UNIVERSITY OF KWAZULU-NATAL

The adoption of a big data approach to advance teaching and learning in the context of South African higher education

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2023

DECLARATION

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ABSTRACT

Higher education institutions now operate in a more intricate and competitive environment. To maintain a competitive edge, these institutions must embrace innovation. Big data analytics can revolutionize higher education institutions' teaching and learning processes. The proliferation of digital technologies and platforms and the abundance of data presents a tremendous opportunity to revolutionize educational practices and enable informed decision-making through big data analytics. Moreover, integrating big data approaches in higher education is an emerging concept in South Africa. As a result, there is limited literature from a South African viewpoint regarding using big data for educational and training purposes in higher education. This study aims to address the gap in the literature by examining the determinants of big data adoption at the University of KwaZulu-Natal. The researcher adopted the Unified Theory of Acceptance and Use of Technology (UTAUT) framework to examine participants' attitudes, perceptions, and behaviors toward adopting and using big data technology. By employing a qualitative research design, this study examines the factors influencing the adoption and implementation of big data in higher education institutions and the barriers hindering its widespread adoption. The results indicate that big data can enhance decision-making, offer valuable insights, accelerate knowledge discovery, and improve learning processes. These findings have significant implications for educational leaders and practitioners in South African higher education who aim to promote adopting and integrating big data approaches. Overcoming identified obstacles like data illiteracy and data security will be crucial in fully harnessing the potential of big data analytics to enhance teaching and learning outcomes in South African higher education institutions.

Keywords: Big data, Adoption, Teaching, Learning, Higher education institutions, Big data analytics.

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LIST OF ABBREVIATIONS

BDA: Big Data Analytics

HEIs: Higher Education Institutions

IoT: Internet of Things

IT: Information Technology

LMS: Learning Management System

POPIA: Protection of Personal Information Act

SIS: Student Information System

SMIG: School of Management, Information Technology, and Governance

UKZN: University of KwaZulu-Natal

UTAUT: The Unified Theory of Acceptance and Use of Technology

CHAPTER ONE: INTRODUCTION TO THE STUDY

1.1 Introduction

In recent years, the use of big data has gained momentum in various sectors, including education. The field of higher education has witnessed a tremendous surge in the availability of digital technologies and the generation of vast amounts of data. This digital revolution has opened new avenues for exploring innovative approaches to teaching and learning, potentially enhancing educational practices significantly. One such approach is adopting a big data paradigm, which involves leveraging sophisticated analytics methods to extract vital insights from the extensive data generated within educational or other contexts. Big data encompasses collecting, processing, and scrutinizing massive volumes of data to uncover valuable insights that can influence decision-making (Ang et al., 2020). The application of big data will aid educational institutes, management, and students in advancing academic standards, improving learning experiences, making informed decisions, and developing predictive teaching and assessment methodologies (Huda et al., 2016). Since data is involved in every stage of teaching and learning, it is interesting to evaluate big data applications in contributing to innovative teaching and learning. More technological approaches in education can expand the usability of learning resources, encourage systematic literacy, and improve students' attitudes toward their academics (Segooa & Kalema, 2018).

While the benefits of big data analytics (BDA) have been widely recognized in various domains, its application and impact in the specific context of South African higher education still need to be explored. Therefore, this study aims to investigate the adoption of big data approaches to advance teaching and learning within South African HEIs. The researcher utilized a qualitative approach to examine the extent of big data adoption in South African HEIs. The study explored crucial factors that impact the adoption and implementation of big data analytics (BDA). Additionally, the study shed light on the potential advantages and obstacles associated with adopting and implementing BDA in this specific context. By exploring the opportunities, concerns, and implications of adopting BDA, this study offers valuable insights into how this emerging paradigm can revolutionize and enable data-driven decision-making within the South African higher education sector.

1.2 Background

Information Technology is crucial in driving today's technological advancements, which have brought about significant improvements benefiting society, such as healthcare, banking, education, and retail. The upsurge of digital technologies has resulted in a global increase in people using digital devices, primarily driven by greater ownership of mobile devices in Africa. As Murumba and Micheni (2017) highlighted in their study, this digital connectivity surge has catalyzed a profound technological transformation across the African continent. This transformation is evident in how digital technologies reshape various aspects of African society, from business and education to healthcare and communication. Furthermore, the prevalence of mobile and smart devices has facilitated internet access and created a digital ecosystem where data is constantly generated and exchanged. This abundance of data presents an opportunity for HEIs to leverage big data analytics (BDA) and extract valuable insights from the data within their ecosystems. BDA has emerged as a promising solution to many of the concerns encountered by HEIs worldwide (Wang et al., 2018). Studies show that adopting big data initiatives in HEIs can improve student results, enhance teaching practices, and inform decisions (Khan & Alqahtani, 2020).

South Africa boasts one of Africa's most expansive higher education systems, comprising over 25 public universities and an enrolment of over 1 million students in various higher education institutions (Stats, 2019). South Africa, with its diverse higher education landscape and a growing emphasis on digital transformation, is well-positioned to explore the potential of big data in advancing teaching and learning. Educators and administrators may obtain more profound insights into student behaviors, performance patterns, and engagement levels by exploiting the massive datasets created within educational institutions, such as student information systems, learning management systems, and digital platforms (Murumba & Micheni, 2017). However, South African higher education still faces several challenges, such as resistance to change, inadequate data infrastructure, funding, lack of data expertise, and concerns about the ethical implications of using big data, such as the potential for discrimination and invasion of privacy. These challenges have resulted in poor student retention, low graduation rates, and a widening skills gap in the country's workforce (Bhadani & Jothimani, 2016). As a result, there is an imperative need for innovative approaches to enhance the quality of education in South African higher HEIs.

Furthermore, understanding the elements that influence the adoption of big data approaches in South African higher education is crucial for realizing its full potential. This study explored the current state of big data adoption in teaching and learning practices within a South African higher education context. By examining the opportunities, challenges, and implications of adopting big data approaches, the study highlighted the potential benefits and concerns of adopting and applying BDA in this context.

1.3 Problem Statement

In the rapidly evolving landscape of education, the effective integration of technology has become increasingly crucial to foster enhanced teaching and learning experiences. Adopting and implementing big data approaches is one such technological advancement with significant potential. Big data analytics holds promise for generating actionable insights that can inform instructional practices, facilitate personalized learning, and improve student outcomes (Lubinga et al., 2023). However, despite its potential benefits, there is a shortage of systematic studies that comprehensively scrutinizes the opportunities, benefits, and challenges associated with integrating big data methods within the South African higher education ecosystem.

The higher education scene in South Africa faces numerous challenges, such as high student-to-teacher ratios, limited resources, inadequate data infrastructure, diverse student populations with varying educational backgrounds, and inadequate student support mechanisms. These concerns were further worsened by the COVID-19 plague, which disrupted education globally. These challenges contribute to the complexity of effectively delivering personalized and high-quality education to students and developing a skilled workforce that can compete in the global market (Segooa & Kalema, 2018). However, the growing availability and accessibility of large volumes of educational data, including student performance data, online learning interactions, and institutional records, provide an opportunity to harness the power of big data analytics to address these challenges. Therefore, this study aimed to address these gaps by conducting a comprehensive investigation into adopting and implementing big data approaches to advance teaching and learning in South African higher education.

