Cape Peninsula University of Technology

Learning analytics to enhance student throughput and success: A case study of the South African Technology Network (SATN)

By

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Thesis submitted in fulfilment of the requirements for the degree:

Master of Technology: Information Technology

in the Faculty of Informatics and Design

at the Cape Peninsula University of Technology

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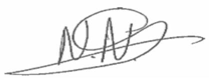
District 6 Campus (October 2020)

Declaration

I, **Ndiyakholwa Ngqulu**, declare that the contents of this dissertation/thesis is my own unaided work, and that the dissertation/thesis has not previously been submitted for academic examination towards any qualification. Furthermore, it represents my own opinions and not necessarily those of the Cape Peninsula University of Technology.

Signed   Date: October 2020



Abstract

Universities in South Africa are faced with low student success and throughput rates. These challenges go beyond the strength of the available tools, yet universities continue to use the same tools in addressing their challenges and yet they expect different outcomes. As a result, universities are taking steps towards improving their students' performance. In addressing these challenges, several universities have taken progressive steps; moving towards a digitalisation of education to apply data-driven decisions. So far, this has been a positive move towards addressing some of the challenges that are contributing to low student performance.

This study aims to investigate the potential of introducing learning analytics as a tool to analyse student data and to respond to the low student performances faced by South African universities. Learning analytics is an emerging field with the potential to enable higher education institutions to gather information and thus provide an understanding of students' learning needs, and to use this to improve student performance and throughput.

Learning analytics has been studied and implemented in other countries, such as the United Kingdom, Australia, and other parts of Europe. In these countries, learning analytics as one of the systematic ways of analysing data, has been reported to have the ability to improve student success and throughput. It also provides an opportunity for the early identification of students who are at risk. Among other things facing the universities of South Africa, are the factors mentioned above.

Informed by the background explained above, the main question of the study is: How will the introduction of learning analytics help South African universities to improve student success and throughput rate? To respond to this question, South African Technology Network (SATN) was used as case study and thematic analysis was applied to analyse the collected data

Acknowledgements

I wish to thank:

The Almighty God first and foremost let me take this moment to Praise God for the guidance and wisdom given to me to do this work. You are great at all times.

My entire family, who have always given me needed support and for that am grateful to you all.

My daughter Thalanda and my son Simele, you always cheered me up on days when I felt so down. I love you kids, and you are great.

Prof Izak van Zyl, my supervisor; he has been so patient with me and encouraged me to keep pushing. Your quick response and good guidance have contributed to my growth.

Dr Hlamulo Makelane, my former line manager who became a friend. You took time to understand my field even though you are a chemistry person. All the support that I received from you assisted me so much. Thank you.

Mr Phumzile Nomnga, a friend and brother. You are always the voice in my ear. You were never afraid to critique me and to remind me of my targets; you were always willing to fill the recommendations for a scholarship. Thank you Madiba.

Ms Ntsako Mhlanga, a friend to me at all times, you helped me with listening and transcribing the interviews. It was an exceptionally long process, yet you went on as if it were nothing. Thank you.

The financial assistance of the National Research Foundation towards this research is acknowledged. Opinions expressed in this thesis and the conclusions arrived at, are those of the author, and are not necessarily to be attributed to the National Research Foundation.

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List of Abbreviations

CHE: Council of Higher Education

HEI: Higher Education Institution

ICT: Information and Communication Technology

LA: Learning Analytics

LMS: Learning Management System

SATN: South African Technology Network

SLA: Social Learning Analytics

TEA: Technological Education Analytics

UoT: University of Technology

Definition of Key Terms

Analytics: the use of analytic tools to analyse big data to understand, to interpret and to solve complex issues.

Learner data: information or data related to the learner, such as registration, applications and degrees; about an individual or a student.

Learning analytics (LA): The usage of analytic methods or procedures to analyse learner data, learning data, students and lecturer's assessments and activities, to gain insight about students, to predict those who are at risk and underperforming and to advance institutional related programs.

Learning data: information or data related to the learning activities, assessment and digital activities involving a learner and a lecturer.

South African Technology Network (SATN): a joint platform of all South African Universities of Technology (UoT), which is responsible for a process of collaborative initiatives, improving quality and curriculum activities, research and quality assurance across the UoT.

Student success: refers to the progress of students from the registered modules or courses during half or yearly examinations.

Throughput rate: The ability of students to finish their qualification in due time as set out by the university.

University of Technology: the merger of two or more former Technikons and later legislated to be a University of Technology (UoT).

Chapter 1: Introduction

1.1 Introduction

In this thesis, the researcher will examine the use of learning analytics in higher education institutions with specific reference to Universities of Technology in South Africa. The aim is to broaden the understanding on how the use of learning analytics can enhance student throughput and success. It is also to dig deeper and to get an understanding of how managers, administrators and academic staff perceive learning analytics in various Universities of Technology. This thesis reports on a qualitative case study, conducted within the South African Technology Network, which is an umbrella body for Universities of Technology, between January 2017 and 2019.

Learning Analytics (LA) can be defined as the “application of analytic techniques to analyse educational data, including data about learner and teacher activities, in order to identify patterns of behaviour and provide actionable information; to improve learning and learning-related activities” (Siemens & Long, 2011:2). If a student logs any digital activity within a university, be it logging into a university network, utilising online library platforms, using a Learning Management System to submit an online assessment, using any provided virtual environment by the university - in all such occasions, a student leaves a digital footprint trail (Sclater, Peasgood & Mullan, 2016). How can and do universities use this data to enhance student throughput and success?

Learning analytics is central to this study; however, it is a complex subject with a unique focus. There is a wide range of learning analytics from social media data, logins, registrations, learning to learner data (academic analytics) (Siemens & Baker, 2012). This research focuses primarily on the use of academic learning data, which involves students, lecturers and digital footprints of activities and assessments. According to Slade and Prinsloo (2013), Ferguson (2012) and Sclater et al. (2016), learning analytics offer the possibility of enabling institutions with insights on their students. With proper learning analytics tools applied to the data, student throughput and success stand a greater chance to improve.

The study comes at a time where higher education institutions (HEI) are faced with hard facts. It is on record by the Department of Higher Education (2013:9) that “only about 27 percent of students finish their studies in minimum time as prescribed, and only half of the students who access higher education will ever graduate”. The majority of HEIs are relying on assumptions insofar as the issue of dropout and failure rate is concerned; and these assumptions will not disappear simply by means of the introduction of learning analytics. However, they will be data based and will be detected for prevention or for long time solutions (Dietz-Uhler & Hurn, 2013).

Mafenya (2014) argued that the low success rate and throughput is arguably the single biggest problem facing South African higher education. At Purdue University, after the implementation of learning analytics, it has been said that the university can now detect students at risk from as early as the second week of the semester; something which was considered rather impossible before (Sclater et al., 2016). A study conducted by Sclater et al. (2016) showed that the analysis of data can show a number of points relating to student success. A study by the University of Maryland showed that students who get a D symbol use Virtual learning environments 40 percent less than those who get a C and higher, and this view has been constant year in, and year out, ever since the implementation of learning analytics. It is for this reason that a study of how learning analytics can enhance student throughput and success in South African Universities of Technology becomes important.

1.2 Background to the Research Problem

1.2.1 The problem of student throughput and success in higher education

The two terms "throughput" and "success" have been a dilemma to explain, in higher educational institutions. The dropout rate in enrolments in the 1990s was attributed to several factors, including a noticeable number of dropouts from historically disadvantaged institutions (HDIs). However, by contrast, former Technikons grew rapidly by 119 percent from 1990 to 2000 and thereafter, the enrolments have been growing rapidly. Despite this, the question of students' success and throughput remains a difficult task to overcome (Council on Higher Education, 2010).

Lewin and Mawoyo (2014) argued that the issues relating to a student's success and throughput have long been addressed in higher education policies and in different university policies. However, the crisis deepens with every succeeding report. The 2013 higher education audited records showed that the throughput rate recorded is still below 30 percent and this point is validated by the (DHET, 2019) higher education statistical report on higher education.

The Department of Higher Education (2013) provides an argument that higher education battles with the complex issue of success and throughput as well as in trying to balance it with quality education. The issue of success and throughput is evidently an issue that still needs to be handled with care, as it is still a major challenge in higher education. Mafenya (2014) concluded that low success rates and throughput are arguably the single biggest problem facing South African higher education.

1.2.2 The rise of learning analytics

Analytics is "the use of data, statistical analysis, and explanatory and predictive models to gain insights and act on complex issues" (Bichsel, 2012:3), **Learning analytics (LA)** is the "application of analytic techniques to analyse educational data, including data about learner and teacher activities, to identify patterns of behaviour and provide actionable information to improve learning and learning-related activities" (Siemens & Long, 2011:2). Davenport, Harris and Shapiro (2010) described analytics as answering questions that produce both information and insight.

According to Slade and Prinsloo (2013), learning analytics is a field with the possibility of enabling institutions of higher learning to grow their understanding of their wide population's learning needs. This understanding can be used positively by decision-makers.

Slade and Prinsloo (2013) stated that assessing student behaviour information could be advantageous if this information is best understood when it is coupled with best interventions; thus allowing students' throughput and success rates to increase. Ferguson (2012) noted that assessing a student remains a great interest and a central part of education. It is argued that student work can transform in ways that are too understated to be monitored by the human eye and thus, the need for learning analytics applications arises (Ferguson, 2012).

The application of learning analytics across the world is growing. Each country is adopting and applying learning analytics using a unique perspective. In England, it is reported that "At the University of New England, learning analytics is part of the wider ecosystem of engagement with students via social media, in order to foster a sense of community among those who may be studying part-time or at a distance, as well as on campus" (Sclater et al., 2016:22). It has been argued that learning analytics can be tailored to various needs. According to Arroway, Morgan, O'Keefe and Yanosky (2016:11) "motivations for pursuing learning analytics are diverse, with respondents identifying a wide variety of competing interests and concerns". The most consistently reported reasons relate primarily to student success and institutional effectiveness; thus providing institutions with an opportunity to create a cohesive, holistic argument in support of the use of learning analytics on campus (ibid.).

According to Sclater et al. (2016), despite all positives regarding learning analytics, there are still concerns to be noted that remain unresolved, such as ethical and data privacy issues, “over-analysis”, the lack of generalisability of the results and the possibility for misclassification of patterns.

However, while there are several researchers focusing on learning analytics such as Prinsloo, Siemens, Ferguson, and Sclater in the context of Southern Africa, there has not been enough research on the implementation of learning analytics. Therefore, the research problem for this study focuses on the extent to which the implementation of learning analytics would improve students’ academic performance at universities.

1.2.3 Statement of the research problem

Low student throughput and success rates in institutions of higher learning are counter-productive to the national economy and hinder the prospects of students to secure a livelihood (Lewin & Mawoyo, 2014; Mafenya, 2014). In addition, poor student performance brings into question the capacity and viability of academic institutions to produce educated minds and essential skills (Council on Higher Education, 2010).

In support of their interventions to improve student performance, most universities are moving towards data-driven decision-making (South African Association for Institutional Research, 2017). As a systematic way of analysing data about academic activity, the application of learning analytics is one data-driven intervention used to help in the early identification of students who are at risk of failing or dropping out (Gašević, Dawson & Siemens, 2015). Indeed, the emerging field of learning analytics has the “potential to enable higher education institutions to increase their understanding of their students’ learning needs and to use that understanding to positively influence student learning and progression” (Prinsloo & Slade, 2013:2).

However, learning analytics has as yet seen only limited, ineffective or insufficient use in the South African higher education environment (Prinsloo & Slade, 2017). While acknowledging criticisms of privacy and legality (ibid.), the literature gives little attention to the issue of how exactly learning analytics can contribute to or enhance student performance and retention in South African HEIs (Lemmens & Henn, 2016).

This has become an important problem to address in the context of the increasing digitisation of African universities, coupled with the systemic challenges of student drop-out and failure rates (Lemmens & Henn, 2016; Prinsloo & Slade, 2017). The research problem that this study is based on is therefore the application and the use of learning analytics as an organisational intervention, to enhance and to improve student throughput and success in universities.

1.3 Research Question(s)

How does the use of learning analytics contribute to or influence student throughput and success?

1.3.1 Research sub-questions

What are the perceptions of university managers, administrators and lecturers in respect of learning analytics?

How is learning analytics incorporated with daily teaching and learning practices?

What are the resources required for the implementation of learning analytics in South African Universities of Technology?

What are the ethical implications related to learning analytics (e.g., in respect of student privacy)?

1.4 Aims and Objectives

The aim of the study is to determine whether the use of learning analytics might improve and enhance the students' throughput and success rate.

The objectives of the research are as follows:

- To understand whether Universities of Technology are aware of learning analytics and whether they have taken steps towards systematic student data collection and analysis.
- To explore how managers understand the concept of learning analytics and its policy implications.
- To understand the role played by the South African Technology Network in respect of Universities of Technology, especially in relation to the adoption of modern technologies such as learning analytics.
- To investigate the resources required for the implementation and utilisation of learning analytics, and
- To discover whether HEIs are ready to incorporate the ways of teaching and learning with Learning Analytics over a particular time frame.

1.4.1 Rationale

The rationale of this research is to find a system that will help Higher Education Institutions, in particular the Universities of Technology, with assessing students beyond the class or the lecture room, to predict students who are at risk and to provide necessary interventions for patterns that either lead to failure or student dropouts. The study identifies potential means to address student performance and success rates. Furthermore, it evaluates international best practices and brings them into the South African higher education context. It is therefore necessary to conduct this study so to provide a general framework for learning analytics adoption and application. Lastly, the concept of learning analytics is arguably a systematic way of the collection and analysis of data and yet, there is still insufficient research work conducted in the South African context. The study provides a general understanding and best practices on learning analytics.

1.5 Research Design and Methodology

This study employs a qualitative method of inquiry. In qualitative research, various knowledge claims, methods of enquiry, data collection methods and data analysis are employed (Creswell, 2003). The research strategy to be adopted will be a case study strategy. A case study is defined as “an **empirical enquiry** that investigates a **contemporary phenomenon** within its **real-life context;** especially when the boundaries between [the] phenomenon and context are not clearly evident” (Yin, 2011:1). The type of the case study will be an **exploratory case study.** This is a study that is used to explore those situations where the interventions being investigated do not have a one-sided outcome (Yin, 2013).

Creswell (2003) explained the main function of qualitative data collection as a matter of observing participants behaviour by being part of the process. Yin (2013:4) describes six ways of collecting qualitative data, namely; documents, archival records, interviews, participant observation and physical artefacts. Documentation, interviews, participant observations and direct observation techniques have been adopted as techniques to collect data. Thematic analysis has been used to analyse data.

The sampling method chosen for the study was purposive sampling, which is when the sampler tries to balance the sample, depending on their opinion or purpose (Barreiro & Albandoz, 2001). The researcher aims at working with South African Technology Network (SATN) which is a forum of 7-member Universities of Technology that deals with issues pertaining to higher education teaching, research, technology transfer and innovation. SATN remains central and important as it is the centre of innovation in Universities of Technology in South Africa and in some of its affiliated universities. These universities exist in different provinces and locations (based on geographic location), varying in size and their potential for the use of technology for teaching and learning.

1.5.1 Ethical considerations

The researcher takes note of an individual's right to refuse to participate, desire to remain unknown or to maintain privacy. The researcher will not be involving any animal or any species except human beings, throughout the course of this research.

The rights of individuals, organisations and groups of people will always be observed and respected. The confidentiality of the information released will be treated with high care and safety and at no time will cultural or religious rituals be performed during this study.

The researcher acknowledges the constitutional rights of every citizen and will respect them accordingly while performing the study.

1.6 Delineation

The South African higher education institutions are geographically located within the nine provinces of South Africa in various campuses. The study has been narrowed down and places a direct focus on Universities of Technology and the SATN executive management that is responsible for decision making. Due to a lack of resources, the study could only be limited to a few chosen representations from all participating institutions. Not everyone in each unit were interviewed. The researcher did not interview everyone and did not review all existing documents. The research study employs a case-by-by-case approach, meaning that it selects singularly and draws conclusions from the data, so that the output may be applicable in other higher educational institutions that are similar in content to those that participated.

1.7 Significance

Barber and Sharkey (2012) observed that the predictive models applied by higher education institutions are likely to estimate a time for graduation at the point when the student enters the system. Between the time of registration and the time to graduate, there are several factors that may interfere and disrupt the life of a student and may contribute largely to failure rates or drop-outs.

According to Barber and Sharkey (2012), there are a number of factors contributing to drop-out rates that mostly occur outside the classroom or institutions. The reasons why students fail to graduate at the predicted time are not easily misunderstood most of the time. Blikstein (2011) argues that students learn best in unscripted and open-ended environments. However, students' work can evolve in a lot of complex ways, which makes it difficult for such evolvement to be observed by humans.

Higher education institutions are suffering from signs and symptoms that are left undetected by the human eye. The factors make it impossible for institutions to account for reasons for higher failure rates and dropout's rates. Looking at the views expressed above, the purpose of the study is to investigate the implementation and the use of learning analytics to increase the success rates and throughput of students in higher education institutions.

The study is expected to facilitate in-depth research on the research question. The expected outcome of the study is a document that will be used as a guiding principle for all institutions of higher learning to ascertain whether learning analytics should be considered or not and whether the resultant document should act as a reference for decision makers, policy formulators in HEI and senior managers. This study is expected to contribute knowledge and fill the gap insofar as learning analytics in South African higher education is concerned

1.8 Outline of the Thesis Structure

This study comprises five chapters:

Chapter 1: Introduces the research problem. It presents the background to the research problem statement. The research questions and sub-questions are explained, and a description of methodological considerations is provided. The contribution of the research is explained, and ethical considerations are discussed. The chapter also provides delineation of the research.

