher education.*

The conceptual hypothesis (H7) can be tested using an ANOVA and post-hoc *t*-tests. A one-way ANOVA is needed because there are more than two different categories of languages. Alternatively, it can be tested using a standard regression model of language on the test score difference. The regression method is used in this study since it is simpler and can be applied to all the demographic characteristics whether they have two or more categories.

> ***H8**: The performance of learning using IM is influenced by the language of students in South African higher education.*

Similarly, the above conceptual hypothesis can be written as the following statistical hypotheses for students in the IM + F2F group:

> *Ho8: There is no test-score difference between the different language groups in South Africa.*
>
> *Ha8: Test score differences among the different language groups are present in South African higher education.*

The regression method is applied to the IM + F2F group sample in this study.

Racial segregation in South Africa influences the performance of learning using digital technologies in higher education (Ndimande, 2013, Biko, 2015). This is because the Apartheid colonial regime in South Africa has created western race supremacy in higher education. Specifically, it created separate higher education institutions for different races. Such institutions are characterised by significant inequalities in areas including funding, instructor qualifications, instructor-student ratios, infrastructure, teaching and learning resources, quality of teaching and learning, and levels of qualifications awarded (Ndimande, 2013). The western race students usually receive the most superior facilities and services for teaching and learning followed by the Indian race. The African race higher education institutions are the most inferior in the Apartheid regime. African students receive substandard education which simply prepares them for vocational qualifications. Their institutions are overcrowded. Furthermore, their infrastructure and learning resources are substandard (Ndimande, 2013, Biko, 2015). As a result, the motivation and self-esteem of mixed race and African students are negatively affected by the generational trauma created in Apartheid. Although the racial segregations were abolished in 1994 after the independence, previously disadvantaged races still require support to motivate them to learn (Ndimande, 2013). As a result, the performance of African students in teaching and learning is unsatisfactory (Department of Higher Education and Training, 2013). Based on this background, the following hypotheses are developed.

***H9**: The performance of learning using LMS is influenced by the race of students in South African higher education.*

Similarly, the above conceptual hypothesis can be written as the following statistical hypotheses for students in the LMS + F2F group:

Ho9: There is no test-score difference between the different racial groups in South African higher education.

Ha9: Test score differences among the different racial groups are present in South African higher education.

Since there are more than two categories in the race variable, the regression method is applied to the LMS + F2F group sample in this study.

> ***H10**: The performance of learning using IM is influenced by the race of students in South African higher education.*

Similarly, the above conceptual hypothesis can be written as the following statistical hypothesis for students in the IM + F2F group:

> *Ho10: There is no test-score difference between the different racial groups in South African higher education.*
>
> *Ha10: Test score differences among the different racial groups are present in South African higher education.*

There are more than two categories in the race variable, the regression method is therefore applied to the IM + F2F group sample in this study.

The age of students is an important determinant for assessing the impact of digital technologies on the performance of learning in higher education (Okazaki and Mendez, 2013, Liébana-Cabanillas et al., 2014). The majority of the related research reveals that younger students perform better than older students in teaching and learning using digital technologies. This is due to the amount of time younger students commonly spend using digital technologies. This leads to increased competence in using these technologies. This, in turn, leads to the development of confidence and increased motivation to learn using digital technologies (Okazaki and Mendez, 2013). This shows that the age of students has an influence on the performance of learning using digital technologies. Based on this background, the following hypotheses are developed.

H11: *The performance of learning using LMS is influenced by the age of students in South African higher education.*

Similarly, the above conceptual hypothesis can be written as the following statistical hypotheses for students in the LMS + F2F group:

Ho11: There is no test-score difference between the different age groups in South African higher education.

Ha11: Test score differences among the different age groups are present in South African higher education.

Since there are more than two categories in the age variable, the regression method is applied to the LMS + F2F group sample in this study.

H12: *The performance of learning using IM is influenced by the age of students in South African higher education.*

Similarly, the above conceptual hypothesis can be written as the following statistical hypotheses for students in the IM + F2F group:

Ho12: There is no test-score difference between the different age groups in South African higher education.

Ha12: Test score differences between the different age groups are present in South African higher education.

Since there are more than two categories in the age variable, the regression method is applied to the IM + F2F group sample in this study.

There are several specific digital technologies for teaching and learning including LMS and IM (Rambe and Bere, 2013, Bouhnik et al., 2014, Salem and Salem, 2015, Salehi, 2017). LMS, however, is the most popular specific digital technology in higher education worldwide (Salem and Salem, 2015). Higher education institutions offer numerous trainings to students and academics for better understanding how LMS can be effectively utilised (Ng'ambi et al., 2016). Such trainings help students and academics develop confidence in the use of LMS (Bharuthram and Kies, 2013, Ng'ambi et al., 2016). As a result, access to teaching and learning using LMS improves (Bharuthram and Kies, 2013, Ng'ambi et al., 2016).

There are several alternative specific digital technologies including IM whose popularity in higher education is growing (Rambe and Bere, 2013, Nkhoma et al., 2018). This is because of the various unique characteristics IM offers to teaching and learning including ubiquity, cheaper connectivity, multi-modality, and advanced interaction in groups or in private (Rambe and Bere, 2013, Tang and Hew, 2017). IM, however, has been adopted in higher education in small projects (Rambe and Bere, 2013, Tang and Hew, 2017, Nkhoma et al., 2018). There are numerous challenges associated with the use of IM in teaching and learning including the use of informal language, lack of technical support from higher education institutions, disruptive in nature during family time, and low battery life (Bouhnik et al., 2014, Tang and Hew, 2017). Also, academics perceive the use of IM in the classroom as unsettling (Rambe and Bere, 2013). This shows that LMS can be more effective than IM with respect to the performance of learning in higher education. Based on this background the following hypothesis is developed.

***H13**: LMS based digital learning LMS + F2F has better performance of learning than IM based digital learning IM +F2F in South African higher education*

In statistical terms, the above conceptual hypotheses can be written as statistical hypotheses. Since the performance of learning is measured using students' test scores, the above hypotheses are equivalent to:

Ho13: test score difference LMS + F2F = test score difference IM +F2F

Ha13: test score difference LMS + F2F > test score difference IM+F2F

The above hypothesis can be tested using a standard one-tail *t*-test and applied to two samples of students who have adopted LMS + F2F and IM + F2F in teaching and learning.

3.3 Concluding Remarks

This chapter develops the hypotheses of the study for exploring the impact of specific digital technologies including LMS and IM on the performance of learning in South African higher education. Such hypotheses are based on a comprehensive review of the related literature on digital learning and the impact of individual characteristics on the performance of learning. The study hypotheses lay the foundation for designing and implementing a quantitative study for better understanding the impact of specific digital technologies on the performance of learning in higher education.

Chapter 4

Research Methodology

4.1 Introduction

A research methodology is a systematic way to solve a research problem in a given situation (An et al., 2017, Chau and Deng, 2018). It provides specific procedures and guidelines for describing, explaining, and predicting specific phenomena in a study. A research methodology offers a blueprint for guiding individual researchers in conducting a research project (An et al., 2017). The objective of the research methodology is to explain (a) the reason for undertaking a specific research project, (b) how a research problem is formulated, (c) the rationale for employing specific data collection methods, (d) why specific data is collected, and (d) the reason for adopting a particular technique for analysing the data (Sek et al., 2016, An et al., 2017).

The selection of a suitable research methodology in a study is crucial for the reliability and validity of the research findings in a research project. This is because the selection of the appropriate research methodology (a) helps understand the purpose of conducting the research project, (b) guides the selection of the research method, and (c) facilitates deciding the appropriate method for analysing and interpreting the data. A well-designed research methodology does not only provide a procedural framework for guiding how the research problem is solved. It also influences the delivery of quality research findings in a research project (Sek, 2016, Creswell and Creswell, 2017).

There are four critical issues that need to be adequately addressed in selecting the appropriate research methodology for a research project including the research paradigm, the research methodology, the research design, and the data analysis techniques (Sek, 2016, Creswell and Creswell, 2017). The research paradigm provides the underlying philosophical foundation for guiding the selection of the research methodology, which in turn determines the research design and the data analysis techniques. A careful consideration of these four critical issues is crucial for the successful selection and implementation of the most relevant research methodology in a given research project (Creswell and Creswell, 2017).

The aim of this chapter is to select and implement a suitable research methodology for achieving the objective of the research in this study. To achieve the objective of the study, this chapter first presents an overview of the research paradigm. This is followed by the discussion of various research methodologies available, leading to the selection of a quantitative research methodology for this study. It then deliberates on the implementation of the quantitative research methodology with an emphasis on various aspects including the criteria for selecting the research sample, the type of the data collected, what data collection methods are used, and how data is analysed and reported.

This chapter is organised into six sections. Section 4.2 presents the research paradigm for guiding the selection of a suitable methodology in the research project. Section 4.3 selects an appropriate research methodology for this study based on a detailed discussion on the three popular research methodologies including quantitative, qualitative, and mixed-methods methodologies. This is followed by the discussion of the research design in Section 4.4, leading to the selection of the appropriate data analysis techniques in Section 4.5. Section 4.6 ends the chapter with some concluding remarks.

4.2 Research Paradigms

A research paradigm is a shared world view (Chilisa and Kawulich, 2012). It represents a basic set of beliefs and values for guiding a research inquiry (Chilisa and Kawulich, 2012). The purpose of a research paradigm is to guide the implementation of a research project. A research paradigm describes (a) how the world is viewed, (b) how knowledge is obtained from the world, (c) what types of questions are to be asked, and (d) what methodologies are adopted in answering these questions (Lincoln and Guba, 2011, Scotland, 2012).

There are three philosophical assumptions associated with the research paradigm including ontology, epistemology, and methodology (Guba and Lincoln, 1994, Lincoln and Guba, 2011). Ontologies are a philosophical study of the nature of reality (Kivunja and Kuyini, 2017, Davies and Fisher, 2018). They present the assumption that individual researchers make to believe that something is real. These assumptions orientate the thinking of the researcher around the research problem, its significance, and how best it can be approached in order to answer the research question (Kivunja and Kuyini, 2017). The purpose of defining an ontology in a research project is to provide an understanding of the things that constitute the world, as it is known. It seeks to determine the foundational concept in a study. Such concepts constitute the themes that are analysed to make sense of the meaning embedded in research data (Kivunja and Kuyini, 2017). An ontology possesses the following questions. *Is there reality out there in the social world or is it a construction, created by one's own mind? What is the nature of reality? What is the nature of the situation being studied?* (Krauss, 2005, Kivunja and Kuyini, 2017, Davies and Fisher, 2018).

An epistemology is a philosophical study of the nature of knowledge (Davies and Fisher, 2018). It describes the base of knowledge, the nature and forms of knowledge, how knowledge can be acquired, and how knowledge can be communicated (Kivunja and Kuyini, 2017). The questions that can be asked in the epistemology assumption are as follows. *What counts as knowledge? What is the nature of knowledge? What does it mean to know? What is the relationship between the inquirer and what is known?*

A methodology is a strategy that outlines the manner in which a research project is conducted (Cuervo-Cazurra et al., 2017). Its purposes are to gather and analyse the data for generating reliable research conclusions (Williamson and Johnson, 2017). To meet its purposes, a methodology describes the research method for a research project (Daniel et al., 2018). Research methods are then used to collect data for making inference and interpretation (Cuervo-Cazurra et al., 2017, Daniel et al., 2018). As a result, a methodology consists of concepts and frameworks in which specific research methods are used. A methodology can pose the following questions. *How can the desired data be obtained? How can data be analysed to enable the answering of the research question*? (Kivunja and Kuyini, 2017).

There are three research paradigms in information systems research including positivism, interpretivism, and critical social research (Orlikowski and Baroudi, 1991, Klein and Myers, 1999). They differ on the basis of their paradigm assumptions including ontology, epistemology, and methodology (Scotland, 2012). Positivism is based on the assumption that there is a single reality in the world (Davies and Fisher, 2018). In order to know this single reality, the study of a phenomenon must be undertaken with objectivity and detached impartiality. The positivism paradigm usually adopts a quantitative methodology. It tests predetermined hypotheses and uses quantitative research methods with large sample sizes for the discovery of a single reality in an objective manner (Davies and Fisher, 2018). The data and its analysis are value-free. Data do not change because they are being observed (Krauss, 2005).

Following the positivism paradigm in a study requires using quantitative methods for investigating a phenomenon (Kivunja and Kuyini, 2017). The study in this paradigm searches for the cause-and-effect relationship in order to explain specific phenomena. Such a study applies rigid rules of logic and measurement, truth, absolute principles and prediction for obtaining the research findings (Weaver and Olson, 2006). Research under the positivism paradigm uses facts and measurable entities to interpret the observation (Kivunja and Kuyini, 2017). The objective of the positivism paradigm is to produce data that is predictive and generalisable to a population. The positivism paradigm answers a research question based on the probability (Davies and Fisher, 2018). The positivism paradigm is mostly represented through (a) the formulation of hypotheses, models, or causal relationships among constructs, (b) the use of quantitative methods to test hypotheses, and (c) the objective and value-free interpretation of the research data (Sek, 2016, Kivunja and Kuyini, 2017).

There are four assumptions that guide the prediction of measurable outcomes in a research project following the positivism paradigm including determinism, empiricism, parsimony and generalizability (Kivunja and Kuyini, 2017). Determinism assumes that observable events are caused by other factors (Kivunja and Kuyini, 2017). Empiricism involves the collection of verifiable empirical data which can support the development of the theoretical framework of the study. Such empirical data must allow the testing of the formulated hypothesis. Parsimony focuses on explaining the phenomena in the most economical way. The generalisability assumption explains that results obtained from a research project in one context must be applicable to other situations by inductive inferences (Kivunja and Kuyini, 2017).

The interpretivism paradigm is based on the assumption that the reality is subjective in nature (Davies and Fisher, 2018). It employs inductive reasoning by developing theories from specific observations. The interpretivism research paradigm adopts qualitative research methodologies. Such research methodologies allow the collection of rich, in-depth data that describes individual experiences from small sample sizes (Davies and Fisher, 2018). The findings are generated through dialogue and interaction between the subject and the researcher. This research paradigm is described as a deeply self-reflective process for the researcher (Davies and Fisher, 2018). In interpretive quantitative research, statistics provide insights on the unobservable data producing processes that underlie observed data. Its major beliefs are the triangulation of the study results obtained through the analysis of data from several perspectives, the integration of measurement and modelling into a more holistic process of discovery and the need to think instinctively about the means in which data have come into existence (Babones, 2016).

The critical paradigm is based on the assumption that knowledge is socially and historically constructed (Davies and Fisher, 2018). The purpose of the critical paradigm is to emancipate groups of people who are marginalised. This is achieved through an investigation of social injustices (Davies and Fisher, 2018). A critical research paradigm adopts qualitative research methodologies to collect data. It encourages participant involvement in the research process. Participant involvement helps to (a) address inequalities in the participant relationship and (b) empower those individuals to take actions for themselves (Davies and Fisher, 2018). As a result, the critical research paradigm raises awareness and promote social changes. Table 4.1 presents an overview of research paradigms.

The paradigm adopted in this research is the positivism paradigm because the objective of this research is to investigate the effectiveness of specific digital technologies in digital learning in South African higher education. Specifically, the research aims to (a) investigate the impact of LMS on the performance of learning, (b) explore the impact of IM on the performance of learning, and (c) examine the relative effectiveness of LMS and IM on the performance of learning in higher education in South Africa. These objectives are best achieved using a value-free, quantitative and positive approach.

Table 4. 1 An Overview of Research Paradigms

Assumptions	Research Paradigms		
	Positivism	**Interpretivism**	**Critical**
Ontology	• Single identifiable reality • Measurable reality	• No single reality. • Reality is socially constructed through interactions	• Reality is socially constructed • Realities are under constant internal influence
Epistemology	• Believe in total objectivity • Values scientific rigour • Thought governed by hypotheses and stated theories.	• Believe in subjectivity • Values exploring human and social interactions through culture.	• Belief in historical realism • Values social constructions • It aims to emancipate the oppressed.
Methodology	• Quantitative	• Qualitative • Quantitative	• Qualitative

4.3 Research Methodologies

A research methodology is a well-planned process which involves the design of data collection methods, data analysis strategies and procedures for presenting the research findings (Kivunja and Kuyini, 2017). It indicates the logic and flow of a systematic process adopted in the implementation of a research project. A research methodology includes the assumption made in the study, the limitation of the study, and the adopted strategy to minimise the limitation (Kivunja and Kuyini, 2017). It can help researchers to gain knowledge about a research problem (Kivunja and Kuyini, 2017). The purpose of adopting a specific methodology is to help the researcher to complete the research project with proper guidance by (a) providing the blueprint for the researcher to successfully achieve the research objective and (b) helping the researcher to complete the research project within the limited resources and time (Sek, 2016).

The commonly used research methodologies in a research project are quantitative, qualitative and mixed-methods (Creswell and Creswell, 2017, Leedy and Ormrod, 2019). A quantitative methodology follows a positivist paradigm for testing objective theories by investigating the relationship between variables in a study. These variables are measured using instruments to allow numeric data to be analysed using statistical procedures (Creswell and Creswell, 2017). Theories are tested deductively for (a) minimising bias, (b) controlling for alternative explanations, and (c) allowing findings to be generalised and replicated (Creswell and Creswell, 2017, Leedy and Ormrod, 2019). A quantitative methodology commonly draws meaningful conclusions from the research data through inference analysis, statistical analysis, and hypotheses testing (Creswell and Creswell, 2017).

A qualitative methodology follows the interpretivism paradigm for discovering and understanding the meaning that humans ascribe to a social phenomenon (Creswell and Creswell, 2017, Leedy and Ormrod, 2019). Data is commonly collected in the participant's setting in a form of narratives which uses words rather than the quantification of a problem (Creswell and Creswell, 2017). Data analysis follows the inductive approach to generate interpretations of the data (Scotland, 2012, Leedy and Ormrod, 2019). The adoption of the qualitative methodology focuses on individual meaning and values rendering the complexity of a phenomenon using qualitative methods (Creswell and Creswell, 2017). Typical examples of qualitative methods include open-ended interviews, open-ended observations, open-ended questionnaires, role-playing, and focus groups (Scotland, 2012, Creswell and Creswell, 2017).

A mixed-methods methodology adopts both quantitative and qualitative methods in a study for collecting and analysing data. The adoption of such a methodology incorporates both forms of data for solving a research problem in a study. A mixed-methods methodology adopts discrete designs including theoretical framework development, hypothesis testing, and philosophical assumptions (Creswell and Creswell, 2017). The key assumption of adopting a mixed-methods methodology is that the integration of quantitative and qualitative methods in a study offers a more comprehensive understanding of the phenomenon than either methodologies alone (Creswell, 2014, Creswell and Creswell, 2017). Common examples of mixed-methods methodologies include convergent parallel mixed-methods, explanatory sequential mixed-methods, and exploratory sequential mixed-methods (Creswell and Creswell, 2017).

This research adopts a quantitative research methodology to meet its objectives. A quantitative research methodology is appropriate for this study due to the following reasons. Firstly, it is capable of testing the hypothesis for investigating the impact of specific digital technologies on the performance of learning in higher education. Secondly, a quantitative research methodology is useful for increasing the generalisability of the findings of the study. As a result, the findings of this study can influence the adoption of specific digital technologies including LMS and IM in higher education, particularly in developing countries.

4.4 Research Design

Research design is a framework of strategies and methods chosen to combine various research elements in a logical manner for efficient handling of the research problem (Leedy and Ormrod, 2019). Its purpose is to provide a blueprint for undertaking a research project (Leedy and Ormrod, 2019). In this study, the research design describes various components of the research project including participant sampling, implementation of quantitative methodology, and the implementation of the experiment design of the study.

Experimental design

The aim of this study is to investigate the impact of digital technologies including LMS and IM on the performance of learning in higher education. To adequately meet the aim of the research study, an experimental design is adopted. Such a design allows the identification of specific cause-and-effect relationships in the study (Leedy and Ormrod, 2019). As a result, an experimental research design is extremely relevant in this study.

There are three major types of experimental designs including true experiments, quasi-experiments, and factorial designs (Leedy and Ormrod, 2019). A true experiment facilitates casual inference (Salkind, 2010). It randomly assigns the unit of the experiment to different treatment conditions (Salkind, 2010, Leedy and Ormrod, 2019). Such an assignment guarantees that any differences between the groups are perhaps small and are utterly due to chance. As a result, true experiments offer greater internal validity and reliability of the research findings (Leedy and Ormrod, 2019).

There are two conditions for describing true experiments (Leedy and Ormrod, 2019). Firstly, experiment units are randomly assigned to treatment groups. Secondly, the effect of the intervention is observed (Creswell and Creswell, 2017, Leedy and Ormrod, 2019). There are three major types of true experiments including the statistic group comparison, the control group pre-test post-test design, and the Solomon Four-Group design (Leedy and Ormrod, 2019).

A static group comparison has two groups including an experimental group and a control group. The first group receives experimental treatment (*Tx*) followed by the observation (*Obs*). A second group is a control group. This experiment does not have an experimental manipulation. An observation is made after some time. The observations of the first group and the second group are compared to reveal the effect of the experimental treatment (Leedy and Ormrod, 2019). The basic format for the static group comparison design is illustrated in Table 4.2.

Table 4. 2 Statistic Group Comparison Experiment Design

Group	Time →	
Group 1	T_x	*Obs*
Group 2	--------	*Obs*

As shown in Table 4.2, each experiment group is indicated in a separate row. The activities that happen to the group over time are presented in a separate cell. Each activity is represented by one of the three following notations. T_x shows that the treatment is presented. *Obs* reveals that an observation is made. ----------- shows that nothing happens at a specific time.

The treatment-comparison group, pre-test and post-test experimental (control group pre-test and post-test) design randomly assigns the unit of the study either to the experimental group or the control group (Creswell and Creswell, 2017). Both the experiment group and control group are observed at the starting (pre-test) and at the end (post-test) of the experiment. The control group does not include the experimental treatment (Creswell and Creswell, 2017, Leedy and Ormrod, 2019). The basic format for the control group pre-test and post-test design is shown in Table 4.3.

Table 4. 3 Control Group Pre-Test Post-Test Experiment Design

Random assignment	**Group**	**Time →**		
	Group 1	Obs	T_x	*Obs*
	Group 2	Obs	-------	*Obs*

The Solomon Four-Group design is suitable for answering the research questions that aim at determining the effect of the pre-test (Leedy and Ormrod, 2019). It consists of four groups. The first group is observed before the experimental treatment and after the experimental treatment. A second group is a control group that is observed at the start and the end of the experiment. The third group includes an experimental treatment. It has only one observation which is made at the end of the experiment. The fourth group is a control group. This group is observed at the end of the experiment (Creswell and Creswell, 2017, Leedy and Ormrod, 2019). The basic format for the Solomon Four-Group design is illustrated in Table 4.4.

Table 4. 4 Solomon Four-Group Experiment Design

	Group	**Time →**		
Radom assignment	Group 1	Obs	T_x	*Obs*
	Group 2	Obs	------	*Obs*
	Group 3	------	T_x	*Obs*
	Group 4	------	------	*Obs*

The quasi-experimental design is used when the random assignment of units of the study is impossible or impractical (Creswell and Creswell, 2017). There is no guarantee that the experimental group and the control group are similar in every aspect prior to the experimental treatment. The initial assessment using pre-test can confirm that the two groups are similar with respect to the dependent variable under investigation (Creswell and Creswell, 2017, Leedy and Ormrod, 2019). The basic format for the quasi-experimental design is illustrated in Table 4.5.

Table 4. 5 Quasi-Experiment Design

Group	**Time →**		
Group 1	Obs	T_x	*Obs*
Group 2	Obs	------	*Obs*

The factorial design is used to investigate the effects of two or more independent variables in a single research project (Leedy and Ormrod, 2019). In a two-factor experiment design, the effect of the first independent variable is explored by comparing the performance of the first group and the second groups with those of the third group and the fourth group (Leedy and Ormrod, 2019). The effect of the second independent variable is investigated by comparing the first group and the third group with groups two and four. The purpose of a factorial design is to examine (a) the effects of two independent variables and (b) the interaction of the variables as they influence the dependent variables (Creswell and Creswell, 2017, Leedy and Ormrod, 2019). The basic format of the two-factor experiment design is shown in Table 4.6.

Table 4. 6 Factorial Experiment Design

Random assignment	**Group**	**Time →**		
		Treatments related to how the two variables may occur simultaneously or sequentially		
		Treatment-related to variable 1	Treatment-related to variable 2	
	Group 1	T_{x1}	T_{x2}	*Obs*
	Group 2	T_{x1}	------	*Obs*
	Group 3	------	T_{x2}	*Obs*
	Group 4	------	------	*Obs*

The Implementation of the experimental design

A treatment-comparison group, pre-test and post-test experimental design is selected and implemented to investigate the impact of specific digital technologies including LMS and IM on the performance of learning in higher education. This design is selected because it allows for the determination of the cause-and-effect relationship between the adoption of specific digital technologies and the performance of learning in higher education. The treatment-comparison group pre-test and post-test experimental design involves the random assignment of the participants in the three groups including LMS, IM (treatment groups) and F2F (comparison group) which in turn improves the internal validity of the research project.

There are four steps in the implementation of the treatment-comparison group pre-test and post-test experimental design in this study. Firstly, the prior knowledge of the participants in the database management course is established using the pre-test survey. Secondly, participants undergo the cognitive skills analysis (CSA) assessment. CSA is a computerised measurement which discloses a learner's inclination (a) to think visually or verbally, and (b) to process information either holistically or analytically (Riding and Cheema, 1991, Riding and Pearson, 1994). This measure produces CSA ratios which are recorded for the random allocation of participants into different experimental clusters. This is achieved by plotting into a graph the CSA ratios obtained from each group. Figure 4.1 represents a graph plotted based on all the CSA ratios obtained to determine the CSA quadrants and establishing the CSA value mid-point of the participant numbers. The three closest points are considered as a matched set. Each is randomly allocated into one of the two treatment groups or the comparison group.

Students who are not part of a three-person matched set are also randomly allocated one of three study groups.

Thirdly, three parallel teaching and learning cohorts consisting of randomly assigned participants are conducted. The three cohorts include LMS with F2F teaching, IM with F2F teaching, and F2F teaching only (comparison group). Note that the different teaching methods are applied to the conduct of tutorials and class discussion only. The F2F only teaching does not include the use of digital technologies for teaching and learning. Instead, participants gather on campus in small teams of up to 10 participants including students and the facilitator. The tutorial has followed the traditional instruction delivery method in which students raise their hands to respond to specific questions posed by the facilitator. Students could ask questions too and actively participate in teaching and learning through interaction with team members. Overall, the facilitator controls teaching and learning. Each block of the F2F only teaching session lasted for 45 minutes.

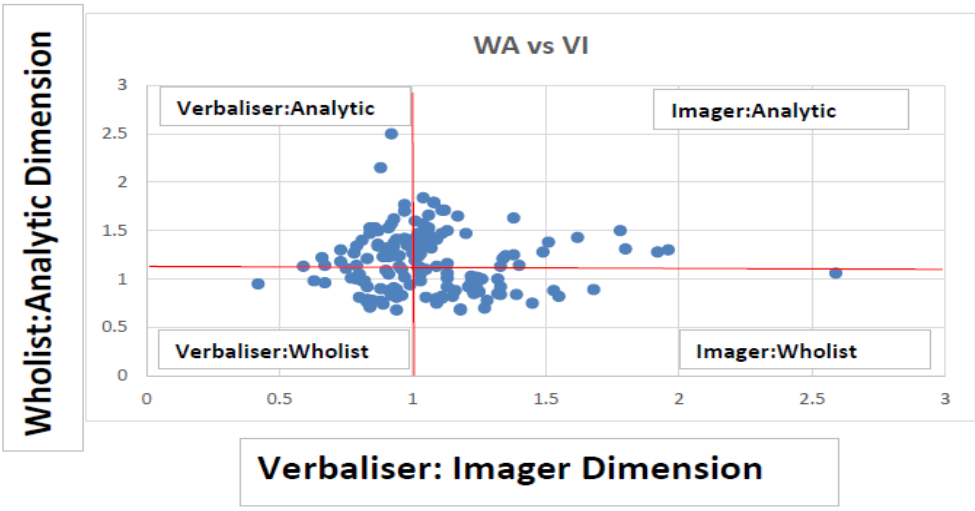

Figure 4.1 An Overview of the CSA quadrants

The LMS with F2F teaching consists of several small groups of up to 10 people. Students and the facilitator are assigned to the LMS-based discussion teams. In each group, facilitator initiates an asynchronous interaction by posting questions to the LMS discussion team. Each participant contributes in various ways including posting questions, providing feedback to peers' questions, and supporting team members. The facilitator has actively participated in the tutorial for 45 minutes per day. Specific times in which the instructor is active on the LMS platform in future are communicated. Participants are encouraged to extend the interaction with their peers outside their learning hours. They are encouraged to take notes of the problem they could not solve and seek clarification from the facilitator in the next tutorial. There are various digital devices used in the LMS experimental treatment including personal laptops, home computers, and university computers in the library or computer laboratories. The participants participating in the experiment off-campus connect to the Internet using their Internet data.

IM with F2F teaching consists groups of up to 10 people. Students and the facilitator are assigned to the IM-based discussion teams using WhatsApp. The facilitator initiates synchronous interactions by posting questions to the WhatsApp IM cyber group. Each participant contributes in various ways including posting questions, providing feedback to the peers, supporting group members with their social and psychological needs. Interactions take place in various forms including text, audio, images, and video. The facilitator actively participates in the tutorial for 45 minutes per day. Students are encouraged to extend the peer-interaction outside their learning hours. Difficult problems which participants could not solve are referred to the next tutorial for clarification. Participants have used their mobile technologies including smartphones, tablets, and IPads for participation in the study. Such devices utilise university WIFI for Internet connection on campus. The participants participating in the experiment off-campus connect to the Internet using their Internet data.