1.4 Purpose of the Study

The use of big data technology has emerged as one of the fastest-growing trends in information technology. It has attracted much research attention to improving teaching and learning outcomes in education (Al-Shiakhli, 2019). However, integrating big data analytics (BDA) in higher education is still a novel concept in South Africa, resulting in limited literature from a South African perspective on the application of big data for educational and training purposes. This study seeks to address the existing gap in the literature by investigating the key elements that influence the adoption and implementation of BDA in South African HEIs. Furthermore, the study also examines how big data analytics can inform and improve instructional strategies in higher education. It explores using data-driven insights to optimize curriculum design, teaching techniques, and personalized learning experiences. Finally, the study aims to significantly contribute to the broader discourse on big data applications in education by providing insights that might inform policy and practice in South African higher education. Embracing the power of big data in education is a forward-looking approach and a strategic investment in shaping the future of learning and educational excellence.

1.5 Research Questions

1. What is the perceived usefulness of adopting and implementing big data in advancing teaching and learning in a South African higher education context?
2. What is the perceived effort needed to adopt and implement big data in advancing teaching and learning in a South African higher education context?
3. What factors influence big data adoption and implementation in advancing teaching and learning in a South African higher education context?
4. What are the perceived opportunities, benefits, and challenges to big data adoption and implementation in advancing teaching and learning in a South African higher education context?

1.6 Research Objectives

1. To determine the perceived usefulness of adopting and implementing big data in advancing teaching and learning in a South African higher education context.
2. To determine the perceived effort needed to adopt and implement big data in advancing teaching and learning in a South African higher education context.
3. To identify the key factors influencing big data adoption and implementation in advancing teaching and learning in a South African higher education context.

4. To identify the perceived opportunities, benefits, and challenges to big data adoption and implementation in advancing teaching and learning in a South African higher education context.

1.7 Significance of the Study

Globally, the adoption and application of big data analytics (BDA) are becoming increasingly popular, and South Africa is no exception. However, despite this growing popularity, several opportunities, and benefits of BDA adoption in higher education have yet to be thoroughly investigated and realized within South Africa. This study's significance lies in its potential to provide valuable insight into the current state of big data adoption in South African higher education and future recommendations. The outcomes of this study will expand the existing knowledge about the application of BDA in education, thereby aiding educators, stakeholders, and educational decision-makers in making informed decisions that will improve overall institutional outcomes. Additionally, the study aims to contribute to the progression of personalized learning approaches, catering to South African higher education students' unique needs. Furthermore, this study identified the potential barriers to adopting big data. It provided recommendations for overcoming these barriers, such as improving infrastructure and investing in training and capacity building for instructors or other stakeholders.

1.8 Delimitations of the Study

Delimitations in any research study are the specific boundaries or limitations that researchers set for their study. Delimitations define the scope of the study by specifying what aspects will be included and excluded (Theofanidis & Fountouki, 2018). They are concerned with the definitions that researchers choose to designate as the boundaries or limits of their work to keep the study's aims and objectives from becoming difficult to attain (Theofanidis & Fountouki, 2018). The study is exclusively focused on the selected traditional university in South Africa (University of KwaZulu-Natal) and does not consider universities located in other regions or countries. The research also does not encompass other types of HEIs, such as Universities of Technology or private universities in South Africa. These limitations allowed the research to maintain a clear and manageable scope, ensuring that the study does not become overly complex or unwieldy in its attempt to encompass a broader geographical range of institutions. By concentrating exclusively on one university, the research delved deeper into the unique characteristics, challenges, and dynamics of this institution. Moreover, it opens the door for future research to expand on this foundation and conduct comparative studies with universities in other geographical settings, thus broadening the scope of knowledge in the field.

1.9 Structure of the Study

The research is structured into the subsequent chapters:

Chapter One: This chapter introduced the study by comprehensively discussing the essential aspects of the study. These included the problem statement, study purpose, study questions and objectives, the study's rationale, delimitations, and structure.

Chapter Two: This chapter covers the literature review part of the study, identifies gaps in existing knowledge, and justifies this study's importance. It comprehensively evaluated and examined the big data paradigm's relevance to the study.

Chapter Three: This chapter covered the adopted theoretical framework used in the study.

Chapter Four: This chapter detailed the research methodology adopted in the study. This chapter outlines the research philosophy, rationale, and design, including the methods for data collection. This chapter also discussed the sampling strategy, data analysis techniques, and the ethical considerations considered during the research process.

Chapter Five: This chapter presented and discussed the study's analyses and findings. The chapter examined the data obtained and presented the results derived from the analysis.

Chapter Six: This chapter concludes the study. The chapter also provided relevant recommendations, highlighted the study constraints, and provided future research directions.

1.10 Summary of Chapter One

This chapter introduces the study, providing a comprehensive overview of its purpose and relevance. This chapter presented the background of the study, the problem statement, the study questions and objectives, the goal, and the rationale. Moreover, the study's delimitations and overall structure were also discussed. The subsequent chapter, Chapter Two, delves into a thorough review of the pertinent literature surrounding the adoption and application of big data in a higher education context.

CHAPTER TWO: LITERATURE REVIEW

2.1 Introduction

In recent years, big data methods and technologies have rapidly transformed various industries, enabling them to harness vast amounts of data for valuable insights and improved decision-making. While sectors such as finance, healthcare, and manufacturing are embracing this paradigm shift, the domain of higher education in South Africa has been relatively slower in adopting big data initiatives to enhance the teaching and learning process (Ang et al., 2020). Several factors contribute to this slow progress, including limited funding, a shortage of skilled data specialists, concerns surrounding data privacy, resistance to change, and other challenges faced by most higher education institutions in South Africa (Ang et al., 2020).

Consequently, there is limited literature from a South African viewpoint involving using big data for educational and training purposes in higher education. Hence, this chapter presents a comprehensive overview of the big data paradigm and its applicability in higher education. By exploring the potentially transformative effects of big data analytics on teaching and learning, this study aims to enrich the discussion surrounding innovative approaches and leveraging technology to enhance the educational landscape in a South African context. Ultimately, this review aims to inform future research endeavors and guide policymakers and educational stakeholders in effectively harnessing big data to transform South African higher education.

2.2 Big Data Paradigm

Big data is an emerging concept that refers to a large volume of organized, semi-organized, or unorganized datasets that can be mined for valuable insights and information. It involves large and complicated data sets that cannot be handled or managed using conventional data management tools (Khan et al., 2018). Previously, data used to be quantified in terms of Megabytes or Gigabytes. However, in the present time, there is a constant generation of enormous data quantities measured in Petabytes (PB) or Zettabytes (ZB), necessitating extensive storage capacity and efficient administration (Khan et al., 2018). The big data paradigm in higher education encompasses the application of big data analytics (BDA), technologies, and methods to derive valuable insights and drive data-driven decision-making in teaching, learning, research, and administrative activities within HEIs. These involve gathering, storing, processing, and examining extensive data from diverse sources, including student records, LMS, virtual learning platforms, and digital resources. (Murumba & Micheni, 2017). According to Padgavankar and Gupta (2014), big data can be referred to as innovative database administration and analytical techniques developed for analyzing, managing, and processing massive or intricate data sets. Examples of big data investments, according to Padgavankar and Gupta (2014), include human capital (such as data specialists); industry and technology resolutions, such as database administration systems (MapReduce, Hadoop); data analytics and graphics tools (such as Python and R); or content-processing and real-time streaming solutions. The big data movement has influenced many sectors, including education, as new technologies are designed and implemented to advance and streamline data analysis and result projection methods.

The five Vs. are the specific attributes that define Big Data. Figure 1 below depicts the five Vs. and their relevance to this study.

Volume: Big data refers to the vast amount of data generated from numerous sources (Amane et al., 2020). It represents the scale or size of the data, which can be enormous and continuously growing. The increasing volume of data generated in higher education provides educators with a wealth of information about student performance, behavior, and engagement. By analyzing large volumes of data, HEIs can gain insights into learning patterns, identify areas of improvement, and personalize the educational experience (Amane et al., 2020).