Chapter 2: Includes an in-depth review of existing literature which includes student success and throughput rates, learning analytics and learning design.

Chapter 3: This chapter presents the research design and methodology and provides an overview of the philosophical assumptions, paradigms, and the research approach. It describes the process of data collection, the collection methods used, and the analysis strategies employed. Validation of methods and ethical considerations are also stated.

Chapter 4: Presents and discusses emergent themes derived from the categories. The research findings are discussed in relation to the literature and research questions stated in Section 1.3. Answers to the research questions are provided and new emergent concepts are adapted to form a conceptual framework.

Chapter 5: Resulting conclusions and recommendations are based on research objectives. Limitations of the research study are stated. A reflection on the research journey and recommendations for future research are provided.

1.9 Summary

Failure and dropout rates are growing in higher education institutions, according to the Council on Higher Education (2010). The new statistical results on post school education and training (2019) report that the issue of drop out and failure rates is still an issue in higher education, despite all efforts made by the department, the universities and the interventions performed on social problems such as hunger and an increase in student accommodation facilities. The consequence of that is the fact that the quality of education and the ability of higher education institutions to deliver is highly questionable. This research examines the use of learning analytics to enhance the success and throughput rates in South African universities.

Siemens and Baker (2012), Ochoa, Suthers, Verbert and Duval (2014), and West, Huijser and Heath (2016) agreed that learning analytics is the essential element that higher education institutions have been missing. The implementation of learning analytics will be beneficial for students as they have the potential to tailor individuals even beyond the formal setting of classrooms.

The question of the capabilities of learning analytics has been addressed in countries such as the United Kingdom (UK), the United States of America (USA) and Australia. However, there is a gap of knowledge in the context of South African universities; especially when taking into consideration the culture, form, character, and infrastructural development differences of those countries. This research attempts to address the following question: how does the use of learning analytics contribute to or influence student success and throughput?

Chapter 2: The Literature Review

2.1 Introduction

In Chapter 2, the researcher draws attention to the discussion of previously published literature on three concepts: throughput, success and learning analytics; with a focus on the relationship between these terms and future suggestions made in the literature. It also gives context to what these terms mean regarding their application, what has been practised around the globe, and whether there are any local cases relating to the references provided.

2.2 Student Throughput and Success

The Higher Education Act of (2006) recognised the process of mergers that occurred during 2004 to 2006 in South African higher education institutions. This process gave birth to what is today known as the University of Technology (UoT), which resulted from the merger of two or more former Technikons (ibid.). According to the White Paper of the Department of Education (2003), the concept of a University of Technology was to combine the biggest universities South Africa has ever offered. Furthermore, it argued that there must be infrastructure investment and innovations, such as transforming teaching and learning through ICT, as the proposed ways to cater for the big numbers they envisaged would be carried out by these universities. Van Zyl (2015) explained the concept of the merger which he termed the unification of technical and industry related fields to apply that knowledge and basic research to what he termed a “differentiation of cultures”.

The UoT has achieved the highest student numbers to date (Council on Higher Education, 2010). However, Lewin and Mawoyo (2014) reported that the performance level remained the main challenge while access remained open to higher numbers. Mafenya (2014) then argued that such a university with such big numbers would contribute largely with low performance rates and if this was not addressed that it could raise questions on the quality of education and the capacity of those big universities which have become Universities of Technology.

The two terms “throughput” and “success” have been a dilemma to explain in higher education institutions. The drop-out rate in enrolments in the 1990s was attributed to a range of factors, including a noticeable number of dropouts from former historically disadvantaged institutions (HDI).

However, former Technikons (currently Universities of Technology); grew rapidly by 119 percent from 1990 to 2000 and from then on, the enrolments have been growing rapidly, despite the fact that the question of students’ success and throughput remains a difficult task to overcome (Council on Higher Education, 2010). Lewin and Mawoyo (2014) argued that the issues relating to success and throughput have been long addressed in higher education policies and in various university policies. However, the crisis deepens with every succeeding report. The audited records show that the throughput has been recorded as still being below 30 percent.

Academic strategies and methods to improve student success and throughput rates have been established and documented within South African higher education ever since it records began (O'Donoghue, Singh & Green, 2004). Despite the different strategies employed to improve students' performance, universities still do not yet understand their students' needs, how they learn, and what challenges they are facing (De Laat & Prinsen, 2014). Low students' throughput and success rates in institutions of higher learning are counter-productive to the national economy and hamper the prospects of students of securing a livelihood (Lewin & Mawoyo, 2014; Mafenya, 2014). In addition, Mafenya (2014) argued that the low success rate and throughput of students are arguably the biggest problems facing South African higher education.

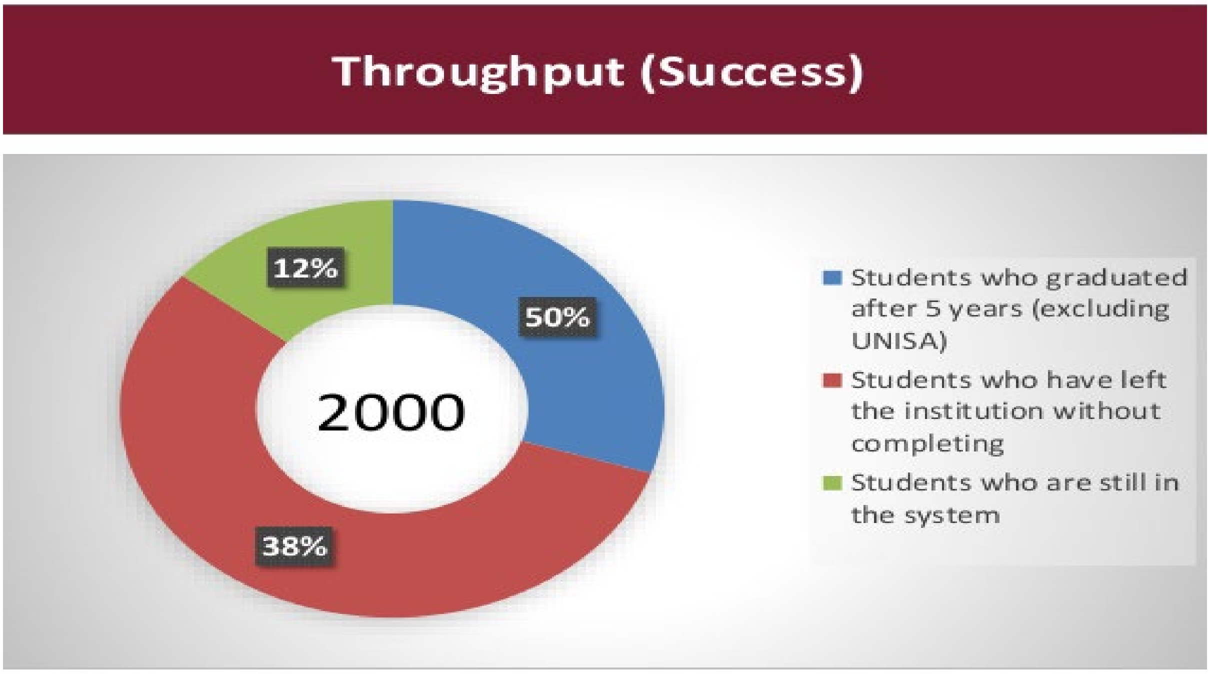
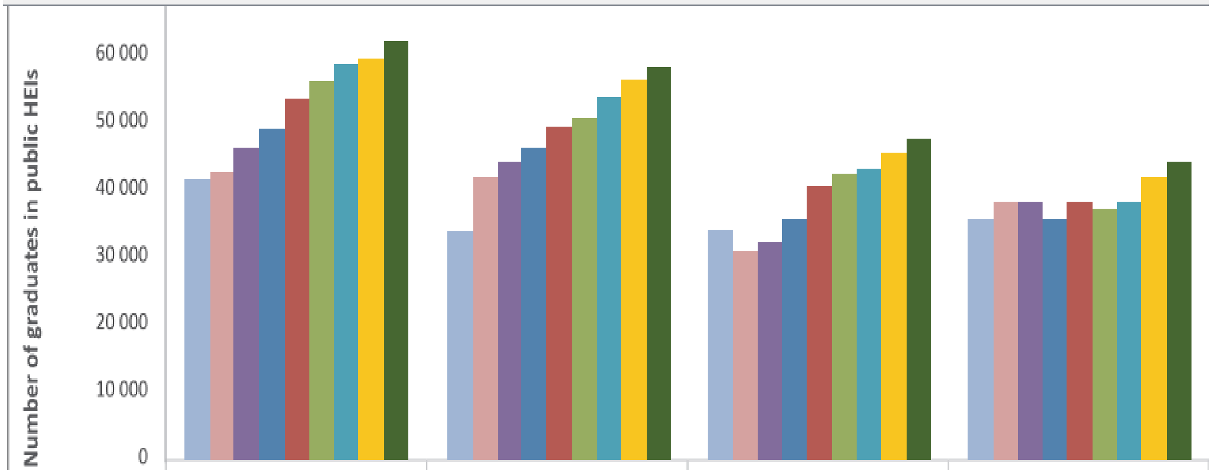


Figure 1: Throughput rate (CHE, 2010).

Furthermore, poor student performance brings into question the capacity and the viability of academic institutions to produce educated minds and essential skills (Council on Higher Education, 2010). Nevertheless, the government continues to increase funds for higher education, with expectations of specific targets of numbers of graduates and levels of quality (Department of Higher Education, 2013). While the country is still faced with these challenges, teaching and learning technologies are evolving, together with the technological tools of the time.

The Department of Higher Education (2013) provides an argument that higher education battles with the complex issue of success and throughput and to balance it with quality. The issue of success and throughput is evidently an issue that still needs to be handled with care as it is still a major challenge in higher education.



	SET	Business and Management	Other Humanities	Education
2009	41 511	33 818	34 523	35 532
2010	42 760	41 657	31 016	37 892
2011	46 100	44 155	32 484	37 879
2012	48 848	46 042	35 618	35 478
2013	53 176	49 051	40 384	38 212
2014	55 574	50 381	42 344	37 076
2015	58 090	53 863	42 917	36 654
2016	59 125	56 364	45 480	42 107
2017	61 581	57 772	47 144	44 434

Figure 2: Students' Success rate (DHET, 2019).

The Department of Higher Education (2019) reported that the last submitted audited statistical report on student's success rate showed a 3.9 percent increase in 2017, compared to that of 2016. This increase marked the highest recorded student success rate improvement during the years 2009 to 2017. This increase was influenced most by the Science, Engineering and Technology sector, the Education sector and Humanities, all of which achieved increases, when compared to earlier years (ibid.). Student success and throughput rates are arguably still a problem that the report is noting. While it appreciates the increase, it is notable that it is still below 50 percent as it recorded 45.1 percent on the last audited records (DHET, 2019).

2.3 Learning Analytics

2.3.1 Definition

Analytics is “the use of data, statistical analysis, and explanatory and predictive models, to gain insights and act on complex issues” (Bichsel, 2012:3), while Learning Analytics (LA) is the “application of analytic techniques to analyse educational data, including data about learner and teacher activities, in order to identify patterns of behaviour and provide actionable information to improve learning and learning-related activities” (Siemens & Long, 2011:2). Davenport et al. (2010) described learning analytics as answering questions that produce both information and insight. It was argued by Sclater et al. (2016) that there was growing divergence in the three major fields, including educational data mining, learning analytics and academic analytics, while there are also continuing overlapping points. There is a consensus shown in discussion that learning analytics can also be defined as being interdisciplinary and is influenced by various fields such as computer sciences, statistics, psychology, and the like (ibid.).

To connect between the need to improve the students’ performance rates and balance this with the changing technologies of the time, most universities are moving towards data-driven decision-making, as a systematic way of analysing data about academic activities (SAAIR, 2017). The application of learning analytics is one of the data-driven interventions used to help in the early identification of students who are at risk of failing or dropping out (Gašević et al., 2015). It is the view of Sclater et al. (2016) that there is a lack of summative data provision, that without doubt affects the relationship between the time spent on learning analytics and the chances of success. Furthermore, they argue that LAs had a positive influence in institutions but that such an impact cannot be attributed only to the individual students’ success. It is their observation that institutions were able to monitor and see who they should spend time on and what they did specifically in their Learning Management System (LMS). However, the success results were still mixed between those who spent time on the system and those who did not (Sclater et al., 2016).

Indeed, as early as 2013, learning analytics was identified as an emerging and yet rapidly growing field which offered higher education institutions an opportunity to deeply understand the factors influencing the learning of their students and the teaching techniques used by their educators (Prinsloo & Slade, 2013). This may present a chance of providing interventions to needy students, institutionalizing methods of teaching and learning that works better and thus it would provide help by increasing the students’ performance rate (Prinsloo & Slade, 2013).

Some have reasoned that the use of learning analytics has allowed students, themselves, to become content producers. Students mostly consume the content produced by the institutions. This provides insightful content which is valuable if collected, analysed and interpreted. As such, learning analytics is designed and developed to dig deeply into such contents which are not formally available to faculties and departments unless learning happens on a remote platform which is dedicated to organizing and systematically structuring data to inform how students should learn (Sclater et al., 2016).

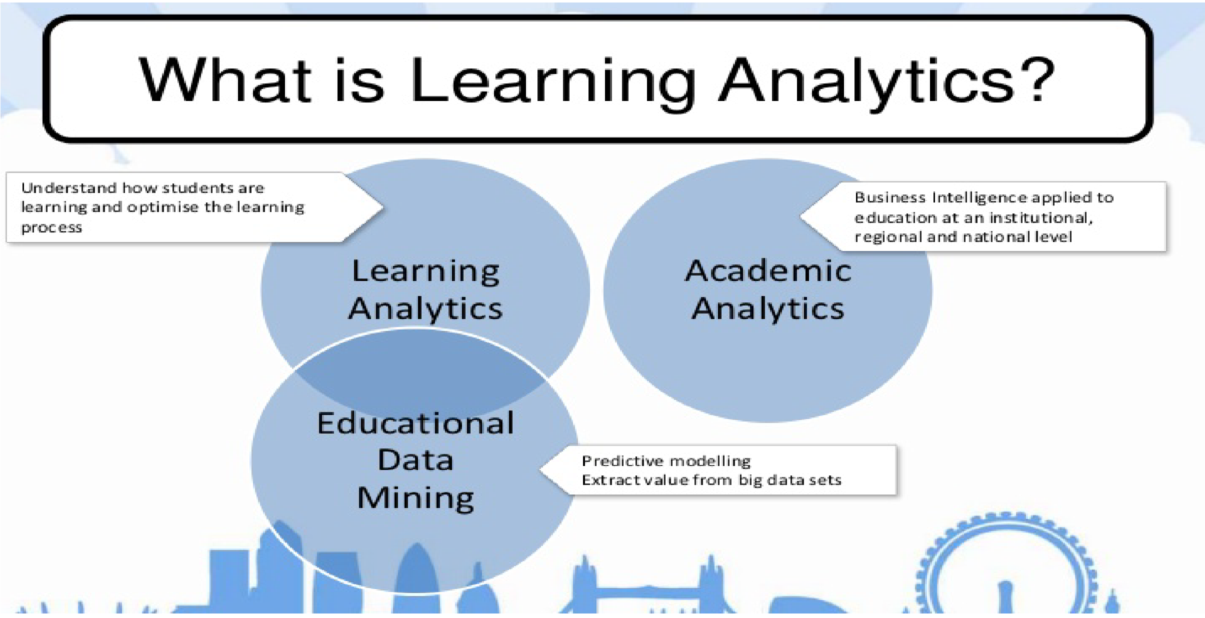


Figure 3: Systematic ways of organising student data (Siemens & Long, 2011).

Above are the three growing fields as explained by Sclater et al. (2016). Educational data mining is the process of applying predictive models and techniques to extract value of data from big datasets, while both academic and learning analytics are systems applied to analyse this data for different outputs. Learning Analytics focuses on understanding how students learn and helps to optimise the learning process. However, academic analytics focuses on business intelligence applied at an institutional or regional level (Alblawi & Alhamed, 2017). Learning analytics has yet seen limited, ineffective, or insufficient use or non-adoption in the South African higher education environment (Prinsloo & Slade, 2017). While acknowledging criticisms of privacy and legality (ibid.), the current literature pays little attention to the issue of how exactly learning analytics can contribute to or enhance student performance and retention in South African HEIs (Lemmens & Henn, 2016). This has become an important problem to address, especially in the context of the increasing digitisation of African universities, coupled with systemic challenges of student drop-out and failure rates (Lemmens & Henn, 2016; Prinsloo & Slade, 2017).

2.3.2 Learning design and learning analytics

Atkinson (2015) introduces an argument that the power of learning analytics depends on the learning designs used, for learning analytics to deliver on tailoring individuals on learning, competence and their life context. There is a need to enable learning designs that will work best with complicated or sophisticated learning analytics. According to Siemens and Baker (2012), there are commonalities between the fields of learning designs and learning analytics. "It is suggested here, that no matter how sophisticated the learning analytics platforms, algorithms and user interfaces may become, it is the fundamentals of the learning design, exercised by individual learning designers and faculty, that will ensure that technology solutions will deliver significant and sustainable benefits" (Atkinson, 2015).

Learning analytics are divergent from fields such as social science, statistics and other fields. As a result, Ferguson (2012) argued that there is a need to build a relationship between learning analytics (LA) and learning science, where learning analytics informs good learning design, effective pedagogy and increases student awareness. The introduction of virtual learning environments (VLEs) or Learning Management Systems (LMSs) resulted in big data being utilised for institutions. Since the analytical strength of these systems is not very strong and data emanates from multiple platforms, there is a demand for developing learning designs to extract meaningful value from data (Pallitt, Carr, Pedersen, Gunness & Dooga, 2018). Taking into consideration the increase in blended learning interest within Africa, there is a lack of understanding of the term learning design, what its activities are, and how it features in the daily activities (ibid.).