Fourthly, a post-test is administered to all the participants who have completed the experiment. The purpose of the post-test is to measure the performance of the participants on their understanding of structured query language (SQL) development in the database management course after the digital technologies intervention. The post-test survey is administered after fifteen sessions of tutorials in three weeks. Figure 4.2 presents an overview of the research procedure.

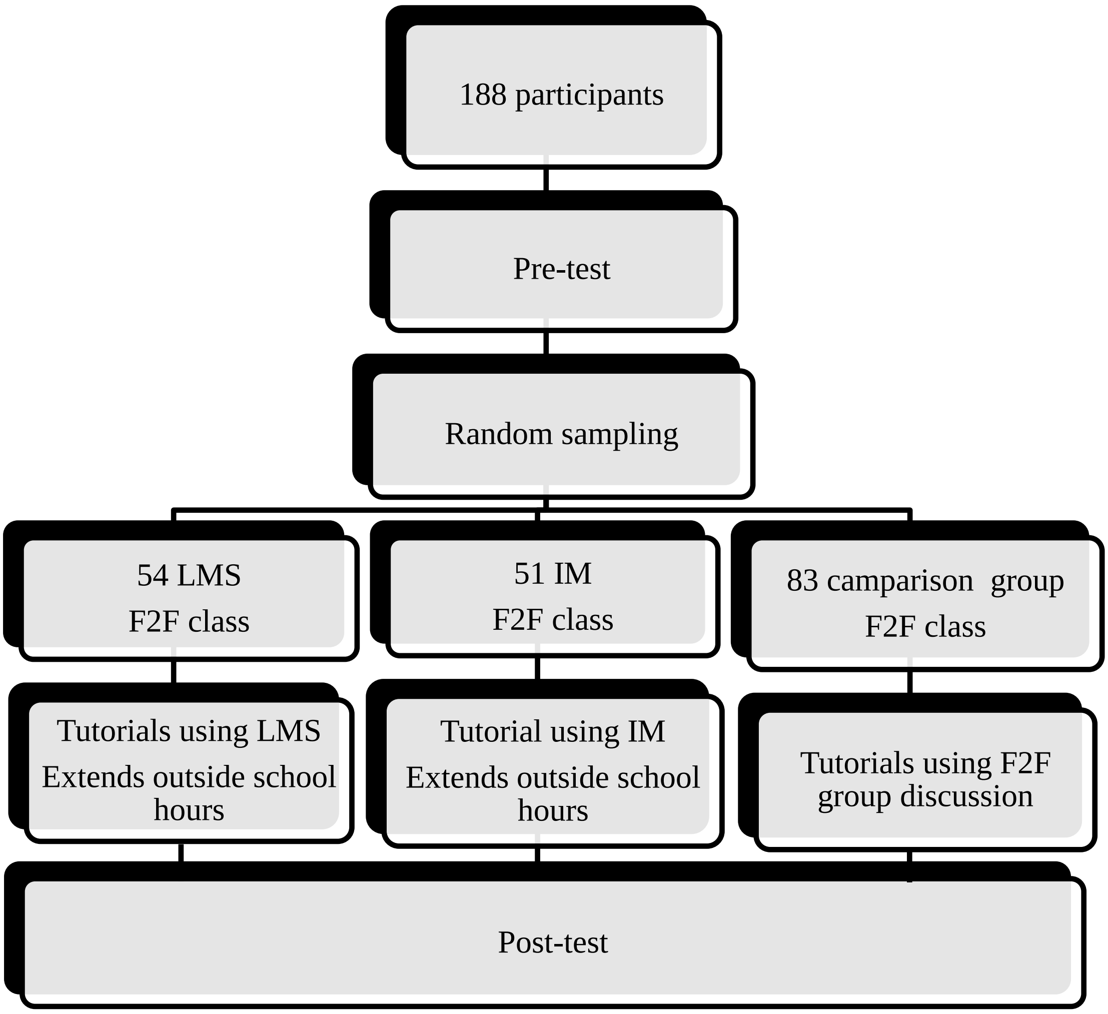

Figure 4. 2 An Overview of the Research Procedure

Sample sizes and allocation of participants

The aim of this study is to investigate the impact of specific digital technologies including LMS and IM on the performance of learning in higher education. To facilitate this study, a total of thirteen hypotheses are proposed as shown in Chapter 3. These hypotheses are to be tested quantitatively using various statistical analysis methods. With the adoption of a quantitative research methodology, surveys including pre-test and post-test are used for collecting data.

The selection of the appropriate sample size is crucial for producing reliable and consistent results in the analysis of the data (Dell et al., 2002, Stokes, 2014). This study adopts power analysis for informing the suitable sample size in the study. This helps to better understand the adequate sample size for subjects to be considered for (a) participating in the study experiment and (b) data collection (Rose and Bowen, 2009).

To obtain an accurate sample size, the power analysis must align with the data analysis model (Dell et al., 2002, Rose and Bowen, 2009). A misalignment of these two models can result in either much lower power or much higher power in the data analysis than predicated (Rose and Bowen, 2009). Having a much lower power caused by under-sampling clusters result in a failure to reject a hypothesis that should be rejected (Dell et al., 2002). When this error occurs, there is a possibility that the treatment has an effect due to the sample size that is too small (Dell et al., 2002, Stokes, 2014). As a consequence, the outcome of the study is incorrectly presented (Dell et al., 2002, Rose and Bowen, 2009). Having a much higher power caused by over-sampling groups can waste resources during the study. This shows that the running costs of the research project increases unnecessarily (Rose and Bowen, 2009).

There are three constraints in power analysis including the effect size, the power of the experiment, and the significance level (Dell et al., 2002). The effect size measures the strength of the relationship between the sample and the population (Sek, 2016). The power of an experiment is the probability that the effect is detected (Dell et al., 2002, Stokes, 2014). The significance level α is the probability that a positive outcome is due to chance alone (Dell et al., 2002). An effect of 0.20, a significance level α of 0.05, and an experiment power of 0.80 are recommended for obtaining a suitable sample size in hypothesis testing based research projects (Dell et al., 2002, Stokes, 2014).

There are approximately 4,200 information technology (IT) students enrolled in a database management course in the 26 public universities in South Africa. This shows that population sampling is not possible due to the costs required in reaching such students that are scattered in different universities and in different cities of South Africa. It is necessary to decide a suitable sample size using a different criterion. The power analysis is adopted using the recommended values for effect size, power, and significant level. The results of the power analysis show that the adequate sample size for this research project is 153. This informs that the findings of this study can be generalised to the students in higher education in South Africa when at least 153 valid surveys are returned for data analysis.

To obtain the findings that can be generalised to higher education in South Africa, it is essential to consider carefully the sampling method and the target population of the research (Leedy and Ormrod, 2015). This study aims to investigate the impact of specific digital technologies including LMS and IM on the performance of learning in higher education in South Africa. The target population of the study involves IT undergraduate students in South African universities who are enrolled in the database management course.

There are two sampling methods adopted in this study including convenience sampling and purposive sampling. Convenience sampling is a type of a non-probability sampling method (Leedy and Ormrod, 2015). It involves the collection of data from individuals who can be easily reached (Williamson and Johnson, 2017). Purposive sampling is a non-probability sampling technique. It relies on the judgement of the researcher for the selection of the participants (Leedy and Ormrod, 2015). Purposive sampling focuses on certain features of a population that are of interest. Such features enable the answering of the research question (Leedy and Ormrod, 2015).

In this study, the population of interest include IT undergraduate students in 26 public universities in South Africa. Convenience sampling is employed for selecting participating universities. Out of the 26 universities, the researcher has obtained the contact details of eight research ethics committees of eight universities. Letters of invitation to participate in the study are sent to these universities. Out of these eight universities, two universities including Central University of Technology (CUT) and Cape Peninsula University of Technology (CPUT) have granted permission for the study to be conducted at their institutions. As a result, these two universities are convenient for the researcher to collect data. After the identification of the convenient institutions for data collection, purposive sampling is adopted for gaining access to undergraduate IT students who are enrolled in the database management course at CUT and CPUT.

Data collection using pre-test and post-test surveys was conducted at CUT and CPUT between March 2017 and August 2017. Purposive sampling is adopted for selecting the research participants. In this study, purposive sampling focuses on the features of a population that are of interest including (a) the qualifying students are undergraduates registered in IT, (b) such students are enrolled in the database management course at either CUT and CPUT, and (c) the students own at least one mobile device including smartphone, tablet, iPad, and laptop.

The consent of individual participants is obtained from students who meet the purposive sampling criteria. Such a consent is conducted in a lecture theatre through two different phases. First, a participant information sheet and written consent form are handed to participants. Second, participants are asked to carefully read the participant information sheet and fill in the written consent form. They are requested to sign the consent form if they agree to participate in the study. Participants receive a verbal explanation of the whole experimental procedure including the data collection process. This process took approximately 30 minutes. Out of the 351 students who met the criteria above, 239 students have consented to participate in the study. This contributes to a 68.09% response rate.

These 239 students were then randomly assigned to the three groups. The three groups include LMS +F2F, IM+F2F, and F2F only (comparison) group. The F2F only have obtained the highest number of participants (83), followed by LMS+F2F group with 79 participants. The IM+F2F group has obtained the least number of participants (77). All the 239 participants completed the pre-test survey. However, there is significant number of dropouts in the LMS+F2F group. A total of 25 participants did not complete the experiment, resulting in a final sample of 54. There are various reasons for their dropout including lack of time to interact after hours, lack of bandwidth to interact off-campus, inability to effectively access the LMS on their mobile devices as they usually access it on campus using institutional desktops Similarly, there are 26 dropouts in IM+F2F group, resulting in a final sample of 51. There are various reasons for their dropout including irrelevant posts in the group, interfering with personal life since some participants posted during family time particularly at night, IM application technical challenges, and costly bandwidth for downloading multimedia for teaching and learning including videos, audios and graphics. There was no drop out in the F2F group.

Demographic characteristics of participants

The demographic information of the sample in this study is examined. The investigation of the demographic information is needed to assess whether the participants of the study are representative of the target population (Leedy and Ormrod, 2013). This leads to the achievement of reliable and generalisable research findings from the study. The investigation of the demographic information is conducted using descriptive statistics, including the measure of central tendency and the measure of variability.

As shown in Table 4.7, a total of 188 students have participated in the investigation of the impact of specific digital technologies, including LMS and IM on the performance of learning in higher education in South Africa. The participants of the study have been allocated into three groups: face-to-face only (F2F; reference) group, LMS with face-to-face F2F+ LMS group, and IM with face-to-face IM + F2F group. Table 4.2 shows that the LMS + F2F group has 54 participants (Count = 54). The IM + F2F group has 51 participants (Count = 51). The F2F group consists of 83 participants (Count = 83).

Table 4.7 Sample Sizes of Participants' Group in the Study

	Sample Sizes	
	Count	**Percentage**
F2F	83	44.15
LMS + F2F	54	28.72
IM + F2F	51	27.13
Total	188	100

The gender profile of the participant in this study is analysed. Table 4.8 shows that there are 107 female (56.9%) and 81 male (43.1%) participants in this study. Although there are no statistics on undergraduate IT students in South Africa, university enrolment is slightly higher among females (58.1%) compared to male (Department of Higher Education and Training, 2018). These results show that the participants in this study are representative of the student population with respect to the gender distribution in higher education in South Africa. Table 4.8 shows that the LMS + F2F group comprises of 26 males and 28 females. The IM + F2F group consists of 20 males and 31 females. The F2F group has 35 males and 48 females. This means that there is a balanced representation of both genders in all three subgroups in the research.

Table 4. 8 An Overview of the Two Main Paradigms

		Male	**Female**	**Total**
F2F+ LMS	Count	26	28	54
	Percentage	32.10	26.17	28.72
IM + F2F	Count	20	31	51
	Percentage	24.69	28.97	27.13
F2F	Count	35	48	83
	Percentage	43.21	44.86	44.15
Total	Count	81	107	188
	Percentage	43.09	56.91	100

The race of the participant in the study shown as in Table 4.9 is examined. An analysis of Table 4.9 shows that there is a fair distribution of the race of the participant in the study. The percentages of African, western and mixed (Coloured) in this sample are 77.1%, 10.1% and 12.8% respectively. This distribution is similar to the distribution of 71.9%, 15.6%, 6.3% for students enrolled in public higher education institutions in South Africa (Department of Higher Education and Training, 2018).

Table 4.9 shows that the LMS experiment group consists of 38 Africans, 10 mixed-race, and 6 western race participants. In the IM experiment group, the values of African, mixed, and western race are 39, 7, and 5 respectively. As indicated in Table 4.9, the F2F group has 68 participants of the African race, 7 participants of a mixed-race, and 8 participants of the western race.

South Africa is a multilingual country, with 11 official languages. However, the language distribution of the students enrolled in higher education is not reported by the Department of Higher Education and Training. This means that no formal comparison can be made with the sample in this study. As shown in Table 4.10, in the LMS + F2F group, native language has the highest representation followed by Afrikaans. English and foreign language have the lowest number of participants. Specifically, the native language has 33 participants. Afrikaans has 9 participants. English and foreign language obtained 6 participants each.

Table 4.9 Race Distribution of Participants

		African	Western	Mixed	Total
LMS + F2F	Count	38	6	10	54
	Percentage	26.21	31.58	41.67	28.72
IM + F2F	Count	39	5	7	51
	Percentage	26.90	26.32	29.17	27.13
F2F	Count	68	8	7	83
	Percentage	46.90	42.11	29.17	44.15
Total	Count	145	19	24	188
	Percentage	77.13	10.11	12.76	100

Table 4.10 shows that the language distribution of the IM + F2F group is as follows. The native language is the most popular language with 36 participants, followed by Afrikaans with 9 participants. Foreign language is the third most popular language with 4 participants. English is the least most popular language with 2 participants. In the F2F group, native language has the highest number of participants (Native language = 53). Afrikaans has the second-highest number of participants (Afrikaans = 14), followed by foreign language with 9 participants. The English language has the lowest number of participants (English = 7).

Table 4. 10 Language Distribution of Participants

		Native	English	Afrikaans	Foreign	Total
LMS + F2F	Count	33	6	9	6	54
	Percentage	27.05	40	28.13	31.58	28.72
IM + F2F	Count	36	2	9	4	51
	Percentage	29.51	13.33	28.13	21.05	27.13
F2F	Count	53	7	14	9	83
	Percentage	43.44	46.67	43.75	47.37	44.15
Total	Count	122	15	32	19	188
	Percentage	64.89	7.98	17.02	10.11	100

The age of the participant in the study is examined. An analysis of Table 4.6 shows the participant age distribution in the study. The age group from 22 to 25 years has the highest representation. The age group of participants in 30 years old or higher has the lowest representation.

As shown in Table 4.11, the age profile of the participant in the study is as follows. In the LMS + F2F group, the age group of 22 to 25 years has the highest number of participants. The age group from 26 to 29 years is the second highest. The third highest age group is from 18 to 21 years. The age group from 30 years and above has the lowest representation. Out of 51 participants in the IM + F2F group, 29 are in the age group ranging from 22 to 25 years. This age range has the highest number of participants. The second-highest number of participants are in the age group ranging from 26 to 29 years old. The third highest number participants are in the age group ranging from 18 to 21 years old. The age group from 30 years and above obtained the lowest number of participants. In the F2F group, the age group from 22 to 25 years shows the highest representation. This is followed by the age group from 18 to 21 years. The age group from 30 years and above obtained six participants. The age group from 26 to 29 years has the lowest representation with one participant.

Table 4. 11 Age Distribution of Participants

		18-21	**22-25**	**26-29**	**30+**	**Total**
LMS + F2F	Count	10	27	12	5	54
	Percentage	31.25	23.48	46.15	33.33	28.72
IM + F2F	Count	5	29	13	4	51
	Percentage	15.63	25.22	50.00	26.67	27.13
F2F	Count	17	59	1	6	83
	Percentage	53.13	51.30	3.85	40.00	44.15
Total	Count	32	115	26	15	188
	Percentage	17.02	61.17	13.83	7.98	100

4.5 Data Analysis Techniques

This study aims to explore the impact of LMS and IM on the performance of learning in South African higher education. To achieve such an objective, some specific statistical methods including descriptive statistics, t-test, Levene's test and regression analysis are used in the study. To facilitate the presentation of the research findings, the statistical methods mentioned above are briefly described.

Descriptive statistics

Descriptive statistics are a set of expressive coefficients that summarise available data to provide a relatively simple and easy way to understand the data (Salkind, 2010). These statistical measures are used either to describe how close to the mean of the sample data is or how dispersed from the mean of the sample the data is. Descriptive statistics are a useful tool for summarising data (Leedy and Ormrod, 2019).

There are two types of descriptive statistics namely the measure of central tendency and the measure of variability (Berenson et al., 2012). The measure of central tendency is used to describe the location of "centre" of data. There are three measures of central tendency including the mean, the median, and the mode. The mean is the average of the data. It is obtained by adding up all the data elements divided by the total number of data items in the data sample. The mean of a sample $X_1, X_2, X_3 \dots \dots . . X_n$ is denoted by $\bar{X}$. The formula to calculate the $\bar{X}$ is presented in Equation 4.1.

$$\bar{X} = \frac{1}{n}\left(\sum_{i=1}^{n} x_i\right) \tag{4.1}$$

The mode is the number that appears most frequently in the set of data. If there is no number in the data set that is repeated, there is then no mode in the data set. The median is the number in the middle of the set of data. It is calculated by arranging the data in numeric order followed by locating the number in the middle of the data set (Berenson et al., 2012, Sharpe et al., 2012).

The measure of variability is used to describe the amount of differences and spreads in the data set (Sharpe et al., 2012). These measures include minimum, maximum, range, variance, and standard deviation. The minimum is the smallest number in the data available. The maximum is the largest element in a set of data. The range is the difference between the maximum and minimum in the data available. The variance is used to describe the extent at which a random variable differs from its expected value. The formula to calculate the variance S^2 is presented in Equation 4.2.

$$S^2 = \frac{1}{n-1}\sum_{i=1}^{n}(X_i - \bar{X})^2 \tag{4.2}$$

The standard deviation is used to describe the spread of data available from the average score of the data set (Berenson et al., 2012, Sharpe et al., 2012). It is the square root of the variance. The formula to calculate the Standard deviation S is presented in Equation 4.3.

$$S = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(X_i - \bar{X})^2} \tag{4.3}$$

Where $(\bar{X})$ stands for the mean value of the sample and n is the number of elements in the sample.

T-tests

A *t*-test is an inferential statistic for determining whether a significant difference between two groups exists or not in a specific situation (Berenson et al., 2012). It involves the use of three paraments in conducting a *t*-test including the *t*-statistic, the *t*-distribution value, and the degrees of freedom for determining the probability of the existence of the difference between two sets of data (Levine, 2010, Berenson et al., 2012). The *t*-test is a hypothesis testing tool. It allows a hypothesis about a specific population to be tested with the data available (Berenson et al., 2012).

There are two types of hypotheses: the null hypothesis and the alternative hypothesis (Berenson et al., 2012, Leedy and Ormrod, 2019). The null hypothesis assumes that there are no differences between the true mean(μ) and the comparison value (m_o). The alternative hypothesis assumes that there are differences between the true mean(μ) and the comparison value (m_o). The objective of the one-sample *t*-test is to inform whether the null hypothesis should be rejected or not. The mathematical representation of the hypotheses for the independent samples *t*-test is as shown in Equation 4.4 and 4.5.

Null hypotheses: $H_o: \mu_1 = \mu_2$ or $H_o: \mu_1 - \mu_2 = 0$ (4.4)

Alternative hypotheses: $H_a: \mu_1 \neq \mu_2$ or $H_a: \mu_1 - \mu_2 \neq 0$ (4.5)

Where μ_1 represents the mean for the first group and μ_2 denotes the mean for the second group. Note that for one sample, the second parameter μ_2 in the null hypothesis can be a constant.

There are four types of *t*-test statistics including one-sample *t*-test, paired-sample *t*-test, independent-sample statistics, and Welch's test (Levine, 2010, Berenson et al., 2012). A one-sample *t*-test compares the mean of a single group with the mean of a known population to establish whether the difference between these two groups is statistically significant or not. The objective of the one-sample *t*-test is to inform whether the null hypothesis should be rejected or not. The formula to calculate the *t*-test value is presented in Equation 4.6. If the *t*-test test is greater than the critical value, then the null hypothesis is rejected. The formula to calculate the *t* is presented in Equation 4.6.

$$t = \frac{(\bar{X}) - (\mu)}{\sqrt{\frac{S^2}{n}}} \qquad (4.6)$$

A paired sample *t*-test evaluates the mean of two paired or matched samples from the same population. For example, the pre-test and post-test scores for a study. The formula to calculate the paired sample *t*-test value is presented in Equation 4.7.

$$paired\ t - test = \frac{\bar{d}}{\sqrt{\frac{s^2}{n}}} \tag{4.7}$$

Where $\bar{d}$ is the mean of the the mean difference. s^2 represents the sample variance. n stands for the population size.

An independent-samples *t*-test is a hypothesis test for determining whether the sample means of two different populations are statistically significant or not (Ruxton, 2006, Derrick et al., 2017). It can help better understand the likelihood that any difference between the two independent samples is real or due to the 'treatment' against caused by chance (Salkind, 2010). The formula to calculate *t*-value using the independent-samples is presented in Equation 4.8.

$$\text{Independent} - \text{samples}\ t - test = \left(\frac{\overline{\mathrm{X}}_1 - \overline{\mathrm{X}}_2}{\sqrt{\frac{\mathrm{s}_\mathrm{p}^2}{\mathrm{n}_1} + \frac{\mathrm{s}_\mathrm{p}^2}{\mathrm{n}_2}}} \right) \tag{4.8}$$

Where $\bar{X}_1$ stands for the population mean of sample one and $\bar{X}_2$ stands for the population mean of sample two. s_p^2 is the spooled estimate of the variance. n_1 and n_2 represents the sample sizes for population sample one and two respectively.

Levene's Test

The Levene's test examines the homogeneity of variances of the two independent samples. It is based on a null hypothesis that there is no difference between the variance of these two independent samples. When the *p*-value is less than 0.05, the Levene's test is significant so equal variances are not assumed. When the *p*-value is greater than 0.05, the Levene's test is non-significant so equal variances are assumed (Ruxton, 2006, Derrick et al., 2017). The formula to calculate Levene's test w is presented in Equation 4.9.

$$w = \frac{n-k}{k-1} \cdot \frac{\sum_{i=1}^{k} n_{1(z_i - z_{..})^2}}{\sum_{i=1}^{k} \sum_{j=1}^{n_i} (z_{ij} - z_{i.})^2} \tag{4.9}$$

Where k is the number of the independent samples to which the sampled cases belong. n_i stands for the number of cases in the i^{th} population sample. n is the total number of cases in all population samples. z_{ij} is equal to $\begin{bmatrix} X_{ij} - & \bar{X}_{i.} \\ X_{ij} - & X_m \end{bmatrix}$ where $\bar{X}_{i.}$ is the mean of the i^{th} population sample, X_m is the median of the population sample, and X_{ij} is the value of the measured variable for the j^{th} case from the i^{th} population sample. z_i represents the mean of the z_{ij} for the population sample i and $z_{..}$ is the mean of all the z_{ij} .

Regression

Regression analysis is a predictive modelling technique which investigates the relationship between a dependent variable and one or more independent variables (Berenson et al., 2012, Foley, 2018). Specifically, it helps to understand how the value of the dependent variable varies when any one of the independent variables changes while the other independent variables are held fixed (Ray, 2015). A regression model relates Y to a function of X and β as shown in Equation 4.10.

$$Y \approx f(X,\beta) \tag{4.10}$$

Where Y stands for a dependent variable. The letter X represents an independent variable. The symbol β denotes an unknown parameter.

There are various types of regression analysis techniques available including linear regression, logistic regression, polynomial regression, and stepwise regression (Ray, 2015). The linear regression is used in this study. Linear regression determines a relationship between a dependent variable Y and at least one independent variable X using a regression line (Ray, 2015). There are two types of linear regression namely: (a) simple linear regression, and (b) multiple linear regression (Berenson et al., 2012). A simple linear regression uses a single independent variable to predict the value of a dependent variable. Multiple linear regression uses at least two independent variables to predict the value of a dependent variable (Berenson et al., 2012).

4.6 Concluding Remarks

This chapter presents the research methodology adopted for achieving the research objective of the study. Based on the nature of this study, a quantitative research methodology is adopted in this research for answering the research questions due to (a) the capability of such a methodology in investigating the impact of specific digital technologies on the performance of learning and (b) the potential of generalising the research findings to a large population. The study adopts the comparison group pre-test and post-test experiment design. This facilitates the collection of quantitative data from participants in higher education in South Africa. A review of quantitative analysis techniques is undertaken in this chapter. This leads to the selection of appropriate data analysis techniques adopted in the study.

Chapter 5

Instrument Development and Validation

5.1 Introduction

A research instrument is a measurement tool for collecting data from research subjects in a study (Creswell and Creswell, 2017, Leedy and Ormrod, 2019). It is critical for helping answer the research question in a study by collecting the right data from the appropriate population. The data collected using a research instrument is analysed using suitable data analysis techniques. This leads to the development of the findings of the study (Creswell and Creswell, 2017). As a result, a research instrument is essential for meeting the objectives of a study.

The objective of the study is to investigate the impact of adopting digital technologies on the performance of learning in higher education in South Africa. To adequately achieve this objective, the pre-test and post-test survey is developed. There are five steps for developing the research instrument in the iterative development process including subject content familiarisation, test analysis, learning hierarchy, instructional matrix, and test-item development. This is followed by the instrument testing step. These six steps are iterated until a satisfactory valid research instrument is developed. This leads to the execution of the exit step which terminates the process.

The pre-test and post-test survey are quantitative in nature. They are for collecting the data before and after the experimental manipulation. The data gathered using the pre-test and post-test survey instruments is objective and value-free (Sek, 2016, Kivunja and Kuyini, 2017). This allows for the determination of the cause and effect relationship of the inquiry in the study.

The aim of this chapter is to discuss the development and validation of the research instrument. To achieve this aim, a seven-stage instrument development cycle is adopted for guiding the development and validation of the pre-test and post-test surveys instrument in this study. This instrument development cycle is based on the instructional sequence theory proposed in Gagné (1985). A pilot study is undertaken to facilitate the calibration of the research instrument and the establishment of the research design schedule through Quest Interactive Test-Analysis System using the Rasch Item Response Theory (IRT) (Adams and Khoo, 1996). As a result, a reliable and valid research instrument is delivered.

The content in this chapter is organised into four sections. Section 5.2 presents the process of developing the research instrument in the study. This is followed by the description of the instrument testing procedure in Section 5.3. Section 5.4 ends the chapter with some concluding remarks.

5.2 Development of the Research Instrument

A quantitative research methodology is adopted in this research for achieving the objective of the study. This is because the adoption of a quantitative research methodology provides more reliable and objective results in the study (Leedy and Ormrod, 2019). This can ensure that the research findings about the impact of specific digital technologies including LMS and IM on the performance of learning in South African higher education can be generalised.

The adoption of a quantitative research methodology in a study requires the use of survey instruments for collecting data from the study population (Creswell and Creswell, 2017). To ensure that the research findings in the study are reliable and validate, the research instrument in the study must be adequately developed and properly validated before collecting the data. This section describes the development and validation of the survey instrument employed in this study including the pre-test and post-test research instruments.

A seven-stage iterative development process is adopted for guiding the development and validation of the pre-test and post-test survey instruments in the study. As illustrated in Figure 5.1, these seven stages include subject content familiarisation, task analysis, learning hierarchy, instructional matrix, test-item development, test-item testing, and exit. The adoption of this process can help develop a valid research instrument.

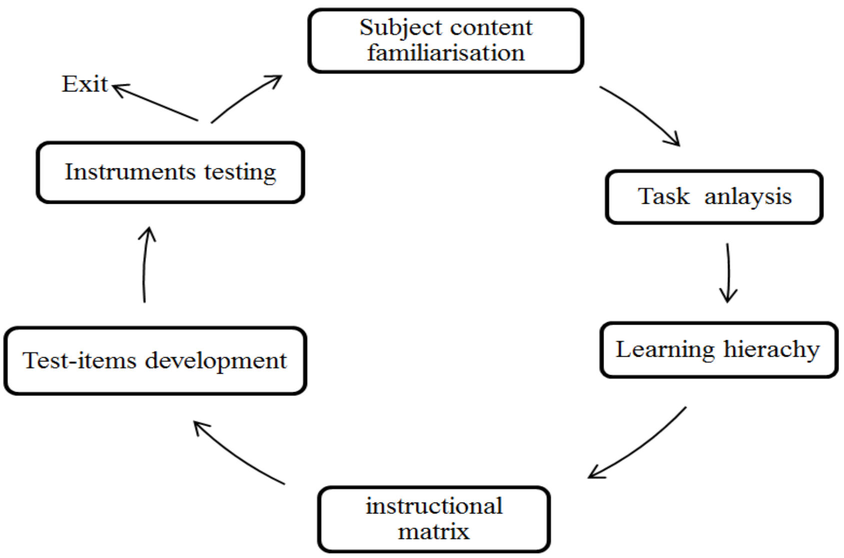

Figure 5. 1 The Survey Instrument Development Cycle

Subject content familiarisation involves developing understanding of the content and the aims and objectives for teaching and learning the database management course. Such familiarisation has been easy because the researcher has previous undergraduate database management course teaching experience in South African higher education. Both CUT and CPUT employ a similar curriculum for the undergraduate database management course. Additionally, a review of the related literature is employed for meeting the objective of the subject content familiarisation. Subject familiarisation is crucial for developing an effective research instrument.