Velocity: The velocity of data can be referred to as the rapidity at which data is generated, processed, and analyzed. The pace at which data is generated and processed can impact the teaching and learning process (Mikalef et al., 2018). Real-time data analytics can enable educators to identify students who may be struggling and provide timely interventions. Additionally, educators can respond swiftly to changing needs and adapt teaching strategies accordingly (Mikalef et al., 2018).

Variety: Big data is a mix of diverse data types, including organized and unorganized data forms. Educators can gain a holistic view of students' learning experiences, preferences, and challenges by integrating various data sources. It enables the development of comprehensive and tailored interventions (Amane et al., 2020).

Veracity: The veracity of data refers to its correctness, reliability, and trustworthiness (Mikalef et al., 2018). In higher education, ensuring data quality is crucial to make informed decisions. HEIs must employ data quality assurance processes to address inaccuracies and biases arising from various sources, providing reliable insights for teaching, learning, and research purposes (Al-Shiakhli, 2019).

Value: The goal of leveraging big data in higher education is to extract value and derive actionable insights that positively impact teaching and learning. By harnessing the power of BDA, educators can uncover patterns, correlations, and predictive models that inform evidence-based decision-making (Mikalef et al., 2018).

Figure 2.1. The Five Vs. of Big Data

2.3 Innovative Teaching in Higher Education

Several theories and applications for creative teaching deal with student behaviors, techniques, approaches, and strategies (Huda et al., 2016). An educator or instructor's competency is critical in offering innovative teaching in higher education. Professional certification, cognitive skills, mastery of teaching and learning materials, and pedagogical style are examples of these competencies (Huda et al., 2016). This study centers on creative teaching and learning due to advances in IT, such as big data analytics. Since data is involved in every stage of the teaching and learning process, it is imperative to evaluate big data applications in contributing to creative pedagogies. Big data analytics (BDA) could be utilized to facilitate creative teaching and learning by including several factors connected to enormous data collection and its expansion.

These are the positives that are supposed to motivate students to expand their learning experiences while also adding value to students' progress, productivity, and success throughout the learning process.

2.4 Need for Big Data in Higher Education

Big data involves an innovative data analytics approach for discovering, analyzing, and extracting value and insights from vast volumes of data (Huda et al., 2016). Big data's capabilities include data transport and sharing, prediction, visualization, capture, and retrieval. Big data capabilities in quantity, rate, and variety increase as information technology (IT) grows and evolves (Anshari et al., 2016). Higher education institutions (HEIs) create a large quantity of data regularly that may be used to provide beneficial services to their stakeholders. For instance, big data may facilitate learning by offering access to credible information sources. Hence, it improves student engagement, interaction, and consistent content delivery. Real-time access to big data enables exploring data and understanding student behavior to provide individualized and customized services to students depending on their areas of interest (Huda et al., 2016).

Furthermore, Anshari et al. (2016) noted that understanding the applications of big data brings up innovative solutions for optimizing the actionable insights collected in virtual learning systems. From the standpoint of its stakeholders, big data allows for the delivery of personalized course content or information with improved accuracy to each student via different channels. For example, students can learn online by utilizing resources provided by the lecturer (Huda et al., 2016). Beyond that, the system would provide appropriate and relevant links to more study materials for each subject of discussion.

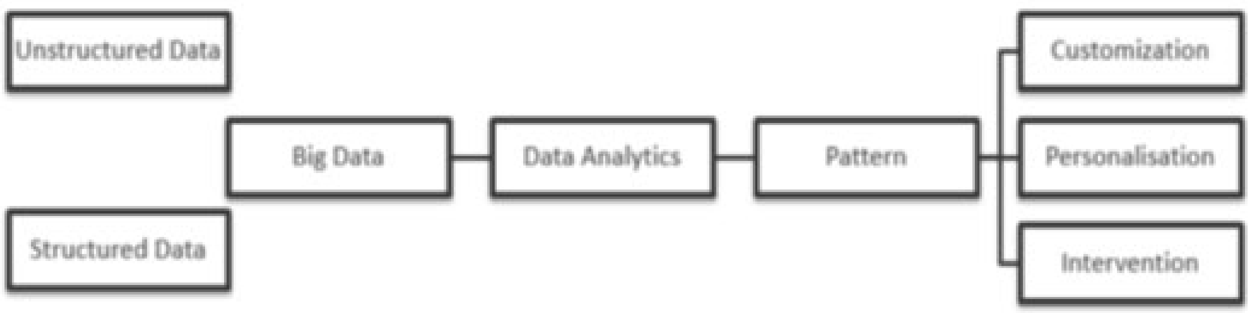

Figure 2.2. Big Data Analytic Process

Source: Huda et al. (2016)

The figure above is discussed further below. The figure depicts an overview of how big data provides value for education. Big data analytics involves using advanced techniques and technologies to extract meaning from vast amounts of structured, semi-structured, and unstructured data (Huda et al., 2016). Structured data sources in education include student data, financial records, e-library records, virtual click behavior, etc. Unstructured data sources, on the other hand, might come from text files, emails, images, audio files, social network interactions, and so on. The prediction and pattern of each student are some of the data analysis outcomes. Prediction and pattern for each student are vital in providing better service to students since it allows personalization of delivery, module customization, and interventions to facilitate performance and quality control (Moharm & Eltahan, 2020). Customization refers to the flexibility of students to select subjects that best fits them. At the same time, intervention is required when learners' performance deteriorates. For example, suppose a student faces difficulties or performs poorly in a particular course. In that case, a proactive approach can be taken by sending them a warning alert or message to motivate them to initiate corrective measures or seek additional assistance (Moharm & Eltahan, 2020).

By examining the data gathered from students' interactions with learning environments such as Moodle, it becomes possible to tailor the content to suit their demands and learning styles, enhancing student engagement and performance (Liang et al., 2016). Big data application in education provides valuable insights into students' learning journeys, including their engagement with learning activities and optimal practice times. It empowers instructors to determine the most effective content and delivery methods, ensuring a high-quality and meaningful learning experience. The implementation of big data presents transformative opportunities in the education domain, revolutionizing both the student learning process and teaching methodologies (Moharm & Eltahan, 2020).

2.5 Big Data Technologies

Big data technologies have emerged as powerful enablers of digital education, revolutionizing how educational institutions deliver learning experiences and enabling personalized and data-driven approaches to teaching (Susanto et al., 2018). Unlocking the value of big data in any organization involves three major stages. The first stage is data collection, which entails identifying valuable and beneficial information from the available data. Once the data's potential usefulness is established, the second stage is analysis, where the data undergo a thorough examination to extract actionable insights. However, analyzing diverse datasets can be complex due to their increasing variety, presenting a challenge within big data. The final stage is visualization and application, where the analyzed data is presented in a user-friendly format that enables understanding and interpretation, facilitating subsequent processes like decision-making (Ibrahim et al., 2020). Big data came with several innovative data access, storage, computation, and transmission technologies. NoSQL databases, Hadoop Ecosystem, and Blockchain are just a few technologies to improve big data systems (Dahdouh et al., 2017).

Big data, a vast information network, is reshaping the goals of knowledge and social theory across multiple disciplines and can revolutionize management decision-making theories (Susanto et al., 2018). Numerous global initiatives have been to leverage big data in the education domain. For example, in Europe, several HEIs are utilizing students' academic data to make informed decisions aimed at enhancing their academic performance (Ibrahim et al., 2020). Higher education institutions (HEIs) now leverage big data to make critical and strategic decisions, benefiting from valuable data collection and analysis insights. Universities are increasingly dedicating resources to gathering and monitoring student data, utilizing data mining tools to track various aspects such as student admission, attrition rates, performance, and other predictive indicators. The integration of big data in education promises improved educational quality and the cultivation of more knowledgeable students and teachers compared to previous practices.