The success and usefulness of learning analytics is dependent on effective, well designed and structured learning designs. The new learning technologies require the designers to bring on fresh approaches which will provide students with better support and greater ability to extract value from data (Venter, van Rensburg & Davis, 2012). Learning design and learning analytics are independent fields of practice, yet these two feed off each other. The learning design provides a solid structure for learning analytics while learning analytics feeds back to inform the specifics of the learning design required (Lwoga & Komba, 2015). McKenney and Reeves (2012) argued that the role of learning design in learning analytics is especially important. Furthermore, they suggested that teachers should be trained and empowered as learning designers. This is informed by their point that learning design is a step to step guide designed to take students from one point to another. In collaborating this point, teachers possess an in-depth knowledge and understanding of the context wherein which teaching happens and the various types of students they have, which should inform what type of learning design is needed to unleash the right perspective onto students (Mor, Ferguson & Wasson, 2015). Holmberg (2014) introduced what he termed Conversations with Material, in defining the process of teachers being learning designers. This process involves the introduction of innovative ideas, implementing them and monitoring them to see the effect.

2.3.3 Applications of learning analytics

Gašević et al. (2015) reminded us that at all times, learning analytics is about learning. The major focus of learning analytics has been on learning performance, not only on learning strategies and practices. Furthermore, they state that while institutions are mostly concerned with students' performance, learning practices are also a key area to focus on (ibid.). In the application of learning analytics the literature shows a need to improve the qualitative tools used to dig deep into available data sources such as online blogs, virtual classrooms, and students' chatrooms, which can provide student data that might not be relevant for scoreboards that measure performance but might however be good for accessing learning practices (Mamcenko & Kurilovas, 2017).

Roberts, Howell and Seaman (2017), when discussing personalised learning analytics, argued that the virtualisation of data is yet another angle which if not properly developed, could lead to wrong conclusions, and particular dashboards; as this is one way to show data output that is often still widely misunderstood or misread. Some of the factors leading to this problem could be how they are designed or developed and their targets which are mostly about underperforming or lower level students and which neglect the high-level students, even if such student may have performed above his or her average.

Contrary to the main argument that there is no correlation between time spent on LAs and student success, Gašević et al. (2015) stated that the number of particular activities performed using an online system correlates with students' performance. However, the only major issue they raised is that learning analytics' real test is the long-term maintenance, sustainability and integration of teaching and learning practices to adapt to charging environments. To deliver to on the latter point, the deployment of data analysis techniques should take into consideration uncontrollable external factors. This is to provide predictive methods that would not only look and compare data with internal measures and score boards but would also look at the surrounding environments, to gain a deeper understanding. Furthermore, the internal measures should also be capacitated so as to be easily interpreted and understood; by using text highlighting, which could be associated or give meaning to content, thus making it easier to comprehend tags which would give indications or direction to help students to understand a module (Alblawi & Alhamed, 2017; Bronnimann, West, Huijser & Heath, 2018; Gašević et al., 2015).

Furthermore, Naidoo and Naidoo (2016) argued that there are various types or categories of learning analytics such as; 1) Descriptive, 2) Diagnostics, 3) Prescriptive and 4) Predictive learning analytics.

1) Descriptive learning analytics attempts to answer a descriptive question about what is happening or what has happened, and by so doing, utilizing the processes of comparison, contrasting and improving a personal performance by getting answers from various relevant data sources. Through an online system that is dedicated to tracking, following and capturing student's activities or most of their digital footprints, this process is enabled to unfold answers (De Laat & Prinsen, 2014; Dietz-Uhler & Hurn, 2013; Naidoo & Naidoo, 2016; Yu & Jo, 2014).
2) Diagnostics learning analytics follows and elaborates in a first phase on 'what happened' and a second phase of answering the major question; 'why did it happen' and then attempts to provide data driven answers to those questions. The course designers work tirelessly to understand what led to a certain error or performance or trend and then provide answers to improve students' understanding and improve their performance (ibid.).
3) Prescriptive learning analytics; focuses on finding out what and why something happened, then follows a process of discovering what should be done as intervention. At that stage, analytics help us to understand if educators rotate or need more time or that simpler activities must be provided, to avoid students failing (ibid.).
4) Predictive analytics assist the faculties and the departments to have future plans that incorporate all the trends, after having understood their students forward planning to avoid certain trends and to prevent particular behaviours (De Laat & Prinsen, 2014; Dietz-Uhler & Hurn, 2013; Naidoo & Naidoo, 2016; Yu & Jo, 2014). All these types of learning analytics provide better analysis to group and to locate the kinds of problems or challenges faced by students (ibid.).

De Laat and Prinsen (2014) introduced the concept of social learning analytics (SLA). According to them, this concept broadens the attempt of open access to higher education. The SLA is one form of data that is useful to students. It gives fruitful insights for students about who to associate with or consult with about their problems with fellow students, where certain learning activities have taken place and who is involved in that activity (ibid.). Social learning analytics is the process of visualizing and locating the indicators of social learning trends and behaviours; and by so doing, this increases the social awareness about the orientation on how to participate in an open network society (De Laat & Prinsen, 2014; Mamcenko & Kurilovas, 2017). This provides an opportunity for students to be practitioners and construct their own way of learning. By doing so, the system can pick the best methods to follow, that students enjoy using and apply to their learning.

Furthermore, the increasing use of social media has forced many traditional organisations to adopt new ways of conducting their businesses to stay relevant. The same goes for higher education. There is a new dimension that comes with trends such as using social media, online and hybrid; together with collaborative learning which demands HE to change or to adapt new ways of conducting teaching and learning (Nielsen Global Connect, 2017). According to De Laat and Prinsen (2014), an attempt to balance the recent changes in higher education has been created. The sticky campuses can be classified as a response to these changes. It provides for students to be in an environment where they are not only studying but can also socialise with other peers and collaborate in diverse topics of interest, while studying. The SLA inherently have similar problems with that of LA which, as argued by Prinsloo, is because SLA is part of learning analytics.

There is a theoretical misconception that data alone is an answer or rather a solution to problems or a prescription, to be exact. This misconception disregarded the fact that SLA or LAs are guided by ones philosophical beliefs and theories of what constitutes information (Bronnimann et al., 2018). The process of data analysis, the success indicators to be measured and or the methods of assessment are all guided by what one believes constitutes knowledge and how it should be measured or assessed. However, the same choices of data collection and the credibility and the validity of data remains a contested subject (Alblawi & Alhamed, 2017).

2.3.4 Model and stakeholders

The process of learning analytics involves various participating stakeholders, dedicated technologies and rigorous methodologies. It is a multi-disciplinary field that cuts across education technology, statistics, data modelling, and big data (Siemens & Baker, 2012). According to Siemens and Long (2011), penetrating the fog on learning analytics requires cooperation from various stakeholders. Whilst many believe that it is merely about students and how they learn, these disciplines involve the professional work done by content designers, data analyst, lecturers, content loaders and admin staff (web managers, student portal administrators etc.). Below is a figure showing how stakeholders, models and technologies relate to the process of learning analytics.

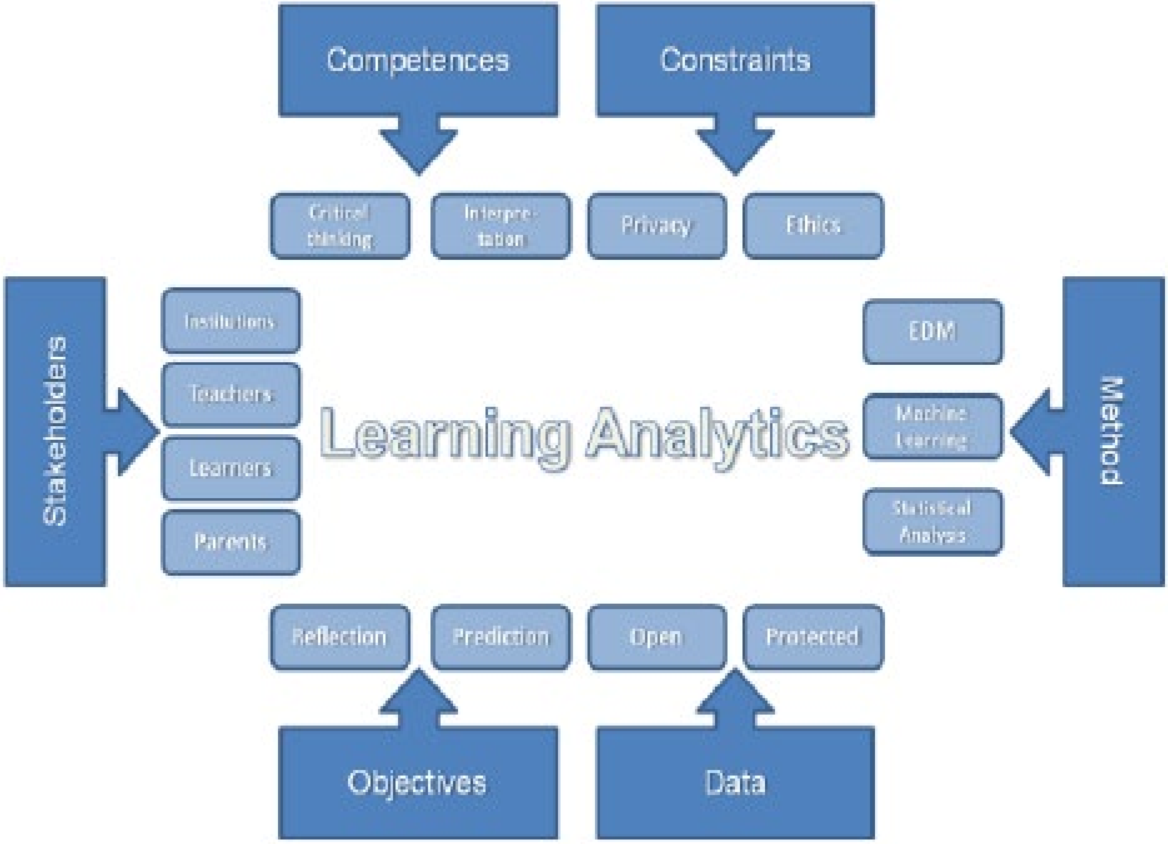


Figure 4: Learning analytics model.

The role players in LAs are demonstrated in Figure 4 above with stakeholders being one of the pillars. The HEI continues to face a challenge in one major aspect of learning analytics, namely; stakeholder cooperation, which has a vast shortage of skilled staff with a background or speciality in learning analytics (Ifenthaler, 2017). There still exists a major observation that the teachers or lecturers, as stakeholders, show a keen interest in learning analytics. However, this cannot be said about their participation or their contribution to enhancing the systems. This is perhaps what could be contributing to this setback; although they demonstrate sufficient understanding of the theory (West, Huijser, Heath, Lizzio, Toohey, Miles, Searle, & Bronnimann, 2016). According to West et al. (2016), teachers find the theory of LAs fascinating and interesting. However, they see it as impractical and impossible, which leads to non-implementation. What remains unanswered is the non-availability of teaching staff to attend workshops and training, which is meant to simplify the practical application of the theory.

On the other hand, there is a disintegration of students' data portals which are of importance for analysis of student's insights. It can be surmised that a very rich collection of student data is still not being analysed for the benefit of the students (Ifenthaler & Widanapathirana, 2014). The institutional commitments and priorities and the institutionalisation of learning analytics and teachers' priorities are key issues that could be tackled in order to address some of the challenges of the application of LAs West et al. (2016).

Furthermore, there is an underlying infrastructural capacity which plays a key role in the process of supplying LA. This ranges from dedicated servers, workspaces, data warehouses and devices to distribute various data reports. This constitutes a very important part in the state of readiness which may prepare stakeholders' psychological readiness (Ifenthaler, 2017). There are various stakeholders involved in the process of collecting and analysing data in learning analytics. However, it is a consensus point that the model is centred around students' data, which makes students the primary stakeholders in the policy setting, because a clear indication of the benefit offered to students is for them to make sure of the correctness and accuracy of the data (Prinsloo & Slade, 2013).

2.3.5 Ethical consideration

In starting the discussion on ethical consideration or privacy in relation to learning analytics data collection and use, Slade and Prinsloo (2013:4) constructed their own definition of learning analytics "as the collection, analysis, use and ***appropriate dissemination*** of student-generated, actionable data, with the purpose of creating ***appropriate cognitive***, ***administrative*** and ***effective*** support for learners". It is their view that from the definition of learning analytics, responsibility has been disregarded by those who are trusted with the data of students (ibid.). The largely accepted definition of LA focuses on the collection of students' data, the application of techniques to analyse data and the use of such outcomes as indicators for intervention to assist students at risk (Siemens & Long, 2011). The interpretation of this definition could be narrowed down to the point of not considering the rights of those individuals whose data is collected.

The perspective with which learning analytics is approached and applied results in various ethically related issues (Booth, 2012). Johnson, Adams and Cummins (2012) argued that most of the critical ethical concerns of learning analytics relate to data ownership and student privacy issues. Institutions of higher learning, from inception, have always analysed students' data to some extent, and have had access to this data for years, which has never posed any real danger to the student's identity (Buchanan, 2011). However, with the growth of data available and the introduction of computational models, institutions want to explore more of this data, and this poses a bigger danger (ibid.). Subotzky and Prinsloo (2011) concluded that between the stakeholders, being students and institutions, there needs to be a sharing of benefits and balance between individual harm and greater knowledge. Apple (2004) argued that ethical issues should be viewed from a socio-critical perspective. He further explained that this means being critical of the cultural, political, social, physical and economic contexts of the people whose data is being collected.

Land and Bayne (2005), Ferguson (2012), and Hall and Stahl (2012) argued that learning analytics' ethical considerations must be viewed within the context of power dynamics in higher education between students, institutions and other stakeholders. To further understand the opportunities and challenges of LA, the attention must be drawn to the role of power within the institutions. Lastly, some argue that transparency is important when dealing with the primary stakeholder (students), when taking into consideration that the students' identity is a transient, temporal and context-bound construct. Therefore, the data can have future implications for the students even though their identity would change (Land & Bayne, 2005; Ferguson, 2012; Hall & Stahl, 2012).

According to Markham and Buchanan (2012), Prinsloo and Slade (2013), ethically-related issues can be classed into three main categories: **1) location and interpretation:** this relates to the vast amount of data kept in various online storages with different standards and interpretation on incomplete or missing data and whereby most assumptions can be drawn from correlated data with analysts' views being a influencing variable, **2) Informed consent and privacy:** while institutions are expected to act on data to improve students' success, students still have the right to privacy and consent on issues relating to surveillance and monitoring of their activities. While this data might be argued to be of benefit to students, their de-identification and anonymity must be assured, **and 3) Management and Storage of data:** this directly speaks to structures responsible for data management and transparency. Oblinger (2012) suggested that Acts like the U.S. family education rights and the right to privacy may be used as exemplary guidance to draw up a framework of how institutions may assure students on data to be used and to what gain it be will beneficially.

Educational institutions have existing guiding policies on the purpose, the application and the protection of student data. However, in the light of the ever-transforming and growing learning analytics', policies have not been updated to fit the changing times and have not taken new challenges into consideration (Prinsloo & Slade, 2013). It is therefore an undisputed point that policy needs to align with the prevailing legislative framework and take into consideration ethical issues inherent in realising that learning analytics can facilitate an environment suitable for its adoption and support (Ivanova, Holotescu, Grosseck & IAPĂ, 2016).

Policy frameworks should provide an optimal and ethical environment for student data collection and use; whilst addressing the consent of benefactors and conditions of benefiting, privacy, vulnerability and harm (Roberts et al., 2017). According to Bichsel (2012), the financial costs carried by institutions for the implementation of data collection and use remains the highest concern relating to learning analytics, rather than the issues relating to privacy or the misuse of data. The greater challenge of the cost cannot be ignored because it is connected to other issues of misuse such as ownership of data or storage of data; all of which require more financial involvement so as not to use cloud spaces. It is for this reason that mitigating costs may be the major challenge, rather than ethical concerns (ibid.).

Various authors such as Parry and Tyson (2011); Kruse and Pongsajapan (2012); Prinsloo and Slade (2013) suggest a model that will be centred around students called **"student-centric",** where students are assured that their data will be protected against unauthorised access and that their consent will be guaranteed before data is used. This sets a process to be followed with clear guidelines on people gaining unauthorised access and students are given access to personalised, stored data and an overview of stakeholders, with access to specific datasets.

Chapter 3: Research Design and Methodology

3.1 Introduction

This chapter explores the research paradigms adopted by the study, the methods to be followed and how the research is designed. It documents the process of participants, data collection and how it will be analysed at the end. It also touches on issues of ethics and partiality.

3.2 Research Paradigms

The term “paradigm” originated from the Greek word ‘paradeigma’ which means ‘pattern’ (Kuhn, 1974). It was firstly used by Thomas Kuhn in the 1960s, to denote a conceptual framework shared by a community of scientists which provided them with a convenient model for examining problems and finding solutions. According to Crotty (1998), a paradigm is an integrated cluster of substantive concepts, variables and problems attached to corresponding methodological approaches and tools. It is imperative for the researcher to explain the philosophical position that is being adopted in the research. Research paradigms can vary from one researcher to another (ibid.).

Ontological and epistemological assumptions focus more on the nature, the structure and the relationship between the knower and the subject, which has a greater influence in world perspectives and on what constitutes knowledge (Lather, 1986). A person’s worldview can be categorised into two forms, namely: constructivism and interpretivism - the use of these two contrasting worldviews has been a long debate in academic spheres. However, neither of them is either considered to be more suitable or less suitable when compared to each other. the cases vary from study to study and on the researcher’s perspective (Hanson & Grimmer, 2007).