Task analysis is a detailed description of how a task can be achieved in specific studies (Gagné et al., 1992). Generally speaking, a procedural-task analysis is often adopted in such a situation (Gagné et al., 1992). The procedural-task analysis describes the steps in performing a specific task by breaking it into smaller manageable activities which can be completed individually to complete the task (Gagné et al., 1992). This means that a procedural-task analysis simplifies a complex task through the decomposition of a complex task into its constituent components.

In this study, the SQL query development task in the database management course is broken down into smaller manageable tasks. Specifically, various sub-tasks are identified from the related literature including SELECT clause, FROM clause, WHERE clause, logic operators, and aggregate functions (Ramakrishnan and Gehrke, 2003, Coronel and Morris, 2016). These sub-tasks are performed individually for better understanding the development of SQL queries in the database management course (Gagné et al., 1992). This leads to the development of clear sequencing options of individual SQL query development elements, as shown in Figure 5.2. As a result, better understanding and clear description of the steps for developing a query in SQL are presented (Gagné et al., 1992).

A learning hierarchy is a top-down modular design tool that shows the breakdown of a task to its lowest manageable components (Gagné et al., 1992). It consists of rectangles connected by lines. These rectangles represent different subordinate skills from task analysis (Gagné et al., 1992). A learning hierarchy is important in test-item development for two reasons. First, it is used as a blueprint in the design of sequencing instructions. Second, it guides the planning process of test-item development during the instructional design (Gagné et al., 1992). As a result, a learning hierarchy is essential in the development of test-items for investigating the impact of specific digital technologies including LMS and IM on the performance of learning in South African higher education.

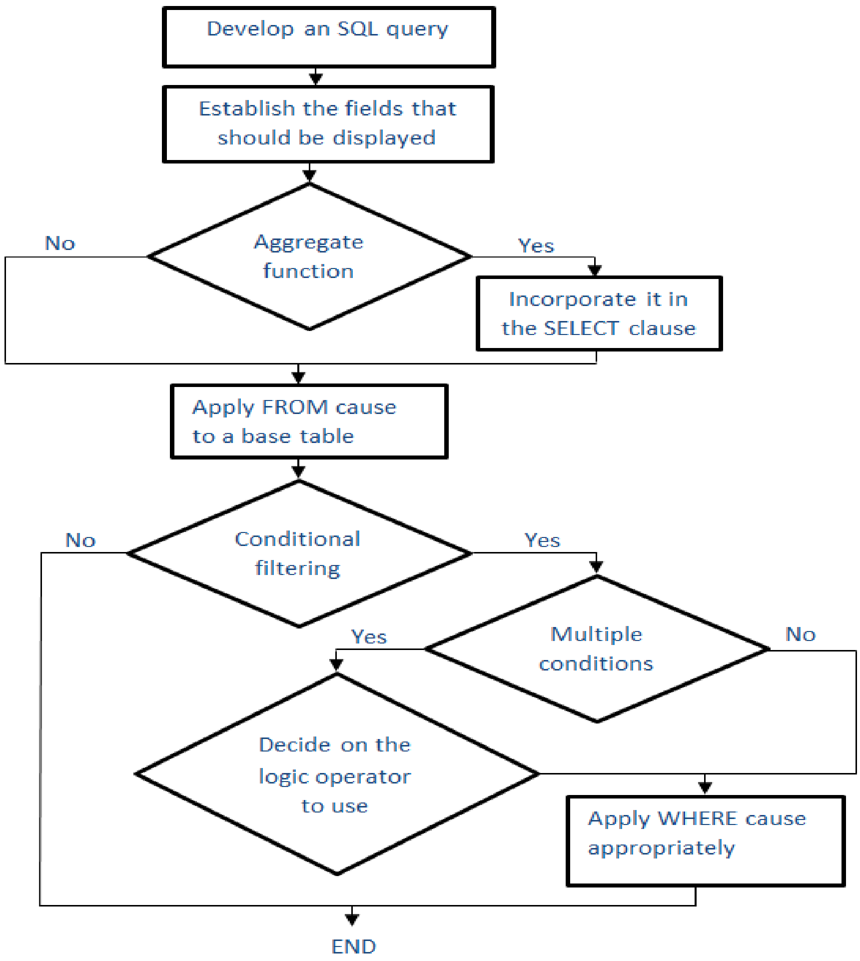

Figure 5.2 Task Analysis for SQL Query Development

In this study, several SQL query development concepts are fragmented into smaller and simpler subordinate skills in the task analysis using the procedural-task analysis technique (Gagné, 1985). These skills are applied in the development of a learning hierarchy using the top-down design principle. In this structure, subordinate and entry skills are presented at the bottom of the hierarchy. Using the related literature for developing queries in SQL and the available teaching and learning resources for a database management course, test-items for the study are developed. The formulation of test-items is guided by the content of a learning hierarchy. As shown in Figure 5.3, a learning hierarchy for SQL query development skills is presented.

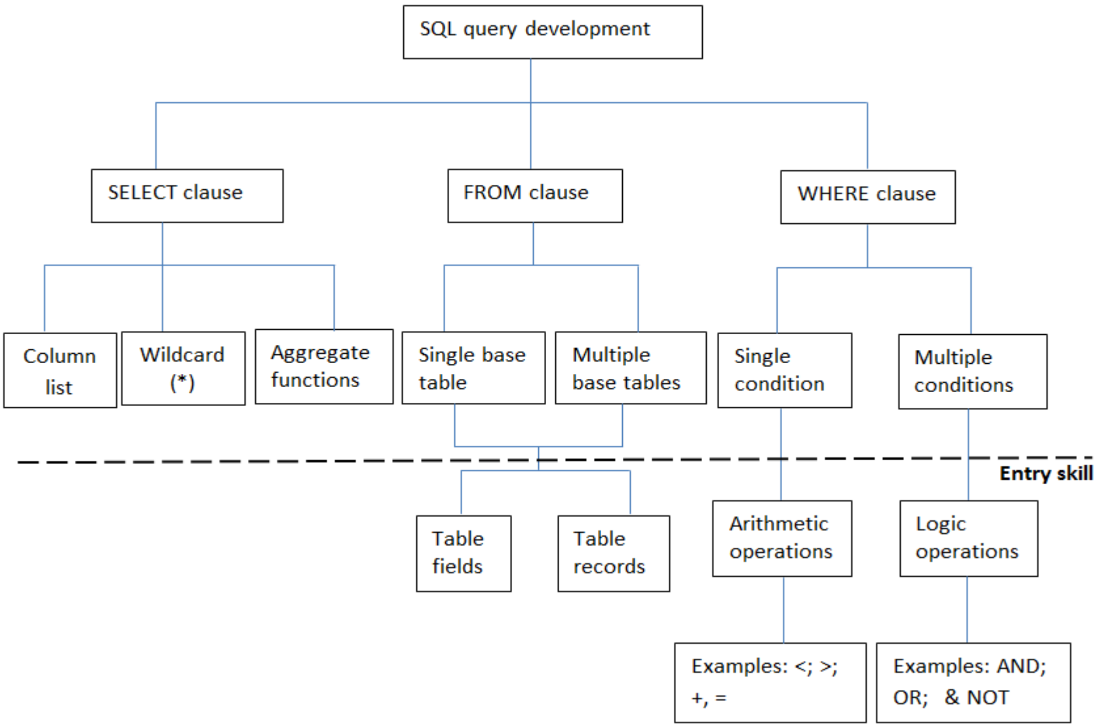

Figure 5.3 Learning Hierarchy for SQL Development Skills

An instructional matrix presents the test-items that belong to specific learned capability principles for every learning domain developed from the subordinate skills of a learning hierarchy (Gagné, 1985, Gagné et al., 1992). The objective of an instructional matrix is to guide the development of test-items based on Gagné's instructional sequence theory (Gagné, 1985, Gagné et al., 1992). As a result, an instructional matrix can help develop valid test-items for the research instrument.

Instructional sequencing is the efficient ordering of learning activities for improving knowledge acquisition of a student. Its objective is to help a student achieve his/her learning objectives in their studies (Morrison et al., 2007). Sequencing is based on pre-requisite skills and the level of cognitive processing involved. The instructional sequencing is facilitated by the Gagné's instructional sequence theory which consists of five learned capability principles (Gagné, 1985). These capability principles consist of various skills and strategies including intellectual skills, cognitive strategy, verbal information skills, motor skills, and attitude (Gagné, 1985, Gagné et al., 1992). Intellectual skills are about the ability to learn how to perform a task. It involves gaining several skills including problem-solving, rule using, and concrete skills. The cognitive strategy describes how a student controls his/her learning through remembering and logical thinking. Verbal information is declarative knowledge. It involves labels and facts. Motor skills are the bodily movements involving muscular movements required in teaching and learning. Attitude is the internal state that influences an individual's choice of action towards some object, person, or event leading to the acquisition of knowledge (Gagné, 1985). As a result, adoption of learned capabilities can help develop an effective instructional sequence.

This study adopts an instructional matrix for developing test-items of the research instrument. The instructional matrix consists of three learned capabilities including intellectual skills, cognitive strategy, and verbal information. These capabilities are adequate for sequencing the learning domain for developing SQL in the database management course. The learned capabilities are categorised into declarative knowledge and procedural knowledge as shown in Table 5.1.

Declarative knowledge consists of two categories including verbal information skill (Band-A) and intellectual skill (Band-B). Verbal information skills address basic knowledge that involves understanding concrete concepts. Intellectual skills involve understanding concepts and principles in teaching and learning. Procedural knowledge has three categories including intellectual skills (Band-C), cognitive strategies (Band-D) and cognitive strategies (Band-E). Intellectual skills (Band-C) support individuals with higher-order problem-solving skills. Individuals capable of identifying sub-tasks and having the ability to recognise unstated assumptions are categorised in the cognitive strategies (Band-D). Cognitive strategies (Band-E) accommodate individuals that are able (a) to recall simple prerequisite rules and concepts, and (b) to integrate learning from different areas into a plan for solving a problem. The level of the instructional complexity increases from Band-A to Band-E (McKay, 2000, Mat Jizat, 2012, Bakkar, 2016).

Table 5. 1 Instructional Matrix for a Task

		Instructional Objectives: Introduction to SQL knowledge acquisition					
		Declarative		**Procedural**			
		Band-A	**Band-B**	**Band-C**	**Band-D**	**Band-E**	
		Verbal information skills Concrete Concept Know Basic Terms Know that”	**Intellectual skills** Basic Rule Discriminates Understands Concepts & Principles	**Intellectual skills** Higher-order Rule Problem Solving Applies Concepts & Principles to new situations	**Cognitive strategy** Identify sub-tasks Recognises instated assumptions	**Cognitive strategy** Knowing the “how” Recall simple prerequisite rules & concepts Integrates learning from different areas into a plan for problem solving	
Task No:	**Learning Domain:**						**Totals**
10	Developing queries					18,22,25,27,28,29, 30,35,38	**9**
9	SQL statements				23,26,32,36		**4**
8	Aggregate functions		12,13		31,34		**4**
7	Logic operations			15,16,19,33, 37	17		**6**
6	Conditional filtering		14	20	21		**3**
5	FROM clause		9	24			**2**
4	Components of SELECT clause		8,10,11				**3**
3	Database types		4, 5				**2**
2	Database operations	1					**1**
1	Database terms	2,3,6	7				**4**
	Totals	**4**	**10**	**7**	**8**	**9**	**38**

There are two research instruments that have been developed and validated in this study including pre-test and post-test surveys. A pre-test survey is used to collect data before the experimental manipulation in the study. Its objective is to establish student performance before the experimental intervention (Leedy and Ormrod, 2019). A post-test survey is used to collect data after the experimental manipulation. Its objective is to evaluate student performance after the experimental manipulation (Leedy and Ormrod, 2019). To achieve this objective, the data gathered using pre-test and post-test surveys are examined quantitatively to determine the impact of the experimental manipulation.

The pre-test survey instrument consists of 38 test-items including 17 dichotomous and 21 partial credit test-items. Dichotomous is a scoring technique that provides two options including a ‘0’ or ‘1’. A test-item is scored ‘0’ if the answer is either incorrect or blank (left unanswered). A score of ‘1’ is allocated when a correct answer has been given. The dichotomous scoring system is applied to test-items that require clear and easy understanding questions. A partial credit scoring technique is used on complex questions that require an ordered sequence of steps to be followed to arrive at a solution. Such questions cannot be answered by a distinct response.

Partial credit test-items are scored using a range of values. The minimum range consists of three values. For example, writing queries in SQL constrained by two mandatory conditions requires a partial credit scoring. The scoring could have values ranging from ‘0’ to ‘5’. A score of ‘0’ suggests that the response is either incorrect or blank. A score of ‘5’ signifies a correctly completed solution. Scores from ‘1’ to ‘4’ suggest that the solution is not fully correct. This means that partial marks can be awarded for correct parts of the solution. To avoid unduly pressures and stress, the pre-test test-items are ordered from the easiest one to the most difficult one (McKay, 2000, Bakkar, 2016).

The post-test instrument consists of 38 test-items including 17 dichotomous and 21 partial credit test-item sores. This instrument is designed in such a way that its content is closely related to that of a pre-test survey. Nevertheless, the test-items of the post-test survey are (a) randomly ordered and (b) the wording for the two instruments is not identical. Such differences are implemented for reducing the memory effect on the post-test survey. The post-test test-items are carefully rephrased keeping in mind that they should measure the same learning content with the pre-test test-items. Table 5.2 represents two versions of a test-item. In the pre-test version, a dichotomous test-item is presented in its original state after being extracted from a pre-test survey. The post-test version shows the same pre-test test-item after it has been reworded and presented in a post-test survey.

Table 5. 2 A reworded dichotomous test-item

Pre-test Question:4	In one word, describe a database that stores data in rows and columns. …………………..………………………………………………………
Post-test Question:10	Fill in the blank with your ‘best’ word: A relational database stores data in………and………..

5.3 Instrument Validation

Instrument testing is a technique for assessing the reliability and validity of a research instrument on a small sample of participants before a full-scale study is undertaken. Its purpose is to identify any problems with a data collection tool including unclear wording, quality of content, visual design, and data collection scheduling (Brancato et al., 2006). To obtain reliable research findings, it is essential to adopt suitable instrument testing prior to data collection in the study (Creswell and Creswell, 2017).

A pilot study is a feasibility investigation which provides a trial run in preparation for the main research (Kezar, 2000, Van Teijlingen and Hundley, 2001). Its purpose is to help identify possible challenges which can be faced in the main study including inappropriate data collection methods, unreliably developed research instruments, and unsuitable research design (Van Teijlingen and Hundley, 2001). This shows that a pilot study is extremely relevant in this study for testing the research instrument.

A pilot study is employed in this study for instrument testing. It was undertaken in 2017 at the Bloemfontein campus in CUT, in South Africa. The qualifying participants are 43 IT students specialising in Web applications. These participants are enrolled in a database management systems course. As shown in Table 5.3, a total of 37 participants gave consent to participate in the pilot study. Later in the study, three withdrew from participating during the pre-test process due to lack of time to continue. Six participants did not complete the experiments although they completed the pre-test and the CSA assessment. As a result, their data are excluded from the analysis. Data from the remaining 28 participants who completed the experiments including the pre-test and the post-test are considered suitable for analysis. Data is analysed using the QUEST Interactive Test Analysis System (Adams and Khoo, 1996) through the Rasch IRT model.

Table 5. 3 Pilot Study Participant Population Distribution

Target population	Consented participants	Pre-Test		Post-test	
		Withdrew	Completed	Not completed	completed
43	37	3	34	6	28

The demographic distribution covers the gender and age of the pilot study participants. The participant gender distribution is 13 males and 15 females. The majority of the participants are in the age group ranging from 22 to 25 years (12 participants), followed by ten participants in the age group ranging from 18 years to 21years. The third highest group has five participants in the 26 years to 29 years age group. The age group with participants older than 30 years has the lowest number of participants (one participant). This demographic distribution is representative of the South African higher education student population.

The pre-test data of the pilot study is examined. A data file for 28 participants is run on the Quest Interactive Test Analysis System (Adams and Khoo, 1996) using an appropriate control (command) and data-file. Both files are prepared in notepad. As shown in Figure 5.4, test-items 9 and 33 overfit the Rasch model. Test-items that overfit the item fit map should be eliminated as proposed by Adams and Khoo (1996).

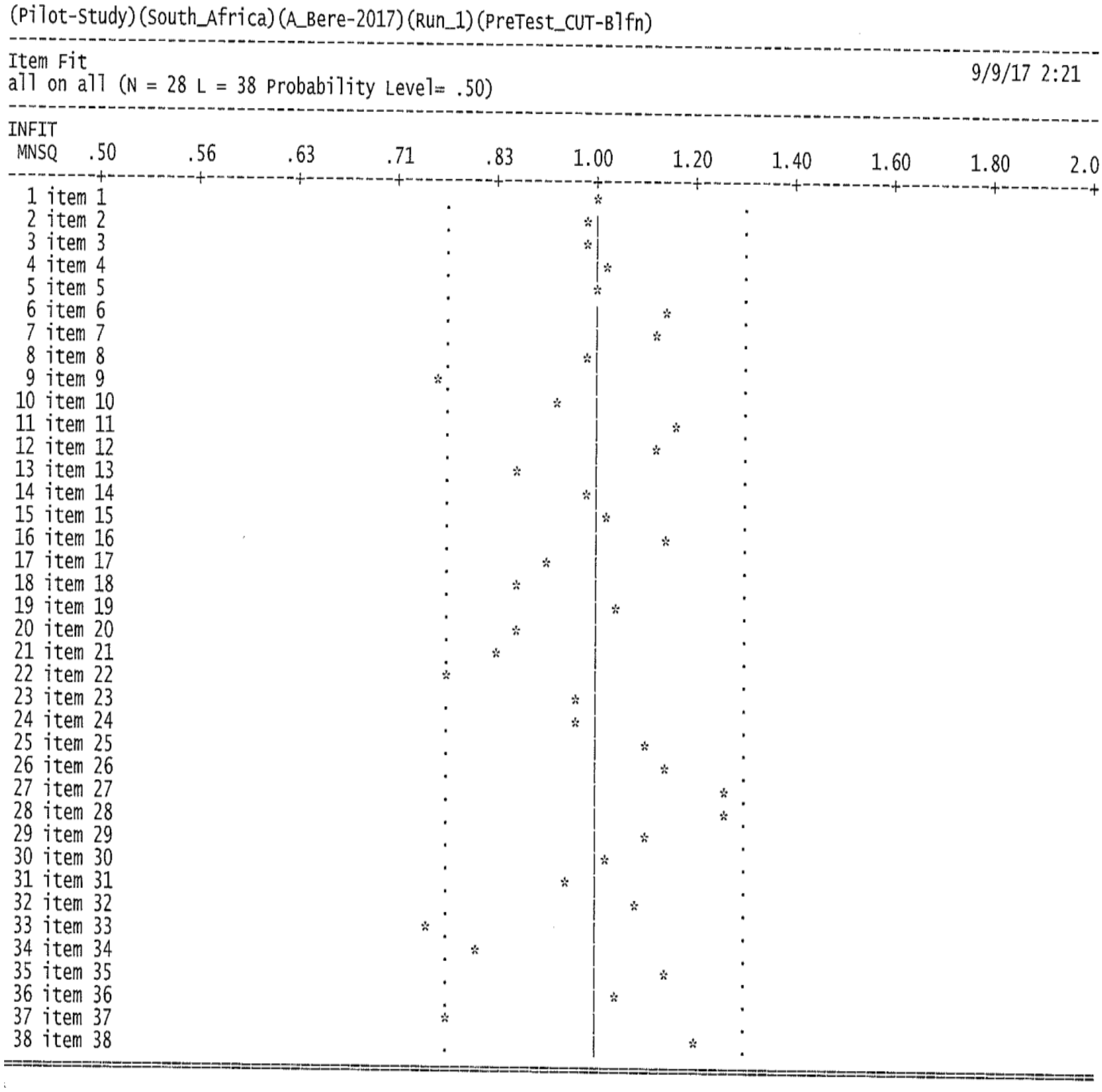

Figure 5. 4 Item Fit Map for Pilot Study Pre-Test Run-1

Test-item-9 is a partial credit item scoring either 0 or 1 or 2 in an open-ended question format. As shown in Table 5.4, the Infit MNSQ for test-item-9 is 0.75 which is close to 0.77 Rasch model lower limit threshold. The discrimination value is 0.66 which is exceedingly more than 0.2 recommended in Wu and Adams (2007). This means that test-item 9 is discriminating well among the participants. It provides a very high discrimination effect on the measurement of developing a query using SQL in the database management course when it is correlated with the overall score of the test. This shows that test-item 9 is a reliable question. As a result, it is justifiable to keep test-item 9 in the pre-test survey instrument of this study.

Table 5. 4 Item Analysis Results for Pre-Test Test-Item 9

Category	**Results**
Infit MNSQ	0.75
Discrimination	0.66

Test-item-9 is an important ability that has to be tested in the database management course in South African higher education. For this reason, it should not be deleted from the pre-test survey instrument. As a result, a decision is made not to remove it.

Test-item 33 is investigated because it misfits the Rasch model. It is a partial credit item scoring either 0 or 1 or 2 in an open-ended question format. As shown in Table 5.5, the Infit MNSQ for test-item 9 is 0.76 which is slightly below the 0.77 Rasch model threshold. It records a 0.73 discrimination value, which is way much more than the recommended value of 0.2 (Wu and Adams, 2007). This leads to the understanding that test-item 33 discriminates well among the participants. Test-item 33 provides a very high discrimination effect on the measurement of query development using SQL when it is correlated with the overall score of the test. As a result, test-item 33 is a reliable question.

Table 5. 5 Item Analysis Results for Pre-Test Test-Item 33

Category	Results
Infit MNSQ	0.76
Discrimination	0.73

Test-item-33 misfits the Rasch model because it tests a construct that has already been tested by test-item 21. The ability tested by these two test-items is usually confusing to beginners in SQL development. For this reason, it is necessary to evaluate student understanding of a single concept using two different questions. Therefore, test-item-33 should not be deleted.

The pre-test survey instrument is validated in a pilot study. As shown in Table 5.6, the pre-test survey instrument supports a very strong internal consistency of 0.82. This value surpasses the recommended value of 0.7 in the study of Wu and Adams (2007). This means that the pre-test survey in this study is a valid data collection instrument. The survey instrument obtained a mean test score of 39.97. This suggests that the participant average score is close to 50% of the total score of 77. A standard deviation of 10.20 suggests that the scores of most participant are clustered close to each other. This leads to the understanding that the survey instrument is a fair measurement for most participants.

Table 5. 6 Pilot Study Pre-Test Validation Results

Measurement	Results
Mean Test score	39.97
Standard Deviation	10.20
Internal Consistency	0.82

Data gathered in the pilot study for testing the reliability and validity of the post-test survey is examined. The data-file for 28 participants is run on the Quest Interactive Test-Analysis System (Adams and Khoo, 1996) using an appropriate control (command) and data-file. Both files are prepared in notepad. As shown in Figure 5.8, test-items 14 overfit the Rasch model. Misfit test-items should be eliminated from the data collection instruments before the next run on the Quest Interactive Test-Analysis System as proposed by Adams and Khoo (1996). There are exceptional cases that must be considered for keeping such test-items in the research instrument (Yuan, 2005).

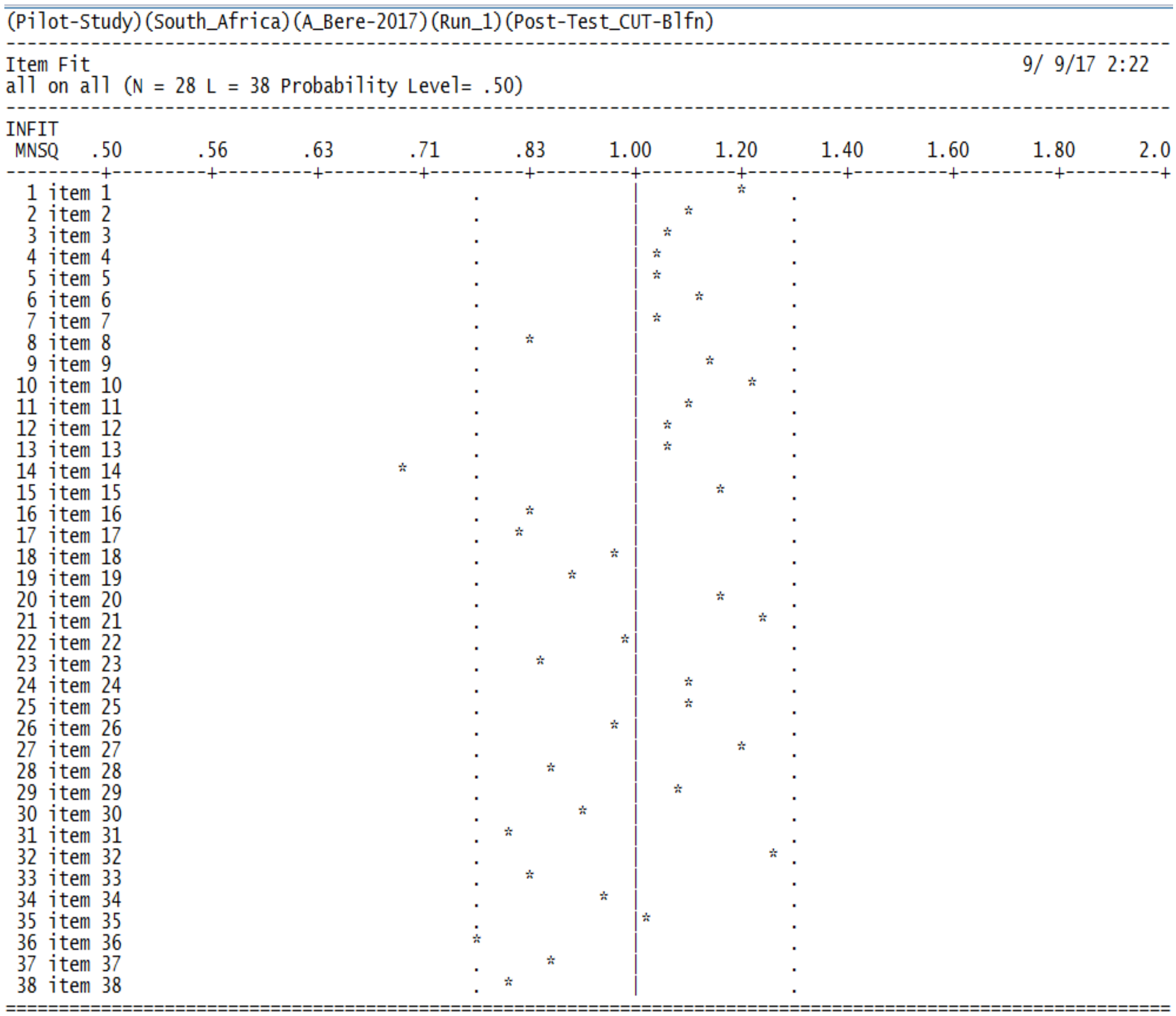

Figure 5. 5 The Item Fit Map for Pilot Study Post-Test Run-1

Test-item 14 of the post-test is investigated because it misfits the Rasch model. It is a partial credit item scoring either 0 or 1 or 2 in an open-ended question format. As shown in Table 5.5, the Infit MNSQ for test-item-14 is 0.68 which is less than 0.77 Rasch model threshold. Its discrimination value is 0.74. As a result, test-item-14 discriminates well among the participants. In this pilot study, the post-test test-item 14 provides a very high discrimination effect on the measurement of SQL query development in Database management systems course when it is correlated with the overall score of the test. As a result, test-item 14 is an important question for the research instrument of this study.

Table 5.7 Item Analysis Results for Post-Test Test-Item 14

Category	Results
Infit MNSQ	0.68
Discrimination	0.74

Test-item 14 is an important ability that participants need to be tested on. As a result, it should not be deleted from the survey instrument. Another motivation for keeping test-item-14 in the post-test instrument is that over-fit test-items can remain in the scales at the discretion of the research investigators (Yuan, 2005). This leads to the understanding that test-item 14 in the post-test survey is an important question in the development of SQL queries in Database management systems course.

The validation of the post-test survey instrument in the pilot study is undertaken. As shown in Table 5.8, the post-test survey instrument supports a very strong internal consistency of 0.92 which surpasses the recommended value of 0.7 in Wu and Adams (2007). This means that the post-test in this study is a valid data collection instrument. The survey instrument obtained a mean test score of 41.07. This means that the participant average score is over 50% of the total score. A relatively small standard deviation of 09.65 is presented. This shows that most participant scores are clustered close to each other. This leads to the understanding that the survey instrument is a valid instrument for measuring the performance in database management course.

Table 5:1 Pilot Study Post-Test Validation Results

Measurements	Results
Mean Test score	41.07
Standard Deviation	13.02
Internal Consistency	0.92

5.4 Concluding Remarks

This chapter presents the development and validation of the survey instruments. A seven-stage iterative development process is adopted to allow the development of the research survey instruments using the instructional sequence theory proposed in Gagné (1985). Test-items at developed from related literature and teaching and learning resources for the database management systems course in South African higher education. A pilot study is employed for survey instrument testing. The Quest Interactive Test-Analysis System is adopted for the validation of the survey instrument through the Rasch IRT model. Both pre-test and post-test survey instruments have returned 38 test-item after instrument validation.