2.6 Big Data Analytics

Al-Shiakhli (2019) states big data analytics unlocks new prospects for higher education institutions. Learning analytics, for instance, is an aspect of big data analytics that enables lecturers to undertake real-time analysis of learning behaviors. In other words, lecturers may use big data analytics techniques to discover areas where students struggle or succeed, assess specific student needs, and devise tailored learning methods (Al-Shiakhli, 2019). Big data analytics, according to Manohar et al. (2016), is vital in tackling a variety of crucial concerns for higher education, the most pressing of which are: I) enhancing teachers’ efficacy, II) obtaining insights from learning experiences, III) providing tools or resources that promotes creative learning; and IV) providing learners with practical skills for their impending careers.

As illustrated in the diagram below, big data in e-learning systems refers to the data generated from various activities conducted within the learning platform. This data encompasses personal information, course content, records of learning activities, collaborative interactions with peers, and more. The collected data is processed and stored in standardized formats such as CSV, JSON, and XML. Big data algorithms and techniques are then applied to analyze these datasets, producing reports, graphs, charts, tables, and other visual representations. These insights can be utilized to make informed decisions and customize the learning experience to address the specific demands of individual students (Dahdouh et al., 2017).

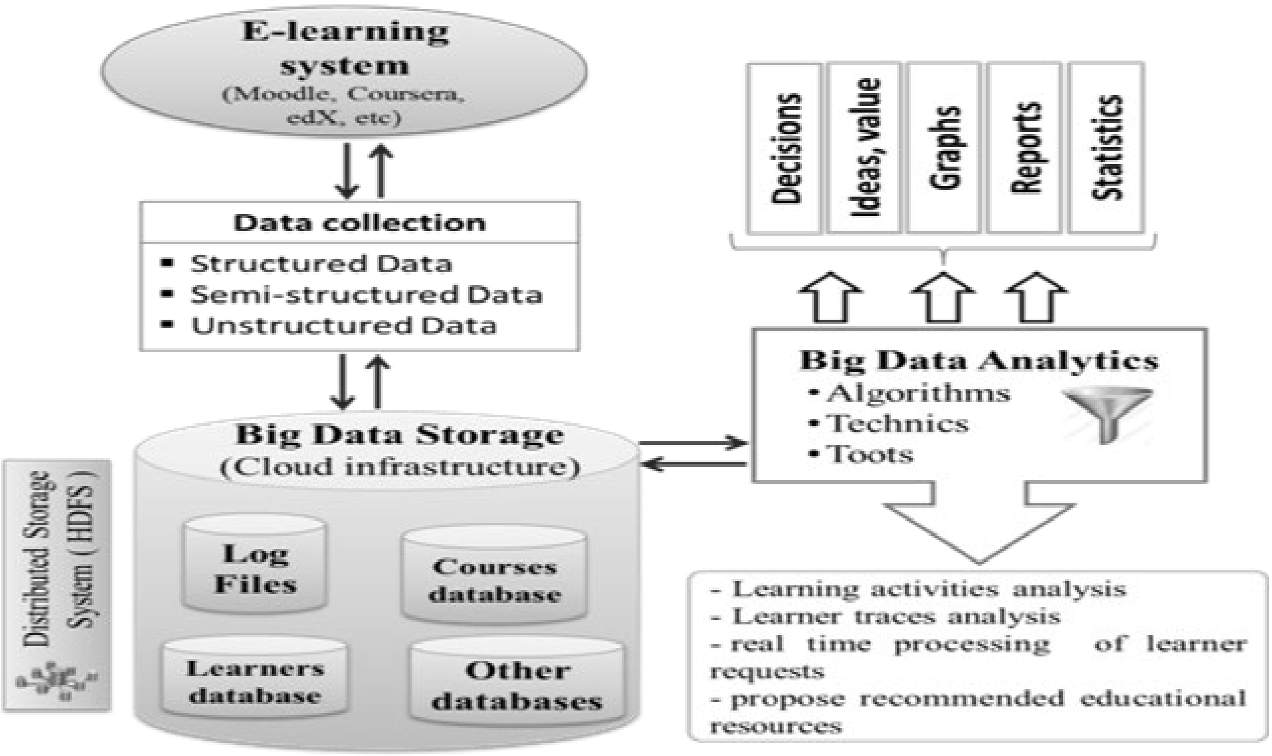

Figure 2.3. Exploring Big Data Analytics in Learning Systems

Source: Dahdouh et al. (2017)

2.6.1 Big Data Analytics (BDA): Procedures and Techniques

BDA in higher education involves applying advanced techniques and technologies to analyze large and complex datasets generated within those institutions to make informed educational decisions (Vassakis et al., 2018). BDA involves the various procedures and techniques explained below:

Data acquisition: Data acquisition is a crucial technique in big data analytics that involves gathering or collecting relevant data from various sources, such as databases, digital platforms, or other data repositories (Segooa & Kalema, 2018). It encompasses gathering relevant data to gain insights and make informed decisions to improve student results, enhance teaching methodologies, and optimize institutional processes.

Data clustering: As described in the literature, data clustering is a powerful technique in big data analytics that can be applied to gain insights and uncover patterns within large datasets. Data clustering involves grouping similar data points based on their intrinsic characteristics and similarities (Ang et al., 2020). Clustering can help segment students into meaningful groups based on academic performance, learning styles, interests, demographics, and engagement patterns. By identifying distinct student segments, institutions can tailor their support services, academic advising, and intervention strategies to address the specific demands of each group (Ang et al., 2020).

Data mining: As described in the literature, data mining involves exploring and analyzing large datasets to discover patterns, relationships, and actionable insights. Data mining techniques can be utilized to develop predictive models in higher education. For example, predictive models can be designed to estimate student enrolment, predict graduation rates, anticipate student success in specific programs, or forecast resource demands. These models provide HEIs with insights into strategic planning and resource allocation (Ang et al., 2020).

Data Visualization: Data visualization, as described in the literature, involves presenting data in visual formats such as charts, graphs, maps, and interactive dashboards to communicate complex information and patterns effectively. Visualizing learning analytics data can provide insights into student engagement, progress, and learning outcomes. Institutions can create interactive dashboards that display data on course completion rates, learning activity patterns, assessment scores, and peer collaboration metrics (Vassakis et al., 2018).

2.7 Current State of Big Data in South African Higher Education

Big data has gained attention in South African higher education, with a growing recognition of its potential benefits. According to recent reports, South African higher education institutions (HEIs) are embracing big data analytics (BDA) for academic and administrative purposes (Lubinga et al., 2023). A survey conducted in 2019 found that around 48% of South African universities and colleges are currently using big data and predictive analytics to improve student success rates and institutional effectiveness (Sekli & De La Vega, 2021). Predictive analytics models are being developed to forecast student performance and help institutions allocate resources effectively (Lubinga et al., 2023). These institutions use BDA to analyze large amounts of data such as student demographics, learning patterns, and performance to identify opportunities for improvement and develop effective intervention strategies. One example of using big data in South African higher education is at the University of the Western Cape (UWC), which has implemented a predictive analytics system to identify students at risk of dropping out. The system uses student academic performance, attendance, and engagement data to generate a risk profile and provide targeted interventions to help students succeed. Another example is the University of Johannesburg (UJ), which has partnered with IBM to develop a data-driven approach to student support and success. The university uses IBM Watson Analytics to analyze data on student performance, engagement, and behavior to identify areas where academic support is needed and to provide personalized interventions. Furthermore, most South African HEIs have established dedicated Learning Management Systems (LMS) such as Moodle, Canvas, Blackboard, or Brightspace to manage and track student learning activities. These institutions also have dedicated Learning Analytics Dashboards such as Course Heat Map to gain valuable insights into course completion rates, student engagement, and performance metrics.