In this study, the researcher follows an interpretivist approach. This includes an inter-subjective assumption towards the reality to be investigated, as well as inductive logic. An Interpretivist approach gives the researcher great scope to address issues of influence and impact and to ask questions such as ‘why’ and ‘how’ particular technological trajectories are created (Deetz, 1996). The purpose of the interpretivist approach in Information Science is to produce an understanding of the context and process whereby information science influences and is influenced by its context (Orlikowski & Baroudi, 1991).

Interpretive studies assume that people create and associate their own subjective and inter-subjective meanings, as they interact with the world around them (Kuhn, 1974). Interpretive researchers thus attempt to understand phenomena through accessing the meanings participants assign to them (Orlikowski & Baroudi, 1991). For the interpretivist at the strong end of the spectrum, there is no reality outside our social constructions. Rather, there exist multiple truths - there is no objective, universal truth, simply contrasting definitions of truth (Walsham, 2006).

The interpretivists' epistemological position is that they believe that research and the researcher both mutually influence and co-construct the 'data'. Research findings are thus formulated by co-construction, emerging from the interaction; not waiting to be discovered (Thomas & Harden, 2008). Subjective theory or knowledge does not predicate on objective reality or theory, thus realty/realities are constructed by social actors in ~~a~~ social interaction; they are subjective, multiple, mutable and context-dependent (Kuhn, 1974). Guba and Lincoln (1994) argued that critical theory follows a more transactional and subjectivist epistemological perspective, where both the researcher and the subject of the research are actively linked with the worldview of the researcher. Furthermore, the positivist and the post-positivist investigation is more focused on explanation, predication and control, whereas critical theory's main objective is to critique and emancipate (Orlikowski & Baroudi, 1991).

In interpretivism, the reliability is low, and validity is high in the findings of interpretive approach. It is suggested that reliability is not as important as in the positivist approach (Collis & Hussey, 2003). In the interpretive approach, researchers are subjective in the way they look to their findings and attempt to understand and describe the way people view the world (Creswell, 2009). Moreover, the researcher in the interpretive approach understands that his or her interpretation of the findings is mostly influenced by his or her own culture, beliefs and experiences (Creswell, 2009).

3.2.1 Rationale for the theories adopted in the study

Each research study should be guided by certain theories which act as a guide showing how the investigator views the world and how to relate to the subject of the research. One or more paradigms can be used in the study, depending on the nature of the study. As briefly explained above, the guiding philosophy for this study is the interpretivist theory. However, this study cannot be completely pure because of the influence and the overlapping that occurs. Therefore there will always be footprints of other theories such as constructivism, as these theories are very similar to each other and the separation line is thin (Baxter & Jack, 2008).

Deetz (1996), when presenting interpretivism, argues that it gives a wide scope for the researcher to address issues of influence, ask descriptive questions and address issues of impact. The main objective of interpretivist approach in information science is to create a balance between the process and the context in which knowledge is produced and to understand how information science influences and is influenced by the context (Walsham, 1993). The interpretivist theory mostly addresses the deeper important shared points, meanings and understandings; whilst a constructivist approach would extend the research as it is concerned with interpreted knowledge. This distinguished assertion is what propels the choice of theory adopted by the researcher.

3.3 Research Methods

Research methodology is a strategy of enquiry which moves from the underlying assumptions to the research design and data collection (Myers, 2009). Research methodology is a systematic way to solve a problem, a science of studying how research is to be carried out and the procedures by means of which researchers go about their work of describing, explaining and predicting phenomena (Myers, 2009). The knowledge claims, strategies and method all contribute to a research approach that tends to be a more quantitative, a qualitative or a mixed approach (Creswell, 2003).

3.3.1 Quantitative approach

In quantitative research, a researcher primarily uses post-positivist claims for developing an investigation (i.e. cause and effect thinking, reduction to specific variables and hypotheses and questions, the use of measurement and observation, and the test of theories). The researcher thus employs strategies of inquiry such as experiments that yield statistical or numeric data (Creswell, 2003). Quantitative research is commonly referred to as hypothesis-testing research. Characteristically, studies begin with statements of theory which the study hypotheses are derived from and then an experimental design is established in which the variables in question (dependent variables) are measured, while controlling the effects of selected independent variables (Creswell, 2009). Subjects included in the study are selected at random, in order to reduce error and bias and the sample of subjects is drawn to reflect the population (Newman, Benz & Ridenour, 1998). In quantitative studies, the researcher considered the primary instrument of data collection and analysis (Creswell, 2003).

3.3.2 Qualitative approach

In qualitative research, the investigator often makes knowledge claims based primarily on the constructivist perspective (i.e. the multiple meaning of individual experiences, meanings socially and historically constructed, with an intent of developing a theory or a pattern) or advocacy/participatory perspectives (i.e. political or issue oriented) or both (Creswell, 2003). A qualitative approach also uses strategies of inquiry such as narratives, ethnographies, grounded theory studies, or case studies (Nyame-Asiamah & Patel, 2009).

The researcher collects open-ended emerging data, with the primary intention of developing themes from the data (Creswell, 2003). The qualitative approach involves an interpretive, naturalistic approach to its subject matter. It attempts to make sense of or to interpret phenomena in terms of the meaning people bring to them (Denzin & Lincoln, 2003). Ritchie and Lewis (2003) stated that qualitative research aims to expose and discover issues about the problem on hand, as very little is known about the problem; and especially if there is uncertainty regarding its dimensions and its characteristics.

The investigator engages with the situation and attempts to make sense of the multiple interpretations in that multiple realities exist in any given context, as both the researcher and the participants construct their own realities (Creswell, 2003). Data collection must be conducted in a non-interfering manner; thus attempting to study real-world situations as they unfold naturally, without predetermined constraints or conditions that control the research or the participants (ibid.).

3.3.3 Mixed approach

In this approach, the inquirer tends to base his or her knowledge claims on pragmatic grounds such as consequence-oriented, problem-oriented and pluralistic grounds, and uses strategies of inquiry that involve collecting data either simultaneously or sequentially, in order to best understand a research problem (Creswell, 2003). The data collection also involves gathering both numerical or statistical information (e.g. instruments) as well as textual information (e.g. interviews), so that the final database represents both quantitative and qualitative information (Ryan & Bernard, 2003).

One of the most difficult and important decisions to make is whether to use quantitative methods, qualitative methods or a mixed methods approach (Myers, 2009). The difference between the qualitative and the quantitative approaches is based on the author's judgment as both may include various methods and none of them is considered intrinsically better than another. The most suitable approach needs to be decided, based on the context, purpose and nature of the research study question (Hanson & Grimmer, 2007). The two approaches also differ in the logic they use. Qualitative research uses deductive logic, and quantitative research uses inductive logic. This means that in qualitative research, a hypothesis is not required to begin the research - it employs inductive data analysis, to provide a better understanding of the interaction of ‘mutually shaping influence’ and explicate interacting realities (ibid.).

3.3.4 Rationale for the research approach

This study will employ a qualitative research method of enquiry. In qualitative research, different knowledge claims, methods of enquiry, data collection methods and data analysis are employed (Creswell, 2003). According to Guba (1981), the process of choosing which research methodology to apply should be a balance between the research paradigm and the phenomenon to be investigated. The research paradigm assumptions should give guidance to the research phenomenon. In this study, the investigation is about human beings, learning interactions and emerging technologies for teaching and learning. The major focus of qualitative research is based on the processes or on the sequences of events or insights and interactions within the systems, rather than the output or the outcome (Myers, 2009).

Additionally, qualitative research approaches provide an account of personal interactions, understandings and perceptions of those who interact with or who are involved in the event. Furthermore, it provides broad and individual insights into understanding the role played by all the actors and their experiences while encountering the investigated phenomena (Creswell, 2009). The need to deeply investigate people’s perceptions of the learning analytics and their understanding of how it works requires more than simply acquiring a statistical set of results.

This study aimed at investigating without any intended misrepresentation the learning analytics adoption process, in higher education institutions in South Africa using the available data from students and educators, to study its systematic setup and the interpretation of individual meanings derived from of the phenomena at hand. The focus was on interviewees’ different perceptions, multiple understandings, different challenges and similar concerns in the adoption of learning analytics. The complexity of this process requires a research approach that can account for interpretations, group behaviours, and education cultural beliefs, by means of a qualitative approach which, according to Xia, Wang, Wang and Song (2016), can better account for these complexities than any other research method. The researcher acknowledges that learning is a complex process. It requires many variables to interact together. For learning assessment to be effective, it should be conducted while learning is taking place (Siemens & Long, 2011), together with a textually rich description, rather than a focus on final outcomes (Thomas & Harden, 2008). This also contributes to why a qualitative approach is best suited to this study. Therefore, the qualitative research approach offers a better framework to attain insights into the experiences of the participants; on which to formulate a basis to document these learning complexities.

3.4 Research Design

Research design can be argued to be the guiding plan of the study which gives direction as to how the research should be conducted. It sheds light on how each major step of the research will be conducted and how all the steps complement each other and fit together. This comprises the way strategy, samples, measurement, etc. work as collective methods, to address the main research question of the study (Orlikowski & Baroudi, 1991). According to Knox (2004), research design can be thought of as providing reasoning to arrive at a set of procedures that optimises the data's validity for the given research problem. Yin (1981) indicated that a research design is a masterplan for getting from point A to point B, where point A would be the set of research questions and sub-questions and point B would provide a set of answers.

3.4.1 The case study strategy

The research strategy employed in this research is a case study. A case study is defined as "an **empirical enquiry** that investigates a **contemporary phenomenon** within its **real-life context,** especially when the boundaries between the phenomenon and its context are not clearly evident" (Yin, 2011:1). It is also an investigation of human beings' interactions within a social context, by acquiring a vast range of evidence from a set group of people, a community, an institution or an organisation who behave similarly, due to some practices, conditions or standards (Gillham, 2000). Ritchie and Lewis (2003) explained a case study's basic distinctive characteristics as being numerous views, opinions and facts, guided by a designed context. The case study best fits an investigation where critical conditions are being studied and where the researcher has little or no influence on the research (Yin, 2003).

The type of case study for this research study is an **exploratory case study**, being a study that is used to explore those situations where the interventions being investigated do not have a one sided outcome (Yin, 2013). A case study investigates the setup scenario, using multiple data sources to gain evidence. This evidence helps to reach the best possible perspectives and insights into the research question (Quinlan, 2011). This strategy of research provides explanations into insights whereby the researcher wishes to understand the deep cause of the problem, various perspectives held by the participants and the extent to which the problem needs to be understood (Green, Willis, Hughes, Small, Welch, Gibbs & Daly, 2007). It also informs the researcher of the critical areas to be investigated for future research, to broaden the understanding of the event or the case. Sometimes a follow-up on statistical research is indicated in order to quantify and code the phenomena, once it has been understood (Thomas & Harden, 2008).

Furthermore, the case study strategy is compatible with various methods of data collection and analysis (Yin, 2003). Thus, multiple methods of data collection were utilised to acquire multiple perspectives on the case and to gain a broader understanding, without being limited by the method of collection. Various methods were used to paint a clearer data-informed picture of the response to the research question (Gale, Heath, Cameron, Rashid & Redwood, 2013). According to Yin (2003), a case study may utilise any or all of the research collection methods such as interviews, documentation reviews, archival records, participation, observation, direct observation or thick description of the research subject. Walsham (1995) argued that thick descriptions allow the researcher to gain a greater understanding of the subtitles of interpretations.

3.4.2 The participants

The study involves all the Universities of Technology in South Africa. The main participants were university representatives who are employees within eLearning units, Management Information Systems (MIS), content managers and data managers. The six UoTs in South Africa fall under the South African Technology network, which became the focus of the case study, as well as being the participants. All the Universities of Technology were afforded an equal opportunity to present themselves for interviews. All did except two who requested to be excused, due to internal changes that were taking place at the time. The sampling was conducted purposely, whilst the researcher remained aware of all the UoTs, to provide an equal opportunity for participation in the research. Whilst the participants are Universities of Technology, the target was specific to senior managers, who work within student's data portals, as mentioned above. The semi-structured interviews provided a chance for a representative(s) to provide insights about specific universities' status and appreciated the knowledge that comes with the experience of working there. The South African Technology Network (SATN) is formed by university representatives who become committee chairs. It referred the researcher to some participants who were already university representatives. Therefore, we could only speak with members of the CEO offices on the general mandate of the network.

3.5 Sampling

Sampling is an action or a process undertaken to find out the ideal, feasible and possible sub-set representation, to focus on, from a large population, for the purpose of understanding and investigation, to examine the notable patterns within a chosen context (Bhattacherjee, 2012).

Out of the various methods used for sampling, in this study the purposive sampling method was chosen and the South African Technology Network (SATN), with its South African institutions, was used as a base. The SATN is the umbrella body of UoTs in South Africa, and as such, the purposive sampling is mostly suitable when a population has the same characteristics (Barreiro & Albandoz, 2001). The selection of all Universities of Technology allowed the research scope to be broadened to dig deeper into the phenomena and to allow for easy access and the generalisation of outcomes. Although these universities exist in different provinces, and from their size, and their potential use of technology for teaching and learning, all the available UoTs were consulted during the study.

3.6 Data Collection

Creswell (2003) explained the main function of qualitative data collection as the observation of participants behaviour by being part of the process. Yin (2013:4) described six ways of collecting qualitative data being; "documentation, archival records, interviews, participant observations and physical artefacts". The documentation, interviews, participant observations and direct observations were adopted as techniques to collect data in this research. Data for this research was sourced from multiple sources which included secondary (Literature) and primary sources (Interviews). Data collection was carried out using face-to-face and telephonic interviews to establish salient points and deeper meanings using a qualitative research method.

3.6.1 Available and relevant documentation

In order to reach qualitative reasoning in explaining how learning analytics are perceived and how learning analytics can enhance student throughput and success, documents such as strategic planning, meeting minutes, turnaround strategies, use of ICT or progress reports have been reviewed with the researcher being a participant, in order to gain an inside view.

3.6.2 Interviews

The interview is a social relationship designed to exchange information between participant and researcher (Seawright & Gerring, 2008). Thomas (2010) stated that semi-structured interviews have the potential to produce rich material that is unobtainable in any other form of data collection. The researcher has conducted semi-structured interviews with different participating members from SATN and the various Universities of Technology.

The face-to-face interviews were arranged with participants who were available and reachable; telephonic interviews were conducted with those who were not available for face-to-face interviews. The time allocations for interviews ranged from 40 to 60 minutes and the participants were staff members from Universities of Technology within the department of eLearning, Learning Design and ICT. Interviewed staff members from these units included managers, administrators and academics. The structure of the interviews was as follows:

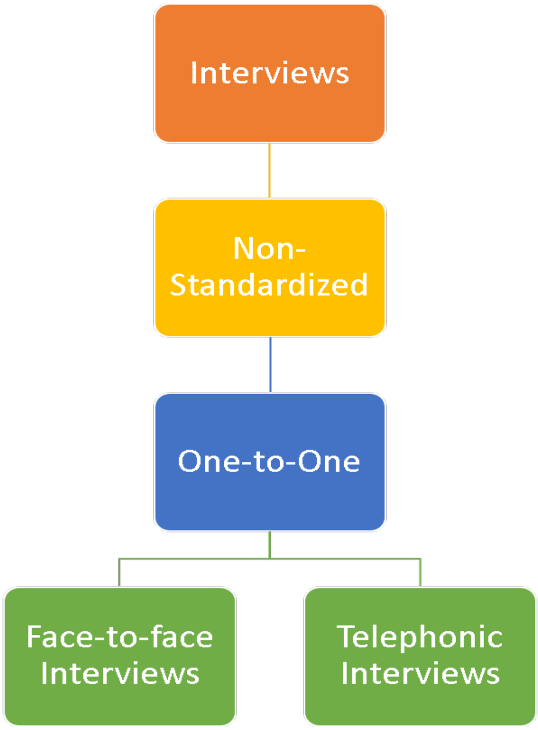


Figure 5: Structure of interviews.

3.6.3 Participant or direct observation

Yin (2013) explains direct observation as a process that involves a researcher observing participants in either a formal or in a casual manner but without interacting. However, Yin (2013) further explains participant-observation as a process whereby the researcher takes up a role in the situation and thus acquires insightful views from the participants. Hartley (2004) stated that direct observation is more effective and fruitful if there are many observers at the same time.

Participant-observation according to Kawulich (2005:2) is defined “as the process of establishing rapport within a community and learning to act in such a way as to blend into the community so that its members will act naturally; then removing oneself from the setting or from the community to immerse oneself in the data, to understand what is going on and able to write about it”. The researcher has attended various sessions from Universities of Technology that deal with the training of educators, on the use of learning management, designing the library within the blackboard learning analytics, and the use of HEMIs data. All these sessions were carried out with pure discretion and respect.

These platforms have given the researcher a general perspective of academic and administrative staff. Further, it allowed the researcher to interact with various stakeholders in a quest to understand how people within higher education institutions view and understand learning analytics.

From the participant-observation, the researcher discovered two major views which can be summarised as follows:

1) **Institutionalisation of learning analytics:** this is what some participants in various platforms and seminars raised repeatedly. The introduction of Learning Management Systems which is linked to learning analytics has been introduced as one of many choices that academics can use at their comfort. Some suggest that the lack of institutionalisation of these inventions has or is contributing to non-use. According to the researcher's analysis this is one point that needs to be engaged with so that the institutionalised use of learning analytics becomes part of the teaching culture and for institutions to own up to the process involved.
2) **Technology as means to an end:** There is a voice of fear that comes from those who are concerned that the use of technology in education means the end of the human element. Amongst the discussions, some participants in seminars question the role of academics and administrators in the long run. There is also the matter surrounding the long-term plan of using Learning Management Systems. When the system becomes competent and fluent, there is a concern about who will require the human element in the form of academics and administrators, for the development of content.