Chapter 6

Impact of LMS on Teaching and Learning

6.1 Introduction

LMS has been being increasingly adopted for teaching and learning in higher education across the world. This is exemplified by nearly 5.3 million higher education students adopting LMS in at least one course in 2014 (Murphy and Stewart, 2017). The popularity of LMS is due to the benefits that LMS offers to both students and higher education providers, including the availability of flexible learning options, improved access to higher education, increased efficiency on teaching and learning, reduced educational costs, and saving of classroom space (Dlodlo, 2009, Murphy and Stewart, 2017).

The potential benefits of LMS lead to the tremendous investment being committed in the adoption of this technology for the delivery of teaching and learning in higher education (Youssef and Dahmani, 2008). A university in the United Kingdom, for example, has initiated an LMS implementation project between 2000 and 2003 which required an initial investment of 35 million pounds (Ravjee, 2007). As a consequence, there is an increasing need for a better understanding of the impact of LMS on teaching and learning in higher education.

The South African government is committed to developing its higher education for improving teaching and learning by adopting the latest digital technologies including LMS in teaching and learning (Murire and Cilliers, 2017, Bere et al., 2018b). It has developed various strategies and policies for the development of higher education blended learning. This leads to the implementation of specific initiatives and projects in the higher education sector in South Africa. There are, for example, several funded projects that have been initiated for establishing the fundamental infrastructure to facilitate the adoption of LMS at higher education institutions. Specific trainings have been provided to encourage academics and students to make use of LMS with the development of various strategies and policies in guiding the use of LMS in blended learning (Ng'ambi et al., 2016). With such a tremendous amount of investment in the adoption of LMS for developing teaching and learning in South African higher education, there is an increasing need for adequately evaluating the impact of LMS on the performance of learning.

Investigating the impact of LMS on the performance of learning in South African higher education is highly desirable. This is because such an investigation can help higher education managers and academics better understand the impact of LMS on the performance of learning. This can lead to the formation and implementation of more effective teaching and learning strategies in higher education for improving the performance of learning through an optimal implementation of LMS. Furthermore, such an investigation can help instructional designers to apply appropriate strategies for designing a better LMS platform in the process of improving the performance of learning in higher education in South Africa.

This chapter presents an investigation of the impact of LMS on the performance of learning in higher education in South Africa. To effectively achieve this objective, some descriptive statistics, t-tests and regression techniques have been applied in this study. These statistical techniques are used to analyse survey data collected in South African higher education. This leads to specific observations on the impact of LMS on the performance of learning in higher education.

This chapter is organised into four sections. Section 6.2 presents the data analysis results for investigating the impact of LMS on the performance of learning in higher education. Section 6.3 provides research findings and discussion. Section 6.4 ends the chapter with some concluding remarks.

6.2 Data Analysis

The analysis of the data is organised as follows. First, the impact of LMS in blended learning on the performance of learning is presented. This is achieved through the use of specific data analysis techniques, including descriptive statistics and paired sample t-test. Second, the impact of individual characteristics of participants, including gender, language, race, and age on the performance of learning using LMS in blended learning is explored. Such an investigation is conducted using descriptive statistics and regression analysis. As a result, a better understanding of the impact of LMS in blended learning on the performance of learning in higher education can be achieved.

Impact of LMS on the performance of learning

In this study, the performance of learning is measured using the grade of the participant. Grades are a reliable measure of the performance of learning in higher education (Davies and Graff, 2005, Bere et al., 2018a). This is because grades are an objective measurement of the performance of learning in a specific situation (Davies and Graff, 2005, Bere and Rambe, 2016). In this study, pre-test and post-test surveys are used to collect data from the participants in the LMS + F2F teaching group in higher education institutions in South Africa for investigating the impact of LMS on the performance of learning.

The impact of LMS on the performance of learning is examined using the measure of the central tendency. These measures include the mean and the mean difference. Table 6.1 presents a summary of the measures of the central tendency in the investigation of the performance of learning using LMS. Such an analysis is crucial because it can help understand whether there is an improvement in the performance of learning or not.

The mean measures the central tendency of the performance of the participant in the investigation of the impact of LMS on the performance of learning. As indicated in Table 6.1, the values of the mean for the LMS + F2F group are 39.24 for pre-test and 55.91 for post-test respectively. The mean differences in the LMS + F2F group is 16.67

and the positive mean difference indicates that the post-test values are higher than the pre-test values. Such results suggest an improvement in the performance of learning through the adoption of LMS in higher education. This means that the use of LMS has a positive impact on the performance of learning in South African higher education.

Table 6.1 Measure of Central Tendency for LMS Group

	Survey	**Mean**	**Mean Difference**
LMS + F2F	Pre-Test	39.24	16.67
	Post-Test	55.91	

An examination of the spread of the data is essential for better understanding the impact of LMS on the performance of learning in higher education. As shown in Table 6.2, the values of the standard deviation for the LMS + F2F group are 14.58 for pre-test and 17.87 for post-test respectively. These standard deviations are associated with the mean values of 39.24 for pre-test and 55.91 for post-test, as shown in Table 6.1. Such results indicate that most participants have scored between 24.66 and 53.82 in pre-test out of 87. Such results show that most participants have obtained a score between 28.34 % and 61.86%. In post-test, the results show that most participants have obtained a score between 38.04 and 73.78 in post-test. This reveals that most of the participants in the post-test have scored between 43.72 % and 84.80 %. These descriptive statistics results suggest that the adoption of LMS in blended learning has a positive impact on the performance of learning in higher education in South Africa.

Table 6.2 Measure of the Variability in LMS Group

	Survey	Standard Deviation
LMS + F2F	Pre-Test	14.58
	Post-Test	17.87

The paired-sample t-test is used to determine whether the mean difference between the pre-test and post-test data in this study is significantly different from zero. This test is done due to the understanding that the paired-sample t-test is a more reliable indication of the impact of LMS on the performance of learning than descriptive statistics.

An analysis of Table 6.3 shows the results of the paired-samples *t*-test for the investigation of the impact of LMS on the performance of learning. Such results are presented in two parts including a paired samples test and paired samples correlations as shown in Table 6.3. The paired samples test results reveal that there is a significant relationship between the use of LMS and the increase in the performance of teaching and teaching. This is demonstrated by a *t*-value of 11,846 with the degree of freedom at 53 and $p < 0.001$ as shown in Table 6.3.

To examine the impact of LMS on the performance of learning, both the pre-test and post-scores need to be assessed in order to account for the influences of general ability and pre-existing knowledge. Students with higher pre-test scores tend to also have high post-test scores because of these influences. This is demonstrated by the correlation efficient at 0.816 and $p < 0.001$ as shown in Table 6.3.

Table 6.3 Paired Samples T-Test in LMS Group

Pair	**Paired Samples Test**			**Paired Samples Correlations**		
	t	df	p (2-tailed)	Count	Correlation	p
Pre-test & Post-test	-11.863	53	0.000	54	0.816	0.000

Impact of gender on learning performance

The measure of the central tendency with respect to the impact of gender on the performance of learning using LMS in higher education is examined. Table 6.4 shows that the mean values for LMS + F2F group of male participants are 41.85 for pre-test and 59.73 for post-test. The value of the mean difference for male participants in this group is 17.88. In the female group, Table 6.4 reveals that the mean values are 36.82 for pre-test and 52.36 for post-test. This leads to a positive mean difference of 15.54. Such results reveal that both male and female participants in the LMS +F2F group have obtained higher mean values in the post-test than those in the pre-test. This means that the adoption of LMS has a positive impact on both male and female students on the performance of learning in higher education.

Table 6.4 Mean of LMS Group Scores by Gender

Gender	Survey	Count	Mean	Mean Difference
Male	Pre-test	26	41.85	17.88
	Post-test	26	59.73	
Female	Pre-test	28	36.82	15.84
	Post-test	28	52.36	

An analysis in Table 6.5 reveals the variability of the data in the investigation of the impact of gender on the performance of learning using LMS in higher education in South Africa. Table 6.5 shows that the standard deviation for the male participants in the LMS + F2F group is 13.75 for pre-test and 18.80 for post-test. Such values of the standard deviation are associated with the mean values of 41.85 for pre-test and 59.73 for post-test as shown in Table 6.4. This leads to the understanding that most male participants in the LMS + F2F group have obtained scores between 28.10 and 55.60 out of the total score of 87. This shows that most male participants have scored in the LMS + F2F group between 32.30% and 65.94% in pre-test. In the post-test, most male participants in the LMS + F2F group have obtained scores between 40.93 and 78.53 out of the total score of 87. Such results suggest that most male participants in the LMS + F2F group have scored between 37.13% and 90.25% in post-test. These results lead to the understanding that the adoption of LMS has a positive impact on male students on the performance of learning in higher education.

An analysis of Table 6.5 shows that the standard deviation of the female participants in the LMS + F2F group is 15.16 for pre-test and 16.51 for post-test respectively. Such standard deviation values are associated with the mean values of the female participants in the LMS + F2F group of 36.82 for pre-test and 52.36 for post-test as shown in Table 6.4. Such results suggest that most females in the LMS + F2F group have obtained scores between 21.66 and 51.98 in pre-test. out of a total score of 87. These results indicate that most female participants in the LMS + F2F group have scored between 24.90% and 59.75% in the pre-test. In the post-test, most females in the LMS + F2F group have obtained scores between 35.85 and 68.87 in pre-test out of a total score of 87. These results indicate that most female participants in the LMS + F2F group have scored between 41.21% and 79.16 % in the post-test. This analysis shows that the adoption of LMS in teaching and learning has a positive impact on female students on the performance of learning in higher education.

An analysis of the impact of gender on the performance of learning using LMS in blended learning in South African higher education has been examined. Findings of the study reveal an improvement in the performance of learning for both male and female participants in the blended learning using LMS group. This finding shows that the adoption of LMS is beneficial for both male and female students with respect to the performance of learning in higher education in South Africa. This shows that the performance of learning in blended learning using LMS is not influenced by the gender of a participant.

Table 6.5 Standard Deviations of LMS Group Scores by Gender

Gender	Survey	Standard Deviation
Male	Pre-test	13.75
	Post-test	18.80
Female	Pre-test	15.16
	Post-test	16.51

The impact of gender on the performance of learning using LMS in higher education in South Africa in this study is also examined using multiple linear regression. Multiple linear regression is more reliable than descriptive statistics for investigating the impact of the participant characteristics on the performance of learning in higher education. It is extremely relevant to adopt multiple linear regression in this study. Such an analysis can help generate more reliable findings for the study with respect to the investigation of the impact of gender on the performance of learning using LMS in higher education in South Africa.

The results of the regression analysis in the investigation of the impact of gender on the performance of learning using LMS is presented in Table 6.6. Such results show that the gender of a participant has no statistically significant impact on the performance of learning using LMS. This is demonstrated by a Beta value of 0.115, t value of 0.833, and p-value of 0.409. This means that the performance of learning using LMS is not influenced by the gender of a participant.

Table 6.6 Regression Analysis of LMS Group Scores by Gender

	Unstandardized Coefficients		Standardized Coefficients		
	B	Std. Error	Beta	t	p
Constant	15.536	1.957		7.939	0.000
Male	2.349	2.820	0.115	0.833	0.409

Impact of language on learning performance

An analysis in Table 6.7 reveals the measure of the central tendency for exploring the impact of language on the performance of learning using LMS in this study. As shown in Table 6.7, the mean values for the LMS + F2F group of native language participants are 32.94 for pre-test and 47.33 for post-test respectively. The mean values for the LMS + F2F group of English language participants are 65.17 for pre-test and 83.33 for post-test. Afrikaans language obtained mean values of 41.11 for pre-test and 60.56 for post-test. In foreign language, the mean values are 45.17 for pre-test and 68.67 for post-test as shown in Table 6.7. This leads to positive mean differences of 14.39, 18.16, 19.45, and 23.50 for native language, English language, Afrikaans language, and Foreign language respectively. These results reveal that participants across different languages in the LMS + F2F group have obtained higher mean values in the post-test than those in pre-test. This means that the use of LMS with F2F teaching has a positive impact on students across different languages on the performance of learning in higher education.

An analysis of the variability is shown in Table 6.8, the standard deviation values of the native language participants in the LMS + F2F group is 10.53 for pre-test and 13.04 for post-test. As shown in Table 6.7, the mean values for native language participants are 32.94 for pre-test and 47.33 for post-test. Such results indicate that native language participants in the LMS + F2F group have obtained scores between 22.41 and 43.47 in pre-test out of a total score of 87. This shows that most native language participants in the group have scored between 25.76% and 49.97% in the pre-test. In the post-test, most native language participants in the group have obtained scores between 34.29 and 60.37 out of 87. This shows that most native language participants have scored between 39.41% and 69.39% in post-test. This finding reveals that the use of LMS with F2F teaching has a positive impact on native language students on the performance of learning in higher education.

Table 6. 7 Mean of LMS Group Scores by Language

Language	Survey	Count	Mean	Mean Difference
Native	Pre-test	33	32.94	14.39
	Post-test	33	47.33	
English	Pre-test	6	65.17	18.16
	Post-test	6	83.33	
Afrikaans	Pre-test	9	41.11	19.45
	Post-test	9	60.56	
Foreign	Pre-test	6	45.17	23.50
	Post-test	6	68.67	

The variability of the data in the investigation of the impact of English language on the performance of learning in higher education is examined. Table 6.8 shows that the standard deviation for English language participants in the LMS + F2F group is 9.00 for pre-test and 8.42 for post-test. As indicated in Table 6.7, the mean values for English language participants are 65.17 for pre-test and 83.33 post-test. This leads to the understanding that most English language participants in the LMS + F2F group have obtained scores between 56.17 and 74.17 in pre-test out of 87. This shows that the performance of most English language participants in the LMS + F2F group is between 64.56% and 85.25% in the pre-test. The post-test scores for most English language participants in the LMS + F2F group is between 74.91 and 87 out of a total score of 87. This shows that most English language participants in the group have obtained scores between 86.10% and 100%. This analysis reveals that the use of LMS with F2F teaching has a positive impact on English language students on the performance of learning in higher education.

An analysis in Table 6.8 shows that the standard deviation for Afrikaans language participants in the LMS + F2F group is 7.47 for pre-test and 2.58 for post-test. These values of the standard deviation are related to the mean values of the Afrikaans language participants in the LMS + F2F group of 41.11 for pre-test and 60.56 for post-test as indicated in Table 6.7. These results show that most Afrikaans language participants in the LMS + F2F group have obtained scores between 33.64 and 48.58 out of 87 in pre-test. As a result, the performance of learning of most Afrikaans language participants in the group is between 38.67% and 55.84% in pre-test. In post-test, most Afrikaans language participants in the LMS + F2F group have obtained scores between 57.98 and 63.14 out of 87. This shows that the performance of learning of most of Afrikaans language participants in the group is between 66.64% and 72.57%. This leads to the understanding that the use of LMS with F2F teaching has a positive impact on Afrikaans language students on the performance of learning in higher education.

The standard deviation of foreign language participants in the LMS + F2F group is 10.29 for pre-test and 9.64 for post-test as indicated in Table 6.8. Such values of the standard deviation are associated with the mean values of 45.17 for pre-test and 68.67

for post-test as shown in Table 6.7. This leads to the understanding that most foreign language participants in the group have obtained scores between 34.88 and 55.46 in pre-test out of 87 scores. This means that the performance of learning of the foreign language participants in the LMS + F2F group is between 40.09% and 63.75%. In post-test, most foreign language participants have obtained scores between 59.27 and 78.31 out of 87. Such results indicate that the performance of learning of the foreign language participants in the group is between 68.12% and 90.01% in post-test. This suggests that the adoption of LMS has a positive impact on foreign language students on the performance of learning in higher education.

An analysis of the impact of language on the performance of learning using LMS + F2F in South African higher education has been examined. Findings of the study show similar improvements in the performance of learning across English with a mean of 18.46 and Afrikaans with a mean of 19.45. However, foreign language participants in the group demonstrate a slightly higher improvement on the performance of learning compared to the other languages in the study (mean = 23.50). In contrast, the native language presents a slightly smaller improvement in the performance of learning compared to other languages. Overall, the finding shows that the use of LMS has a positive impact on student across different languages on the performance of learning in higher education in South Africa. This shows that the performance of learning using LMS is not significantly influenced by the language of a participant.

Table 6. 8 Standard Deviations of LMS Group Scores by Language

Languages	Surveys	Standard Deviation
Native	Pre-test	10.53
	Post-test	13.04
English	Pre-test	9.00
	Post-test	8.42
Afrikaans	Pre-test	7.47
	Post-test	2.58
Foreign	Pre-test	10.29
	Post-test	9.64

The impact of language on the performance of learning using LMS is examined using regression analysis in this study. Table 6.9 reveal that the language of a participant across English (Beta = 0.116, t = 0.840, p = 0.405), Afrikaans (Beta = 0.184, t = 1.328, p = 0.190), and foreign language (Beta = 2.028, t = 0.280, p = 0.058) has no significant impact on the performance of learning using LMS. This means that the performance of learning using LMS is not influenced by the language of instruction.

Table 6. 9 Regression of LMS Group Scores by Language

	Unstandardized Coefficients		Standardized Coefficients		
	B	Std. Error	Beta	t	p
Constant	14.394	1.761		8.174	0.000
English	3.773	4.490	0.116	0.840	0.405
Afrikaans	5.051	3.804	0.184	1.328	0.190
Foreign	9.106	4.490	0.280	2.028	0.058

Impact of race on learning performance

The impact of race on the performance of learning in higher education using LMS is examined using the mean values of the data. As shown in Table 6.10, the mean values for the LMS + F2F group of African participants are 34.53 for pre-test and 49.92 for post-test. This leads to a positive mean difference of 15.39. The mean values for the LMS + F2F group of mixed-race participants are 42.20 for pre-test and 65.60 for post-test. Such data provides a positive mean difference of 23.40. In the western race, the mean values of 64.17 for pre-test and 77.67 for post-test are obtained as shown in Table 6.10. Such results reveal a positive mean difference of 13.50. Such results reveal that participants across different races in the LMS + F2F group have obtained higher mean values in the post-test than those in pre-test. This finding shows that the adoption of LMS with F2F teaching has a positive impact on students across different racial groups in their performance of learning.

Table 6. 10 Mean of LMS Group Scores by Race

Race	Survey	Count	Mean	Mean Difference
African	Pre-test	38	34.53	15.39
	Post-test	38	49.92	
Mixed	Pre-test	10	42.20	23.40
	Post-test	10	65.60	
Western	Pre-test	6	64.17	13.50
	Post-test	6	77.67	

The variability of the data in the investigation of the impact of race on the performance of learning in higher education using LMS and F2F teaching is examined. As shown in Table 6.11, the standard deviation for African participants in the LMS + F2F group is 11.17 for pre-test and 14.74 for post-test. As indicated in Table 6.10, the mean values for African participants in the group are 34.53 for pre-test and 49.92 for post-test. This shows that most African participants in the LMS + F2F group scored between 23.36 and 45.70 in pre-test out of 87. This leads to the understanding that the performance in most African participants in the LMS + F2F group is between 26.85 % and 52.52% in the pre-test. In post-test, most African participants scored between 35.18 and 64.66 out of 87. This indicates that the performance in most African participants in the LMS + F2F group is between 40.44% and 74.32%. in the post-test. This finding shows that

African race participants perform better in post-test than in the pre-test. This analysis reveals that the use of LMS with F2F teaching has a positive impact on African students on the performance of learning in higher education.

The impact of mixed-race on the performance of learning using LMS and F2F teaching in higher education in South Africa is examined using the variability of the data. As shown in Table 6.11 the standard deviation of mixed-race participants in the LMS + F2F group is 13.58 for pre-test and 17.61 for post-test. These standard deviation values are associated to the mean values of 42.20 for pre-test and 65.60 for post-test as indicated in Table 6.10. Such results show that most mixed-race participants in the LMS + F2F group scored between 28.62 and 55.78 in pre-test out of 87. This shows that most mixed-race participants in the group have scored between 32.90% and 64.11% in the pre-test. In post-test, most mixed-race participants in the LMS + F2F group have obtained scores between 47.99 and 83.21 out of 87. This leads to the understanding that most mixed-race participants in the group have scored between 55.16 % and 95.64% in post-test. This analysis indicates that the adoption of LMS with F2F teaching has a positive impact on mixed-race students on the performance of learning in higher education.

The impact of western race on the performance of learning using LMS and F2F teaching in higher education in South Africa is examined using standard deviation. As indicated in Table 6.11 the standard deviation of western race participants in the LMS + F2F group is 8.18 for pre-test and 13.79 for post-test. Table 6.10 shows that the mean values of western race participants in the LMS + F2F group is 64.17 for pre-test and

77.67 for post-test. This shows that most western race participants obtained scores between 55.99 and 72.35 in pre-test out of a total score of 87. This indicates that most western race participants have scored between 64.36% and 83.16% in pre-test. In post-test, most western race participants in the LMS + F2F group have scored between 63.88 and 87 out of 87. These results show that most western race participants in the LMS + F2F group have scored between 73.46% and 100% in post-test. This analysis reveals that the use of LMS with F2F teaching has a positive impact on western race students on the performance of learning in higher education.

An analysis of the impact of race on the performance of learning using LMS + F2F in South African higher education has been examined. Findings of the study reveal similar improvements in the performance of learning for both African and western race participants (means of 15.39 and 13.5 respectively). The improvement of mixed-race participants is relatively higher than the performance in African and western race participants (Mixed-race mean = 23.40). Overall, the adoption of LMS has a positive impact on students of all races in their performance of learning in higher education in South Africa.

Table 6. 11 Standard Deviations of LMS Group Scores by Race

Race	Survey	Standard Deviation
African	Pre-test	11.17
	Post-test	14.74
Mixed	Pre-test	13.58
	Post-test	17.61
Western	Pre-test	8.18
	Post-test	13.79

The impact of race on the performance of learning using LMS is examined using regression analysis. This because regression analysis can help predict the impact of race on the performance of learning. Table 6.12 shows that the results of the regression analysis indicate statistically not insignificant results across African and mixed-race in the investigation of the impact of race on the performance of learning using LMS in higher education. This is demonstrated by a Beta-value of 0.085, t-value of 0.432, and p-value of 0.667 for African race and Beta-value of 0.376, t-value of 1.922, and p-value of 0.060 for mixed-race as shown in Table 6.12. This means that the performance of learning using LMS is not influenced by the race of a student.

Table 6.12 Regression Analysis of the LMS Group Scores by Race

	Unstandardized Coefficients		Standardized Coefficients		
	B	Std. Error	Beta	*t*	*p*
Constant	13.500	4.072		3.315	0.002
African	1.895	4.382	0.085	0.432	0.667
Mixed-race	9.900	5.151	0.376	1.922	0.060

Impact of age on learning performance

The measure of the central tendency about the impact of age on the performance of learning using LMS and F2F teaching is examined. As shown in Table 6.13, the mean values for 18 -21 years age group are 36.60 for pre-test and 49.00 for post-test. The age group from 22 years to 25 years has mean values of 45.07 for pre-test and 63.56 for post-test. The 26-29 years age group has mean values of 33.92 for pre-test and 50.75 for post-test. The participants who are 30 years and older have obtained mean values of 25.80 for pre-test and 40.80 for post-test. This shows that the participants across all ages in the LMS + F2F group have obtained higher mean values in the post-test than those in pre-test. It means that the use of LMS with F2F teaching has a positive impact on the performance of learning in higher education.

Table 6.13 An Overview of the Means of the LMS Group Scores by Age

Age	Survey	Count	Mean	Mean Difference
18-21	Pre-test	10	36.60	12.40
	Post-test	10	49.00	
22-25	Pre-test	27	45.07	17.86
	Post-test	27	63.56	
26-29	Pre-test	12	33.92	16.83
	Post-test	12	50.75	
30Plus	Pre-test	5	25.80	14.28
	Post-test	5	40.80	

The impact of gender on the performance of learning in higher education in South Africa is examined. As shown in Table 6.14, the standard deviation for the 18 to 21 years old participants in the LMS + F2F group is 17.69 for pre-test and 20.34 for post-test. Table 6.13 shows that the mean values for participants in the 18 to 21 years age group are 36.60 for pre-test and 49.00 for the pre-test. This shows that most participants from 18 years to 21 years have obtained scores between 18.91 and 54.29 out of 87. In post-test, most 18 to 21 years old participants have obtained scores between 28.66 and 69.34 out of 87. This analysis indicates that the adoption of LMS with F2F teaching has a positive impact on the performance of learning.

An analysis of Table 6.14 indicates that the standard deviation of the 22 to 25 years old participants is 13.75 for pre-test and 14.88 for post-test respectively. These standard deviation values are linked to the mean values of the 22 to 25 years old participants in the LMS + F2F group of 45.07 for pre-test and 63.56 for post-test as shown in Table 6.13. Such results show that most 22 to 25 years old participants in the group have obtained scores between 31.32 and 58.82 out of 87. In the post-test, most participants from 22 to 25 years of age have obtained scores between 48.68 and 78.44. This analysis shows that the use of LMS with F2F teaching has a positive impact on the performance of learning in higher education.

The standard deviation of the participants from 26 to 29 years of age is 8.97 for pre-test and 16.76 for post-test respectively as shown in Table 6.14. Such standard deviation values are associated to the mean values of the 26 to 29 years old participants in the LMS + F2F group of 33.92 for pre-test and 50.75 for post-test as shown in Table 6.13. This shows that most participants from 26 to 29 years of age in the group have obtained scores between 24.95 and 42.89 in the pre-test out of a total score of 87. Such results indicate that most participants from 26 to 29 years old in the group have scored between 28.68% and 49.30% in the pre-test. In the post-test, most participants from 26 to 29 years of age have obtained scores between 33.99 and 67.51 out of 87. Such results show that most 26 to 29-year-old participants in the group have scored between 39.07 % and 77.60 % in the post-test. This analysis shows that the use of LMS with F2F teaching has a positive impact on 26 to 29-year-old students in their performance of learning in higher education.

An analysis of Table 6.14 reveals that the standard deviation of the participants from 30 years and above is 10.26 for pre-test and 14.48 for post-test respectively. Such standard deviation values are related to the mean values of the participants from 30 years and over in the LMS + F2F group of 25.80 for pre-test and 40.80 for post-test as shown in Table 6.13. Such results show that most participants from 30 years and older in the group have obtained scores between 15.54 and 36.06 in the pre-test out of a total score of 87. These results show that most participants from 30 years and older in the group have scored between 17.86% and 41.45% in the pre-test. In the post-test, most participants from 30 years and older have obtained scores between 26.32 and 55.28 out of 87. These results indicate that most 30 years and older participants in the group have scored between 30.25 % and 63.54 % in the post-test. This analysis indicates that the use of LMS with F2F teaching has a positive impact on students from 30 years and older in their performance of learning in higher education.

An analysis of the impact of age on the performance of learning using LMS + F2F in South African higher education has been examined. This study reveals similar findings in the performance of learning for participants in the 18-21 years and 30 years and older age groups. Participants in the 22-25 years and 26-29 years age groups demonstrate similar improvements in their performance of learning. This shows that younger and older students perform slightly lower than average age students in the performance of learning using F2F and LMS. Overall, the finding shows that the adoption of LMS has a positive impact on students of all ages with respect to their performance of learning in higher education in South Africa.

Table 6. 14 Standard Deviations of LMS Group Scores by Age

Age	Survey	Count	Standard Deviation
18-21	Pre-test	10	17.69
	Post-test	10	20.34
22-25	Pre-test	27	13.75
	Post-test	27	14.88
26-29	Pre-test	12	8.97
	Post-test	12	16.76
30Plus	Pre-test	5	10.26
	Post-test	5	14.48

The impact of age on the performance of learning using LMS in higher education is examined using regression analysis. Table 7.15 presents the results of the regression analysis. It shows that participants from the 22 to 25 age group has a Beta value of 0.297, t-value of -1.586, and p-value 0.119. The age group from 26 to 29 years has a Beta-value of 0.180, t-value of 1.000, and p-value of 0.322. The age group from 30 years and above obtained a Beta-value of 0.074, t-value of 0.458, and p-value of 0.649. Such results show statistically not significant results across different participant ages in the investigation of the impact of age on the performance of learning using LMS in higher education. This leads to the understanding that the performance of learning using LMS is not influenced by the age.

Table 6. 15 Regression of LMS Group Scores by Age

	Unstandardized Coefficients		Standardized Coefficients		
	B	**Std. Error**	**Beta**	**T**	**p**
Constant	12.400	3.276		3.786	0.000
Age 22-25	6.081	3.835	0.297	1.586	0.119
Age 26-29	4.433	4.435	0.180	1.000	0.322
Age 30 plus	2.600	5.674	0.074	0.458	0.649

6.3 Research Findings and Discussion

Impact of LMS on learning performance

The data analysis results for investigating the impact of LMS on the performance of learning in higher education is presented. These results are obtained using the measure of central tendency and the measure of the variability of the data. The evaluation of the mean and standard deviation values of the data collected from participants in South African higher education show that LMS has a positive impact on the performance of learning in South African higher education as shown in Table 6.1 and Table 6.2. The hypothesis of the study (*Digital learning using LMS influence the performance of* *learning*) is examined using paired samples t-test statistics as indicated in Table 6.3. A t-test statistical analysis as sown in Table 6.3 reveals statistically significant results. Such a result reveals that the hypothesis of the study is consistent. This means that the adoption of LMS has a positive impact on the performance of learning in blended learning in South African higher education.

The finding of the study is consistent with the research in the use of LMS (Means et al., 2013, Gross et al., 2015, Okaz and Sciences, 2015, Shu et al., 2018, Li et al., 2019). Li et al. (2019), for example, show that LMS with F2F teaching has a positive impact on the acquisition of knowledge in teaching and learning in higher education. This is because LMS with F2F integrates the strengths of digital learning and F2F learning (Li et al., 2019). The adoption of LMS improves self-regulation and facilitates independent and collaborative experience outside the classroom setting. It builds a community of inquiry and a platform for free and interactive engagements. As a result, it creates opportunities for negotiating meaning, collaboration, and scaffolding (Okaz and Sciences, 2015). This leads to the understanding that the adoption of LMS in blended learning has a positive impact on the performance of learning.