However, the adoption of big data analytics (BDA) in South African Higher Education is still at an early stage, and several challenges remain to overcome. One of the primary challenges is the lack of skilled data personnel to manage and analyze the obtained data proficiently. This scarcity of skilled personnel directly impacts the implementation and accuracy of big data analysis in HEIs (Sekli & De La Vega, 2021). The demand for data analytics expertise is soaring, but unfortunately, there is a notable shortage of qualified data scientists within South African HEIs (Bamiah et al., 2018). Additionally, there are concerns about data privacy and security, which require cybersecurity measures to be implemented to protect sensitive information.

Despite these challenges, big data technologies can potentially revolutionize decision-making, increase productivity, and enhance student success in South African HEIs. HEIs can leverage BDA to improve student learning outcomes, identify areas for improvement in teaching and learning, and develop evidence-based policies and strategies. Therefore, to effectively embrace the benefits of big data in South African higher education, it may be necessary for institutions, governments, and relevant industries to collaboratively invest and provide the required funding, infrastructure, training, and expertise for its effective implementation. This collaborative effort will foster a holistic and data-driven educational environment, creating pathways for innovation and continuous improvement in the educational landscape.

2.8 Implementations of Big Data in Higher Education

Big data has emerged as a powerful tool in various industries, and higher education is no exception. With the increasing availability of digital technologies and the vast amounts of data generated within educational institutions, big data analytics is transforming the education sector. Here are some implementations of big data in higher education:

2.8.1 Educational Data Mining

Educational Data Mining (EDM) is a data mining subfield that analyzes educational data to gain insights and make informed decisions (Calvet Liñán & Juan Pérez, 2015). The implementation of EDM facilitates the evaluation of learning practices by examining students' interactions with the classroom environment, including e-learning systems, course management systems (CMSs), and simulations (Calvet Liñán & Juan Pérez, 2015). By applying data mining algorithms and statistical tools, educators can uncover patterns and relationships within the data that can inform decision-making and improve learning experiences (Slater et al., 2017). The goals of EDM include enhancing personalized learning, spotting at-risk students, improving instructional design, optimizing educational interventions, and gaining a deeper understanding of the learning process (Slater et al., 2017).

2.8.2 Learning Analytics (LA)

The examination of data derived from user interactions with technology has garnered the interest of researchers as a promising approach to enhancing comprehension of the learning process. This objective has spurred the emergence of a new research field known as learning analytics (LA), which is closely intertwined with educational data mining (EDM) (Chaurasia et al., 2018). Learning Analytics (LA), according to Viberg et al. (2018), involves collecting, analyzing, and interpreting data produced throughout the learning journey with the goal of enhancing students' overall success rates. Learning analytics relies on leveraging sizeable datasets, often known as big data, which encompasses the activities of all stakeholders engaged in the learning process. These activities are recorded by the Virtual Learning Environment (VLE) and subsequently stored in databases (Chaurasia et al., 2018).

2.8.3 Performance Prediction

Big data analytics can be utilized for predictive analysis to forecast the future performance of learners. Big data analytics can lead to performance prediction by analyzing large datasets and identifying patterns, trends, and relationships that are not easily discernible using traditional methods (Khan & Alqahtani, 2020). With big data analytics, educational institutions can develop predictive models that leverage past performance and behavior to forecast future performance (Liang et al., 2016). The models can identify at-risk students early and provide appropriate support interventions (Liang et al., 2016). By analyzing patterns and trends, predictions can be made based on various factors such as demographic data, academic achievements, attendance records, and engagement levels (Khan & Alqahtani, 2020).

Furthermore, observing students' behaviors and engagements makes it possible to identify those at a high risk of dropping out of their degree programs. This enables the implementation of timely intervention and retention approaches to address the issue at an early stage (Liang et al., 2016). Higher education institutions must begin incorporating predictive analytics into their data analysis process to obtain valuable knowledge about the potential outcomes of prospective students (Al Amri & Almaiah, 2021). Using predictive analytics empowers institutions to improve their capacity for predicting and comprehending future student outcomes. This analysis will examine students' performance throughout the year and indicate if they might drop out (Liang et al., 2016). Additionally, predictive analytics can be utilized to conduct scenario analyses on prospective courses before their inclusion in the curriculum, thereby avoiding trial and error (Hwang, 2019).

2.8.4 Course Recommendation

Big data analytics (BDA) can lead to appropriate course recommendations by analyzing and interpreting large datasets educational institutions generate. Using big data analytics, academic institutions can analyze student data to identify trends and patterns in course selection, performance, and outcomes (Khan & Alqahtani, 2020). One of the essential components of a practical course recommendation system is the ability to analyze student data to determine their interests and academic strengths. By leveraging big data analytics algorithms, institutions can identify the courses students are most likely to enjoy and excel in based on their enrolment history, academic performance, and other demographic data. It will prevent students from being misled into majoring in fields in which they are uninterested or unwilling to engage (Liang et al., 2016). According to Bhadani and Jothimani (2016), big data analytics (BDA) can inform course development and delivery. By leveraging BDA, HEIs can also gauge the efficacy of their current course offerings and make informed conclusions about which courses to offer in the future (Bhadani & Jothimani, 2016).

2.8.5 Smart Feedbacks

Big data analytics offers instructors rapid constructive feedback on the structure of their modules and the effectiveness of their teaching and evaluation methods. It allows for module progress tracking and simplifies predicting student performance by examining previous results to indicate future outcomes (Khan & Alqahtani, 2020). Big data analytics (BDA) can provide brilliant feedback through real-time personalized feedback. For example, BDA can be utilized to examine student interactions with a digital book or learning management system, determining how long the student has spent on each page, which pages attract the most attention, and track the pace of the student's reading (Vassakis et al., 2018). Based on the analyzed data, the system can generate tailored recommendations, summary reports, and personalized feedback messages, providing valuable support to students in their learning endeavors (Vassakis et al., 2018).

2.8.6 Data Visualization

Data visualization is a powerful application of big data. It involves using visual representations, such as charts, graphs, and interactive dashboards, to communicate complex educational data in a visually appealing and easily understandable manner (Murumba & Micheni, 2017). Data visualization plays a crucial role in learning analytics by presenting insights derived from big data. Visualizing student engagement, progress, and performance across different learning activities and resources can help identify effective instructional practices, optimize course design, and personalize learning experiences (Khan & Alqahtani, 2020). Higher education institutions (HEIs) may use data visualization to assess and evaluate their performance to their peers or industry standards. These institutions can evaluate their position and pinpoint areas that require enhancement or potential collaboration through visual representations of data related to key performance indicators like graduation rates, research output, and faculty productivity (Al-Shiakhli, 2019).

2.9 Determinants of Big Data Adoption

Understanding the elements that drive or hinder the adoption of big data analytics is crucial for institutions seeking to harness its potential benefits.