It is the view of the researcher that these concerns form a substantial and justified point, with the introduction of robots in industries as a substitute for people. Any person concerned with long-term goals is justified in asking such questions and there is a need to deconstruct this question and give a clear indication of the role of how human beings can remain greater stakeholders and teachers than teaching with technology alone.

This process enabled the researcher to acquire useful insights from the current enfolding different committees and university related seminars and forums. Such insights have indeed helped the researcher to understand the data from interviews and to contextualise it.

3.7 Data Analysis

Data analysis is explained by Baxter and Jack (2008) as a process of purifying, and arranging data and giving meaning to collected data. Hartley (2004) explains that analysing qualitative data is an active and interactive process. The data's trustworthiness credibility, dependability and transferability are issues that the researcher should examine during the data analysis process, as these are important when research findings reflect the perceptions of people within the study (Elman, Gerring & Mahoney, 2016).

3.7.1 Thematic analysis

Thematic analysis refers to the process of analysing qualitative data with a bigger focus on identifiable themes and patterns of living or behaviour (Benner, 1985). Aronson (1995) argued that although thematic analysis has been explained by the likes of Benner (1985), Leininger (1985) and Stiles and Taylor (2001), the processes of applying them have not been sufficient.

Thematic analysis is a rigorous method used to organise and to analyse qualitative data. Thematic analysis seeks to uncover the themes significant in the data at different levels (Attride-Stirling, 2001). The aim of the thematic analysis in this study was to uncover the deep data provided by participants and to give a detailed presentation of the data. The outcomes of the analysis are systematic themes and sub-themes (Vaismoradi, Turunen & Bondas, 2013). Rule and John (2011) argued the question of trustworthiness in the qualitative data. They further provided a proposal to present vast descriptions, to present a critical review and to verify the steps of data analysis.

This process involves four major steps:

1. Collecting data using various methods;
2. Identifying data that relates to a classified pattern;
3. Combining the related patterns to form sub-themes; and
4. Building valid arguments for choosing the theme (Aronson,1995; King, 2004; Braun & Clarke, 2006)

The first step in analysing data collected in a study is the representation of that data in formalised written form (Thornhill, Saunders & Lewis, 2009). All audio data collected was transcribed and documented in MS-Word, using the Microsoft Word package. In applying this method of data analysis, the following steps of data coding have been employed to organise and to characterise the collected data (see Figure 6).

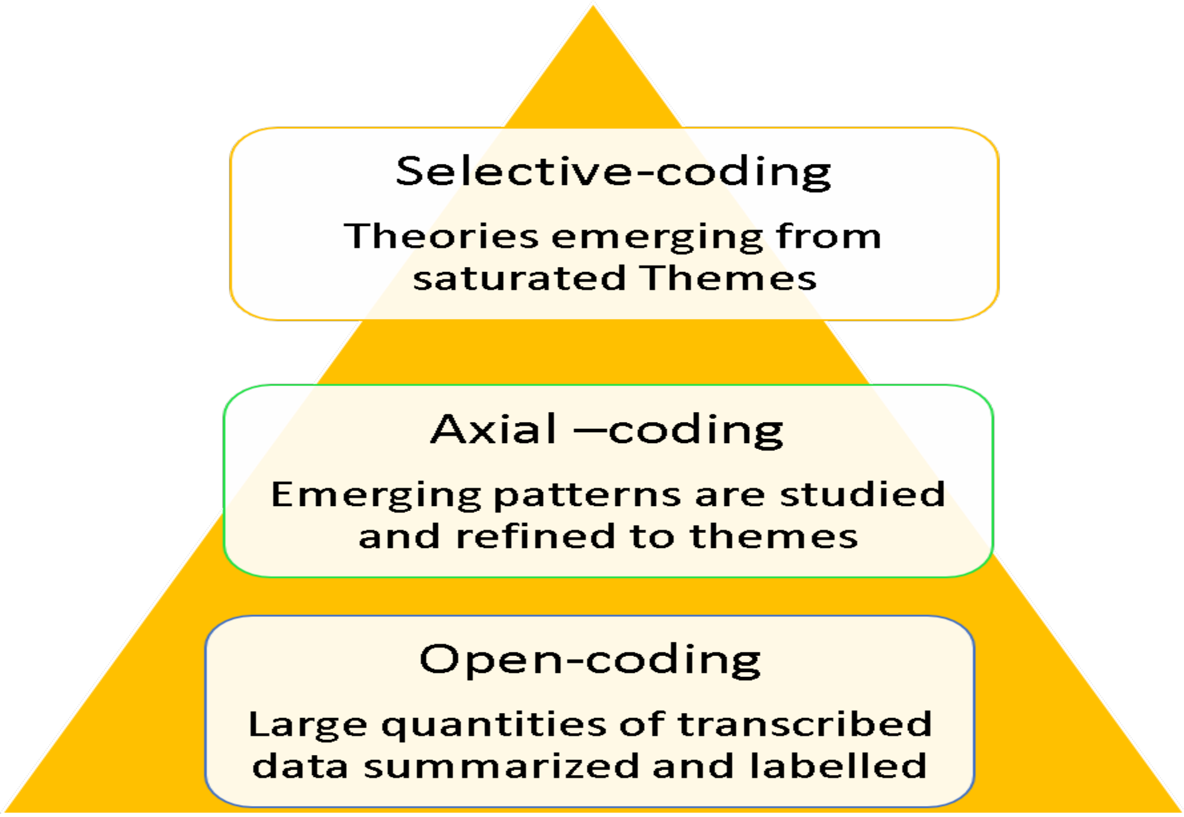


Figure 6: Stages of coding the data.

3.8 Summary

This chapter has provided an overview of the research philosophy followed, from which the ontology and the epistemology guiding the research was presented. The research paradigm was then described. The research design was laid out including the description of the approach, as well as the strategy and the methods of data collection in both qualitative and quantitative form. The ethical considerations and the processes followed were also explained in this chapter.

Chapter 4: Findings and Discussion

4.1 Introduction

In this chapter, the researcher explains the qualitative analysis of the data process as well as the analysis of the data and the steps involved in analysing the data. In this qualitative process, the data has been analysed and presented, according to different themes, with an explanation provided for each. Furthermore, the researcher will illustrate how the themes overlap. Chapter 5 will evaluate whether the data presented answered the research questions and the sub-questions.

4.2 Interpretive Paradigm

Analysis of the data of the current study was guided by an interpretive paradigm, as described in Chapter 3 as its guiding theory. The aim is to view the perspective in contrast to the context that was put in place and to present the subjective viewpoints of the participants. The participants in the research already have views of their own in relation to 'teaching and learning', according to their own methodologies and pedagogies of conducting teaching. Indicators of success, which have been gained through experience and knowledge form part of the current cultural traditions of teaching which are institutionalised through written rules, daily practices and oral methods (Geertz, 2008; Denzin, 1989).

In a quest to understand and to interact with the participants' theories of interpretation, the participants' perspectives and their understanding, are guided by the conceptual framework, which will be revealed (Denzin, 1989). It has been established that an interpretive framework has been appropriate for the current study as it has enabled the researcher to explore the participants' perceptions in the context of their individual space and to from their own understanding and perspective formed by their traditional teaching and learning beliefs. The subject is new to some people and some hold purely contrary views both in content and in form. This has necessitated a certain level of sensitivity to all the arguments presented by the participants.

During the analyses and the interpretation of data, the researcher had to put aside his own views and perspectives regarding teaching with technologies; to remain objective when engaging with different participants. This was important to allow the process to be directed by the participants' responses and to avoid the researcher's own theories indirectly imposing upon the interview process and the interpretations required during the analytical phase of the research process (Kruger, De Vos, Fouché & Venter, 2005). After each session, self-reflection was conducted to pick up on new and repeated points and to have them recorded in a notebook. The concerns which arose from the researcher's own reflection processes are described in Chapter 5.

4.2.1 Data analysis process

In analysing data to produce readable outcomes, the process includes the organizing of data as well as giving order, structure and meaning to the population or to the community, regarding the collected data (Hartley, 2004). There is no clear cut, clean or linear process. Instead it comprises back and forth steps. It starts with reducing the recorded information and breaking it down into smaller pieces. This means that the separation of significant data from less significant data, the identification of similar or related information that forms trends, and the grouping of similar topics to identify themes (O'Connor & Gibson, 2003). The process of data analysis, requires understanding, objectivity and a plan on how to make sense of the collected data. This requires a deep interaction with the data. Objectivity entails removing one's everyday position on issues to honestly represent everyone's view, without imposing one's personal stance.

The processes of data collection and analysis coexist. These two processes have a close relationship with each other and this distinguishes qualitative research from traditional research (King, 2004). Vaismoradi et al. (2013:400) stated that: "the process of data analysis does not in itself provide answers to research questions as these are found by way of interpretation of the analysed data". Identifiable trends can form patterns of expressions. It is alarming that more trends can be discovered as more data is transcribed. The interpretation of data encapsulates proper explaining and giving context to the data, while not misrepresenting the participants (Aronson, 1995). This is not a linear process; it includes constant engagement with the data, whereby the interpretation and the analysis are intertwined while the researcher is analysing, and interpretation is also taking place simultaneously. From this concurrent process of data collection and analysis, a 'plausible and coherent' interpretation is developed (King, 2004).

4.3 Generating Themes

Each interview is carefully transcribed by listening to the overall responses presented by the participants and then carefully reading through each transcribed interview, to gain insights and understanding. According to Fereday and Muir-Cochrane (2006), the diligence of this phase requires immersing oneself in the details, by trying to get a sense of the interview as a whole before breaking it into its component parts. The data showed similar trends emerging from different participants and continuous patterns which then gave an indication of what the participants "felt most strongly about and what expressed the strongest view about success and throughput which is typical of what is common to all" (Ryan & Bernard, 2003:88). The utmost phase of data analysis is to recognise noticeable themes, repeated ideas, phrases or use of language and patterns of belief that link back to their views (Green et al., 2007). Throughout the process of interviews one can perceive noticeable patterns and commonalities, as repeated by the various participants, resulting in the formulation of themes.

The difficulty arises from trying to include every participant's view in form and content, whilst simultaneously, generating broader interpretations, significances and meanings and transforming this information into themes that were common to most or all the participants (Fereday & Muir-Cochrane, 2006). Gale et al. (2013) stated that the outcomes of a conducted study cannot only be about collection and representation of individualised case histories. Thomas and Harden (2008:5) presented "a notion of generalization that preserves the richly individualized, socially constituted nature of concrete individuals, while enabling social interpretations that transcend the particular case".

The process of forming themes was, among others, guided by one of the goals of analysis, which is to "produce meaningful condensations that make it possible to gain from one participant an understanding that can enhance one's understanding of other participants as well" (Ryan & Bernard, 2003:93). The generating of themes took into consideration how each participant's view fitted into the pattern of the formed theme, as well as points of convergence and divergence. The content of individual themes kept changing as the interview process continued. During the interview process, some commonly used phrases emerged which gave a sense of understanding of the viewpoint of the participant and provided a sense of direction to the participant's argument or highlighted his or her subjective views concerning learning analytics. The result affirmed that similar patterns kept popping up or were affirmed by various participants. To harmonise various expressions and similar patterns, coding was used to bring structure and direction to the research.

4.4 Coding of Themes

The theme analysis process included various processes of coding. This coding process entails reading, listening, transcriptions and interview recordings. In this process, the researcher notes and highlights each point of concentration from each participant. The process helps to incorporate all views in the formation of themes which later, made it easier to quote verbatim in the write-ups. The analysis process, as explained by O'Connor and Gibson (2003), was the guideline for the coding of themes.

4.4.1 Open coding

The process started with open coding which includes grouping the identified patterns under a meaningful name or phrase, systematically studying them, finding points of divergence and points of convergence, and then interrogating each phenomenon that is reflected in them (King, 2004). The open coding process demands back and forth reading of data in the hope of identifying code and cluster patterns. In the conceptualisation of the data process, the researcher grouped and highlighted identifiable patterns or themes each in a different colour and renamed each theme using a descriptive word that explained its focus (ibid.).

The naming of each theme identifies the phenomena. Similar or the same phenomena are identified using the same variable or name. The process guides the research and narrows down the phrases or names, which then allows the researcher to create an 'essay' of phrases. Naming a theme or a pattern defines the broad scope of the theme in a manner that is logical and attractive enough for the reader (Green et al., 2007). To summarise; the data was classified into themes that provided a broader understanding of what the participants were saying.

4.4.2 Axial coding

The next phase was axial coding, which was conducted immediately after clustering, coding and the naming of themes. The identified themes were evaluated according to similarities, associations and overlapping points, with the aim of merging some themes to produce sub-themes or clusters. According to Ryan and Bernard (2003), this process extends to evaluating categories of meaning regarding both inner-convergence and outer-divergence. The researcher then grouped themes that were similar in content into highlighted themes thus reducing the number of themes. Thomas and Harden (2008) argued that themes should remain internally consistent while maintaining their diversity.

4.4.3 Selective coding

Selective coding was the last phase of the process of themes analysis. In this stage, the researcher added all the individual participants' themes highlighted above, and then clustered them to form final themes which were representative of the whole data unit, and not just individual participants. Finally, sub-themes and categories of sub-themes were created to present the sorted data as well as small bits and controllable themes (Aronson, 1995). This is referred to as grouping a family of themes while sub-themes are the offspring and categories are the extended offspring (ibid.). In conclusion, the researcher noticed that the three stages of coding are not very distinct from each other and are not formally consecutive, in that the line of separation is very narrow (Boyatzis, 1998).

4.5 Themes

Three themes were derived from the participants' perspectives:

- Resources and sustainability.
- Participants' beliefs regarding 'teaching & learning' and technology.
- Possibilities, learning analytics and concerns, as viewed by the participants.

The themes and their offshoots are presented in tabular format below. A detailed explanation for each theme will follow. For the purposes of correct representation and confidentiality, participants were named "A", "B", "C", "D", "E", and "F") and were regarded as such throughout the document. When a direct quote was used, an indication of which coded name it represents will be provided to compare views where necessary.

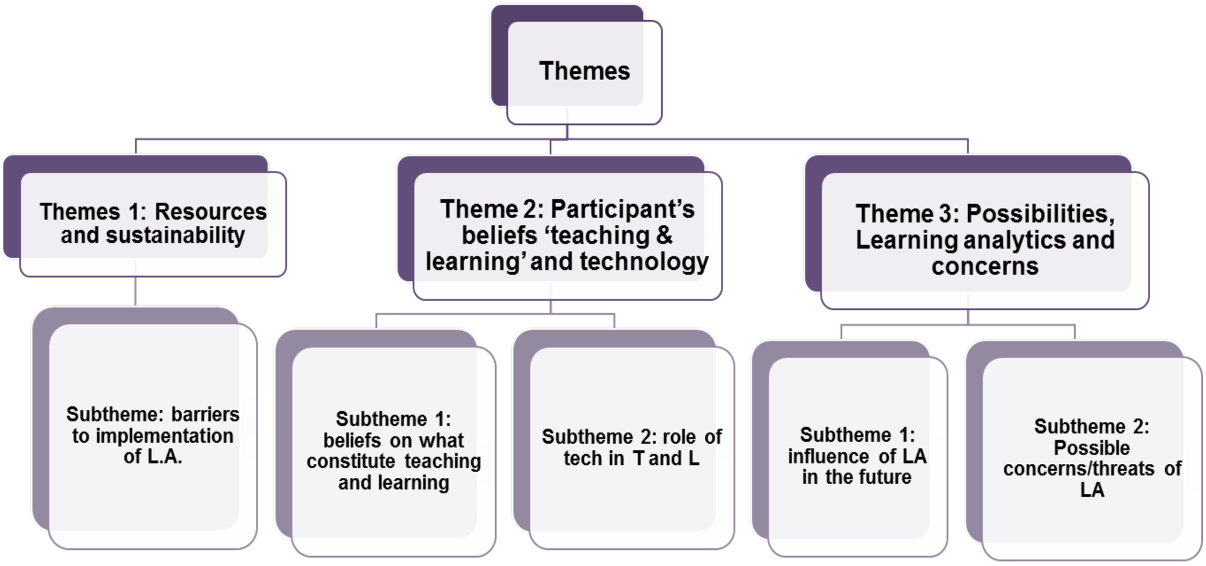


Figure 7: Themes and sub-themes.

4.5.1 Theme 1: Resources and sustainability

Sub-theme 1: Barriers to the implementation of learning analytics

Inclusion criteria: The financial resources required, the capacity of staff and the university infrastructure.

Exclusion criteria: External barriers, limitations of the South African government.

Throughout the participants' discussions, it was noted that most came out strongly and harshly on addressing the resources involved in the process of learning analytics. Not only did they dwell heavily on financial costs, but also, on human resources and their capacity. The participants expressed their various views on how this process needed to be addressed before it became a threat.

Capacity and cooperation by staff members

West et al. (2016) argued that the capacity of staff refers to constant training as well as workshops provided either internally or externally, in order to prepare the users of the system for simple and easy ways to use it. The benefits of either the Learning Management System or the Learning Analytics are linked to the capacity of the staff. The power of these platforms is centred on the use of dashboards, built in reports and live assessments, which all require a personalised trained staff member for each course (Sclater et al., 2016). Therefore, the researcher observed how capacity was the focal point, or at least one of the pivotal factors in Learning Analytics.

The participants, in no particular order, have raised various views. The broader issues that arose ranged from human capacity, cooperation from various departments to internal support. 'Participant C', as mentioned in Table 1, presented the argument that there was no cooperation of lecturers regarding using the Learning Management Systems (LMSs) provided to them by universities. This was, of course, raised by other participants as well and means that if this not resolved, there exists the potential of having a system that is not providing the necessary data to produce acceptable outcomes.