The finding of the study contradicts that of Tarus et al. (2015) and Kaur and Sciences (2013). Kaur and Sciences (2013), for example, indicate various challenges of adopting LMS including technical, organisational, and instructional design challenges. Such challenges lead to inadequate access of digital technologies. This leads to a lack of experience in the use of LMS in teaching and learning. Such lack of experience directly affects a student's level of self-efficacy of LMS in teaching and learning.

Students with lower LMS self-efficacy experiences higher levels of anxiety when using digital technologies for teaching and learning (Huffman et al., 2013). These views suggest that the adoption of LMS with F2F is not beneficial with respect to the performance of learning.

Impact of gender on learning performance

The impact of gender on the performance of learning using LMS in higher education is examined using descriptive statistics and regression analysis. Findings of the descriptive statistics as shown in Table 6.4 and Table 6.5 suggest an improvement in the performance of learning using LMS for both male and female participants. Such results reveal that gender of a student has no influence on the performance of learning using LMS in higher education. Regression analysis is employed for examining the following hypothesis of the study. *Performance in teaching and learning using LMS is influenced by the gender of a student*. An analysis in Table 6.6 shows statistically nonsignificant results with respect to the impact of gender on the performance of learning in higher education. Such results show that the performance of learning using LMS is not influenced by the gender of a participant.

The finding of the study is consistent with the research on the impact of gender in the adoption of LMS in teaching and learning in higher education learning (Admiraal et al., 2014, Harb et al., 2014). Harb et al. (2014), for example, show that there is no gender disparity between male and female student with respect to knowledge acquisition using LMS. Such a finding is influenced by male and female's similar computer experience obtained from their higher education institutions and homes. This shows that the impact of gender differences on the performance of learning using LMS no longer exists due to increase in computer access for both male and female students.

The finding of the study contradicts with studies conducted by Ong and Lai (2006), Huffman et al. (2013) and Tai et al. (2013). Tai et al. (2013), for example, show significant gender differences with respect to attitudes towards the adoption of LMS and student outcomes. Such gender differences in teaching and learning using LMS are caused by student socio-cultural factors which might have existed before they enter higher education (Tai et al., 2013).

Impact of language on learning performance

The impact of language on the performance of learning using LMS in higher education is examined using values of mean, values of standard deviation, and regression analysis. Findings of the descriptive statistics as shown in Table 6.7 and Table 6.8 show an improvement on the performance of learning using LMS across different languages. This leads to the understanding that the language of a participant has no influence on the performance of learning using LMS in higher education. Regression analysis is adopted for testing the following hypothesis of the study. *Performance of learning using LMS is influenced by the language of a student*. The regression analysis results as shown in Table 6.9 reveals statistically nonsignificant results with regards to the impact of the language of a student on the performance of learning in higher education. This shows that the performance of learning using LMS is not influenced by the language of a participant.

The finding of the study is consistent with the research on the impact of language on the performance of learning (Swain and Lapkin, 1982). According to Swain and Lapkin (1982), the performance of learning does not change with the change in student language. This shows that student language has no effect on the impact of teaching and learning using LMS in higher education.

The finding of the study is inconsistent with the studies conducted by Eriksson (2014), (Seid, 2016) and Taylor and von Fintel (2016). Seid (2016), for example, indicate that the mother tongue improves performance of learning. As a result, it improves access to education and reduces drop-out rates (Seid, 2016). However, the disparity between the findings in this study and in Eriksson (2014), Seid (2016), and Seid (2016) could be due to two reasons. First, the studies of Eriksson (2014), Seid (2016), and Seid (2016) are conducted in primary education while this study is conducted in higher education. Second, their studies are based on F2F only while this study involves blended learning.

Impact of race on learning performance

The impact of race of a student on the performance of learning using LMS in blended learning in higher education is examined. Findings of the descriptive statistics as shown in Table 6.14 and Table 6.15 indicate an improvement in the performance of learning using LMS across different races. This indicates that the race of a participant has no influence on the performance of learning using IM in blended learning. To test the hypothesis of the study, regression analysis is adopted. The hypothesis of the study is as follows. *Performance of learning using LMS is influenced by the race of a student*. As shown in Table 6.12, regression analysis reveals statistically insignificant results across all races in the investigation of the impact of race on the performance of learning in higher education. This leads to the understanding that the performance of learning using LMS not influenced by the race of a participant.

The finding of the study is inconsistent with research conducted by Atkinson (1997) and Shi (2006). The findings in Atkinson (1997) and Shi (2006) proclaims that Africans are less eager to participate in teaching and learning activities compared to western race students. As a result, their performance of learning is lower than that of western race students (Atkinson, 1997, Shi, 2006). Such inconsistencies could be caused by the differences in contexts between the studies. For example, this study is conducted in blended learning while their studies are conducted in F2F only.

Impact of age on learning performance

The impact of the age of a participant on the performance of learning using LMS in blended learning in higher education is examined. The regression analysis is employed for testing the following hypothesis of the study. *Performance of learning using LMS is influenced by the age of a student*. In regression analysis, Table 6.15 shows statistically insignificant results for all age groups in the investigation of the impact of age on the performance of learning in higher education. Such results show that the performance of learning using LMS is not influenced by the age of a participant.

The finding of the study is consistent with the research conducted by Chung et al. (2010) and Tarhini et al. (2014b). Such studies show that student's perceived usefulness, perceived ease of use, and intentions to use LMS do not change with age in teaching and learning using LMS (Chung et al., 2010, Tarhini et al., 2014b). This means that the performance of learning using LMS is not influenced by the age of a student.

The finding of the study is inconsistent with the research on the impact of the age of a student on the performance of learning using LMS (Šumak et al., 2010, Tarhini et al., 2014a). Tarhini et al. (2014a), for example, reveals that the perceptions of a student on usefulness, ease of use, and behavioural intention to use LMS in teaching and learning using LMS changes with the age of a student. This shows that the age of a students has influence on the performance of learning using LMS in blended learning.

6.4 Concluding Remarks

The aim of this chapter is to investigate the impact of LMS on the performance of learning in higher education. This investigation is done by using various statistical data analysis methods including descriptive statistics, t-test, and regression analysis of the surveyed data collected from students in South African universities.

The findings reveal that the use of LMS has a positive impact on the performance of learning in higher education. Furthermore, findings also show that students characteristics including gender, language, race, and age have no influence on the performance of learning using LMS in higher education. The results of this study provide academics and LMS designers with a deep understanding of the impact of LMS on the performance of learning. Such understanding is useful for predicting the adoption of LMS in higher education, particularly in developing countries including South Africa.

Chapter 7

Impact of IM on Teaching and Learning

7.1 Introduction

The adoption of IM in teaching and learning leads to student-centred learning in higher education (So, 2016, Nkhoma et al., 2018). This is due to the technological and pedagogical affordances that these technologies offer. The technological affordance of IM includes temporal, multi-modal, user-friendly, minimal cost, and social presence (Rambe and Bere, 2013, Tang and Hew, 2017). The pedagogical affordances of IM in higher education include journaling, dialogic, transmissive, constructionist with peer feedback, helpline, and assessment (Tang and Hew, 2017).

There is lack of policies that guide the use of IM in teaching and learning in higher education (Alsaleem, 2013). As a consequence, there are various drawbacks for adopting IM in higher education including improper language use, dissemination of inappropriate materials, and interference with private lives (Tang and Hew, 2017). The development of ICT strategies and policies leads to a greater investment of financial and human resources by higher education institutes (Keakopa and Bwalya, 2011). To justify such financial investments, evidence must be provided on the potential benefit of adopting IM with regards to the improvement of the performance of learning in higher education.

Investigating the impact of IM on the performance of learning in South African higher education is highly desirable. This is because such an investigation can help academics better understand strategies for improving access to education for various students including those who are from low financial backgrounds, and those students who are shy to express themselves publicly in the classroom (Rambe and Bere, 2013). This can lead to the implementation of more efficient teaching and learning strategies in higher education for improving the performance of learning through an optimal implementation of IM.

The aim of this chapter is to investigate the impact of IM on the performance of learning in higher education. To achieve this objective, various statistical analysis including descriptive statistics, paired-samples *t*-test, and regression analysis are adopted for analysing data collected in this study. These analyses will provide empirical evidence on the impact of IM on the performance of learning in higher education. The chapter then discusses the findings of the study.

This chapter is organised into four sections. Section 7.2 shows the data analysis and results of the investigation on the impact of IM on the performance of learning in higher education. Section 7.3 provides research findings and discussion. Section 7.4 ends the chapter with some concluding remarks.

7.2 Data Analysis

The impact of IM on the performance of learning is examined using the measure of central tendency. As shown in Table 7.1, the mean and the mean difference provide an overview of the central tendency in the investigation of the performance of learning using IM. Such measures of central tendency are relevant because they can help to show whether there is an improvement in the performance of learning or not in higher education through the adoption of IM.

Table 7. 1 An Overview of the Mean of the IM Group

	Survey	Count	Mean	Mean Difference
IM + F2F	Pre-Test	51	38.08	14.72
	Post-Test	51	52.80	

The performance of learning using IM is examined using the mean as a measurement of the central tendency. Table 7.1 indicates that the values of the mean for the IM + F2F group are 38.08 for pre-test and 52.80 for post-test respectively. These mean measurements lead to a positive mean difference of 14.72. Such a result shows that the post-test mean value is higher than the pre-test mean value. This means that the use of IM with F2F teaching has a positive impact on the performance of learning in higher education in South Africa.

An examination of the variability of the empirical data using the standard deviation is essential for better understanding the impact of IM on the performance of learning in higher education. This is because the standard deviation gives a more accurate view of how the scores of individual participants are distributed in the analysis of the impact of IM on the performance of learning. Table 7.2 shows a summary of the measure of the variability examined in this study.

Table 7. 2 A Summary of the Standard Deviation of The IM Group

	Survey	Standard Deviation
IM + F2F	Pre-Test	9.71
	Post-Test	12.57

The standard deviation measures the variability of the data of the participant in the investigation of the impact of IM on the performance of learning in higher education in South Africa. Table 7.2 shows that the values of the standard deviation for the IM + F2F group are 9.71 for pre-test and 12.57 for post-test respectively. These standard deviations are associated to the mean values of 38.08 for pre-test and 52.80 for post-test, as shown in Table 7.1. Such results mean that most participants in the pre-test have scored between 28.37 and 47.79 out of a total score of 87. Such results reveal that most participants have obtained a score between 32.61 % and 54.93%. In the post-test, the results indicate that most participants have obtained a score between 40.23 and 65.37. This shows that the majority of the participants in the post-test have scored between 46.24% and 75.14%. This leads to the understanding that the use of IM with

F2F has a positive impact on the performance of learning in higher education in South Africa.

Table 7.3 shows that the pre-test score and post-test score in the IM + F2F group has a correlation coefficient of 0.717, with a degree of freedom (df) of 50, a *t*-value of 11.972 and a p-value < 0.001. Such results indicate that there is a significant relationship between pre-test and post-test scores. Students who scored higher in the pre-test also scored higher in the post-test. Therefore, when analysing students' learning, it is important to control for prior knowledge and general abilities using a pre-test.

Table 7. 3 Correlation Between IM Pre-test and Post-test Scores

	Correlation	**df**	**t**	**p**
IM + F2F	0.717	50	11.972	0.000

Impact of gender on learning performance

The measure of the central tendency with respect to the impact of gender on the performance of learning using IM with F2F teaching is examined. Table 7.4 shows that the mean values for the IM + F2F group of male participants are 40.74 for pre-test and 51.90 for post-test. This leads to a positive mean difference of 15.05. In the female group, Table 7.4 reveals that the mean values are 38.87 for pre-test and 53.39 for post-test. The value of the mean difference for female participants in the group is 14.52. These results show that both male and female participants in the IM + F2F group have obtained higher mean values in the post-test than those in the pre-test. Such results show that the use of IM with F2F teaching has a positive impact on both male and female students on the performance of learning.

Table 7. 4 An Overview of the Mean of the IM Group by Gender

	Gender	Survey	Count	Mean	Mean Difference
IM + F2F	Male	Pre-test	20	40.74	15.05
		Post-test	20	51.90	
	Female	Pre-test	31	38.87	14.52
		Post-test	31	53.39	

The variability of the data in the investigation of the impact of gender on the performance of learning in higher education in South Africa in this study is examined. As shown in Table 7.5, the standard deviation for the male participants in the IM + F2F group is 9.12 for pre-test and 13.51 for post-test. As indicated in Table 7.4, the mean values for male group are 40.74 for pre-test and 51.90 for the pre-test. Such results indicate that most male participants in the group have obtained scores between 31.62 and 49.86 out of the total score of 87. This indicates that most male participants in the group have scored between 36.34% and 57.31% in pre-test. In post-test, most male participants in the group have obtained scores between 38.39 and 65.41 out of the total score of 87. Such results show that most male participants in the group have scored between 44.13% and 75.18% in post-test. This analysis reveals that the use of

IM with F2F teaching has a positive impact on male students in the performance of learning in higher education.

An analysis of Table 7.5 shows that the standard deviation of the female participants is 10.14 for pre-test and 12.12 for post-test respectively. Such standard deviation values are related to the mean values of the female participants in the IM + F2F group of 38.87 for pre-test and 53.39 for post-test as shown in Table 7.4. This leads to the understanding that most females in the group have obtained scores between 28.73 and 49.01 in the pre-test out of a total score of 87. Such results indicate that most female participants in the group have scored between 33.02% and 61.67% in the pre-test. In the post-test, most females have obtained scores between 41.27 and 65.51. Such results show that most female participants in the group have scored between 47.43 % and 75.29 % in the post-test. This analysis shows that the use of IM with F2F teaching has a positive impact on female students on the performance of learning in higher education.

An analysis of the impact of gender on the performance of learning using IM + F2F in South African higher education has been examined. Findings of the study reveal a similar improvement in the performance of learning for both male and female participants (means of 15.05 and 14.52 respectively). This finding shows that the adoption of IM has a positive impact on both male and female students on the performance of learning in higher education in South Africa. This leads to the preliminary understanding that the performance of learning using IM is not substantially influenced by the gender of a participant.

Table 7. 5 Standard Deviations of IM Group Scores by Gender

	Gender	Survey	Standard deviation
IM + F2F	Male	Pre-test	9.12
		Post-test	13.51
	Female	Pretest	10.14
		Posttest	12.12

The results of the regression analysis in the investigation of the impact of gender on the performance of learning using IM is presented in Table 7.6. Such results show that the gender of a participant has no statistically significant impact on the performance of learning using IM (Beta = 0.300, t = 0.210, p = 0.835). This means that the performance of learning using IM is not influenced by the gender of a participant.

Table 7. 6 Regression Analysis of the IM Group by Gender

	Unstandardized Coefficients		Standardized Coefficients		
	B	**Std. Error**	**Beta**	**t**	**p**
Constant	14.516	1.593		9.112	0.000
Male	0.534	2.544	0.300	0.210	0.835

Impact of language on learning performance

The measure of the central tendency with respect to the impact of language on the performance of learning using IM is examined. Table 7.7 shows that the mean values for the IM + F2F group of native language participants are 37.31 for pre-test and 50.58 for post-test respectively. The mean values for the IM + F2F group of English language participants are 60.50 for pre-test and 79.50 for post-test. In the Afrikaans language, the mean values are 37.33 for pre-test and 54.78 for post-test. The foreign language obtained the mean values of 35.50 for pre-test and 55.00 for post-test. This leads to positive mean differences of 13.27 for native language, 19.00 for English language, 17.45 for Afrikaans language, and 19.50 for foreign language participants. These results show that participants across different languages in the IM + F2F group have obtained higher mean values in the post-test than those in pre-test. Such results show that the use of IM with F2F teaching has a positive impact on students across different languages on the performance of learning.

Table 7. 7 A Summary of the Mean of the IM Group by Languages

Languages	Surveys	Count	Means	Mean Difference
Native	Pre-test	36	37.31	13.27
	Post-test	36	50.58	
English	Pre-test	2	60.50	19.00
	Post-test	2	79.50	
Afrikaans	Pre-test	9	37.33	17.45
	Post-test	9	54.78	
Foreign	Pre-test	4	35.50	19.50
	Post-test	4	55.00	

An understanding of the variability of the data in the investigation of the impact of language on the performance of learning is important. This is because the measure of variability using standard deviation can help determine the impact of language by estimating the distribution of participants who have benefited from teaching and learning within a specific language group. As indicated in Table 7.8, the standard deviation for native language participants in the IM + F2F group is 9.00 for pre-test and 11.80 for post-test. As indicated in Table 7.7, the mean values for native language participants are 38.15 for pre-test and 49.09 for post-test. This shows that native language participants in the group have obtained scores between 29.15 and 47.15 in pre-test out of a total score of 87. This shows that most native language participants in the group have scored between 33.51% and 54.20% in the pre-test. In the post-test, most native language participants in the group have obtained scores between 37.29 and 60.89. This leads to the understanding that most native language participants have scored between 42.86% and 70.00% in post-test. This analysis indicates that the use of IM with F2F teaching has a positive impact on native language students on the performance of learning in higher education.

The variability of the data in the investigation of the impact of English language on the performance of learning in higher education is examined. As shown in Table 7.8, the standard deviation for the English language participants in the IM + F2F group is 10.61 for pre-test and 3.54 for post-test. Such values of the standard deviation are associated with mean values of 60.50 for pre-test and 79.50 post-test as shown in Table 7.7. These results show that most English language participants have scored between 44.96 and 66.18 in pre-test out of 87. This finding means that the performance in most English language participants in pre-test is between 51.86% and 76.07% in the pre-test. The post-test scores of most English language participants are between 56.89 and 63.97 out of a total score of 87. This shows that most English language participants in the IM + F2F group have scored between 65.39% and 73.53% in post-test. This analysis reveals that the use of IM with F2F teaching has a positive impact on English language students on the performance of learning.

An analysis of Table 7.8 shows that the standard deviation of Afrikaans language participants is 7.62 for pre-test and 11.14 for post-test. Such values of the standard deviation are linked to the mean values of the Afrikaans language participants in the

IM + F2F group of 37.33 for pre-test and 54.78 for post-test as indicated in Table 7.7. These results show that most of participants in the Afrikaans language category in the group have scored between 29.71 and 44.95 out of 87 in pre-test. This means that most participants in the Afrikaans language group have scored between 34.15% and 51.67% in the pre-test. In post-test, most participants in the Afrikaans language group have scored between 43.64 and 65.92 out of 87. This shows that the performance of learning of most of participants in the Afrikaans group is between 50.16% and 75.78%. This finding suggests that the use of IM with F2F teaching has a positive impact on Afrikaans language students on the performance of learning.

In a foreign language, Table 7.8 shows that the standard deviation of foreign language participants in the IM + F2F group is 8.96 for pre-test and 11.58 for post-test. These standard deviation values are associated to the mean values of 35.50 for pre-test and 55.00 for post-test as shown in Table 7.7. This shows that most of the foreign language participants in the IM + F2F group have scored between 26.54 and 44.46 in pre-test out of 87. This indicates that the performance of learning for foreign language participants in the IM + F2F group is between 30.51% and 51.10%. In post-test, most foreign language participants in the IM + F2F group have scored between 43.42 and 66.58 scores out of 87. Such results reveal that most foreign language participants have scored between 49.91% and 76.53% in post-test. This analysis shows that the use of IM with F2F teaching has a positive impact on foreign language students on the performance of learning in higher education.

An analysis of the impact of language on the performance of learning using IM + F2F in South African higher education has been examined. Findings of the study reveal similar improvements in the performance of learning across English, Afrikaans, and foreign langue participants (means of 19.00, 17.45, and 19.50 respectively). The native language demonstrates a slightly lower improvement on the performance of learning compared to the other languages in the study (mean = 13.27). This finding shows that the adoption of IM has a positive impact student across different languages on the performance of learning in higher education in South Africa. This leads to the understanding that the performance of learning using IM is not significantly influenced by language.

Table 7. 8 Standard Deviations of IM Group Scores by Language

Language	**Survey**	**Standard Deviation**
Native	Pre-test	9.00
	Post-test	11.80
English	Pre-test	10.61
	Post-test	3.54
Afrikaans	Pre-test	7.62
	Post-test	11.14
Foreign	Pre-test	8.96
	Post-test	11.58

The impact of language on the performance of learning using IM is examined using regression analysis in this study. As indicated in Table 7.9, the results show that the language of a participant has no significant impact on the performance of learning using IM. Specifically, English language participants have obtained Beta = -0.099, t = -1.170, and p = 0.244. In Afrikaans language, the following results are obtained Beta = 0.129, t = 1.523, and p = 0.130. The foreign language participants have obtained Beta = -0.044, t = -0.518, and p = 0.606. This means that the performance of learning using IM is not influenced by language.

Table 7.9 Regression of IM Group Scores by Language

	Unstandardized Coefficients		Standardized Coefficients		
	B	**Std. Error**	**Beta**	**t**	**p**
Constant	13.278	1.456		9.117	0.000
English	5.722	6.348	0.128	0.901	0.372
Afrikaans	4.167	3.256	0.183	1.280	0.207
Foreign language	6.222	4.605	0.192	1.351	0.183

Impact of race on learning performance

The impact of race on the performance of learning in higher education using IM and F2F is examined through the mean values of the data. As shown in Table 7.10, the mean values for the IM + F2F group of African participants are 37.05 for pre-test and 50.41 for post-test. This leads to a positive mean difference of 13.36. In the mixed-race group, the values of the mean are 34.29 for pre-test and 54.14 for post-test. Such data provides a positive mean difference of 19.85. In the western race group, the mean values of 51.40 for pre-test and 69.60 for post-test are obtained. Such results reveal a positive mean difference of 18.20. These results show that participants across different racial categories in the IM + F2F group have obtained higher mean values in the post-test than those in pre-test. Such results show that the use of IM with F2F teaching has a positive impact on students across different racial groups in their performance of learning in higher education.

Table 7. 10 Mean of IM Group Scores by Race

Race	Survey	Count	Mean	Mean Difference
African	Pre-test	39	37.05	13.36
	Post-test	39	50.41	
Mixed	Pre-test	7	34.29	19.85
	Post-test	7	54.14	
Western	Pre-test	5	51.40	18.20
	Post-test	5	69.60	

The impact of race on the performance of learning in higher education using IM and F2F teaching is examined. As indicated in Table 7.11, the standard deviation for African participants in the IM + F2F group is 8.79 for pre-test and 11.32 for post-test. Such values of the standard deviation are associated with the mean values of 37.05 for pre-test and 50.41 for post-test as shown in Table 7.10. These results indicate that most African participants in the IM + F2F group have scored between 28.26 and 45.84 in pre-test out of 87. This means that most Africa participants in the IM + F2F group have scored between 32.48 % and 52.69% in the pre-test. In post-test, most African participants scored between 38.82 and 61.73 out of 87. This shows that the performance in most African participants in the IM + F2F group is between 44.62% and 70.95% in the post-test. This finding indicates that African race participants perform better in post-test than in the pre-test. This analysis shows that the use of IM with F2F teaching has a positive impact on African students on the performance of learning in higher education.

The impact of mixed-race on the performance of learning using IM and F2F teaching in higher education in South Africa is examined using standard deviation. Table 7.11 shows that the standard deviation of mixed-race participants in the IM + F2F group is 7.63 for pre-test and 12.58 for post-test. These standard deviation values are related to the mean values of 43.29 for pre-test and 54.14 for post-test as indicated in Table 7.10. This shows that most mixed-race participants in the IM + F2F group have scored between 35.66 and 50.92 in pre-test out of 87. This reveals that most mixed-race participants have scored between 40.99% and 58.53% in the pre-test. In post-test, most mixed-race participants have scored between 41.56 and 63.50. This indicates that most mixed-race participants in the IM + F2F group have scored between 47.78 % and

72.99% in post-test. This analysis shows that the use of IM with F2F teaching has a positive impact on mixed-race students on the performance of learning in higher education.

The impact of western race on the performance of learning using IM and F2F teaching in higher education in South Africa is examined using standard deviation. As indicated in Table 7.11 the standard deviation of western race participants in the IM + F2F group is 9.92 for pre-test and 10.43 for post-test. Such standard deviation values are associated to the mean values of 51.40 for pre-test and 69.60 for post-test as shown in Table 7.10. This indicates that most western race participants in the IM + F2F group have scored between 41.48 and 61.32 in pre-test out of 87. This shows that most western race participants have scored between 47.68% and 70.48%. In post-test, most western race participants in the IM + F2F group have scored between 59.17 and 80.03. This finding reveals that most western race participants in the IM + F2F group have scored between 68.01% and 91.99%. This analysis shows that the use of IM with F2F teaching has a positive impact on western race students on the performance of learning in higher education.

An analysis of the impact of race on the performance of learning using IM + F2F in South African higher education has been examined. Findings of the study reveal similar improvements in the performance of learning for both mixed and western race participants (means of 19.85 and 18.20 respectively). The improvement of African participants is relatively lower than the performance in mixed and western race participants (Africa race mean = 13.36). Overall, the adoption of IM has a positive impact on students of all races in their performance of learning in higher education in South Africa.

Table 7. 11 Standard Deviations of IM Group Scores by Race

Race	Survey	Standard deviation
African	Pre-test	8.79
	Post-test	11.32
Mixed	Pre-test	7.63
	Post-test	12.58
Western	Pre-test	9.92
	Post-test	10.43

The impact of race on the performance of learning using IM is examined using regression analysis. This statistical method predicts the impact of race on the performance of learning. As shown in Table 7.12, the results of the regression analysis indicate that mixed-race (Beta =0.257, t = 1.843, p = 0.071), and western race (Beta = 0.166, t = 1.187, p = 0.241). Such results show statistically insignificant results across different races in the investigation of the impact of race on the performance of learning using IM in higher education. This means that the performance of learning using IM is not influenced by race.

Table 7. 12 Regression of IM Group Scores by Race

	Unstandardized Coefficients		Standardized Coefficients		
	B	**Std. Error**	**Beta**	**t**	**p**
Constant	13.359	1.375		9.714	.000
Mixed-race	6.498	3.525	0.257	1.843	0.071
Western race	4.841	4.080	0.166	1.187	0.241

Impact of age on learning performance

The measure of the central tendency with respect to the impact of age on the performance of learning using IM and F2F teaching is examined. Table 7.13 shows that the mean values for 18 -21 years age group are 38.00 for pre-test and 54.80 for post-test. The age group from 22-25 years has mean values of 40.59 for pre-test and 56.72 for post-test. The 26-29 years age group has mean values of 36.08 for pre-test and 47.69 for post-test. Table 7.13 also shows that participants who are 30 years and over have obtained mean values of 26.50 for pre-test and 38.50 for post-test. This leads to positive mean differences of 16.80 for 18-21 years, 16.13 for 22-25 years, 11.61 for 26-29 years, and 12.00 for 30 years and over. These results show that participants across different age group in the IM + F2F group have obtained higher mean values in the post-test than those in pre-test. Such results show that the use of IM with F2F teaching has a positive impact on students across different age groups on the performance of learning in higher education.

Table 7. 13 Mean of IM Group Scores by Age

Age	Survey	Count	Mean	Mean Difference
18-21	Pre-test	5	38.00	16.80
	Post-test	5	54.80	
22-25	Pre-test	29	40.59	16.13
	Post-test	29	56.72	
26-29	Pre-test	13	36.08	11.61
	Post-test	13	47.69	
30Plus	Pre-test	4	26.50	12.00
	Post-test	4	38.50	

The impact of age on the performance of learning in higher education in South Africa in this study is examined. As shown in Table 7.14, the standard deviation for the 18 to 21 years old participants in the IM + F2F group is 19.18 for pre-test and 18.82 for post-test. As indicated in Table 7.13, the mean values for participants in the 18 to 21 years age group are 38 for pre-test and 54.80 for the pre-test. Such results indicate that most participants from 18 years to 21 years have obtained scores between 18.82 and 57.18 out of the total score of 87. This indicates that most 18 to 21 years old participants in the group have scored between 21.63% and 65.72% in pre-test. In post-test, most 18 to 21 years old participants in the group have obtained scores between 36.98 and 72.63 out of the total score of 87. Such results show that most 18 to 21 years old participants in the group have scored between 42.51% and 83.47% in post-test. This analysis reveals that the use of IM with F2F teaching has a positive impact on 18 to 21 years old students in their performance of learning.

An analysis of Table 7.14 shows that the standard deviation of the 22 to 25 years old participants is 8.51 for pre-test and 9.60 for post-test respectively. Such standard deviation values are related to the mean values of the 22 to 25-year-old participants in the IM + F2F group of 40.59 for pre-test and 56.72 for post-test as shown in Table 7.13. This leads to the understanding that most 22 to 25 years old participants in the group have obtained scores between 32.08 and 49.10 in the pre-test out of a total score of 87. Such results indicate that most 22 to 25 years old participants in the group have scored between 36.87% and 56.45% in the pre-test. In the post-test, most participants from 22 to 25 years of age have obtained scores between 47.12 and 66.32. Such results show that most 22 to 25 years old participants in the group have scored between 54.16 % and 76.23 % in the post-test. This analysis shows that the use of IM with F2F teaching has a positive impact on 22 to 25 years old students in their performance of learning in higher education.