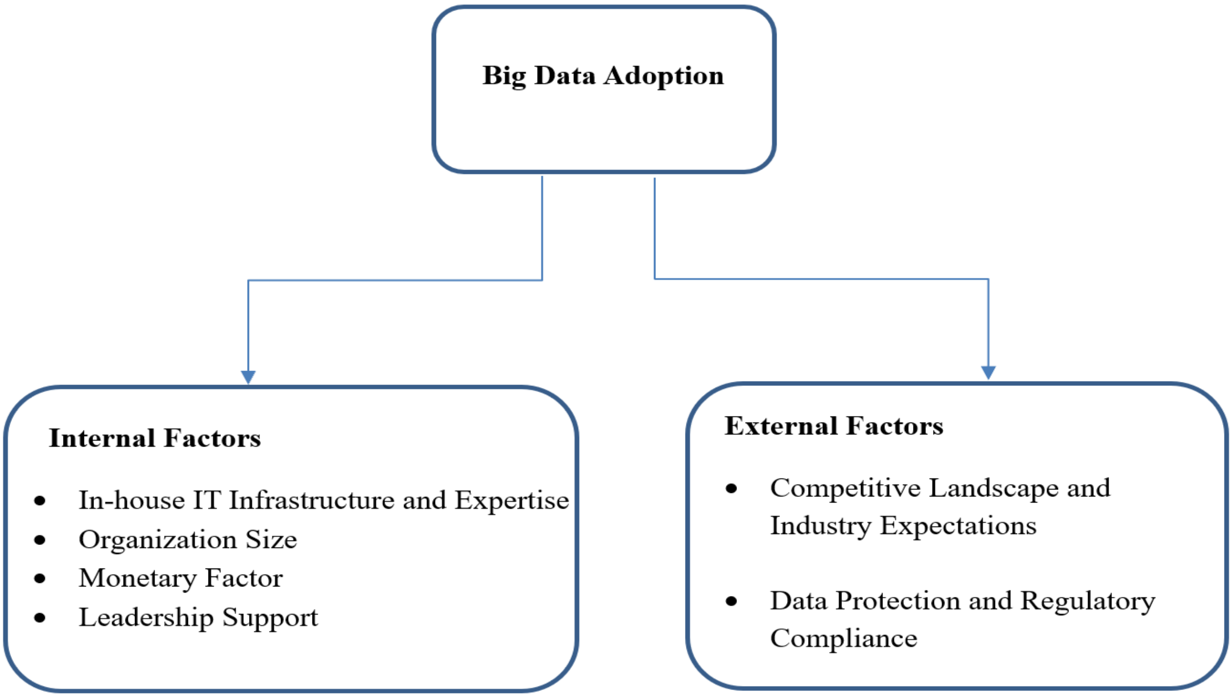

Figure 2.4. Determinants of Big Data Adoption

Internal Factors

In-house IT Infrastructure and Expertise

In-house IT infrastructure and expertise are vital to big data adoption (Sam & Chatwin, 2018). In-house IT infrastructure is essential for higher education institutions (HEIs) because it is crucial in thrusting and implementing technology-based solutions. It provides dependable storage, rapid processing, and seamless integration for managing large volumes of data (Sekli & De La Vega, 2021). Additionally, IT expertise in this domain refers to staff with the necessary skills and knowledge to utilize big data analytics (BDA) (Sekli & De La Vega, 2021). Proficiency in programming and logical thinking are essential in effectively adopting and using big data. HEIs with a solid internal IT team would understand the complexities of data architecture, database management, and data integration, enabling them to seamlessly incorporate big data solutions (Sam & Chatwin, 2018).

Organization Size

Organization size serves as a significant determinant of big data adoption. An educational institution's size can substantially impact its capacity to adopt and implement big data analytics (Chong & Olesen, 2017). According to Baig et al. (2019), organizational size is directly proportional to the adoption of big data analytics. Larger institutions typically have superior resources, both financial and human, which can facilitate the adoption process. They often have more extensive IT infrastructure, enabling them to handle ample data storage and processing demands (Baig et al., 2019). Conversely, smaller institutions may face resource constraints, limited budgets, and a minor IT team, making adopting big data analytics more challenging. However, smaller institutions can leverage cloud-based solutions and strategic partnerships to overcome some of these challenges (Baig et al., 2019).

Monetary Factor (Cost of big data)

The availability of financial resources refers to the budget allocated for adopting and implementing innovative technologies and hiring competent employees. It is a critical factor that sets apart organizations that adopt these technologies from those that do not (Baig et al., 2021). Regarding higher education institutions (HEIs), careful consideration must be given to the financial implications of acquiring, implementing, and maintaining big data analytics solutions. These costs include procuring hardware and software, licensing fees, establishing data storage infrastructure, hiring IT personnel, and providing ongoing maintenance and support. The affordability of these resources significantly impacts an institution's decision to adopt big data analytics (Tasmin & Huey, 2020). Larger institutions with higher budgets may have the financial capability to invest in comprehensive big data systems. In contrast, smaller institutions with limited resources might face challenges bearing the upfront and ongoing costs.

Additionally, there may be ongoing expenses for training IT staff, hiring data analysts, and ensuring compliance with data privacy regulations. However, it is essential to note that advancements in cloud computing, particularly pay-as-you-go models and cost-effective cloud-based big data solutions, have made adoption more viable for institutions with limited budgets (Baig et al., 2021). Nonetheless, the price or cost factor remains crucial in determining the feasibility and pace of big data adoption in higher education. Institutions must weigh the potential benefits of big data analytics against the associated expenses to make informed decisions about its adoption (Baig et al., 2021).

Leadership Support

Leadership support is a critical determinant of big data adoption. The endorsement and commitment of senior leaders within educational institutions are crucial for driving the adoption and successful implementation of BDA and overcoming potential obstacles (Chong & Olesen, 2017). Their support ensures that big data initiatives receive the necessary funding, infrastructure, and human resources. Top management can communicate big data analytics' worth and potential pros to stakeholders, including faculty, staff, and students, fostering buy-in and collaboration. They can also establish policies and guidelines that promote data governance, privacy protection, and ethical use of sensitive data (Chong & Olesen, 2017).

External Factors

Competitive Landscape and Industry Expectations

The competitive landscape is another vital determinant of big data adoption. Institutions must find ways to differentiate themselves and stay ahead of their peers in an increasingly competitive higher education environment. Adopting and utilizing big data analytics has become crucial for institutions to gain a competitive edge (Chong & Olesen, 2017). Industry expectations also play a pivotal role in driving big data adoption. In response to industry expectations, these institutions recognize the need to employ big data analytics to enhance teaching and learning processes, improve student outcomes, and address industry demands for skilled graduates. Institutions that fail to adapt to these industry expectations risk falling behind their competitors and may struggle to attract and retain students or secure funding (Tasmin & Huey, 2020). Thus, the competitive landscape and industry expectations are catalysts for HEIs to adopt big data analytics, enabling them to stay relevant, differentiate themselves, and meet the industry's evolving demands.

Data Protection and Regulatory Compliance

With the increasing digitization of student records and the collection of personal information, institutions must adhere to data privacy laws and regulations such as the POPIA and other related regulations (Baig et al., 2021). Adhering to data protection and regulatory compliance requirements is essential to safeguard the privacy and rights of individuals, build trust within the education community, and avoid legal and reputational risks. Higher education institutions (HEIs) must also establish robust data governance frameworks, implement appropriate security measures, and ensure transparency in data collection, usage, and sharing practices (Drachsler & Greller, 2016). By demonstrating a commitment to data protection and regulatory compliance, these institutions can foster a conducive environment for big data adoption, enabling them to leverage data-driven insights effectively while maintaining ethical standards and meeting legal obligations.

2.10 Big Data Platforms, Tools, and Technologies

Big data technologies, tools, and platforms are becoming increasingly important in advancing teaching and learning in higher education. Big data technologies act as enablers, empowering educators and institutions to leverage data-driven insights and transform the landscape of digital education (Susanto et al., 2018). Big data platforms/tools/technologies enable educators and institutions to obtain, hoard, and examine extensive volumes of data from various sources, including SIS, online learning platforms, and other digital platforms (Susanto et al., 2018). By leveraging these platforms/tools/technologies, instructors can acquire significant insight into student behavior, learning preferences, and academic performance, which can help them improve their teaching methods and create more personalized learning experiences for students (Dahdouh et al., 2020). The following are several big data platforms/tools/technologies that can facilitate teaching and learning processes in South African higher education.