Furthermore, almost all the participants agreed that necessary skills need to be invested in by all institutions, to avoid the migration of internally trained people towards better offers. There is also a need for proper workshops for lecturers about best practices of LMS, to have a fully functional and supported system. 'Participant F' alluded to the fact that workshops needed to be coupled with side contracts binding lecturers to perform their part, whereas 'Participant E' argued that it is not in the scope of lecturers to update the Learning Management System (LMS) and that they are not even forced to use them. This means that in order to see the investment of skills and best practices, LMS needs to mature as a priority. This also points out the conflict of understanding of the various role(s) of academic staff considering these Learning Management Systems (LMSs). The narratives also suggested that there are no consistent relations between new systems that enhance teaching and the people responsible for daily teaching. There is still a struggle in incorporating LMS in the day-to-day teaching activities of institutions. These are sometimes specific departments that are not global. Some challenges also include infrastructural support and capacity support. However, there is a keen interest in adopting innovative technologies, to improve teaching and learning.

Table 1: Extracts on capacity and cooperation.

Respondents	Quotations or References
Participant A	"The specialists to guide the process implementing LA must be trained".
Participant C	"Lecturers are still not using learning management as a tool for assessment, many citing personal challenges".
Participant E	"Content management is still a scarce skill and institutions always lose their internally trained resources, while they are needed". Participant E strongly felt that, "it is not the duty of academic staff to provide activities to be conducted through learner management systems".
Participant F	"Workshops are provided and paid for by the institution to speed-up the process of fluent usage of the LMS. A contract should be signed by academics committing them to update the system, provide online assessments and the consistent uploading of grades."

Financial resources support

Arroway, et al. (2016) strongly argued that for the effective and sustainable use of learning analytics, institutions need to engage various stakeholders, to diversify the funding provided, to avoid this responsibility being solely for universities. Overall, participants argued that the cost of these modern technologies is high. However, most of the participants argued that the cost is not high if looked at per student. Furthermore, they argued that the potential return by the systems seemed greater when compared to the initially cautious views which had seen those systems as a waste of resources.

It has been posited that the success of students brings benefits to institutions while high failure rates cost more or delay revenue. Thus, the usage of the system maximises the chances of students' performance becoming a justifiable cost from a business point-of-view (Siemens, Dawson & Lynch, 2013). The participants raised suggestions to mitigate costs over individual institutions such as buying as a consortium and using a network as a front. However, there are still administration dilemmas to deal with that tend to prohibit the process. The participants therefore suggested the intervention of registrars and that spheres of higher education should look at these ways of buying, as a consortium. Furthermore, the government should consider offering grants institutions for the implementation and the sustainability of these technological enhancements. The motivating force for investment in learning analytics is the potential retention rate, which institutions are looking for (Arroway et al., 2016). This is also something the government is willing to invest in, as well as the private sector. This theme attempts to evaluate the readiness of institutions for LA, both financially and in terms of human resources. This phase is important to implement before the adoption of any system or software. It provides a broader view and indicates certain aspects of resolution before adoption.

Table 2: Extracts on financial resources.

Respondents	Quotations or References
Participant A	"As a response to the struggles of universities, we initiated a process of buying as a consortium on behalf of Universities of Technology. The process failed because of not being a registered entity but rather, just a network".
Participant B	"Some universities if not given extra funding will never afford these software systems".
Participant C	"The cost is high, however looking at the return [on investment] universities can make big returns. We have weighed the cost over benefits, to justify it for senior management".
Participant F	"Everything is costly, we have [to] accept that and we are fighting to reap the benefits".

4.5.2 Theme 2: Participants' beliefs regarding 'teaching and learning' and technology

Sub-theme 1: Beliefs on what constitutes teaching and learning (T and L)

Inclusion criteria: Traditional teaching, pedagogical beliefs and modernised beliefs.

Exclusion criteria: Universal beliefs.

The beliefs regarding teaching and learning: An analysis and presentation of data is not enough to provide the context of data and thus, interpretation of each table or figure is always the next step. The participants' excerpts below reveal that there are divergent views on what constitutes teaching and learning. The table presents various kinds of participants: (1) traditionalist (those who are not so fluent and not fond of technology and thus are committed to the traditional ways of teaching) and (2) Modernist (those who embrace technology to enhance teaching). The traditionalists view technology as the means to end the human aspect of education and thus reflect a fear of cooperating with the processes, whereas modernists view technology as a tool to transform teaching. However, it is not meant to replace the human aspect, but rather, to assist humans.

The word "**technophobia"** comes from Greek (τέχνη technē, "art, skill, craft" and φόβος phobos, "fear") and is the fear or the dislike of advanced technology or complex devices, especially computers. The term is generally used in the sense of an irrational fear, but others contend that fears are justified (Oxford English Dictionary, 1989). This explains how one interprets what arises from the narrative by means of the word 'traditionalist' when explaining teaching. These participants prefer to explain what it is not, and their explanations reveal the outright rejection of the use of technology, by providing alternatives. Participant "F" provided interesting interventions in responding to this phobia. In their institution, a contract has been provided, to be signed by academic staff. However, it has an option to decline and this option allows anyone who can work on the system to provide instant assessment mechanisms and rapid monitoring options, such as the one offered by a Learning Management System (LMS). Capable enough staff who are approved to use such options, are provided with a solution which gives responsibility to these staff members. The general overview that the researcher has obtained from the data is that teaching beliefs have transformed. However, the rate of transformation has been obscured by those who arguably view the transformation as an extra responsibility, which requires much work.

Table 3: Extracts on beliefs about teaching and learning.

Respondents	Quotations or References
Participant C	"Teaching and learning have transformed to not only mean attending but also that we must keep up with the speed".
Participant E	"Teaching and learning requires attendance and a person in front." Participant E strongly argued that: "Traditional ways of teaching have a track record and are still relevant". Lastly, "Humanity is part of teaching and that should at all times be respected".
Participant F	"Teaching has evolved; it can now happen inside and outside the classroom. The pedagogy of teaching should evolve with the times and technology. Attending a class/lecture is no longer a success indicator, meaning that teaching and learning goes beyond what we can currently offer, thus there is a need to adopt new technologies".

Sub-theme 2: The role of technology in teaching and learning

Inclusion criteria: Learning Management Systems, gradebooks, ITS, library information systems and learning analytics.

Exclusion criteria: Virtual classes, mobile labs, living labs.

Minkler and Wallerstein (2003) defined technology's role in education as facilitating learning to enable better teaching, assessment monitoring and improve performance. Numerous participants agreed with this explanation. Furthermore, the data shows that there is a consensus on the potential of technology to facilitate instant assessment.

The data shows that a move by universities to centralise data decisions requires the use of technology. In addition, technology provides effective communication methods for education with some participants feeling strongly about the significant role that technology provides for teaching and learning. There are still those who dismiss the gains that technology brings to education and feel that the traditional ways of teaching and learning have provided answers. Even though these participants feel strongly about their views, they cannot provide similar methods which bring instant assessment and evaluation that are provided by modern technologies for teaching and learning. There is also a great concern with fighting against the dehumanisation of education. These arguments not only show a rejection of technology but also represent the pedagogical argument that part of education is to teach humanity.

According to an SAAIR (2017) report, the potential of moving toward the digitalisation of education is the instant response it provides on issues that rise from assessments and discussion platforms with students. However, a great counter argument is also presented by the data that a concerned focus on the role of technology in education is directed towards what technology can deliver. No one has taken into consideration the effect of institutionalisation of these technological interventions. Institutionalisation means that participants (academics, administrators and managers) have not engaged with institutional cultural practices concerning technology. There is a need to acknowledge that academic staff are at different levels and ages. These variables are most important to consider when designing necessary interventions. If the institutionalisation of the role of technology in education is not taken into consideration, based on ageism and lower levels of comfort with the internet, this will mean that many of the staff will reject the new systems.

Table 4: Extracts on role of tech in teaching and learning.

Respondents	Quotations or References
Participant A	“Technology give[s] universities ways to reach their students in various ways”. Also, “To give insight about how other learners learn”.
Participant B	“Technology provide[s] concrete digital data to inform teaching pedagogy”.
Participant C	“Technology enables rapid-assessments, and improves ways of reaching students in their comfort space”.
Participant D	“Teaching has continued without technology and teachers were aware of students’ challenges and ways to address them. Technology is expensive and does not provide answers to our problems”.
Participant F	“Technology allows us to monitor how students learn, how they are performing and to intervene in time. It gives us enough space and time to assess our students before their final assessments and thus be able to predict those at risk”.

4.5.3 Theme 3: Possibilities of ‘Learning Analytics’ and concerns as viewed by participants

Sub-theme 1: Possible influence of learning analytics

Inclusion criteria: Student success, students’ throughput, the ways students learn.

Exclusion criteria: Social problems, financial needs.

Learning Analytics (LA) is explained as “the measurement, collection, analysis and reporting of data about learners and their contexts, for the purposes of understanding and optimizing learning and the environments in which it occurs” (Siemens & Long, 2011). In line with this explanation, the participants appeared to grasp in context what learning analytics is about. There seems to be a consensus that the context of learning analytics is new in South African higher education, but on a more optimistic note, universities are indicating positive strides towards developing it and defining its best practices. Various participants reached similar conclusions that learning analytics have a great chance of improving students’ performances. This conclusion is drawn from the phrases that the participants used to describe what learning analytics’ potential could provide. This conclusion is, however, based on the theory of this concept and the practices reported from various countries. Up to this point, no South African university has fully adopted learning analytics and monitored its gains. It is worth noting that various universities are at various levels of understanding and in divergent phases of adopting learning analytics.

There is a minimal view that sharply raises the issue of the government playing an active role if South African universities are to successfully adopt and apply learning analytics. Moreover, this is not only a move to support universities, but rather, a description of the process needed to provide a platform for government spheres such as the Council for Higher Education (CHE) to proceed. Participants have argued that there is difficulty in the current way of reporting to the CHE and its failure to respond in time to issues and; as a result, it provides audited statistics of the previous two years. Such reports are already too late to resolve problems and its recommendations are faced with unfamiliar problems by the time the issues are addressed.

Furthermore, when viewing the Council of Higher Education reports they are indeed in a continuous pattern of two years after issues are raised. Participants argued that if the government initiated and funded the process of universities procuring LMS platforms’, they would then be able to monitor its application and gains in a broader context. Another issue is that while universities continue to review such systems individually, changes to students’ performances will not have much impact due to non-affordability. All the participants agreed that universities have secured Learning Management Systems. However, the option of introducing learning analytics is what most universities are struggling to secure, thus rendering the LMS as not being highly effective. One participant described having a Learning Management System without the option of learning analytics as: "having a car without lights at night". The adoption of learning analytics is still an option for each university even though there is a growing interest shown by all universities.

Table 5: Extracts from interviews on possible influence by LA.

Respondents	Quotations or References
Participant A	"To give insight about students and their learning. How can we teach students what we do not know?"
Participant C	"To invest in rapid monitoring systems" and "potential increase of pass rates and graduation quotas".
Participant E	Strongly feels that: "LA has no potential to address the main SA's HEI problems". Strongly argues that: "Being active online or doing assessments while away or at home is not a significant factor to predict students' performance".
Participant F	"Identify of students at risk. Linking our different student datasets to assess performance. Always assess the lecturers' performance to understand if there is miscommunication between students and the lecturer to advise institutions of necessary changes in the pedagogy of teaching, ways of communication and grade books indicators".

Sub-theme 2: Potential concerns/threats of learning analytics

Inclusion criteria: Student privacy, Ethics, Data protection.

Exclusion criteria: Data Misuse, external access.

In no uncertain terms, all the participants have raised the view that the possibilities of learning analytics are not disputed. However, if they are applied blindly without caution, there could be a greater threat to human privacy. Any system that has the potential of contradicting the laws of ethics and morals demands to be streamlined and precautions and measures need to be put in place to avoid any harm to either animals or humans. Participants from various institutions argued that disclaimers, confidentiality and guiding contracts should be in place in response to these potential threats. Participant "F" argued that the system does not pose a threat. However, the way people interact with the data and the reports generated by the system should be streamlined. Most participants do not think that there is a threat great enough to stop the adoption and the implementation of learning analytics. Participant "C" explained that whether digital or manual, universities are in possession of sensitive student data and how they control it or continue to control it makes no difference regarding learning analytics as universities are ultimately guided by laws.

Table 6: Extracts on potential concerns.

Respondents	Quotations or References
Participant C	"Ethical implications, if not addressed, can be tricky".
Participant D	"The data does not only include students but also lecturers. Thus, a disclaimer must be provided. Students sign an agreement with institutions and their data is the institution's property".
Participant E	"Students did not sign up for the online process".
Participant F	"Our interest is to generate data and instant reports. Thus, no harm can be done by LA. However, people getting access to this data can be a problem. LA only provides us with data we do not have. However, we already have sensitive and confidential student data such as grade books and ITS. To minimise problems, academic staff will have to sign contracts binding them not to use direct names or publish reports or information from the system".
Participant A	"Privacy is a concern; however, it does not outweigh the need to implement the system. If handled right from the start, possible threats can be neutralised".

4.6 Overlapping of Themes

Throughout the entire study, the major challenges have always been to keep the themes separated and to some extent, discrete from each other, as the context appears to be similar across the themes. Alternatively, one theme or subtheme may have contradicted another theme and therefore, a new theme may have resulted from the discussion. The participants' views on financial and infrastructural resources were one of the most sharply raised issues that could cloud the potential of learning analytics at various institutions. Their standing beliefs of what constitutes teaching and learning appeared to be the underlying reason for non-cooperation in providing a process which makes use of technology. This was revealed by the least number of participants involved in academics, who do use Learning Management Systems albeit the fact that such systems have already been procured by institutions for around half a decade.

There is a resounding agreement regarding the potential of learning analytics, which has not been disputed. Nevertheless, the researcher has noted that a potential threat exists in terms of the application of digitisation of data. Some minor threats concern staff and student privacy, especially if the data were to land up in the wrong hands. The abilities of these systems reveal a compelling case for being able to detect problems and provide instant solutions, by virtue of the platform created by Learning Analytics. The diagram below demonstrates the complexity of the different themes, the different understandings and the views of participants from various institutions, and the challenges that institutions face in attempting to establish these technological interventions in daily teaching and learning activities.

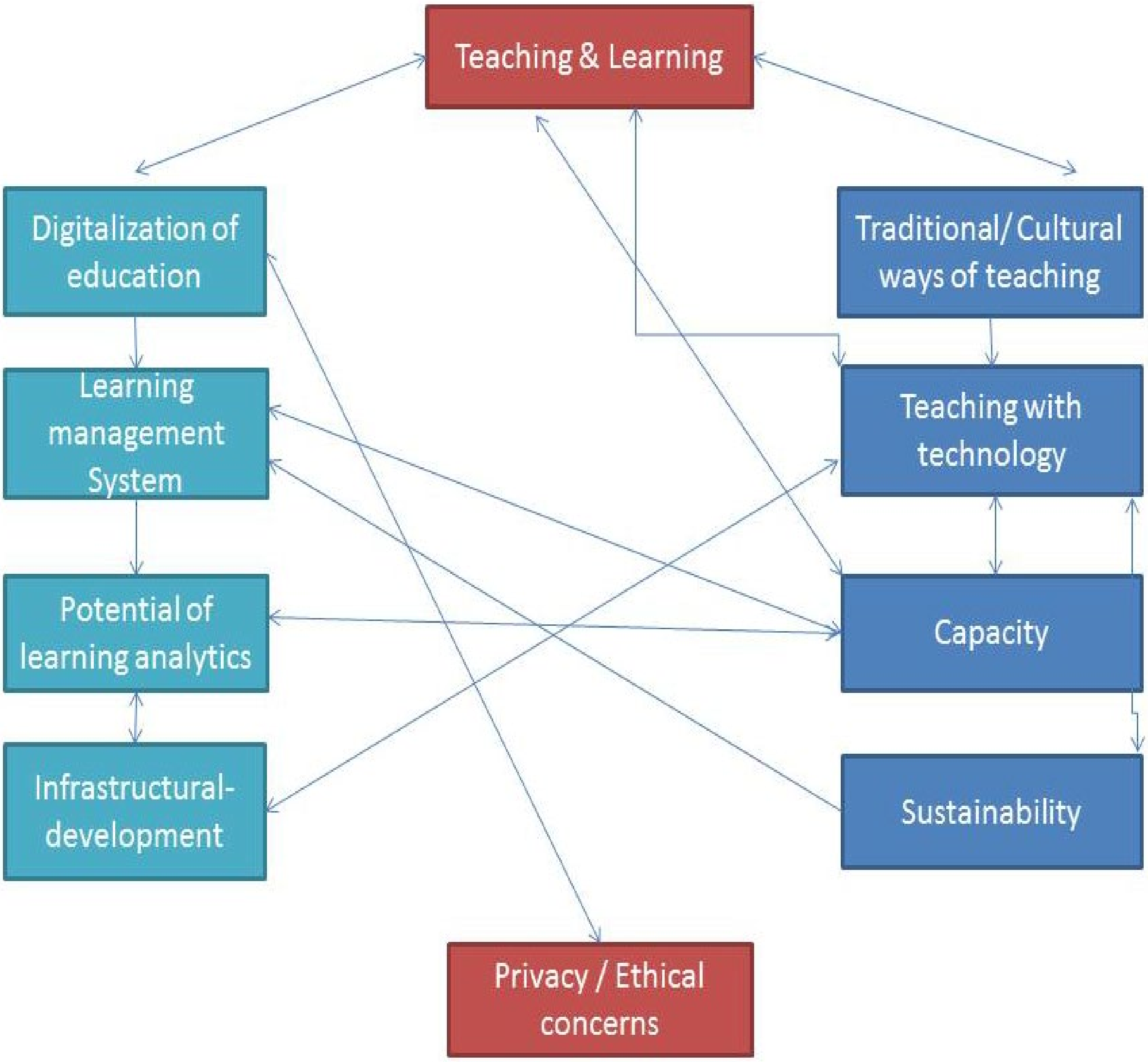


Figure 8: Overlapping themes.