The standard deviation of the participants from 26 to 29 years of age is 5.74 for pre-test and 12.82 for post-test respectively as shown in Table 7.14. Such standard deviation values are associated to the mean values of the 26 to 29 years old participants in the IM + F2F group of 36.08 for pre-test and 47.69 for post-test as shown in Table 7.13. This shows that most participants from 26 to 29 years of age in the group have obtained scores between 30.34 and 41.82 in the pre-test out of a total score of 87. Such results indicate that most participants from 26 to 29 years old in the group have scored between 34.87% and 48.07% in the pre-test. In the post-test, most participants from 26 to 29 years of age have obtained scores between 34.87 and 60.56. Such results show that most 26 to 29-year-old participants in the group have scored between 40.08 % and 69.61 % in the post-test. This analysis shows that the use of IM with F2F teaching has a positive impact on 26 to 29-year-old students in their performance of learning in higher education.

An analysis of Table 7.14 shows that the standard deviation of the participants from 30 years and above is 3.87 for pre-test and 12.29 for post-test respectively. Such standard deviation values are related to the mean values of the participants from 30 years and over in the IM + F2F group of 26.50 for pre-test and 38.50 for post-test as shown in Table 7.13. This leads to the understanding that most participants from 30 years and over in the group have obtained scores between 22.63 and 30.37 in the pre-test out of a total score of 87. Such results indicate that most participants from 30 years and above in the group have scored between 26.01% and 34.91% in the pre-test. In the post-test, most participants from 30 years and above have obtained scores between 26.21 and 50.79. Such results show that most 30-year-old and above in the group have scored between 30.13 % and 58.38 % in the post-test. This analysis shows that the use of IM with F2F teaching has a positive impact on students from 30 years and above in their performance of learning in higher education.

An analysis of the impact of age on the performance of learning using IM + F2F in South African higher education has been examined. Findings of the study reveal similar improvements in the performance of learning for participants in the 18-21 years and 22-25 years age groups (means of 16.80 and 16.13 respectively). Also, participants in the 26-29 years and 30 years and above age groups demonstrate similar improvements in their performance of learning. This shows that younger students perform slightly better than older students in the performance of learning using F2F and IM. Overall, the finding shows that the adoption of IM has a positive impact on students of all ages with respect to their performance of learning in higher education in South Africa.

Table 7. 14 Standard Deviations of IM Group Scores by Age

Age	**Survey**	**Count**	**Standard Deviation**
18-21	Pre-test	5	19.18
	Post-test	5	17.82
22-25	Pre-test	29	8.51
	Post-test	29	9.60
26-29	Pre-test	13	5.74
	Post-test	13	12.82
30Plus	Pre-test	4	3.87
	Post-test	4	12.29

The impact of age on the performance of learning using IM in higher education is examined using regression analysis. Table 7.15 shows the results of the regression analysis. It indicates that participants from the 22 to 25 age group has a Beta value of -0.038, t-value of -0.156, and p-value of 0.877. The age group from 26 to 29 years has a Beta-value of -0.260, t-value of -1.122, and p-value of 0.268. The age group from 30 years and above obtained a Beta-value of -0.148, t-value of -0.815, and p-value of 0.419. Such results show statistically not significant results across different participant ages in the investigation of the impact of age on the performance of learning using IM in higher education. This leads to the understanding that the performance of learning using IM is not influenced by age.

Table 7. 15 Regression of IM Group Scores by Age

	Unstandardized Coefficients		**Standardized Coefficients**		
	B	**Std. Error**	**Beta**	**t**	**p**
Constant	16.800	3.927		4.278	0.000
Age 22-25	-.662	4.252	-0.038	-0.156	0.877
Age 26-29	-5.185	4.620	-0.260	-1.122	0.268
Age 30 plus	-4.800	5.890	-0.148	-0.815	0.419

7.3 Findings and Discussion

This section of the study aims to discuss the findings for the research project. To effectively achieve this aim, this section is organised into three sub-sections. The first Sub-section discusses the findings of the impact of IM on the performance of learning in higher education. This is followed by the discussion of the impact of gender on the performance of learning using IM in higher education. The next sub-section discusses the impact of language on the performance of learning using IM in higher education. A discussion of the findings of the impact of race on the performance of learning using IM in higher education is undertaken. The section ends with a discussion of the finding of the impact of age on the performance of learning using IM in higher education.

Impact of IM on learning performance

The statistical analysis of the data in the study is undertaken using descriptive statistics in the investigation of the impact of IM on the performance of learning. Specifically, the measure of central tendency using the mean, and the measure of the variability of the data using the standard deviation is examined. Such descriptive statistics show that IM is beneficial with respect to the performance of learning in higher education as shown in Table 7.1 and Table 7.2. The result shows that the post-test mean value is higher than the pre-test mean value. This means that the adoption of IM is beneficial with respect to the performance of learning in higher education in South Africa.

The finding of the study is consistent with some of the research in digital learning using IM (Ogara et al., 2014, Tang and Hew, 2017, Nkhoma et al., 2018, Bere and Rambe, 2019). Nkhoma et al. (2018), for example, show that the adoption of IM in higher education creates social bonding between the student and facilitator. Such relationships enable a tentative student to be assertive and develop the confidence to seek clarity from peers and facilitators on the ambiguous concepts learnt in class. This leads to an increased student active learning sustaining an information seeking practices and critical questioning culture. As a result, better collaborative learning is obtained which can influence better student learning outcomes (Nkhoma et al., 2018). This shows that the adoption of IM has a positive impact on the performance of learning in higher education.

The adoption of IM improves performance of learning in higher education through the provision of better online collaborative learning (Rambe and Bere, 2013, So, 2016, Tang and Hew, 2017). This is because IM is a ubiquitous social tool which enables students to interact in dialogic discourses at anytime and anywhere (Rambe and Bere, 2013). Such interactions are enhanced by the quasi-synchronous nature of IM. This feature allows students to contribute and obtain clarification and confirmation on confusing concepts through elaboration and repeating the original message (So, 2016, Tang and Hew, 2017). As a result, quasi-synchronous nature of IM offers students more space and time to think and ask the right questions before responding, while the chat records provide electronic libraries. Such libraries allow students to access conversions contents easily for teaching and learning. Furthermore, Collaborative learning using IM provides increased online social presence (Rambe and Bere, 2013, Tang and Hew, 2017). This is offered using emojis for expressing emotions including thumbs-up, sad face, and smiling faces. This leads to the development of goodwill in learning through nonverbal cues. As a result, online social presence can help reduce feelings of stress and loneliness on digital learning students (Rambe and Bere, 2013).

The finding of the study contradicts some of the research in digital learning using emerging technologies including IM (Allagui, 2014, Bouhnik et al., 2014, Kim et al., 2014, Almekhlafy and Alzubi, 2016). Allagui (2014), for example, shows that digital learning students using IM worry about poor Internet connection, in particular in developing countries like South Africa. As a consequence, student attention continuance and learning are negatively impacted. Apart from poor connectivity, digital learning students using IM perceive that small keyboard and screen on devices supporting IM including mobile phones constrains them from contributing lengthy opinions. As a result, the adoption of IM negatively affects the performance of learning.

There has been growing concerns over student use of informal language including shortenings, slangs, and emoticons in teaching and learning using social media platforms including IM (Almekhlafy and Alzubi, 2016). Such non-authentic communication practices create a negative impact on the performance of learning (Bouhnik et al., 2014). As a result, teaching and learning using IM are not beneficial with respect to the performance of learning (Almekhlafy and Alzubi, 2016).

Impact of gender on learning performance

The impact of gender on the performance of learning using IM in higher education is examined using descriptive statistics and regression analysis. Findings of the descriptive statistics as shown in Table 7.4 and Table 7.5 suggest an increase in the performance of learning using IM for both male and female participants. Regression analysis is adopted for testing the hypothesis of the study which follows. *Performance of learning using IM is influenced by the gender of a student*. As shown in Table 7.6, the results of the regression analysis show statistically insignificant results with respect to the impact of gender on the performance of learning in higher education. This leads to the understanding that the performance of learning using IM is not influenced by the gender of a participant.

The finding of the study is consistent with some of the research conducted by Glass and Li (2010) and Anasi (2018). Anasi (2018), for example, indicates that both male and female students have positive attitude towards the adoption of IM. As a result, there is no statistical significance with respect to the gender difference in the performance of learning using IM. This shows that the adoption of IM has no influence on the performance of learning using IM for male and female students (Anasi, 2018).

The finding of the study contradicts some of the research in the impact of gender on the adoption of emerging technologies in teaching and learning (Shashaani, 1994, Kaplan and Haenlein, 2010, Wood et al., 2012, Liaw and Huang, 2013). Empirical studies reveal gender differences in task-performance using IM. Kaplan and Haenlein (2010), for example, reveals that women dominate men with respect to the adoption of IM. As a result, they tend to perform better in teaching and learning using such emerging technologies due to their higher confidence towards use. Contrary to the findings in Kaplan and Haenlein (2010), Shashaani (1994) indicates that females have low self-esteem on their ability to use emerging digital technologies including IM. This leads to the understanding that males students have more positive perceptions towards teaching and learning using emerging digital technologies including IM (Liaw and Huang, 2013).

Impact of language on learning performance

The impact of language on the performance of learning using IM in higher education is examined using values of mean, values of standard deviation, and regression analysis. Findings of the descriptive statistics, as shown in Table 7.7 and Table 7.8, suggest an improvement in the performance of learning using IM across different languages of the participants. Regression analysis is adopted for testing the hypothesis of the study that *performance of learning using IM is influenced by the language of a student*. In regression analysis, Table 7.9 reveals statistically insignificant results with respect to the impact of the language of a student on the performance of learning in higher education. This leads to the understanding that the performance of learning using IM is not influenced by the language of a participant.

The finding of the study contradicts some of the research on the impact of language on the performance of learning (Brock-Utne, 2007, Altinyelken et al., 2014, Vuzo, 2018). Vuzo (2018), for example, reveals that the language of instruction has a significant impact on the performance of learning. The use of a non-first language of a student is a major contributor to student poor outcomes and drop-out due to lack of interest in and disconnection from learning (Vuzo, 2018).

Impact of race on learning performance

The impact of race of a student on the performance of learning using IM in higher education is examined. Findings of the descriptive statistics as shown in Table 7.10 and Table 7.11 indicate an increase in the performance of learning using IM across different races of the participants. To test the hypothesis of the study, regression analysis is adopted. The hypothesis of the study is *performance of learning using IM is influenced by the race of a student*. As shown in Table 7.12, regression analysis reveals statistically insignificant results with respect to the impact of the race of a student on the performance of learning in higher education. This means that the performance of learning using IM is not influenced by the race of a participant.

The finding of the study contradicts some of the research on the impact of race on the performance of learning using IM (Kalantzis and Cope, 2012, Ndimande, 2013, Biko, 2015). Ndimande (2013), for example, indicated that African race students belong to previously disadvantaged communities caused by colonial policies. As a result, they lack access to teaching and learning resources including emerging digital technologies such as IM. This leads to the understanding that African race students have computer anxiety. As a consequence, their performance of learning is lower compared to students from better economic backgrounds including western race students.

Impact of age on learning performance

The impact of the age of a participant in the performance of learning using IM in higher education is examined. As shown in Table 7.13 and 7.14, findings from the descriptive statistics analysis indicate an improvement in the performance of learning using IM across different participant age groups. Regression analysis is employed for testing the following hypothesis that the *performance of learning using IM is influenced by the age of a student*. In regression analysis, Table 7.15 shows statistically insignificant results with respect to the impact of the age of a student on the performance of learning in higher education. This leads to the understanding that the performance of learning using IM is not influenced by the age of a participant.

The finding of the study is consistent with some of the research on the impact of age on the performance of learning using emerging digital technologies (Wang et al., 2009, Chung et al., 2010, Glass and Li, 2010). The findings in these studies show that age differences have no influence on task performance using new digital technologies.

The finding of the study contradicts some of the research conducted by Jung et al. (2010) and Rambe and Bere (2013). Jung et al. (2010), for example, reveals that older adults have low self-efficacy in using IM due to their beliefs that they are too old to learn how to use emerging digital technologies. This leads to the understanding that younger people have lower levels of computer anxiety than older individuals. This is because younger adults are willing to engage in opportunities to learn emerging digital technologies including IM (Jung et al., 2010).

The finding in Rambe and Bere (2013) show that older participants, in particular, married students perceive teaching and learning after hours using IM as disruptive of family life. Paying attention to digital technologies during such time for teaching and learning can seamlessly integrate quality family time into academic pursuits (Rambe and Bere, 2013). This leads to the understanding that older adults have low performance of learning using IM in higher education.

7.4 Concluding Remarks

The aim of this Chapter is to investigate the impact of IM on the performance of learning in higher education. To effectively achieve this aim, the following hypotheses are examined (a) *Digital learning using IM influence performance of learning, (b) Performance of learning using IM is influenced by the gender of a student*, *(c) Performance of learning using IM is influenced by the language of a student*, *(d) Performance of learning using IM is influenced by the race of a student*, and (e) *Performance of learning using IM is influenced by the age of a student*. This is done by using various statistical data analysis methods including descriptive statistics, and regression analysis of the survey data collected from students in South African higher education.

The findings show that the adoption of IM has a positive impact on the performance of learning in higher education. Furthermore, the findings also reveal that the performance of learning using IM is not influenced by the participant characteristics including gender, language, race, and age. The results of this study provide higher education managers, academics, and digital learning instructional designers with a profound insight into the impact of IM in the performance of learning in higher education.

Chapter 8

A Comparative Analysis

8.1 Introduction

There is a growing demand for skilled human resources, particularly in Science, Technology, and Engineering (SET), and predominantly in developing countries, including South Africa (Lotriet et al., 2010, Bere and McKay, 2017b). As a consequence, IT-related professions including database development are listed in the government scarce skills of South Africa. Skills shortages in these high-demand professions are forecasted globally (Mills, 2017).

There have been several strategies developed and implemented for improving the performance of learning in higher education to mitigate skills shortages in SET. A common strategy is through the adoption of emerging digital technologies (Castillo-Merino and Serradell-López, 2014, Harandi, 2015). This is because research in digital learning indicates the potential benefits of adopting digital technologies in higher education, including the capacity to improve the student outcomes (Xu and Jaggars, 2013, Bere et al., 2018a).

The adoption of digital technologies for teaching and learning in South Africa is in its infancy stage, while the performance of learning in higher education is deteriorating

(Bhuasiri et al., 2012, Council on Higher Education, 2013a). Such low acceptance and use of digital technologies can be caused by a lack of evidence on the impact of digital technologies on teaching and learning (Zhang et al., 2004, Bere et al., 2018a). This leads to the understanding that such evidence can help improve the adoption of specific digital technologies in higher education.

Investigating the impact of specific digital technologies, including LMS and IM, on the performance of learning in South African higher education through a comparative analysis is desirable. This is because such an investigation can help (a) higher education managers, academics and students to better understand the potential benefit of such technologies on performance of learning, (b) the government to identify teaching and learning systems that can help reduce skills shortages, and (c) motivate academics and students to improve their adoption of digital technologies. As a result, such an investigation can influence an increase in the adoption of digital technologies for teaching and learning in higher education.

The purpose of this chapter is to undertake a comparative analysis in the investigation of the performance of learning in higher education in South Africa. This is done using several statistical analyses, including descriptive statistics such as the measure of central tendency and the measure of variability. The hypotheses of the study are then explored using independent samples t-test. As a result, teaching and learning strategy with the highest impact on the performance of learning is identified. This leads to a discussion of the findings of the study.

This chapter is organised into four sections. Section 8.2 shows the data analysis results of the investigation of the impact of specific digital technologies including LMS and IM on the performance of learning in higher education. Also, it examines the comparative analysis of between specific digital technologies and F2F teaching. Section 8.3 provides the research findings and discussion. Section 8.4 ends the chapter with some concluding remarks.

8.2 Data Analysis

The The impact of the specific digital technologies, including LMS and IM, on the performance of learning is examined using the measure of central tendency. As shown in Table 8.1, the mean and the mean difference provide an overview of the measure of central tendency in the investigation of the performance of learning using specific digital technologies, including LMS and IM. Such measures of central tendency are relevant because they can help to show whether the adoption of specific digital technologies leads to an improvement or not on the performance of learning in higher education.

Table 8. 1 Summary of the Mean of the Group Performance

	Survey	Count	Mean	Mean Difference
LMS + F2F	Pre-Test	54	39.24	16.67
	Post-Test	54	55.91	
IM + F2F	Pre-Test	51	38.08	
	Post-Test	51	52.80	14.72

The analysis of the central tendency as shown in Table 8.1 shows that the values of the mean for the LMS + F2F group are 39.24 for pre-test and 55.91 for post-test respectively. In the IM + F2F group, the values of the mean are 38.08 for pre-test and 52.80. These mean measurements lead to a positive mean difference of 16.67 for LMS + F2F group and 14.72 for IM + F2F group. Such a result shows that the mean values of the post-test in the LMS + F2F and IM + F2F experiment groups are higher than the pre-test mean values. This means that the adoption of specific digital technologies, including LMS and IM, has a positive impact on the performance of learning in higher education in South Africa.

The standard deviation measures the variability of the data of the participant in the investigation of the impact of the specific digital technologies, including LMS and IM, on the performance of learning in higher education in South Africa. As shown in Table 8.2, the values of the standard deviation for the LMS + F2F group are 14.58 for pre-test and 17.87 for post-test respectively. These standard deviations are linked with the mean values of 39.24 for pre-test and 55.91 for post-test, as shown in Table 8.1. This means that most participants in the pre-test have scored between 24.66 and 53.82 out of a total score of 87. Such results reveal that the performance of most participants that have utilised LMS is between 28.34% and 61.86% in the pre-test. This means that the average performance of most LMS users is 42.60% in the pre-test. In post-test, the majority of the participants that adopted LMS scored between 38.04 and 73.78. Such results indicate that the performance of most participants that have adopted LMS is between 43.72% and 84.80% in the post-test. As a result, the average performance of most LMS users in post-test is 64.26%. The results of this analysis reveal higher average performance on post-test compared to the pre-test. This means that the adoption of LMS has positive impact on the performance of learning.

In the IM + F2F group, Table 8.2 shows that the values of the standard deviation for the group are 9.71 for pre-test and 12.57 for post-test respectively. These standard deviations are associated with the mean values of 38.08 for pre-test and 52.80 for post-test, as shown in Table 8.1. Such results mean that most participants that utilised IM have scored between 28.37 and 47.79 in the pre-test out of a total score of 87. Such results reveal that the performance of most participants that have adopted IM is between 32.61% and 54.93%, with an average score of 43.77%. In the post-test, the results indicate that most participants have obtained a score between 40.23 and 65.37. This shows that most of the participants that used IM have scored between 46.24% and 75.14% in the post-test. This leads to average performance of 60.69%. This analysis shows that post-test has higher average performance (60.69%) than pre-test (43.77%). This means that the adoption of IM has a positive impact on the performance of learning in higher education in South Africa.

Table 8. 2 Standard Deviation of Scores by Groups

	Survey	Standard Deviation
LMS + F2F	Pre-Test	14.58
	Post-Test	17.87
IM + F2F	Pre-Test	9.71
	Post-Test	12.57

An analysis of Table 8.3 shows that the LMS + F2F group has a correlation coefficient of 0.816 at the degree of freedom (df) of 53, a t-value of -11.862 and a p-value of 0.000 at two-tailed significance. In the IM + F2F group, a correlation coefficient of 0.717 is obtained at the degree of freedom of 50, a t-value of -11.972 and a p-value of 0.000. These results indicate that students who performed better in the pre-test also performed better in the post-test. Therefore, it is important to control for students' pre-test performance when examining the impact of digital technologies on students' learning.

Table 8. 3 Correlation Between Pre-test and Post-Test Scores

	Correlation	df	t	Sig. (2-tailed)
LMS + F2F	0.816	53	-11.862	0.000
IM + F2F	0.717	50	-11.972	0.000

A comparative analysis between LMS and IM

The descriptive statistics are crucial for examining the comparative analysis between independent samples. It can help determine the values of the mean of a sample with regards to its pre-test and post-test scores. More importantly, the mean difference between the pre-test and post-test scores can be calculated to provide a measure of the amount of students' learning occurring in the courses. As a result, a higher value of mean learning score would suggest a higher impact of digital technologies. Furthermore, descriptive statistics can help estimate the range of scores which have been obtained by most participants in a specific sample. Such results can help to determine the spread of student scores from the mean. Such descriptive statics using the measure of central tendency and measure of variability can help better understand the performance of learning in each group. These findings lead to the initial findings in the comparative analysis between independent samples.

The paired-sample *t*-test is adopted for further investigating the impact of specific digital technologies including LMS and IM on the performance of learning in higher education in South Africa. The paired-sample *t*-test is a reliable measure for testing the hypotheses of the study as follows:

> *Digital learning using LMS has better performance of learning than F2F learning.*
>
> *Digital learning using IM has better performance of learning than F2F learning.*

In this study, there are three comparative analyses conducted including between LMS and F2F, IM and F2F, and between LMS and IM. Each comparative analysis involves descriptive statistics and independent-sample t-test. The descriptive statistics adopt the use of central tendency using mean values and the variability of data using standard deviation values. The independent-sample t-test follows the Levene's test for homogeneity of variance and the independent sample t-test.

LMS + F2F versus F2F

The comparative analysis between LMS + F2F and F2F teaching on the performance of learning in higher education is examined. It is examined using the measure of the central tendency and through the assessment of the variability of the data. Table 8.4 shows that the mean values of the LMS + F2F group are 39.24 for pre-test and 55.91 for post-test respectively. These mean values are related to the standard deviation of 14.58 for pre-test and 17.87 for post-test as shown in Table 8.1. This means that most participants in the LMS + F2F group have scored between 24.66 and 53.82 in pre-test out of 87. This finding leads to the understanding that most participants in the LMS + F2F group scored between 28.34% and 61.86% in pre-test. The average performance of LMS + F2F users is 45.10% in the pre-test. In the post-test, the majority of the participants in the LMS group have obtained scores between 38.04 and 73.78 out of a total score of 87. This finding shows that most participants that adopted LMS scored between 43.72% and 84.80%. This shows that the average performance of LMS users is 64.26% in the post-test.

An analysis shown in Table 8.4 is used to examine the relative impact between LMS + F2F and F2F only with respect to the performance of teaching performance of learning. Table 8.4 shows that the mean values of F2F only group are 40.30 for pre-test and 50.51 for post-test. These values of the mean are associated with the standard deviation value of 10.68 for pre-test and 9.05 for post-test. This means that most participants in the F2F group have scored between 29.62 and 50.98 in pre-test. Such results show that most participants in the F2F group scored between 34.04% and 58.60% in pre-test. The average performance of participants in the F2F group is 46.32% in pre-test. In the post-test, most participants in the F2F group have scored between 41.46 and 59.56 out of a total score of 87. This shows that the participants in the F2F group scored between 47.65% and 68.46%. The average performance of participants in the F2F group is 58.06%.

The initial results of the comparative analysis between the LMS + F2F and F2F only groups with respect to the performance of teaching performance of learning show that LMS + F2F is more effective than F2F only teaching. The evidence for this finding is bifold: (a) most participants in the LMS + F2F group have obtained higher average performance of learning compared to that of most participants in the F2F only group. The LMS + F2F group has an average performance = 64.26% while the F2F group has an average performance = 58.06%); and (b) most participants in the LMS + F2F group have obtained an average performance increase of 19.16% between pre-test and post-test while most of the participants in the F2F only group have obtained an average performance increase of 11.74% between the pre-test and post-test. This means that the adoption of LMS has a higher impact than the F2F alone with respect to the performance of learning in higher education.

Table 8. 4 Test Scores for LMS and F2F

	LMS + F2F		F2F	
	Pre-Test	**Post-Test**	**Pre-Test**	**Post-Test**
Sample Size	54	54	83	83
Mean	39.24	55.91	40.30	50.51
Mean Difference	16.67		10.21	
Standard Deviation	14.58	17.87	10.68	9.05

The independent-sample t-test is adopted to further examine the comparative analysis between LMS + F2F and F2F only groups with respect to the performance of learning. This is because the independent-sample t-test is a more reliable and valid method than descriptive statistics at carrying out comparative analysis particularly through hypothesis testing. The following hypothesis is tested.

> *Digital learning using LMS has better performance of learning than F2F learning.*

In this study, the comparative analysis between LMS + F2F and F2F only groups with respect to the performance of learning involve two independent samples with unequal sample sizes, with n = 54 in the LMS + F2F group and n = 83 in F2F only group. It is essential to test the homogeneity of the variances of these two samples. Table 8:5 shows that the Levene's test is significant (F =6.836, p-value = 0.010). This means that equal variance cannot be assumed (Tomarken and Serlin, 1986, Derrick et al., 2017). Such results show that the variances of the data of the LMS + F2F and F2F samples are not homogeneous. As shown in Table 8:5, the independent-sample t-test shows significant results ($t = 4.067$, $df = 82.523$, $p\text{-value} < 0.001$). This means that the adoption of LMS has a better impact than F2F alone with regards to the performance of learning in higher education in South Africa. Such a finding is consistent with the hypothesis that digital learning using LMS has better performance of teaching than F2F alone teaching.

Table 8. 5 Comparative Analysis Between LMS and F2F

	Levene's Test for Equality of Variances		**Independent-sample t-test**		
	F	**Sig.**	**t**	**df**	**p (2-tailed)**
Equal variances assumed	6.836	0.010	4.430	135	0.000
Equal variances not assumed			4.067	82.523	0.000

IM + F2F versus F2F

The comparative analysis between IM + F2F and F2F only groups on the performance of learning is examined. As shown in Table 8.6 the values of the mean of the IM + F2F group are 38.08 for pre-test and 52.80 for post-test. These mean values are associated with standard deviation values of 9.71 for pre-test and 12.57 for post-test as shown in

Table 8.6. Such results show that the majority of the participants who utilised IM have scored between 28.37 and 47.79 in pre-test out of 87. As a result, the performance of most IM users is between 32.61% and 54.93% in pre-test. This analysis shows that the average performance of IM users is 43.77% in the pre-test. In the post-test, most participants in the IM + F2F group have obtained scores between 40.23 and 65.37 out of a total score of 87. This finding leads to the understanding that the performance of most participants in the IM + F2F group is between 46.24% and 75.14% in post-test. This shows that the average performance of IM users is 60.69% in post-test. Such results show that the adoption of IM leads to a 16.92% improvement with respect to the average performance of learning.

An analysis shown in Table 8.6 is used to examine the relative impact of IM + F2F and F2F only with respect to the performance of learning. Table 8.11 show that the mean values of the F2F only participant score are 40.30 for pre-test and 50.51 for post-test. These values of the mean are associated with the standard deviation value of 10.68 for pre-test and 9.05 for post-test. This means that most participants in the F2F only group have scored between 29.62 and 50.98 in pre-test. Such results show that the performance of most participants in the F2F only group is between 34.04% and 58.60% in pre-test. The average performance of participants in the F2F only group is 46.32% in pre-test. In post-test, most participants in the F2F only group have scored between 41.46 and 59.56 out of a total score of 87. This shows that the performance of most participants in the F2F only group is between 47.65% and 68.46%. The average performance participants in the F2F group is 58.06% in the post-test.

The initial findings of the comparative analysis between IM + F2F and F2F with regards to performance of learning show that IM + F2F is more effective than F2F. This is because most participants in the IM + F2F group has a higher average performance in the post-test compared to most of the participants in the F2F only group, with IM + F2F having an average performance of 60.69% and F2F only having an average performance of 58.06%. Also, most of the participants in the IM + F2F group have obtained an average performance increase of 16.92% between pre-test and post-test while most of the participants in the F2F only group have obtained an average performance increase of 11.74% between the pre-test and post-test. These findings show that the adoption of IM has a higher impact than the F2F only teaching with regards to the performance of learning.

Table 8. 6 Summary Statistics of IM and F2F

	IM + F2F		**F2F**	
	Pre-Test	**Post-Test**	**Pre-Test**	**Post-Test**
Sample Size	51	51	83	83
Mean	38.08	52.80	40.30	50.51
Mean Difference	14.72		10.21	
Standard Deviation	9.71	12.57	10.68	9.05

The independent-sample t-test is used to examine the comparative analysis between IM + F2F and F2F only teaching with respect to the performance of learning. This analysis is used to test the hypothesis of the study which follows:

> *Digital learning using IM has better performance of learning than F2F learning.*

The Levene's test is adopted for assessing the homogeneity of the variances of the data. As shown in Table 8.7, the Levene's test is not significant (F =2.830, p-value = 0.095). Such a result means that equal variance can be assumed (Tomarken and Serlin, 1986, Derrick et al., 2017). The independent-sample t-test shown in Table 8.7 indicates significant results (t = 3.348, df =132, p-value = 0.001). This result is consistent the hypothesis that digital learning using IM has better performance of learning than F2F teaching. This means that the adoption of IM is more effective than F2F with respect to the performance of learning.

Table 8. 7 Comparative Analysis Between IM and F2F

	Levene's Test for Equality of Variances		**Independent-sample t-test**		
	F	**Sig.**	**t**	**df**	**Sig. (2-tailed)**
Equal variances assumed	2.830	0.095	3.348	132	0.001
Equal variances not assumed			3.147	86.047	0.002

LMS versus IM

The descriptive statistics with respect to the comparative analysis between LMS + F2F and IM + F2F on the performance of learning is examined. Table 8.8 shows that the values of the mean of the LMS + F2F group are 39.24 for pre-test and 55.91 for post-test. These mean values are related with standard deviation of 14.58 for pre-test and 17.87 for post-test as shown in Table 8.8. This means that most participants that adopted LMS have scored between 24.66 and 53.82 in pre-test out of 87. This finding leads to the understanding that the performance of most LMS adopters in pre-test is between 28.34% and 61.86%. The average performance of LMS users is 45.10% in the pre-test. In the post-test, the majority of the LMS users have obtained scores between 38.04 and 73.78 out of a total score of 87. This finding shows that the performance of most participants that adopted LMS is between 43.72% and 84.80%. This shows that the average performance of LMS users is 64.26% in post-test. This means that the adoption of LMS leads to a 19.16% increase on the average performance of learning in higher education.