Table 2.1. Big Data Platforms, Tools, and Technologies

Platform/Tools/Technologies	Features & Description
Learning Management Systems (LMS)	Learning Management System (LMS) platforms like Canvas, Blackboard, and Moodle offer diverse data analytics capabilities that enable instructors and administrators to monitor student engagement, performance, and participation. These platforms aid in identifying areas where students may require additional assistance and offer valuable insights into the effectiveness of courses or modules (Rahman et al., 2019).
Adaptive Learning Platforms	Adaptive analytics are crucial in evaluating a student's proficiency and engagement in a course or subject. Adaptive analytics aims to improve study outcomes by offering targeted learning experiences that empower students with the needed skills to enhance their

	comprehension of the subject matter (Muñoz et al., 2022). Adaptive learning platforms such as Smart Sparrow, Cerego, and Knewton use big data analytics to create personalized learning experiences for individual students. These platforms adapt and customize the learning content, pace, and delivery based on individual student needs, preferences, and performance. These platforms use data about a student's learning history and performance to generate customized learning pathways and activities (Kasinathan et al., 2017)
Virtual Learning Environments (VLE)	VLEs are flexible and adaptable, allowing for personalized and self-paced learning experiences. They provide a centralized platform for students and teachers to access course materials and collaborate regardless of their physical location, enabling remote learning and asynchronous participation (Alves et al., 2017). VLEs often provide communication tools such as discussion boards, email, and instant messaging to facilitate student-teacher and student-student interaction and collaboration (Alves et al., 2017). VLEs include Brightspace, Moodle, and Schoology, where extensive data is produced. This data can be harnessed to analyze student engagement levels and overall academic performance (Gautam et al., 2021).
Predictive Analytics Software	These software tools leverage sophisticated algorithms to identify patterns, links, and tendencies in large datasets, enabling businesses and organizations to make informed decisions and take proactive actions. Predictive analytics software like RapidMiner and IBM SPSS can help instructors and administrators identify patterns and trends in student data. This valuable insight enables them to make predictions regarding students who may be at risk of dropping out or encountering difficulties in specific courses and programs (Chaurasia et al., 2018).
Socrative	Immediate feedback is essential to the learning process, and the Socrative tool provides just that. Socrative is now becoming a

	popular app in education because it allows instructors to quickly create and administer assessments while providing real-time feedback on student performance (Faya Cerqueiro & Martín-Macho Harrison, 2019). Furthermore, Socrative provides instructors with a dashboard that displays student performance data in real-time. This tool allows instructors to see how students perform on assessments, identify areas where they struggle, and adjust their instruction accordingly. In addition, Socrative provides reports that can be used to assess student development over time and identify areas where additional education or support may be needed (Gómez-Espina et al., 2019).
Civitas Learning	The Civitas Learning Platform is an educational technology platform designed to support student success and improve outcomes in HEIs. It utilizes data analytics and predictive models to provide insights and actionable recommendations to educators and other stakeholders (Mustafina et al., 2018). The platform also offers a range of dashboards allowing HEIs to track and monitor student progress, engagement, and success metrics (Mustafina et al., 2018). One of the key features of this platform is its ability to identify at-risk students and provide personalized interventions. The platform analyses data using machine learning algorithms to find patterns and trends in student behavior, such as attendance, grades, and engagement (Robinson et al., 2018). This information is then used to generate real-time alerts and suggestions for instructors and counselors, who can reach out to students and provide support as needed (Robinson et al., 2018).
Apache Cassandra	The utilization of Apache Cassandra, a distributed NoSQL database management system, in higher education for educational objectives, has recently experienced a notable upsurge (Ang et al., 2020). Apache Cassandra exhibits immense potential in the realm of higher education, particularly concerning the management of student data. With its ability to efficiently handle vast amounts of

	information and its resilient nature, Apache Cassandra enables seamless storage and processing of student data (Al-Shiakhli, 2019). Furthermore, Cassandra is designed to ensure high availability and fault tolerance, critical factors for educational institutions that require 24/7 access to data and services. With its ability to replicate data across multiple nodes and data centers, Cassandra minimizes the risk of data loss and system downtime.

2.11 Benefits of Big Data Analytics

Big data has transformed multiple sectors, including business technology companies, healthcare, and education. The specific applications of big data analytics vary across these industries. In the context of this study, the focus is on exploring some of the benefits within the education sector:

Personalized Learning Pathways

Big data analytics in learning is essential for providing personalized education. Personalized learning involves tailoring learning to students' interests and learning styles (Bulger, 2016). This personalization enables instructors to provide targeted interventions and resources, maximizing student engagement and achievement. Personalized learning allows students to progress through the curriculum at their own pace. Some students can move ahead quickly, while struggling students can spend more time on challenging concepts, ensuring that each student receives the appropriate level of support. For students, this means everything from a personalized learning path to proactive feedback and results tailored to each student's specific needs. As a result, big data provides practical solutions to improve students' productivity and employability (Veldkamp et al., 2021). Furthermore, personalized learning empowers students to take ownership of their learning journey. They become active participants in setting goals, monitoring their progress, and exercising discretion in decisions related to their learning. This promotes autonomy, self-direction, and a lifelong love of learning.

Improved E-Learning Systems

Big data analytics is critical to the advancement of online learning. According to Veldkamp et al. (2021), big data empowers e-learning specialists to identify areas within an e-learning course that may require refinement. For instance, if a significant number of students take undue time to complete a specific course or module, it suggests the need to modify the module or subject to better suit the students. Furthermore, Amane et al. (2020) stated that big data analytics allows educators to gain deeper insights into student engagement and performance across various e-learning activities. By analyzing this data, educators can identify areas of improvement in e-learning systems, understand student challenges, and make data-driven decisions. They can track student progress, identify areas of improvement in e-learning systems, and optimize the design (Amane et al., 2020).

Enhancing Parental Engagement

Using BDA in education can enhance parental engagement by providing insights into students' progress and performance (Boonk et al., 2018). With access to real-time data, parents can stay informed of their child's academic performance, strengths, weaknesses, and areas for improvement. This approach allows parents to actively participate in their child's education, engaging in informed discussions with teachers, establishing educational objectives, and offering personalized assistance when necessary. By harnessing the potential of BDA to enhance parental engagement, HEIs can create a nurturing and collaborative ecosystem that fuels student growth and achievement. By prioritizing transparency and fostering meaningful communication, this data-driven approach empowers all stakeholders to actively contribute to a supportive and conducive learning environment for students (Boonk et al., 2018).

Enhancing Student Safety and Security

By analyzing various data sources, such as attendance records, behavior patterns, and social media activity, higher education institutions can identify potential safety risks or signs of distress among students. Early warning systems can trigger timely interventions and support systems to address these concerns and ensure student well-being (Bamiah et al., 2018). Furthermore, big data analytics can improve student safety and security on campus. Educational institutions can identify potential security risks or anomalies by analyzing data from various sources, such as surveillance systems, access control systems, and student behavior patterns. This information can help implement preventive measures and enhance safety protocols to ensure a secure learning environment (Abdel-Basset et al., 2019).

2.12 Challenges to the Adoption of Big Data in Higher Education

The adoption and implementation of big data in higher education face several challenges.