4.7 Observations

The data analysis process has been conducted as an attempt to respond to the main research question of this study: "How might the use of learning analytics contribute to or influence student throughput and success". The results of the data analysis were based on the researcher's observations and by means of interacting with the data. In attempting to answer the central research question and the first sub-question which relates to perceptions and opinions of academics; the participants raised several concerns and challenges which directly point towards hindering the prospects of Learning Analytics (Las) in higher education institutions in South Africa. In analysing all the themes explained above, the researcher noticed that there were sharp issues that the participants raised, which were grouped into relative points for the purposes of the research. These points are summarised as five points of concern. They do not follow any hierarchical format. The following diagram presents these points with a detailed discussion of each point provided below.

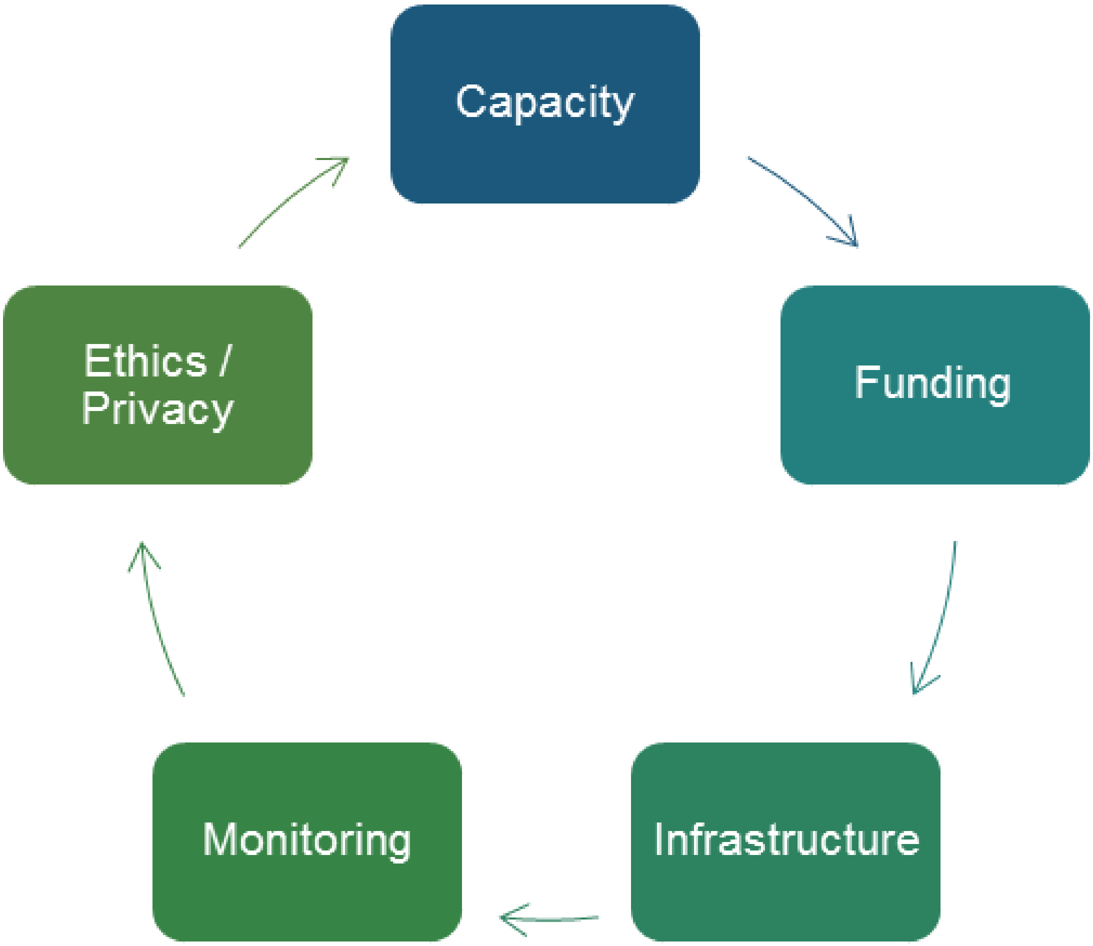


Figure 9: Challenges of learning analytics.

4.7.1 Capacity

There is a strong perspective that emanates from the data and encompasses all participants. They all hold the view that capacity of the staff (both academics and administrators) is lacking where technological challenges are concerned. This happens in a world where the technologies of the day seem to have the potential to address several of the systematic problems that higher education is faced with. Sclater et al. (2016) argued that staff development is part of investing in learning analytics, so as to produce desired outcomes. This point comes out strongly regarding potential challenges that can render the whole learning analytics system ineffective, if not addressed. One of the participants argued that: “Learning analytics is dependent on the data that is available in datasets and staff members are responsible for those inputs".

Several of the participants suggested that staff capacity requires more than volunteer training. Training should be mandatory and should be part of the staff contract. Furthermore, the recruitment departments of the universities should Insist on and necessitate such competency skills from the staff. However, these skills will not be acquired overnight. Hence, the participants suggested that the option of in-house training, to acquire the necessary skills to use the required software fluently, should be implemented. It is the view of Siemens et al. (2013) opined that in improving higher education's capacity and productivity, some policies and strategies would have to be effected in order for learning analytics to be a success. This speaks directly to the policies guiding the academic staff. These findings complemented the views of West et al. (2016) when they conducted a study on the experiences of teachers whose first-time use of learning analytics posed a number of challenges. However, when training sessions were conducted and the policies were changed, a glimpse of light came out (ibid.). It is their conclusion that staff development is one subject that enables learning analytics to reach its capacity, and thus it becomes an important stakeholder.

4.7.2 Funding

The funding issue has been a heated debate for some time. According to the Department of Education (2003), in their white paper, funding models were inherited from the apartheid system which disadvantaged black institutions over white institutions. As a result, the department has not so far been able to level the playing field between the institutions. Furthermore, the Council on Higher Education (2010) in their report, concluded that former disadvantaged institutions still struggle, even in the existing democratic dispensation. These findings strongly suggest that part of the government funding should subsidise the adoption of technologies for teaching and learning. Currently, universities depend on their internal funds to secure these software programmes. The funding, in no uncertain terms, tops the list of challenges. Participants felt that it should no longer be a barrier to the adoption of learning analytics. Many participants suggested that universities who have limited funding could not sustain the purchase of these software programmes without financial assistance. Part of the arguments by the participants was the strong suggestion on the role that the government could play in securing these software programmes as a consortium. They could then provide them to higher education institutions at a central point. In addition, Lewin and Mawoyo (2014) explained that access and success necessitated the government to play a critical role, often beyond the scope of simply providing funding. In this connection, the government should also be suggesting guidelines. For learning analytics to be adopted in South Africa, the government must avail funds for this and play an active role in ensuring that these strategies are adopted and implemented.

4.7.3 Infrastructure

It appears that whilst all the participants understand that learning analytics is a virtual system provided on an external basis, there exists a need to meet certain computer competencies, to use them effectively. Central to infrastructural development, the participants felt strongly that the datasets that institutions use are disconnected, making it impossible to monitor them. The participants strongly suggested that if learning analytics were to be used as one way to increase students' performance, other datasets, such as national financial systems, residences, demographics of students and the library system, should also be included. Many institutions already have most of these systems. However, they operate in isolation from one another and thus, there is a strong proposal for combining these systems, so that they can communicate with each other. It is noted that institutions can rent virtual spaces to host the learning analytics system. However, the internal infrastructure should still deliver credible data, which can be systematically analysed to gain necessary insights.

4.7.4 Monitoring

Atif, Richards, Bilgin and Marrone (2013) argue that the monitoring systems in any project are of vital importance, when evaluating tools and approaches on learning analytics, they suggest that if we cannot monitor what we do, we are unable to see progress or immediate problems. At this point, it is not necessary to categorise monitoring as a strong barrier against the adoption and the implementation of Learning Analytics (LA). However, as a cautionary measure, monitoring should be included as part of the planning process. According to Xavier, d'Orsi, de Oliveira, Orrell, Demakakos, Biddulph & Marmot (2014), monitoring systems in learning analytics provide an opportunity to access and respond, while learning is taking place. For this reason, learning analytics is mostly advantageous. Only a few of the participants seemed to be concerned about monitoring, but nevertheless, they showed a strong depth of understanding of the need for Learning Analytics (LA).

4.7.5 Ethics

Lastly, the question of ethical implications was discussed. Many authors writing about learning analytics have outlined the ethical issues, such as the collection of data. The use of collected data is faced with a number of ethical challenges, including location and the interpretation of data (Slade & Prinsloo, 2013). Ethical oversight of student data in learning analytics is a typology derived from a cross-continental, cross-institutional perspective (Willis, Slade & Prinsloo, 2016). In addition, there is the exploring of the relationship of ethics and privacy in learning analytics; and there are design implications for the field of educational technology (Ifenthaler & Tracey, 2016). In all the papers mentioned above, what is common is their conclusion that ethical implications are a threat to learning analytics, whilst simultaneously noting and agreeing on its potential.

The researcher's observations are that contrary to many authors, as stated above, the South African higher education institutions strongly felt that they were not conflicted and that they do not face similar ethical issues in terms of learning analytics. Furthermore, they argued that students' data, whether manual or systematic, has always been in the hands of the institutions and their employees. The institutions are governed by a policy that protects students from victimisation. Therefore, it can be concluded from this analysis that a lack of ethics can be a threat to a country which can then notably be attributed to the high levels of cybercrime. However, in South Africa, this is the least of the challenges or barriers to the non-adoption of learning analytics. Participants felt strongly that students' data is a sensitive issue and as such, it must be handled with care, be it manually or via system modification. In summary, the researcher observed that many participants were comfortable in engaging with the subject. A few sub-questions were well-answered in helping to provide an overview of the current views and status of institutions, their concerns as well as the vast advantages that Learning Analytics (LA) are currently providing for institutions, in acquiring their students' insights. This, in turn, is helpful in improving student's throughput rates. The table below helps to summarise the points discussed above.

Table 7: **Summary of the challenges facing learning analytics.**

Challenges/Barriers	Comment	Level of Agreement
Capacity	Staff development, internal learning designers	Strongly agreed
Funding	Government subsidies, Consortiums	Strongly agreed
Infrastructure	Data sources, learning systems, proper centres	Strongly agreed
Monitoring	Reports, evaluations	Not a major concern yet
Ethics	Disclaimers, institutional policies	Not a major concern yet

4.8 Chapter Summary

Themes generated in this chapter revealed that the participants responded to questions in the study by expressing:

- Traditional arguments of what constitutes teaching and learning.
- Their concerns about student performances rates.
- Their personal perspectives concerning the use of technologies to conduct teaching and learning.
- The financial frustrations experienced by universities, particularly previously disadvantaged black institutions.

The themes that emerged from the data, along with sub-themes and categories, have all been discussed with supporting quotes from the recorded interviews. It may be noted from the quotation tables that there was a strong reflection of responses (quotations) allocated in all sessions, with the participants. This indicated how the participants felt about the topic, their comfort about expressing themselves, as well as their understanding of the subject questions.

Chapter 5: Discussion and Conclusion

5.1 Introduction

Chapter 5 will briefly explain the conclusions and the recommendations derived from the study, on the experiences of Universities of Technology, in their adoption of learning analytics. This chapter starts with a brief overview of the study aims and objectives and methodology, followed by an engagement of the research questions and sub-questions, which have helped to inform the conclusion. The conclusions established herein are derived from the purpose, questions and findings of the study. The lessons from the study, the limitations of the study and its contributions are also outlined in this chapter. Lastly, recommendations for future studies are given and explained.

5.2 Overview

This study adopted an exploratory, descriptive approach, together with a contextual, qualitative methodology. The researcher followed a set of carefully predetermined steps, to achieve the study objectives. The researcher conducted semi-structured, one-on-one qualitative-based interviews with four higher education institutions (Universities of Technology), which fall under the South African Technology Network. These institutions were all purposively selected. All the interviews were conducted at the convenience of the participants, in the English language. They were recorded and later transcribed for coding and analysis.

In the process of transcribing the recorded interviews, to ensure the fairness and the true reflection of the interviews, the researcher enlisted a transcriber who listened to the interviews and made her own transcriptions. The researcher and the transcriber then met to compare notes, identify discrepancies and similarities before analysing the raw data. The researcher then coded the data, which led to the formation of themes and categories from the data. The formation of these themes and categories was aided with literature from various sources, such as the internet, online journal databases etc. Guba and Lincoln (1994) stated that, in the process of coding, the data's trustworthiness must always be maintained and should uphold ethical considerations. Throughout this process, the researcher upheld the research guidelines of the Cape Peninsula University of Technology (CPUT), ethical clearances and all other relevant documents to maintain a high standard.

The findings and the recommendations described below are based on the knowledge, experiences and views of the five participants from the participating institutions, the aim and the objectives, the research question and themes which emerged from the data coding process and analysis. The study investigated the following research question:

"How does the use of learning analytics contribute to or influence student throughput and success?"

In attempting to answer this question, the researcher developed the following research objectives:

- To understand whether Universities of Technology are aware of learning analytics and if they have taken steps towards systematic student data collection and analysis.
- To explore how managers, comprehend and understand the concept of learning analytics and its policy implications.
- To investigate the necessary resources required for the implementation and the utilisation of learning analytics.
- To discover whether HEIs are ready to incorporate the ways of teaching and learning, as prescribed by learning analytics over a timeframe.
- To understand the role played by the South African Technology Network for Universities of Technology, in relation to the adoption of innovative technologies such as learning analytics.

5.3 Discussion of Primary Findings

In attempting to answer the research questions, the collected data was analysed, and themes were formed by means of coding the data and creating meaningful units. Three themes with five sub-themes emerged from the data, following three stages of data coding. The findings of the study's discussion~~s~~ are based on the three themes that emerged from the data:

Theme 1: Resources and Sustainability.
Theme 2: Beliefs in teaching, learning and technology.
Theme 3: Possibilities and concerns regarding learning analytics.

5.3.1 Implications of the themes

Theme 1: The application or the adoption of learning analytics required the investment of a great deal of resources by universities. This was the predominant factor which emerged from the data. The term "resources" was delineated to mean finances which are required to secure learning analytics platforms, and to maintain their updates. Secondly, it meant the necessary employment of the skilled and trained human resources required to design, extract and feed the learning analytics to acquire enough relevant data to analyse; such as learning designers, data scientists, statisticians, etc. The last point referred to the institutional infrastructure required. Thus, a systematic upgrade was required, to link all university students' related systems to feed data onto one platform for analysis.

The central argument in relation to finances, is on how the funding model for higher education institutions is framed. The participants suggested that Universities of Technology must utilise the funds they are allocated for registered students and invest it into learning analytics, since they do not receive a grant which is dedicated to these kinds of interventions. According to the Council of Higher Education (2010), university funding is based on the number of registered students and their output. Additionally, prescribed grants can be applied for and will be granted at the discretion of the Minister of Higher Education. The participants were concerned that the Department of Higher Education had not made provision for accommodating modern technologies into its funding models. Furthermore, the Universities of Technology comprise a merger of former Technikons (Higher Education Act, 2004). Most of them do not have enough funds to spend on anything outside of formal teaching and learning programmes.

Regarding the human resources aspect, there were several issues that emerged as points of frustration for the participants. For example, new posts are approved based on the university's model and to change this model, there needs to be enough finance to fund these new posts. As stated above, without proper funding new infrastructures cannot and will not be approved to solely focus on this work. While Universities of Technology have few people tasked for this job, such as a HEMIS officer; the capacity to sustain these technological platforms and infrastructure is still not enough. The training on the use of learning analytics can be offered by external service providers, as universities are reluctant to invest in their internal staff due to staff migration, which takes place after they have acquired these new skills. An additional funding model issue pertains to staff development grants, which are available, but mainly for academics and which do not usually support staff members.

The last point on resources that the participants felt was being ignored by university managers was the university's infrastructure, in relation to the operation of information systems. For example, many faculties and departments still use a manual method of capturing students' marks and in addition, the students who applied for various grants, loans and bursaries do not have access to their university's database. They felt that university managers and the Department of Higher Education desires results, but resists having to invest in them. It is also a concern that university residences and lecture halls are not connected to Wi-Fi and those that are connected have connection issues. This remains a major negative factor if we are to gain insights on a student's digital footprint. Therefore, the current infrastructure requires upgrades, to connect well with LAs.

Sustainability: having argued above on the resources needed to level the ground on the application of learning analytics, the major concern of whether this is self-sustaining for long-term processes remains. While all the participants confirmed to have been introduced to the Learning Analytics platform, some argued that they had not used it. Some reasons for this included a non-renewal of the yearly subscription, based on their inability to see a return on their investment/value for money.

What was argued was that if there is no protection for universities, many will cancel their subscription, due to the financial burden. The long-term investment which extends to academics to accept the systematic intervention means that those responsible for the application of this system felt that they were being rejected by academics. Comments such as "we are not going to be monitored", "this is against what I signed-up for", "I am a lecturer, not some data scientist" were used by academics, even though they were encourage to attend training and workshops to build a capable future.