The descriptive statistics shown in Table 8.8 are used to examine the impact of IM with respect to the performance of learning. Table 8.8 indicates that the mean values of the participant score are 38.08 for pre-test and 52.80 for post-test. This cohort has a standard deviation of 9.71 for pre-test and 12.57 for post-test. This means that most participants in IM + F2F group have scored between 28.37 and 47.79 in pre-test. This analysis leads to the understanding that the performance of most participants in the IM + F2F group is between 32.16% and 54.93% in pre-test. This shows that the average performance of participants in the IM + F2F group is 43.77% in pre-test. In post-test, most participants who have adopted IM have scored between 40.23 and 65.37 out of a total score of 87. This indicates that the performance of participants in the IM + F2F group is between 46.24% and 75.14%. The average performance of participants in the IM + F2F group is 60.69%.

The initial findings of the comparative analysis between LMS + F2F and IM + F2F groups with regards to the performance of learning indicates that LMS is more effective than IM as a supplement to F2F teaching. This is because most LMS participants have a higher average performance of learning of most than most IM participants. Specifically, the average performance of the LMS users is 64.26% in the post-test whereas average performance of IM participants is 60.69%. Also, the LMS + F2F cohort has a performance increase of 19.16% between pre-test and post-test while the IM + F2F group has obtained a performance increase of 16.92% between pre-test and post-test. These findings lead to the understanding that the adoption of LMS (in addition to F2F teaching) has higher impact on the performance of learning compared to the use of IM.

Table 8. 8 Summary Statistics of LMS and IM Groups

	LMS + F2F		IM + F2F	
	Pre-Test	**Post-Test**	**Pre-Test**	**Post-Test**
Sample Size	54	54	51	51
Mean	39.24	55.91	38.08	52.80
Mean Difference	16.67		14.72	
Standard Deviation	14.582	17.869	9.705	12.570

The independent-sample t-test is used to test the hypothesis for examining the comparative analysis between the LMS + F2F and IM + F2F groups with respect to the performance of learning. In this study, the following hypothesis is tested.

Digital learning using LMS has better learning performance than digital learning using IM.

The Levene's test is adopted for assessing the homogeneity of the variances of the data of the two independent samples: LMS + F2F and IM + F2F samples. As shown in Table 8.9, the Levene's test is not significant F =0.706, p-value = 0.403. Such a result indicates that equal variance can be assumed (Tomarken and Serlin, 1986, Derrick et al., 2017). As shown in Table 8.9, the independent-sample t-test is statistically significant (t = 1.012, df =103, p-value = 0.041). This means that the finding of the study is consistent with the hypothesis that digital learning using LMS has better learning performance than digital learning using IM. Such a finding shows that the adoption of LMS as a supplementary teaching tool has a higher impact compared to the use of IM with respect to the performance of learning in higher education.

Table 8. 9 Comparative Analysis Between LMS and IM

	Levene's Test for Equality of Variances		Independent-sample t-test		
	F	Sig.	t	df	p (2-tailed)
Equal variances assumed	0.706	0.403	1.012	103	0.041
Equal variances not assumed			1.043	101.915	0.031

8.3 Findings and Discussion

LMS + F2F versus F2F

The descriptive statistics using central tendency and variability of the data as shown in Table 8:4 indicates that LMS + F2F has better impact than F2F only with regards to the performance of learning. The independent-sample t-test results as shown in Table 8.10 shows that the hypothesis that the use of digital technologies using LMS has better performance of teaching than F2F only teaching is supported by the data. These results are consistent with the finding in Eichler and Peeples (2013) and Harandi (2015). This is because students that use LMS are motivated by several factors including timely feedback, tailored set of learning activities, and individualised teaching and learning

(Eichler and Peeples, 2013). Motivated students actively participate in teaching and learning through interaction with other students in relaxed LMS environments (Sek et al., 2016). Such students achieve their objectives of teaching and learning through critical thinking, knowledge construction, and collaboration with peers and instructors (Harandi, 2015, Sun et al., 2018). This digital tool not only provides effective collaborative learning, it also creates ubiquitous learning environments for students who enjoy studying using portable devices including laptops, IPads, and tablets (Sun et al., 2018). As a result, LMS provides convenient and flexible teaching and learning (Harandi, 2015).

The finding of this study is different from the findings from studies conducted by Brown and Liedholm (2002), Talpin and Wojcik (2010), and Xu and Jaggars (2013). One study has found that F2F only teaching has between six and seven percent higher impact than LMS only with respect to the performance of learning (Brown and Liedholm, 2002). This is because F2F teaching caters for the emotions of the students and instructors which fosters knowledge assimilation (Talpin and Wojcik, 2010). Geographical dispersion in LMS leads to the development of feelings of isolation (Xu and Jaggars, 2013). Such feelings lead to lack of self-discipline to learn independently (Brown and Liedholm, 2002). As a result, LMS users lack motivation to learn (Xu and Jaggars, 2013). Students lack digital skills and the active participative skills required in teaching and learning using LMS due to their reliance on F2F teaching (Andersson and Grönlund, 2009). As a result, higher education students particularly in developing countries like South Africa develop a phobia against the adoption of LMS. Such students develop low confidence on the use of LMS which causes poor performance of learning (Bharuthram and Kies, 2013). Provision of better digital skills training and better access to LMS can help improve the performance of learning using LMS in higher education. Nevertheless, it should be noted that LMS is used as supplementary teaching tools in our study and not as the sole teaching method. Therefore, it is expected the use of LMS should produce the better or equal performance than relying on F2F alone.

IM + F2F versus F2F

The measure of central tendency using mean and the measure of the variability of the data using the standard deviation is examined. These analysis reveals that IM + F2F has better impact than F2F only with regards to the performance of learning as shown in Table 8.6. The hypothesis of the study is examined using the independent-sample t-test as shown in Table 8.7. The hypothesis testing of the assumption that the adoption of digital technologies using IM has better performance of teaching than F2F only teaching shows statistically significant results that support the hypothesis. This means that the adoption of IM in higher education is more effective than F2F only with respect to teaching and learning.

The finding of the study is consistent with the research in digital learning using IM (Rambe and Bere, 2013, Kuznekoff et al., 2015, Robinson et al., 2015, So, 2016). Kuznekoff et al. (2015), for example, reveal that lecture content-related interactions using IM allow students to comprehend and encode the contents of the lecture better than in F2F teaching. The interactions using IM provide students with opportunities to negotiate the meaning of course content (Baguma et al., 2019). As a result, the negotiation of the meaning of course content through the various IM interactions promote deeper and long-lasting learning through social learning and critical thinking. This increases their ability to transfer learning to new contexts and to create new meanings, knowledge, and solutions (Baguma et al., 2019). This leads to the understanding that the use of IM in teaching and learning help students to develop high order thinking skills (Baguma et al., 2019). Such skills lead to the improvement of student's test scores (Kuznekoff et al., 2015).

The adoption of IM strengthen the confidence of shy students who perceive F2F teaching as intimidating, hegemonic spaces that disrupt transparent communication (Rambe and Bere, 2013). As a result, IM broaden participation in teaching and learning through sustaining a critical questioning culture and information seeking practices which strongly support individual content creation, sharing and efficacy of personal connections (Rambe and Bere, 2013). The use of IM in teaching and learning not only strengthen the confidence of shy students, it also enables student cognitive scaffolding. This is achieved through group sharing of information and ease the pressure of individual problem solving and reflection (Rambe and Bere, 2013). As a result, IM provides better performance than F2F with respect to teaching and learning.

The finding of the study is different from some other research in digital learning using new technologies, including IM (Wei et al., 2012, Wood et al., 2012). Wood et al. (2012), for instance, indicates that off-task multi-tasking is common in teaching and learning using IM. Such off-task multi-tasking distract students from teaching and learning. IM students need more time to comprehend the lecture due to their limited information-processing ability when switching between listening to lectures and texting, thereby reducing their cognitive learning compared to F2F (Wei et al., 2012).

LMS + F2F versus IM + F2F

The analysis presented in Table 8.8 and Table 8.9 show that LMS + F2F has better impact than IM + F2F with respect to the performance of learning. Table 8.8 show the values of the mean and standard deviations of the data in the comparative analysis of the specific digital technologies, including LMS and IM, with respect to the performance of learning. Table 8.9 reveals the results of the independent-sample t-test for examining the significance of the hypothesis of the study. Table 8.9 show results that are statically significant in the assessment of the hypothesis that digital learning using LMS + F2F has better learning performance than digital learning using IM + F2F. The findings of this study show that LMS + F2F is slightly more effective than IM + F2F with regards to the performance of learning.

The finding of the study is different from some previous research in the comparative analysis between the adoption of IM and LMS on the performance of learning (Bere, 2012, Rambe and Bere, 2013), for example, reveal that the affordances of IM make teaching and learning using IM more effective than using LMS. Such affordances allow ease personalisation of teaching and learning, they influence students to view IM as non-intrusive teaching and learning platforms, and they encourage ubiquitous access to teaching and learning resources, and instruction. As a result, adoption of IM is encouraged in higher education particularly in developing countries where digital skills and digital technologies resources are limited.

There are several challenges on the use LMS. These digital technologies are designed around complex interfaces, access to learning resources (Rambe and Bere, 2013). Teaching and learning using LMS require a considerable amount of Internet data which is costly for most students particularly in developing countries like South Africa. Also, the LMS content is static and pre-packed (Rambe and Bere, 2013). As a result, teaching and learning is not designed around the needs of the student.

The IM is designed for mobile use (Tang and Hew, 2017, Bere and Rambe, 2019). This leads to the development of a convenient mode of communication compared to LMS which is predominantly dependent on desktop computers and laptops (Tang and Hew, 2017). As a result, the adoption of IM on mobile phones allow easier interaction amongst peers and instructors anytime and anywhere at their convenience. Additionally, the integration of audio, text, and video into one interface makes IM a very user-friendly multi-modal platform (Rambe and Bere, 2013, Tang and Hew, 2017). The capacity to take a photo using the mobile phone built-in camera, attach it immediately to a IM platform, type some text to accompany the photo, and share it for academic interaction purposes improves the impact of IM over LMS with respect to performance of learning (Rambe and Bere, 2013, Tang and Hew, 2017). As a result, LMS using desktop computers, or laptops cannot rival IM using mobile phones in such temporal, user-friendly, minimal cost, and multi-modality affordances (Tang and Hew, 2017).

On the other hand, the finding of the study is consistent with some previous research in teaching and learning using specific digital technologies (Bhuasiri et al., 2012, Robinson et al., 2015, Westerman et al., 2016). Students that adopts IM perform worse in class than the students that use LMS (Westerman et al., 2016). This is due to the destructiveness of IM on students' in-class attention and presence (Westerman et al., 2016). The content of LMS is designed and developed by skilled instructional designers. This leads to the dissemination of quality teaching and learning information which is accurate, complete, relevant, and consistent (Bhuasiri et al., 2012) unlike in IM where content is developed by the participants and instructors (Bere and Rambe, 2016). As a result, non-verified and non-accurate material can be distributed in IM teaching and learning (Robinson et al., 2015).

8.4 Concluding Remarks

The aim of this Chapter is to investigate the impact of the specific digital technologies on the performance of learning in higher education. Specifically, the chapter examines the comparative analysis between specific digital technologies and F2F only teaching, thus providing answer for the following hypotheses: (a) *Digital technologies using LMS as a supplementary tool has better performance of learning than F2F only teaching, (b) Digital technologies using IM as supplementary tool has better performance of learning than F2F only teaching, and (c) Digital learning using IM has better learning performance than digital learning using LMS.* This is done by using various statistical data analysis methods including descriptive statistics, pared sample t-test, and independent-sample t-test of the surveyed data collected from students in South African higher education.

The findings of the study are bi-folded. Firstly, the adoption of specific digital technologies, including LMS and IM, as supplementary teaching tool is more effective than F2F only teaching with respect to the performance of learning in higher education. Secondly, LMS has slightly better performance than IM with respect to teaching and learning in higher education but the difference is not statistically significant. This study provides academicians and higher education institution managers with useful insights on the impact of using LMS and IM as supplementary teaching tools on teaching and learning.

Chapter 9

Conclusion

9.1 Introduction

The objective of this research is to investigate the adoption of specific digital technologies including LMS and IM in higher education in South Africa for better understanding the impact of these digital technologies on the performance of learning. Specifically, the research aims to (a) investigate the impact of LMS on the performance of learning, (b) explore the impact of IM on the performance of learning, and (c) examine the relative effectiveness of LMS and IM on the performance of learning in higher education in South Africa.

To achieve these research objectives, the main research question for the study is formulated as follows:

How effective are specific digital technologies including LMS and IM on the performance of learning in higher education in South Africa?

To answer this research question, several subsidiary questions are developed as follows:

(a) *How effective is LMS on the performance of learning in higher education in South Africa?*

(b) *How effective is IM on the performance of learning in higher education in South Africa?*

(c) *What is the impact of student characteristics, including gender, language, race, and age, on the performance of learning using LMS in higher education?*

(d) *What is the impact of student characteristics, including gender, language, race, and age, on the performance of learning using IM in higher education?*

(e) *What is the relative effectiveness of LMS and IM on the performance of learning in higher education in South Africa?*

To adequately answer the research questions above, a quantitative research methodology is adopted in this study. Using pre-test and post-test paper-based surveys, the study has examined the impact of LMS and IM on the performance of learning in higher education in South Africa. Various statistical data analysis methods have been used in the study.

This chapter discusses the research findings of the study and their contributions and implications. The rest of the chapter is organised into four sections. Section 9.2 presents a summary of the research findings of this study. Section 9.3 covers the contribution and the implication of the study. Section 9.4 conclude the chapter with the discussion of the limitation of this study and some suggestions for further research.

9.2 Summary of the Research Findings

There are growing interests in improving the performance of learning through the adoption of specific digital technologies in higher education (Bere et al., 2018a). This is due to the benefits that specific digital technologies offer, including encouraging collaboration, developing active learning skills, fostering interpersonal relationships, promoting cooperation, and enhancing social skills (Karunasena et al., 2012, Karunasena et al., 2013a, Karunasena et al., 2013b, Sek et al., 2015, Sek et al., 2016). The benefits of specific digital technologies including LMS and IM motivate governments across the world to invest a huge amount of financial resources in the development and implementation of various strategies and policies for improving the adoption of specific digital technologies in teaching and learning (Sridharan and Deng, 2014, Bere et al., 2018b).

Following the global trend, the South African government has developed and implemented several strategies and policies for promoting the adoption of specific digital technologies in teaching and learning (Vandeyar, 2015). This leads to the passing of the national ICT strategy in 2001. In 2004, the e-education policy was implemented. The development and implementation of such strategies and policies require a tremendous amount of financial and human resources (Vandeyar, 2015). To justify such investments, there is a need for better understanding the impact of specific digital technologies on the performance of learning in higher education.

This study investigates the impact of LMS and IM on the performance of learning in South African higher education. The study finds that the adoption of LMS has a positive impact on the performance of learning. This is demonstrated by a higher mean value of the post-test (post-test = 55.91) than the mean value of the pre-test (pre-test =39.24). This finding is reinforced by the paired samples *t*-test results. The study shows that there is a significant improvement of the performance of learning by comparing the pre-test and post-test scores in the LMS + F2F group. This is further confirmed by a *t*-value of 11.9 with the degree of freedom of 53 and $p < 0.001$. This finding supports the hypothesis that digital learning using LMS influences the performance of learning in South African higher education.

The study shows that the adoption of IM has a positive impact on the performance of learning in South African higher education. This is because a higher mean value of 52.80 for the post-test is obtained compared to the mean value of 38.08 for the pre-test. Such descriptive statistics results are supported by the paired samples *t*-test results. The paired samples *t*-test reveals statistically significant results with a *t*-value of 11.97 with degree of freedom of 50 and $p < 0.001$. This finding therefore supports the hypothesis that digital learning using IM influences the performance of learning in South African higher education.

Student demographic characteristics are used to investigate the impact of specific digital technologies including LMS and IM on the performance of learning South African higher education. The study shows that the adoption of LMS has a positive impact on both male and female students on the performance of learning in higher education. This is demonstrated by a higher mean value of the post-test (post-test = 59.73) than the mean value of the pre-test (pre-test =41.85) for male participants. In the female group, the mean values are 36.82 for pre-test and 52.36 for post-test. These findings show that both male and females participants benefited from using LMS for teaching and learning.

The regression analysis shows a statistically insignificant relationship between the use LMS and student gender. This is illustrated by a beta value of 0.115, t-value of 0.833, and p-value of 0.409. This finding rejects the hypothesis that *performance of learning using LMS is influenced by the gender of a student*.

The results show that the use of LMS with F2F teaching has a positive impact on students across different languages on the performance of learning. This is demonstrated by a higher mean value of the post-test (post-test = 47.33) than the mean value of the pre-test (pre-test =32.94) for native language. The participants in English language have obtained the mean values of 65.17 for pre-test and 83.33 for post-test. In Afrikaans, participants have obtained the mean values of 41.11 for pre-test and 60.56 for post-test. The participants in the foreign language group have obtained the mean values are 45.17 for pre-test and 68.67 for post-test. These findings show that participants across different languages performs better with the use LMS in teaching and learning.

The regression analysis results show that language of instruction has no significant impact on the performance of learning using LMS. The regression analysis results of different language groups including English group (Beta = 0.116, t = 0.840, p = 0.405), Afrikaans (Beta = 0.184, t = 1.328, p = 0.190), and foreign language (Beta = 2.028, t = 0.280, p = 0.058) reveals statistically insignificant relationships with performance in teaching and learning using LMS. This leads to the rejection of the hypothesis that *performance of learning using LMS is influenced by the language of instruction*.

The study shows that the adoption of LMS with F2F teaching has a positive impact on students across different racial groups on the performance of learning in higher education. This is supported by a higher mean value of the post-test (post-test =49.92) than the mean value of the pre-test (pre-test =34.53) in African race group. The participants in the mixed-race group have obtained the mean values of 42.20 for pre-test and 65.60 for post-test. In western race, participants have obtained the mean values of 64.17 for pre-test and 77.67 for post-test. This shows that the use of LMS improves the performance of learning for students form different races.

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The regression analysis results show that there is no relationship between student age and the performance of learning using LMS. The results reveals that African race (Beta = 0.085, t = 0.432, p = 0.667) and mixed-race (Beta = 0.376, t = 1.922, p = 0.060). are statically not significant on the performance of learning. This leads to the rejection of the hypothesis that *performance of learning using LMS is influenced by the race of a student*.

The study shows that the adoption of LMS with F2F teaching has a positive impact on students across different age groups on the performance of learning in higher education. This is demonstrated by a higher mean value of the post-test (post-test =49.00) than the mean value of the pre-test (pre-test =36.60) in 18-21 years age group. The participants in 22-25 years have obtained the mean values of 45.07 for pre-test and 63.56 for post-test. In 26-29 years, participants have obtained the mean values of

33.93 for pre-test and 50.75 for post-test. The participants in the 30 years and older have obtained the mean values of 25.80 for pre-test and 40.80 for post-test.

The regression analysis results show that there is no relationship between student age and the performance of learning using LMS. The results show that 22-25 years age group (Beta = 0.297, t = 1.586, p = 0.119), 26-29 years (Beta = 0.180, t = 1.000, p = 0.322), and 30 years and older (Beta = 0.074, t = 0.458, p = 0.649) are statically insignificant results with respect to the performance of learning. This means that the hypothesis that *performance of learning using LMS is influenced by the age of a student* is rejected.

The study shows that the adoption of IM has a positive impact on male and female students with respect to the performance of learning in higher education. This is demonstrated by a higher mean value of the post-test (post-test =51.90) than the mean value of the pre-test (pre-test =40.74) for male participants. In the female group, the mean values are 38.87 for pre-test and 53.39 for post-test. These findings show that both male and females participants benefited from using IM for teaching and learning.

The regression analysis shows a statistically insignificant relationship between the use IM and student gender. This is illustrated by a beta value of 0.300, t-value of 0.210, and p-value of 0.835. This finding rejects the hypothesis that *performance of learning using IM is influenced by the gender of a student*. This means that the performance of learning using IM is not influenced by gender.

The results show that the use of IM with F2F teaching has a positive impact on students across different languages on the performance of learning. This is illustrated by a higher mean value of the post-test (post-test = 50.58) than the mean value of the pre-test (pre-test =37.31) for native language. The participants in English language have obtained the mean values of 60.50 for pre-test and 79.50 for post-test. In Afrikaans, participants have obtained the mean values of 37.33 for pre-test and 54.78 for post-test. The participants in the foreign language group have obtained the mean values are 35.50 for pre-test and 55.00 for post-test. These findings show that participants across different languages performs better with the use IM for teaching and learning.

The regression analysis results show that language of instruction has no significant impact on the performance of learning using IM. The results show that English language participants have obtained Beta = -0.099, t = -1.170, and p = 0.244. In Afrikaans language, participants have obtained Beta = 0.129, t = 1.523, and p = 0.130. The foreign language participants have obtained Beta = -0.044, t = -0.518, and p = 0.606. These findings reject the hypothesis that *performance of learning using IM is influenced by the language of a student*. This means that the performance of learning using IM is not influenced by language.

The study shows that the adoption of IM with F2F teaching has a positive impact on students across different racial groups on the performance of learning in higher education. This is supported by a higher mean value of the post-test (post-test =50.41) than the mean value of the pre-test (pre-test =37.05) in African race group. The participants in the mixed-race group have obtained the mean values of 34.29 for pre-test and 54.14 for post-test. In western race, participants have obtained the mean values of 51.40 for pre-test and 69.60 for post-test. This shows that the use of IM improves the performance of learning for students of different races.

The regression analysis results show that there is no relationship between student age and the performance of learning using IM. The results show that mixed-race (Beta =0.257, t = 1.843, p = 0.071), and western race (Beta = 0.166, t = 1.187, p = 0.241) are statically insignificant with respect to the performance of learning. This means that the hypothesis that *performance of learning using IM is influenced by the race of a student* is rejected.

The study shows that the adoption of IM with F2F teaching has a positive impact on students across different age groups in their performance of learning in higher education. This is demonstrated by a higher mean value of the post-test (post-test =54.80) than the mean value of the pre-test (pre-test =38.00) in 18-21 years age group. The participants in 22-25 years have obtained the mean values of 40.59 for pre-test and 56.72 for post-test. In 26-29 years, participants have obtained the mean values of 36.08 for pre-test and 47.69 for post-test. The participants in the 30 years and older have obtained the mean values of 26.50 for pre-test and 38.50 for post-test.

The regression analysis results show that there is no relationship between student age and the performance of learning using IM. The results show that 22 to 25 years age group (Beta =-0.038, t = -0.156, p = 0.877), 26 to 29 years (Beta = -0.260, t = -1.122, p = 0.268), and 30 years and above (Beta = -0.148, t = -0.815, p = 0.419). are statically insignificant results with respect to the performance of learning. These findings have led to rejection of the hypothesis that *performance of learning using IM is influenced by the age of a student*.

The study reveals that the use of LMS with F2F is more effective than the adoption of F2F in South African higher education. This is because most participants in the LMS + F2F group have obtained better performance in teaching and learning compared to that of most participants in the F2F group. The LMS + F2F group has an average performance of 64.26% while the F2F group has an average performance of 58.06%. Furthermore, most participants in the LMS + F2F group have obtained an average performance increase of 19.16% between pre-test and post-test while most of the participants in the F2F group have obtained an average performance increase of 11.74% between pre-test and post-test. This means that the adoption of LMS has a higher impact than F2F with respect to the performance of learning in South African higher education.

The independent-sample *t*-test shows significant results ($t = 4.067$, $df = 82.523$, p-value < 0.001) with respect to the comparative analysis between the use of LMS and the use of F2F in South African higher education. This finding confirms the descriptive statistics finding that the adoption of LMS has positive impact than F2F with regards to the performance of learning in higher education in South Africa. Such a finding supports the hypothesis that digital learning using LMS has better performance in teaching and learning than F2F in South African higher education.

The comparative analysis between IM + F2F and F2F using descriptive statistics shows that the adoption of IM is more effective than F2F. The evidence for this finding is bifold. First, most participants in the IM + F2F group have a higher average performance in the post-test compared to most of the participants in the F2F group, with IM + F2F having an average performance of 60.69% and F2F having an average performance of 58.06%. Second, most of the participants in the IM + F2F group have obtained an average performance increase of 16.92% between pre-test and post-test while most of the participants in F2F have obtained an average performance increase of 11.74% between pre-test and post-test. These findings show that the adoption of IM has a higher impact than F2F with regards to the performance of learning in South African higher education.

The independent-sample *t*-test also reveals that the adoption of IM is more effective than F2F with respect to the performance of learning in higher education in South Africa. This is demonstrated by a *t*-value of 3.348 with a degree of freedom of 132 and a p-value of 0.000. This result supports the hypothesis that digital learning using IM has better performance in teaching and learning than F2F.

The study indicates that LMS is more effective than IM in South African higher education. This is because most LMS participants have a higher average performance in teaching and learning than most IM participants. Specifically, the average performance of LMS users is 64.26% in the post-test whereas the average performance of IM participants is 60.69%. Furthermore, the LMS + F2F cohort has a performance increase of 19.16% between pre-test and post-test while the IM + F2F group has obtained a performance increase of 16.92% between pre-test and post-test.

The independent-sample *t*-test reveals results that are statically significant in the assessment of the relationship that digital learning using LMS has better learning performance than digital learning using IM. This is demonstrated by a *t*-value of 1.012 with a degree of freedom of 103 and a p-value of 0.041. This finding confirms the descriptive statistics finding that the adoption of LMS has a higher impact compared to the use of IM with respect to the performance of learning in higher education in South Africa.

Overall this study reveals that the adoption of LMS and IM has a positive impact on the performance of learning in South African higher education. It shows that the use of LMS is more effective than IM with respect to the performance of learning in higher education although the difference is not statistically significant. The study also finds out that the adoption of LMS and IM is more effective than the use of F2F in South African higher education. Such findings of the study suggest that an increase on the adoption of specific digital technologies including LMS and IM in South African higher education can help improve the performance of learning.

9.3 Research Contributions and Implications

This study makes a major contribution to the field of the digital learning research from both the theoretical and the practical viewpoints. Theoretically, this study contributes to existing literature in the field of digital learning in higher education by (a) exploring the impact of LMS and IM on the performance of learning, (b) investigating the effect of student characteristics including gender, language, race, and age on the performance of learning using specific digital technologies, and (c) conducting a comparative analysis between LMS and F2F, IM and F2F, and LMS and IM on the performance of learning in higher education. It provides better understanding of the impact of using specific digital technologies including LMS and IM on the performance of learning.

There is much research investigating the impact of user characteristics on the performance of learning using digital technologies (Tan et al., 2012, Awopetu, 2016, Bere and Rambe, 2016). Existing research, however, does not have a general agreement on the effect of user characteristics on the performance of learning using digital technologies. Furthermore, there are unique circumstances surrounding the South African students due to the social inequalities resulted from colonisation. As a result, existing findings on the investigation of the impact of student characteristics on the performance of learning in higher education may not be suitable for the South African higher education audience. This study fills this gap by providing empirical evidences for investigating the impact of adopting specific digital technologies including LMS and IM on the performance of learning in South African higher education.

Practically, this study leads to several valuable findings to various stakeholders in the adoption of digital technologies for teaching and learning including government departments, higher education institutions, and digital technologies instructional designers and developers. Specifically the results of this study can (a) help government departments develop and conceptualise policies and strategies for adopting specific digital technologies including LMS and IM for improving the performance of learning, (b) provide South African higher education institutions with useful information in developing guidelines for facilitating improved digital technology adoption, and (c) challenges LMS and IM instructional developers and developers for the continuous development of user friendly and more effective digital technologies for teaching and learning.

The importance of this study to the South African government lies in its contributions in providing rigorous empirical evidences towards the formulation and development of specific policies and strategies for improving the adoption of specific digital technologies including LMS and IM for teaching and learning. Better adoption of specific digital technologies can help challenge private and government agencies in South Africa to continuously improve specific policies and strategies for better guiding the adoption of specific digital technologies in higher education. The development of clear policies and strategies for improving the adoption of specific digital technologies can help the government to develop a framework for funding specific digital learning projects in higher education. Such funding can help redress social inequalities in South Africa by increasing access to digital learning to students belonging to previously disadvantaged communities and those that come from low-income families. These initiatives can help improve the performance of learning in South African higher education.

The significance of this study for South African higher education institutions lies in its contributions in offering these establishments useful information for guiding the selection of the most effective digital technologies. Such a selection can help South African higher education to develop guidelines for implementing digital learning technologies which improve performance in teaching and learning for both male and female students, different races, and different age groups in higher education. Such guidelines can help enhance the adoption of specific digital technologies on the performance in teaching and learning.

The importance of this study to digital learning application developers lies in encouraging the digital technologies including LMS and IM adoption in higher education institutions through offering these developers useful information in applying appropriate design strategies for the development of digital learning applications. The digital learning developers are able to apply suitable design strategies in designing user-friendly interface to accommodate both male and female student from different races who learn using a second language.

9.4 Limitations and Future Research

There are some limitations to this study. First, this study investigates the impact of only two specific digital technologies, LMS and IM, on the performance of learning in South African higher education. Future studies can expand the focus of the study by considering other digital technologies in higher education.

Second, the sample that this study has used is selected from a single department of two universities in South Africa. To generalise the findings, the sample should be extended. Third, the sample is selected from the South African higher education. To gain a more reliable and general view of the impact of the emerging digital technologies on the performance of learning in higher education, the same study can be extended to more universities in other developing countries as well as developed countries.