Theme 2: The participants highlighted that there is an issue relating to teaching and learning beliefs by many academics. Whilst age cannot be a confirmed variable, many senior academics preferred their old, traditional ways of teaching and learning. Comments like, "I have always used this method and got good results", "students are lazy - we studied under worse conditions and we passed", were notably used by some academics to justify their non-participation in systematic interventions such as learning analytics. There is a deep philosophical concern that is raised by others on the attributes of teaching and learning. Some do not trust the system and, as a result, tests to be conducted online were not included in the assessment structure of students by some lecturers. The lack of support from senior management to encourage the use of systems, such as the Learner Management System, also contributes to these refusals to cooperate by some academics. Incentives for those who give extra time to learning and using the system may result in increased usage by staff members.

Participants, in many ways, verbalised and strongly articulated that some of their stakeholders might think of technology in education as a waste of time, and they claimed that they did not have time to waste. This demonstrated what some called a lack of understanding of the role technology can play in education in how it helps stakeholders to be more effective and efficient, rather than being a waste of time. As a result, the participants argued that these technological interventions must be preached from top to bottom. Some made an example of private companies in that when a new strategy is adopted, everyone is measured and scaled on it, and universities should adopt the same approach, rather than allowing it to be an open choice.

Theme 3: All the participants acknowledged the possibilities that come with the application of learning analytics. There is no doubt about what the system can do for Universities of Technology. There is enough data to show the benefits of Learning Analytics, especially from other countries (mostly European countries). However, the African continent is lacking this evidence. Nevertheless, there exists some evidence which points to the beneficial use of Learning Analytics by some developing countries, including South Africa.

While a lot of possibilities and opportunities have been acknowledged, there is still a pending argument around the question of ethics and students' privacy. Some participants felt that academics are using the issue of ethics and students' privacy to overrule the application of these interventions. Most argued that students' data, whether manual or digital, has always been at the disposal of the university's management staff, and if that data is used to improve students' throughput rates, it will not become a red flag. Participants felt that even in the case of manual data, students who do not do well would be picked-out, assessed and assisted. Nevertheless, the problem with this method has always been the turn-around time. Some of these problems can only be detected after the damage has already occurred.

The ethical question in relation to learning analytics remains an unresolved question even with the participants. However, none of them argued this as a reason to withhold the adoption of Learning Analytics. Nevertheless, they suggested that a policy of accommodation must be made in relation to the use of this data. They all argued that some academics might be rejecting it due to its ability to also report and monitor what they use every minute for. It has been said that except for time spent in classes, academics cannot account what they do with the rest of their time. With the introduction of this technology, every academic will have to have a digital footprint in interacting with learners in chatrooms, as well as uploading assessments, videos and notes.

5.3.2 Summary

The study confirmed that Universities of Technology are aware of learning analytics and are all taking steps to either prepare for the adoption of or have already started filtering it into their teaching and learning. They have utilised different strategies to introduce learning analytics and are using whatever is recommended to improve their staff's interest in these interventions. It was evident in the study that each university needed to find a way to improve their student's success and throughput rate. Most universities relied on each other's experiences regarding learning analytics and were sharing good practices - this is because they were believed to be effective on various levels of both understanding and application.

It was evidently clear that Universities of Technology required financial support dedicated to fund these kinds of interventions. It was also sharply revealed that universities have tried out many options to improve students' success and throughput rates. However, they have not proven to be successful and thus came to rely on live systematic data analysis, which seemed to be a far better tool. Planned staff capacitation should integrate training seminars and workshops on these technologies as primary requirements. On a practical level, it should be enforced that a certain amount of academic work must be required to be done online and that all administration work should also be done online.

It is also evident that access to the internet by students at some Universities of Technology remained a challenge. This was proven to differ from one university to another. However, all those who stayed outside of the university residence were excluded from all after hour's arrangements of access to central internet points. This, therefore, meant that almost 40 percent of the student population might not be included in the main plans to improve student throughput rates, as they only included or were limited to those students who are part of internal accommodation. The price of data for external residence students to have access to these interventions had been suspected to be the issue that universities were mostly concerned about.

All the e-learning specialists and ICT personnel who took part in this study explained that the process could be tiring, draining and discouraging. They also mentioned that university top managers have not yet fully supported the technological interventions recommended, despite the finance which had already been invested into the project. They explained that time effort and investment are only projects that produce maximum results.

One of the ways is to this achieve is to institute measurable key performance indicators for academics. The problem of improving students' throughput rates is an institutional problem and as such, it must be given a sufficient level of attention and support. This issue should incorporate the cooperation of both academics and administration staff. The academics involved in top management prefer to leave the issue to their faculties and departments, yet every resource should be enlisted to assist the institution of this technology, as it should be part of the primary core of the existence of any university.

After all the discussions and findings mentioned above, the researcher re-examined the research questions, the research aims and objectives. After examining the data collected and analysed in Chapter 4, as well as the conclusions and the recommendations indicated in Chapter 5, the researcher was satisfied that the set objectives for the research were met.

5.4 Recommendations of this Study

This study was based on observations by the researcher. As such, the researcher makes the following recommendations for the South African Technology Network (SATN) and Universities of Technology (UoTs).

5.4.1 Develop/amend data policy management

Many people's fear revolves around the collection, management, usage and storage of the substantial amounts of data involved. The data management framework, data policies and security related access can be improved. There are several steps that need to be taken to address the issues of ethical considerations concerned with learning analytics. Prinsloo and Slade (2013) argued that universities have always had access to and managed students' data. However, the development in accessing substantial amounts of student data is growing at a high speed and universities are not keeping-up with these developments, on the policy side to regulate these new challenges and available solutions.

In line with the above, the following recommendations are made:

- Develop data management policies which protect student data from any usage except for the academic welfare of students, social factors related to academics or any assessment that may improve student learning outcomes. The use of such data by individuals for any malicious acts must be prosecuted with heavy consequences.
- Create a data management structure which will be in authority over data requests, as well as the management of security, storage and all data curations. To train all data managers, content developers and data analysts one must be able to understand the security related measures regarding data access. The structure must also advise senior management on new security measures, new amendments and new challenges relating to student data. Senior Management will be responsible for charging and prosecuting those who violate data access laws. Data restrictions must be enforced, monitored and must protect a student's image. Student privacy must be regarded as violated if use of the data involves the disclosure of student identification or anything else that may link to the individual student. However, it is important to note that if data is collected and analysed on a large scale, then student privacy is not violated (Prinsloo & Slade, 2013).

- Develop an undertaking form - this will be used to give access to all authorised individuals to access data and extract any sections they need. This will improve access management over data. It will also create a sense of responsibility in data users. This will also need to be signed by those who want to opt out of Learning Analytics initiatives, with plausible reasons which they should provide, as well as identifying an alternative support system if they wish not to use the analytics system.
- Develop a student undertaking form, which will give permission to collect their data, analyse it and use it for the benefit of their academic performance. If a student is not comfortable with that, then she or he may be allowed to suggest an alternative on how He or she would like to be assisted and supported in their academic progress.

5.4.2 Use of consortium bargain

The South African Technology Network, which was formed as an umbrella body of all Universities of Technology, provides an objective to improve practices and gives technology support to formerly poverty-stricken institutions of higher education (South African Technology Network (SATN). 2017). The SATN, noting the financial inabilities of most UoTs, have been engaging with funders on behalf of UoTs, to solicit funds that may improve the technological infrastructure. Upon the introduction of learning analytics and related systems such as the Learner Management Systems (LMSs), the researcher has discovered that most UoTs will not be able to afford the systems. Even if they procure them, they will not be able to maintain them or have access to their full potential.

In relation to the points discussed above, the following is recommended:

- Register a unit with the Department of Higher Education and Training (DHET) which will be used to procure the available technologies and then share them among its own higher education institutions. According to the Higher Education Act (of 1996); while universities may have independence, they remain DHET branches. The consortium option when procuring software or systems provides an opportunity for a huge discount. Each university would then pay a portion to the DHET registered centre. This option would give the DHET access to a great deal of live data, in comparison to the current setup of HEMIS data, which is always around two years late. It would also guarantee the DHET support to universities, as is required by the Higher Education Act of 1996.
- Invest in developing an in-house version of the Learning Management System. The DHET and the Department of Science and Technology, together with all other state technology agencies must invest in designing similar Learning Management Systems,

that will be subsidised by government as an intervention to assist students' academic performance. This will certainly help to remediate the national crisis of poor student throughput rates. For long term purposes, this option would be a financially sound and sensible decision. The private companies that designed the current systems are in business to generate a profit from these opportunities. The higher the demand, the higher the price and the greater the improvement and additions, the greater the price will be. Lastly, these systems are essentially hired and would thus be based on the renewal of a license, by a university, to keep them functioning. Furthermore, despite the finance-related issue, the safety of students' data can be sold to the highest bidder who wishes to make an offer to the owners of the software. For example, in the case of the elections in the USA (in 2016), citizens' contacts were used as a target to advertise political campaigns.

5.4.3 Technology education

Dhanarajan (2001) argued that the use of technology can benefit education in numerous ways. Using the same concept, Kruse (2001) argued against technology, stating that it might impose potential drawbacks to students, due to various issues such as their exposure to technology itself and its tools. This study helped to reveal that students of the current generation are well-acquainted with technological developments – thus, it would be a sorely missed opportunity, by universities, if technology was not used in the collection and in the analysis of data. O'Donoghue et al. (2004) described both the advantages and disadvantages of using technology in education and further concluded their argument that while it is worth noting the disadvantages of using technology in education, these still did not outweigh the benefits that come with the use of technology in education.

The participants argued sharply that the question of the use of technology in education has long been debated and that a decision to include it had been taken by many. The moving debate has now shifted to the technological tools that are being used and how effective they are in addressing the main problems faced in education.

Evans and Fan (2002) postulated that the two main benefits that come with the use of technology in education are: 1**) Learner-determined location:** this expresses how students determine where they will study, instead of just using conventional classrooms; and **2) Learner-determined time:** This allows students to determine when learning can take place (time) instead of pushing learning into odd and inconvenient hours. As such, this technological advantage could even help improve the attitude of students towards their education.

The following are, therefore, recommended:

- Formalise technology as an inclusive teaching and learning tool. Further to this, universities should consider adopting certain tool(s) to be included as methods of teaching and as such, all employees must be competent in the disciplines. The participants suggested that the use of technological tools should remain optional for staff to facilitate reducing overly large expenditure for the university in that area. This will help to motivate the implementation of interventions required to understand key performance indicators – an essential tool that academics frequently require and use.
- Higher education institutions should also build systems to measure the impact of technological tools on the teaching and learning outcomes across its faculties. They should develop internal technical support, which will allow a process of learning to occur, while being assisted at the same time. The aim of that support would be to implement the system with staff while they are learning to be competent and autonomous in working with the system. The danger of self-learning is that it drains the interest and energy of participants and makes them feel abandoned.

5.4.4 Centralise student systems

In the time of digitalised education, student systems became a key area of focus. This is because if one needs to collect and analyse student data manually, as opposed to using designed systems this would have more than 60 percent of related data to compare. Over time, universities have adopted the use of Learner Management Systems (LMS), which has become the main data feeder for tools such as learning analysis, etc. In a paper on the use of LMS, Mtebe (2015) argued that it is not enough to analyse the academic data of students which is solely derived from LMS. The collection and the analysis of student data must expand beyond academic data.

The participants claim that all institutions had initially procured an Integrated Tertiary System which mainly focused on a university's daily operations and on how students were interacting with the university. Some of the participants added that the financial and bursary systems were completely autonomous compared with any other existing systems. Lastly, the residential application system was also a stand-alone portal. Data from the above-mentioned systems is equally important to improve student life. Higher education institutions should integrate all students' data collecting systems so that they may be linked to the Learning Management System. This will enable learning analytics to create a comprehensive analysis that will incorporate all other systems contributing to student life. The integration should allow for an independent analysis of any data and the comparison thereof.

5.4.5 Staff capacitation

In any form of change, human beings cannot be left out since they will mostly still be the agents of interaction with these systems. It has come to light that many staff claimed non-capacitation of humans when new systems were introduced. As a result, in some universities, participants claimed that LMS had been used as a "dumping site" by academics. These interactive systems are built with many interactive options for lecturers, but they are merely being used to drop notes, study guides and any other PDF related documents into; with no learning or interaction taking place between lecturers and students. The participants are of the view that most of their colleagues view the system as confusing, and not helpful to them in their day-to-day work. They cannot spend time learning about a new system, while they have targets to meet. As a result, the following recommendations are made:

- Prepare compulsory beginner training sessions and workshops which will introduce the new system and show the importance of using it. It must be seen to be effective and efficient.
- Introduce a scoring model. This will score how everyone uses the system and how effective it is. This must be coupled with attached incentives to motivate more employees to use the system. This, of course, may be a temporary suggestion until all staff members (including academics and support staff) are on board.
- Top management should lead by enforcing the use of all adopted technologies, which will focus on all subordinates to follow a specific trend for reporting purposes. For example, when the Dean of a faculty wants to assess student pass rates, she or he must use the system and must not simply rely on the report provided by the Head of Department, to see updates of statistics.

5.5 Limitations

Throughout the course of the study, some notable limitations have been identified and documented. These include selection of participants, interviews, data collection and analysis.

5.5.1 Selection of participants

Most notably, not all Universities of Technology in South Africa participated, even though the study was open to all. Only four out of six participated in the study, together with the SATN body. The number of participants from each institution was not equal. In some institutions, only one participant was available for an interview and thus, would be the sole employee dealing with e-learning and related learning systems. For other institutions, more than two people would be available for interviews, based on the structure of the e-learning departments. Due to the nature of the operation the SATN referred the research interviews now and again to the conveners of its committees who were often the same people who led e-learning units in UoTs. Therefore, they would have already provided input to the research. All Universities of Technology were given an equal opportunity to contribute to the research. Even the two non-participating universities, who requested to be excused from the research, showed a keen interest in studying the results of the report.

5.5.2 Interviews

The method of collecting data was semi-structured interviews across all participants. Due to the adaptation of each interview, some of the questions were informed by the last interview, meaning that some interviewees missed-out on being asked certain questions which had been sufficiently dealt with in earlier sessions. All interviews were meant to be face-to-face. However, three of them could only be arranged through a skype video call, due to the busy schedule of the participants. This inconsistency could have produced different reactions and results in the interview process. Some physical expressions and reactions were not fully captured in the video call interviews which could hinder the cohesive analysis of the interviewees' feedback.

5.5.3 Data collection and analysis

The nature of a qualitative data study relies mostly on the objectivity of the researcher, regarding their judgements and their knowledge. The researcher was the only instrument for both semi-structured interviews and for data analysis. Interviews and transcriptions require time which was why the data collection stretched over a lengthy period from one interview to the next. The use of a co-transcriber assisted a lot on minimising the bias of the interviewees. None of the Institutions claimed to have procured LMS yet and were then asked to produce or reveal their system. Academics, lecturers and students were not interviewed due to the nature of their study. This study focussed on the views, the adoption and the application of learning analytics by higher education institutions (Universities of Technology).

5.6 Further Research Recommendations

Considering the above-mentioned limitations and some points that came from the participants, the following are the recommendations made for further research on this subject (or related to this subject):

- The effective use of Learner Management Systems by academics**:** There is still a gap in the understanding of the role of academic staff in learning analytics. This could be attributed to what they perceive as “teaching” and “learning”.
- The role of students in providing accurate data about themselves**:** It is argued that for learning analytics to be used for the purposes of learning about students and to predict their behaviour, students must, themselves, accept responsibility for improving their performance. A big gap exists between what learning analytics is supposed to be and how students perceive it. Thus, the question of student privacy arises.
- What are the success indicators to measure in learning analytics? With an exceptionally large amount of data available; it may be impossible to analyse every behaviour and every action of a student. Therefore, a study to confirm the main variables should be considered, as part of the success indicators to be measured. This must not take away the personalised feature of the tailoring of Learning Analytics. There should be a systematic way of identifying a lecturer who is at risk of failing students, such as the concept of identifying at-risk students. Researchers may find that a gap exists in relation to this concept.
- A comparison study could be performed on student performance rates in institutions fully using LMS as compared to those who do not use it. With few universities having adopted learning analytics, an evaluation must be conducted to check if there is any notable difference; especially if we are to argue for the widespread adoption of Learning Analytics.

5.7 Conclusion

In conclusion, this research provided evidence on the research topic which is captured as:

“Learning analytics to enhance student throughput and success: a case study of South African Technology Network”.

The outcomes of the study showed that Universities of Technology have all procured the Learning Management System (LMS), which is the first stage of adopting learning analytics as a tool to collect and analyse students’ data. Yet, the level of using these Learning Management

Systems varies from one university to another. The study showed that while the benefits for using these tools are promising, universities still need to exert a great deal of financial pressure to keep these tools alive. The remedy suggested arising from the study is an option of offering grant funding for technological interventions; as well as consideration of consortium registration as a front for all institutions; for when a need like this one arises. The literature, without doubt, showed that student performance remains one of the core problems in higher education and as such, all interventions are welcomed.

Furthermore, the study demonstrated that some universities still suffer from a lack of internet access. As such, this is worse for outside-of-residence students, who may be a factor affecting the level of student participation in Learning Management Systems. It was also noted that, even at an internal level, universities still have internet access challenges. The researcher's last conclusion was that staff development and policy re-alignment do not take into consideration the technological shift that is happening in higher education.

Thus, a suggestion to review policies that speak to student data management and usage and compulsory staff training should be urgently considered; and implemented. If nothing is done, the quality of education remains at risk and consequently, students' academic performance. It is the researcher's opinion that universities should speedily consider their shortfalls and monitor the application and the adoption of learning analytics timeously.

The experience of long-serving e-learning specialists, senior data managers, content creators and statisticians may become fruitful for acting as the basis of assessment for each University of Technology, in assessing their status and position in the digital era. Each university needs to formulate a guiding framework for the adoption and the application of learning analytics. An assessment of the progress in the application of Learning Management Systems is also required. The main aim of this guiding strategy would be to monitor the usage and the integration of modern technologies for teaching.

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