Fourth, this study employs a quantitative methodology for exploring the impact of emerging digital technologies including LMS and IM on the performance of learning in South African higher education. Further research can incorporate the use of qualitative methodologies. This allows researchers to seek in-depth understanding of why the impact of certain digital technologies is different. The use of qualitative methodologies can help researchers to explore various views of participants in the study with respect to the adoption of specific digital technologies on their performance in teaching and learning.

Fifth, the objective of this research is to investigate the adoption of specific digital technologies in higher education in South Africa to better understand the effectiveness of these technologies on the performance of learning. There are other stakeholders in the adoption of specific digital technologies in higher education including instructors, higher education managers, system developers and instructional designers. Such stakeholders' insights are also important for a complete assessment of the impact of such technologies on the performance of learning in higher education. Future research should consider these stakeholders for gaining a better representation of the issues facing the successful implementation of digital technologies in developing countries.

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Appendices

APPENDIX 1

RMIT UNIVERSITY

a. PARTICIPANT INFORMATION AND CONSENT FORM (PICF)

b. PARTICIPANT INFORMATION

Project Title: Investigating the Impact of ICT Tutorial Strategies to Enhance Instructional participation: Application of the Rasch Model

Investigators:

- Associate Professor Elspeth McKay, PhD, Fellow ACS
  eMail:
  Phone:
- John Lenarcic, PhD
  eMail:
  Phone:
- Aaron Bere, PhD candidate
  eMail:

Dear Student

You are invited to participate in a research project being conducted by the RMIT University. Please read this sheet carefully and be confident that you understand its contents before deciding whether to participate. If you have any questions about the project, please ask one of the investigators.

Who is involved in this research project? Why is it being conducted?

This research is conducted as part of a PhD degree in Business Information Systems. The senior supervisor for this research project is Associate Professor Elspeth McKay. Dr John Lenarcic is the second supervisor. Both research supervisors are academics in the School of Business Information Technology (IT) and Logistics at the RMIT University in Melbourne, Australia. The research candidate is Aaron Bere enrolled in a Doctor of Philosophy in Business Information systems, at RMIT University. This research study has been approved by the RMIT Business College Human Ethics Network (BCHEAN).

Why have you been approached?

The participant target group for this research are third year students, enrolled in the Information Technology National Diploma programme, who are currently registered for the Database Systems Course at the Central University of Technology, South Africa. Since your profile meets the participant criteria required in this research, the researchers invite you to participate in this study. The researchers obtained your details from the Central University of Technology enrolment list.

What is the project about? What are the questions being addressed?

The research aims to investigate the effectiveness of information communications technology (ICT) tutorial strategies in promoting instructional performance in database systems knowledge acquisition in South African higher education. Fundamentally the study examines students' performance as influenced by the instructional ICT strategies and cognitive media preferences. The research study is guided by the following research question: What are the interactive effects of instructional strategies and cognitive preferences on database design and implementation knowledge development?

If I agree to participate, what will I be required to do?

If you agree to participate the following steps will be followed:

1. you will be requested to gather in a lecture theatre (on a specified date and time) to receive a short verbal explanation of the whole experimental procedure. You will be further requested to undergo a cognitive assessment process using software called the Cognitive Style Analysis (CSA) for the purpose of allocating you to the experimental instructional treatment mode.
2. you will then be requested to undergo a small pre-test of your prior domain knowledge.
3. following the collection of this pre-test, you will be advised of your ‘treatment mode.'
4. In the instructional tutorial session: You will undergo the instructional tutorial, either via the Blackboard Learning Management System (LMS), or receiving exactly the same assignment using an alternative mobile ICT tool.
5. Post-test: After the instructional intervention session, you will return to the lecture theatre to perform the post-test questionnaire to assess your knowledge of database modelling.

What will happen to the information I provide?

The University for which the researcher is studying requires him to conduct his research with high-level ethics integrity and to complete an empirical research thesis. The information provided by you will be pooled with other participants in the study and stored in a strictly confidential manner in a locked, secure University student researcher's locker at the Business College premises. Moreover, the electronic data will be stored on the researcher's private computer, for a period five years and then destroyed. The results of this data will be published in the student's research thesis and may appear in academic publications. However, all information regarding you participation will remain anonymous; this is why you are given a research-code when you register your participation.

What are the possible risks or disadvantages?

Please note that there is no deception or hidden purpose to any of the questions. As a participant of this study, you will be required to academically interact with other students, in the same Course/Module in specially prepared cyber-spaces (Blackboard and instant mobile messaging). Please note that while other participants may misuse these learning platforms and submit offensive material, to keep this risk minimal, the researcher will make clear certain ground rules that will set the boundaries of these online cyber-space environments.

What are the benefits associated with participation?

Participating in this study helps you on your revision of the database modelling topic within your Database Systems course. Additionally, your participation will help the researchers to design an instructional model to improve South African higher education instructional strategies that employ effective ICT tools.

What are my rights as a participant?

It is important for you to remember that participation in this study is voluntary and it is your right to refuse to participate. Furthermore, you have the right to withdraw at any stage of the research. However, please note that since your data is anonymous, it cannot be withdrawn once submitted. Completing and submitting your questionnaire implies that you have given full and informed consent to be part of this research. No extra marks are awarded for participation.

Whom should I contact if I have any questions?

In the event that you have any concerns or complaints about the manner in which this research is being conducted, or the way you have been treated, or if you have a query that one of the investigators has not been able to satisfy, you may write to the RMIT University Business

College Human Ethics Committee (BCHEAN) at the following email address: humanethics@rmit.edu.au.

Any such concerns or complaints will be strictly confidential. You will be informed of the outcome of the investigation. Furthermore, if you do have any questions or concerns regarding this study please feel free to contact one of the investigators on the details provided above.

What other issues should I be aware of before deciding whether to participate?

All the information you need about the research that is useful for you to decide whether or not to participate has been provide in this document. Therefore there are no further issues you should be aware of prior to your decision to participate.

Yours sincerely

Associate Professor Elspeth McKay, PhD, Fellow ACS ……………………………………
John Lenarcic, PhD ……………………………………………………………………………
Aaron Bere,PhD candidate ……………………………………………………………………………

If you have any concerns about your participation in this project, which you do not wish to discuss with the researchers, then you can contact the Ethics Officer, Research Integrity, Governance and Systems, RMIT University, GPO Box 2476V, Vic 3001. Tel: or eMail

RMIT UNIVERSITY

PARTICIPANT'S CONSENT

1. I have had the project explained to me, and I have read the information sheet
2. I agree to participate in the research project as described
3. I agree**:**
    - to undertake the procedures outlined
    - to complete a questionnaire

4. I acknowledge that:

(a) I understand that my participation is voluntary and that I am free to withdraw from the project at any time and to withdraw any unprocessed data previously supplied (unless follow-up is needed for safety).

(b) The project is for the purpose of research. It may not be of direct benefit to me.

(c) The privacy of the personal information I provide will be safeguarded and only disclosed where I have consented to the disclosure or as required by law.

(d) The security of the research data will be protected during and after completion of the study. The data collected during the study may be published, and a report of the project outcomes will be provided to me on request. Any information which will identify me will not be used.

AParticipant's Consent

Participant: ______________________________ Date: ________________

(Signature)

If you have any concerns about your participation in this project, which you do not wish to discuss with the researchers, then you can contact the Ethics Officer, Research Integrity, Governance and Systems, RMIT University, GPO Box 2476V, Vic 3001. Tel: or eMail

RMIT UNIVERSITY

APPENDIX 2

INVITATION TO PARTICIPATE IN A RESEARCH PROJECT

Investigators:
Aaron Bere, MTech IT
School of business information technology and logistics RMIT University, Melbourne-Australia

Primary Supervisor
Dr. Elspeth McKay, PhD, Fellow ACS Associate Professor
School of business information technology and logistics RMIT University, Melbourne- Australia
GPO Box 2476
Melbourne VIC 3001 Australia
www.rmit.edu.au

5 May 2016

To whom it may concern

Investigating the Impact of ICT Tutorial Strategies to Enhance Instructional participation: Application of the Rasch Model

Kindly we would like to request your permission to conduct this research study in your university; your university is invited to participate in a research project being conducted by RMIT University, Melbourne, Australia.

This research is being conducted by Aaron Bere, a PhD candidate in Business Information Systems enrolled in the School of Business Information Technology and Logistics (SBIT&L). The research is supervised by Associated Professor Elspeth McKay and Dr John Lenarcic, both of the SBIT&L, RMIT University. The main aim of this research study is to investigate the effectiveness of ICT tutorial strategies in promoting instructional performance in database systems knowledge acquisition at Central of university of technology (CUT), in South Africa. Fundamentally the study examines students' cognitive performance as influenced by the instructional ICT strategies and their cognitive media preferences. This research project has been approved by the RMIT Human Research Ethics Committee on 20 June 2016. Thereafter we will be in a position to send this Ethics Committee's approval to your University.

We anticipate there will be one or two database systems class/es (approximately 150 participants) required from your university; they will be invited to participate in this research, during one classroom lecture. Participation is voluntary and no extra marks are awarded for participation. The data collection method for this research is by conducting: a simple questionnaire to establish entry level knowledge; a training session on modelling techniques in entity relationship models, followed by another questionnaire to capture instructional outcomes. The overall duration time required for each participant is two hours.

If you have any questions regarding this research, please contact the researcher Aaron Bere or the primary supervisor (see details above).

Appreciate your approval to conduct this research in your university. Yours sincerely,

E.McKay
Associate Professor Elspeth McKay, PhD, Fellow ACS

If you have any concerns about your participation in this project, which you do not wish to discuss with the researchers, then you can contact the Ethics Officer, Research Integrity, Governance and Systems, RMIT University, GPO Box 2476V, Vic 3001. Tel: or eMail

RMIT UNIVERSITY

APPENDIX 3

PERMISSION LETTER TO CONDUCT RESEARCH IN YOUR DEPARTMENT

Attention: Information Technology Head of Department, Central University of Technology

I am currently enrolled for a PhD Business Information Systems at RMIT University, Australia. I wish to seek permission to carry out my research in your department. I will conduct my research on third year Information Technology (IT) students to examine their cognitive performance as influenced by the instructional Information communications technology (ICT) strategies and their cognitive media preferences.

The purpose of this study is to investigate the effectiveness of using ICT tutorial strategies to promote improved instructional performance in database systems knowledge acquisition at your institution. The study will employ a 2 x 2 factorial quasi-experimental design. Data will be collected using a paper-based questionnaire. I would be grateful for this permission and for your support.

I guarantee total confidentiality of information. I will only report information that is in the public domain and within law. The report will not report anything of a personal or comprising nature. If I intend to use information that may be in any way sensitive I will seek the permission of the originator before using it. There will also be total confidentiality of all names and I will not name the department without your permission.

Yours faithfully

Aaron Bere

APPENDIX 4

PRE-TEST AND POST-TEST QUESTIONNAIRES WITH SOLUTIONS

PRE-TEST

Please write the time you begin here: ……………………

Research Code: ☐

Demographics

Tick the appropriate box

Nationality: ☐

First language: ☐

Gender: Male ☐ Female ☐

Race: African ☐ Mixed ☐ White ☐ Indian ☐ Other ☐

Age: Under 18 ☐ 18-21 ☐ 22-25 ☐ 26-29 ☐ 30+ ☐

Introduction to SQL queries

Answer each of the following questions in the space provided

Section A:

1. In one word, write an operation performed by a database system apart from input and process.
   …………output …√…………………………………………………………………………………

2. In one word, state the building blocks of information.
   ……..… Data …√……………………………………………………………………………..…

3. In one word, describe a collection of computer system components that define and control the storage, management, and use of data.

…………database…√…….…………………………………………………………………….

4. In one word, describe a database that stores data in rows and columns. …………relational...√…………………………………………………………………………

5. In three words, describe a relational database's powerful tool used for extracting information and managing data.
   ………… structured query language …√…………………………………………………….

6. In one word, describe an alternative name for a database filed.
   …………. attribute …or … column…√……………………………………….……..…

7. Database table rows are called tuples. In one word, write an alternative term to tuples.
   …………records…√…………..…………………………………………………….

8. In one word, describe an SQL clause located at the start of a query.
   ………SELECT…√……………..……………………………………………………………

9. Explain the purpose of a FROM clause in an SQL query.
   ………it specifies the base table√ in which data should be queried√………………………

10. Explain the purpose of the (*) wildcard character in SQL.
    ………… it displays√ all database table fields …√…………………………………..

11. Suppose you want to display non-duplicate customer names from the Customers database table. In one word, write the SQL clause that queries non-duplicate data. ……………DISTINCT…√………………………………………………………………

12. Explain the purpose of the COUNT aggregate function in an SQL query.
    ………… it displays the number√ of items with non-null√ values in a column…………

13. In one word, state an aggregate function that displays an arithmetic mean in a given column
    ………………AVG…√……………………………………..………………………………

14. In one word, state the major clause used for conditional filtering in SQL.
    ……………..WHERE…√……………………………………………………………………….

15. There are three major logic operators in SQL. In one word, state an SQL logic operator apart from AND, and OR operators.
    …………NOT…√……………………………………………………………………………….

16. In one word, describe a logic operator that filters data when both conditions are satisfied.
    ………..AND..√.......................…………………………………………………………………

17. Suppose you have two conditions (Age < 35; and Position = ‘manager’), write an example of a conditional filtering statement that uses an OR logic operator.
    …………WHERE Age < 35 OR Position = ‘manager’…√…………………………………….

18. In one word, write a logic operator used to select rows that do not match a condition in the WHERE clause.
    ……………………………NOT…√…………………………………..………………………………

19. A university organised an excursing for students enrolled in at least one of the following courses: 1) Network security, and 2) Network principles. Write a single conditional filtering statement that meets the requirements of this situation.
    …WHERE √course= ‘Network security’ OR√ ‘Network principles ‘√..........………

20. Beneficiaries of a loan should meet the following conditions: 1) Gender = ‘Female’; 2) Age =< 23. Using these conditions and an appropriate logic operator, write a single conditional filtering statement.
    …WHERE √Gender =’Female’ AND√ Age =< 23……………………………………….....

21. A company has an internship opportunity for students younger than 25 years and candidates course-level should not be postgraduate studies. Use appropriate logic

operators and these two conditions (Age > 25; and course-level ='Postgraduate') to write a single WHERE statement that satisfies this situation.

……..WHERE√ NOT√ Age >25 AND√ NOT √Course-Level = 'Postgraduate√'………

Section B: Questions in this section uses Learners database-table

The table below was extracted from the college database and it is called the Learners table. The table presents data about Engineering Students taking Information Technology (IT) subjects. It contains student unique identifier (std_Num); first name (FirstName); family name (Surname); and gender (Gender). It also contains subject name (Subject) taken by a student and the corresponding mark (Mark).

Use learners database table to answer questions from 22 to 38.

Learners

Std_Num	FirstName	Surname	Gender	Subject	Mark
1001	John	Smith	Male	Database systems	75
1002	Eve	Smith	Female	Database systems	54
1003	Anna	Tanya	Female	Database systems	84
1006	Paul	Anderson	Male	Database systems	45
1008	Bill	Terry	Male	Programing	67
1010	Thabo	Zulu	Male	Programming	77
1012	Theresa	Roberts	Female	Programming	36
1001	John	Smith	Male	Network systems	66
1002	Eve	Smith	Female	Network systems	68
1003	Anna	Tanya	Female	Network systems	81

22. Study the database-table above and write an SQL query that displays all unique or non-duplicate surnames.

**********************************Solution**************************************

………………… SELECT√ DISTINCT√ (surname) √ ………………………………

……………………FROM Learners√…………………………………………………

23. Write a SQL statement that utilises a wildcard character for displaying all database table fields.

***********************************Solution*************************************

………SELECT *√…………………………………………..………………..……
………FROM Learners…√………………….……………………………………….

24. Suppose you want to display all female students in the Learners database table. In one word, state the database-object that should be specified after the FROM clause in that query.

***********************************Solution*************************************

………………Learners…√………….…………………………………………………….

25. Write a query that display female individual's first name, surname and gender.

***********************************Solution*************************************

……SELECT√ firstname, surname, gender√……………………………..…………
……FROM Leaners√……………………………………..…………………………
……WHERE gender= 'Female'√…………………………………..…………..……

26. Write a conditional statement that filters students enrolled in network systems subject.

***********************************Solution*************************************

………WHERE√ Subject = 'Network systems'√….……………….…………………….

27. Write a query that displays the lowest mark obtained in Network systems subject.

***********************************Solution*************************************

……………………SELECT√ MIN(Mark) √……………………….……………………….
……………………FROM Learners√……………………………………………….……..
……………………WHERE √Subject = 'Network systems'√…………………….……….

28. Write a query that calculates the average mark for database systems.

*********************************Solution*************************************

………………………SELECT√ AVG (Mark) √………………………………………………
……………………….FROM Learners√…………………………………………………………
………………………WHERE√ subject ='Database systems'√……………………………

29. Write a query that selects the largest mark in the learners' database table.

*********************************Solution*************************************

………………………SELECT√ MAX (Mark) √ ………………………………………………
……………………….FROM Learners√……………………………………………………………

30. Write a query that displays the total number of learners.

*********************************Solution*************************************

………………………SELECT√ COUNT(Std_Num) √ ………………………………………
……………………….FROM Learners√ ………………………………………………………

31. SELECT COUNT (*)
FROM Learners
WHERE subject ='programming' AND Mark > 65;

Write the output for the query above.

……………2…√…………………………………………………………………………………

32. Study the learners table above and study the output table below.

	Surname	gender	subject	mark
1	Smith	Male	Database systems	75
2	Smith	Male	Network systems	66

Write a query capable of displaying the out in the table above.

************************************Solution**

……….Select Surname, gender, subject, mark√……….
……….From Learners√……….……….……….…….
……….….Where √ forename = 'John'; √……….………

33. The lecturer wishes to display details for students who obtained a mark less than 70 in each subject; however, he is not interested in seeing information for students whose surname is Smith. The following query was written to provide the information required by the lecturer. Study the query and the output provided and then complete the spaces on the query labelled a, b, c, d and e.

```
Select Forename, Surname, …(a)……………………………,Mark
 From Learners
   Where …(b)………….. Mark …(c)………70
AND ……(d)…………………… surname= …(e)……………………………;
```

Output

	Forename	Surname	Subject	Mark
1	Paul	Anderson	Database systems	45
2	Bill	Terry	Programming	67
3	Theresa	Roberts	Programming	36

************************************Solution**

………..Select Forename, Surname, Subject√, Mark………..………..……
………..from Learners………..………..………..………..………..………..
…………Where NOT√ Mark >√ 70 AND NOT√ surname='Smith'√;……..

34. A software development company wishes to conduct a job interview to students irrespective of their gender. However, students who obtained a minimum of 70 in either programming or database systems were considered for the interview. You are requested to write a query, which displays the number of students who qualifies to be interviewed.

*********************************Solution*************************************

………..Select Count(mark) √………..………..………..…………
………..From Learners………..………..………..………..………..

……….Where subject ='programming' AND Mark >=70√ ……..

…..………..OR√ subject ='programming' AND Mark >=70√;……

35. Identify a statement that causes an error in the following query

SELECT Forename, Surname
FROM Learners
WHERE COUNT (Mark >=50) AND Gender='Female';

*********************************Solution*************************************

……… WHERE COUNT (Mark >=50)…√……………..……………………………….

36. The Learners table has three subjects namely: database systems; network systems; and programming. Write separate SQL commands that enforce conditions that learners can be enrolled in either database systems or networks systems or both.

*********************************Solution*************************************

a)……subject√ = 'database systems'√……………………………………………..…
b)……subject√= 'network systems'√…………………………………………………………

37. The following query displays the lowest mark in all subjects in the Learners database table excluding programming. Study the query and write a conditional filtering statement that provides the same output without using the NOT logic operator. Hint use the OR logic operator.

```
SELECT MIN (MARK)
 FROM Learners
     Where NOT subject = 'Programming';
```

**********************************Solution**************************************

```
SELECT MIN (MARK)
 FROM Learners
          Where subject = 'Database systems’√ OR√ subject = 'Network systems'√;
```

38. An SQL query presented below was written with the intention to calculate the average mark for male students who obtained at least 75 in database systems; and programming. However, the code generated syntax errors.

```
SELECT *, avg(‘mark’)
FROM Learners
  WHERE gender ='male' OR Mark <=70
    WHERE NOT subject = Network systems;
```

Identify five parts of the SQL query causing syntax errors.

**********************************Solution**************************************

(i)……*… √…………………………….…….

(ii)……avg(‘mark’) √……………………………

(iii)………OR…√…………………….……….

(iv)………Where…√……………………..………

(v)………subject = ‘Network systems’…√………

Complete correct query

```
Select avg(mark)
From Learners
Where  Gender ='male' AND Mark >=75
```

Please write the time you finished here: ……………………

```
AND NOT subject = 'Network systems';
```

APPENDIX 5

POST-TEST

Please write the time you begin here: ……………………

Research Code:

Demographics

Tick the appropriate box

Nationality:

First language:

Race: African ☐ Mixed ☐ Western ☐ Other

Gender: Male ☐ Female ☐

Age: Under 18 ☐ 18-21 ☐ 22-25 ☐ 26-29 ☐ 30+

Introduction to SQL queries

Answer each of the following questions in the space provided

Section A:

1. Fill in the blank with your best 'word':

   A database table column can also be referred to as either a field or an …attribute…√………

2. Fill in the blank with your best 'word':

   All databases perform three main operations that can be described as input, …process√, ……and output.

3. Database table rows are called tuples. In one word, write an alternative term to tuples.

…………records…√……………..……………………………………………………….
….

4. Fill in the blank with your 'best' word:
   The ...NOT... √...…...logic operator filters records that do no match a condition in a conditional filtering statement.

5. An organisation would like to offer a 5% salary increase to some of its employees. To be eligible an employee should have more than 8 years working experience and current job position should not be manager. Use appropriate logic operators and these two conditions (Experience < 8yrs; and position = 'manager') to write a single WHERE statement that satisfies this situation.
   ……WHERE √NOT √Experience < 8yrs AND√ NOT√ and position = 'manager√'…………

6. Fill in the blank with your 'best' word:
   A…SELECT…√……clause is situated at the beginning of an SQL query.

7. In one word, describe an aggregate function that calculates the average of the values within a single database table field.
   ……………AVG…√……………………………………………………………….

8. Fill in the blank with your 'best' word:
   The ……OR…√………. operator filters the query output to display results that meet at least one condition specified in the conditional filtering statement.

9. In one word, describe the database inputs that require processing to form information.
   …………Data…√…………………………………………………………………
   ……….

10. Fill in the blanks with your 'best' words:
    A relational database stores data in …rows…√.and …columns…√

11. In one word, state the major clause used for conditional filtering in SQL.
…………….WHERE…√……………………………………………………………
……….

12. Fill in the blank with your 'best' word:
A part from data management, a …database…√.system governs the manner in which data is stored and used.

13. Fill in the blank with your 'best' word:
The …………COUNT…√..... aggregate function calculates and display the number of database-table rows excluding rows with non-null values.

14. Suppose you have two conditions (1. Gender ='male'; 2. Salary < 6,000), Write a conditional filtering statement that meets both conditions.
……………WHERE√ Gender ='male' AND √Salary < 6,000)…
………………………..

15. Write a conditional filtering statement for a query that display employees who earn a salary under 6,000 regardless of their gender and the query should also display all male employees.
…………WHERE√ Gender ='male' OR √Salary < 6,000√………

16. Explain the purpose of a FROM clause in an SQL query.
………it specifies the base table√ in which data should be queried√………………………

17. Suppose you have two conditions (Gender ='male'; and Salary < 6,000), in one word describe, a logic operator that filters all male employees who earn less than 6, 000.
……………AND…√…………………………………………………………………
………..

18. Fill in the blank with your 'best' phrase:
Relational databases extracts facts and numbers, and manages data using database's tool called……structured query language…√…

19. Fill in the blank with your 'best' word:

    The most commonly used logic operators in SQL are AND, NOT, and …..OR…... √.

20. Fill in the blank with your 'best' word:

    The …DISTINCT…√. clause enables a query to display non-duplicate data.

21. Fill in the blank with your 'best' word:

    The …wildcard√….character that is denote by a …*…√….. symbol is used in SQL to substitute field names when selecting all attributes.

Section B: Questions in this section uses Lecturers database table

The table below was extracted from a university database and it is called the Lecturers table. It contains a lecturers' unique identifier (Lec#); First name (FirstName); Last name (surname); gender (Gender). It also contains the details of the subjects taught by a lecturer, which include: subject code (SubjCode); and subject name (Subject). Additionally, it contains lecturer's subject lecturing experience in years (Experience).

Use the lecturers table to answer questions from 22 to 38.

Table name: Lecturers

Lec#	**FirstName**	**Surname**	**Gender**	**SubjCode**	**Subject**	**Experience**
Lec2342	Peter	Erickson	Male	Db101	Database systems	2
Lec3423	Tanya	Moyo	Female	DB101	Database systems	7
Lec5343	Mary	Thompson	Female	Db101	Database systems	5
Lec2342	Peter	Erickson	Male	Prog101	Programming	8
Lec7623	Derrick	Evans	Male	Prog101	Programming	4
Lec7862	Maria	Erickson	Female	Prog101	Programming	6

Lec3423	Tanya	Moyo	Female	Net101	Network systems	7
Lec5343	Mary	Thompson	Female	Net101	Network systems	5
Lec7862	Maria	Erickson	Female	Net101	Network systems	4
Lec1122	Peter	Erickson	Male	IS101	Information systems	8
Lec7623	Derrick	Evans	Male	IS101	Information systems	6
Lec7862	Maria	Erickson	Female	IS101	Information systems	1

22. Study the SQL query below.

    SELECT COUNT (Lec#)

    FROM DISTINCT Lecturers

    WHERE Subject <>'Programming';

    Write a statement that causes an error in the query above.

    ……… FROM DISTINCT Lecturers …√……………………..

23. Write a query that display female individual's first name, surname and gender.

    ……SELECT√ firstname, surname, gender√……………………………..……………

    ……FROM Lecturer√……………………………………..……………………………

    ……WHERE gender= 'Female'√……………………………………..…………..……

24. Write a query that displays the number of female information systems lecturers.

    …………SELECT √ COUNT (Lec#)√…………………………………………………………

    …………FROM Lectures√……………………………………………………………………

    …………WHERE√ subject = 'information systems'√………………………………………

25. SELECT AVG (Experience)

    FROM Lectures

    WHERE NOT(Subject <> Programming);

    Write the output for the query above.

    ………5…√...

    …..

26. Write a query that displays the highest subject lecturing experience

    ……SELECT √MAX(Experience) √…………………………………………….

    ……FROM

    Lectures√……………………………………………………………………

27. Study the database-table above and write an SQL query that displays all non-duplicate female lecturer surnames.

    SELECT DISTINCT√ (surname) √
    FROM Lecturers√
    WHERE Gender = 'Female'√;

28. Write a query that displays all lecturer details with at least 5 years database systems lecturing experience.

    SELECT *√
    FROM Lecturers
    WHERE subject = 'database systems'√ AND√ Experience >= 5√;

29. Write a query that displays the number of female lecturers in the Lecturers table, excluding those lecturing programming.

    SELECT COUNT (*) √
    FROM Lecturers
    WHERE Gender = 'female'√ OR√ NOT√ subject='Programming'√;

30. The query below was written to displays unique lecturer's firstname and surname with a minimum of 7 years lecturing experience using the Lecturers table shown

above. Unfortunately, the query could not run due to syntax errors. List the errors in spaces labelled (a) to (d) below.

```
SELECT UNIQUE (Firstname), Surname
FROM Learners
    WHERE NOT experience =7;
```

(a)………UNIQUE…√……………………………
(b)………Learners …√…………………………….
(c)……… NOT ……√……………………………..
(d)……… experience =7……√…………………….

****************Correct Solution***************************

```
Select DISTINCT (Firstname), Surname
 From Lecturers

      Where experience >= 7;
```

31. Write an SQL command that filters network systems lecturers.
   ………………WHERE √SUBJECT = 'network systems' √……………………………..

32. In one word, write the table name that should be written after the FROM clause in a query involving displaying all lecturers.
   ………………………Lecturers…√………………………………………………………
   ……

33. Write two separate conditions that fulfils the following business rule: lecturers should teach either database systems or networks systems.
   a)…………………subject√ = 'database systems' √……………………………….
   b)………………..subject √= 'networks systems' √……………………………….

34. The query present below contains syntax errors, you are required to debug it. Your resulting query should display the total number of lecturers in the Lecturers table excluding programming lecturers. Complete spaces (a) to (c) provided below with syntax errors in the query below.

Select Sum (lec#)
From lecturers
Where IS NOT (subject = programming);

(a) …… Sum (lec#) ……√………………………………..

(b) …… IS NOT ………√…………………………………

(c) …… subject = programming …√……………………

****************************Correct solution*************************************

Select count (lec#)
From lecturers
Where NOT (subject='programming');

35. Use With a query that calculates total lecturing experience in the following subject: database systems; network systems; and programming.

Select SUM (experience) √
From Lecturers
Where subject = 'Database systems' OR√ subject = 'Network systems'√
OR√ subject = 'Programming'√;

36. Write a query that displays the lowest subject lecturing experience for programming.

…………SELECT MIN (Experience) √………………………………………………

…………FROM Lecturers√………………………………………………………………

…………WHERE subject = 'programming'√…………………………………………

37. Use an appropriate wildcard character to write a the first command for query that displays all lecturer information.

………SELECT *√……………………………………………..……………………..……

38. Write a query that calculates lectures' average subject lecturing experience.
……SELECT AVG (Experience) √………………………………………..……………………
……FROM Lecturers√………………………………………………………………………..…

Please write the time you finish here: ……………………