Data Privacy and Security

Data privacy and security are paramount concerns that must be addressed to ensure responsible big data implementation (Ahmad et al., 2023). Higher education institutions collect and analyze massive volumes of data, including sensitive personal data. There is a need to ensure that data privacy and security policies are in place to protect student data (Ahmad et al., 2023). In similar research, Drachsler and Greller (2016) indicated that adopting data-related innovation necessitates security assurance. Implementing robust data privacy protocols will stimulate trust and confidence among students, faculty, and stakeholders, ensuring that data is utilized responsibly and ethically. Security measures, such as data encryption, anonymization, access controls, and real-time monitoring, are crucial for safeguarding sensitive student and academic data (Drachsler & Greller, 2016). The continued reinforcement of learners' data protection and security will require ongoing investment in infrastructure and maintenance (Bamiah et al., 2018). Failure to address these concerns could result in data breaches, loss of trust, and legal repercussions (Ahmad et al., 2023).

Technical Infrastructure

Institutions need a robust technical infrastructure to leverage big data analytics effectively, including hardware, software, and skilled IT staff. Developing such an infrastructure requires significant investment, which may not be feasible for all institutions (Nasser & Tariq, 2015). According to Bamiah et al. (2018), adopting a big data approach requires significant investment in technology infrastructure such as data warehousing, data integration tools, distributed storage, and funding can help institutions acquire the necessary equipment and infrastructure to support the administration and analysis of large data sets.

Lack of Skilled Personnel

Institutions require individuals with expertise in data analysis techniques, statistical modeling, and data interpretation to implement big data analytics. Without skilled professionals with these capabilities, institutions may struggle to effectively extract meaningful insights from large and complex datasets (Murumba & Micheni, 2017). Finding and retaining such skilled personnel can be challenging for some institutions (Murumba & Micheni, 2017). According to Nazarenko and Khronusova (2017), although big data is cutting-edge, there is a lack of qualified individuals and the required skills to run or implement big data solutions. While experienced data experts are in high demand, there is insufficient supply. However, most high education institutions have yet to address this gap, as data science programs are still scarce. The lack of skilled personnel also influences the precision and consistency of the data analysis, which may lead to incorrect conclusions and decisions (Bamiah et al., 2018). Therefore, institutions need to invest in training their staff and recruiting data science experts to guarantee the adoption and implementation of big data in higher education (Ahmad et al., 2023).

Institutional Culture

Adopting big data analytics (BDA) requires a culture of data-driven decision-making. Many educational institutions may not be accustomed to this approach, making adopting big data analytics more challenging. According to Rahman et al. (2021), institutional culture can also influence the willingness of employees to adopt and implement big data initiatives. Adopting and implementing big data initiatives can be challenging if employees resist change or are uncomfortable learning new technologies and techniques. Furthermore, Rahman et al. (2021) stated that the culture of an institution is often set by its leaders. Institutional leaders committed to fostering a culture that values data-driven approaches and innovation in decision-making processes can communicate the worth and potential benefits of big data analytics (BDA) to various stakeholders, such as faculty, staff, students, etc., thereby fostering engagement and collaboration (Rahman et al., 2021).

Data Capture, Storage, and Quality of the Data

Data capture, storage, and quality are potential challenges to adopting big data analytics in HEIs because sizeable datasets are continuously generated and collected from various sources, including SIS, LMS, and other digital academic platforms (Nasser & Tariq, 2015). Storing such massive data is a challenge for many institutions, and the technical infrastructure needed to keep, process, and analyze big data can be intricate and costly. (Dahdouh et al., 2019). Furthermore, maintaining data quality is crucial for meaningful analysis and decision-making. Data collected from several sources may be inaccurate, incompatible, or low-quality. Inaccurate or unreliable data can lead to flawed analysis and erroneous conclusions. Cleaning the data involves identifying and rectifying issues such as missing values, outliers, and inconsistencies. These tasks are incredibly challenging in big data scenarios, where the volume, velocity, and variety of data are substantial. Manual data cleaning can be resource-intensive and unfeasible, and automated processes may struggle to address all the nuances in the data. The challenges of data extraction and cleaning contribute to the overall complexity of the big data analytic process. They require specialized skills, tools, and techniques to ensure that the data used for analysis is of high quality and relevance. Without proper handling of these challenges, the insights derived from big data analytics could be compromised, leading to erroneous conclusions and unreliable outcomes (Al-Shiakhli, 2019).

2.13 An Ethical Perspective of Big Data Adoption in an Educational Context

Striking a balance between leveraging the potential benefits of big data and upholding ethical principles is vital to ensure the responsible integration of data-driven approaches in education. Using big data in educational settings raises ethical concerns that must be addressed to ensure accountable and respectful implementation.

Informed Consent

Students and faculty should be informed about the data collection and analysis processes and how their information will be used. Transparent communication is crucial for obtaining informed consent and fostering a sense of trust among all stakeholders (Ahmad et al., 2023).

Bias and Fairness

The utilization of big data analytics (BDA) has the potential to inadvertently propagate and amplify pre-existing biases inherent within the data, consequently resulting in unjustly skewed outcomes (Regan & Jesse, 2019). It is crucial to identify and mitigate bias to ensure that decisions based on data do not discriminate against any group of students.

Data Ownership and Control

Determining who owns and controls the data is essential. Both students and educators should have a say in how their data is collected, used, and shared. Institutions should establish clear policies regarding data ownership and control (Ahmad et al., 2023).

Equity and Accessibility

The use of big data should not exacerbate existing educational inequalities. HEIs must ensure that all students, regardless of their background, have equal access to educational opportunities and resources (Regan & Jesse, 2019).

Transparency

The algorithms and methodologies used in big data analytics should be transparent. Stakeholders should clearly understand how data is being analyzed and how conclusions are drawn from it (Regan & Jesse, 2019).

Accountability

Educational institutions should take responsibility for the ethical implications of their big data initiatives. If negative consequences arise due to data use, mechanisms for accountability and rectification should be in place (Ahmad et al., 2023).

2.14 Summary of Chapter Two

Most of the research conducted in this chapter has taken a broad perspective on big data technology, primarily due to the limited literature focused on advanced technologies like big data analytics (BDA) in education from a South African perspective. Developed countries have widely adopted big data analytics to enhance teaching and learning, and some developing countries, including Brazil and India, are following suit. However, the researcher has deduced that, based on literature from these developing nations, big data could serve various purposes in South Africa, including advancing higher education's teaching and learning process. Therefore, South African HEIs must take proactive steps to establish the essential infrastructure and personnel to successfully employ BDA and continue exploring novel avenues for harnessing the power of big data.

CHAPTER THREE: THEORETICAL FRAMEWORK

3.1 Introduction

Chapter two delved into the literature examined in this research, pinpointed the gaps uncovered, and elucidated how the framework employed in this investigation played a role in tackling several of those gaps. This chapter explains the theoretical framework and its application within an IT adoption research context. According to Lederman and Lederman (2015), a theoretical framework refers to a set of interconnected theories, principles, and concepts that form the foundation for a research study. Essentially, a theoretical framework establishes the groundwork for the study's objectives and questions, and it acts as a theoretical lens through which the findings of this investigation are analyzed (Osanloo & Grant, 2016). The chapter discusses several technology acceptance frameworks under consideration for this investigation. Subsequently, each of these frameworks is subjected to a deeper analysis, wherein their respective merits are explained, and the rationale behind choosing not to use certain ones for this study is expounded upon.

3.2 Overview of Theoretical Frameworks Used for IT Adoption Research

The following section outlines several theories, commencing with the Theory of Reasoned Action and culminating with the framework that underpins this study, namely, the UTAUT.

3.2.1 The Theory of Reasoned Action (TRA)

The Theory of Reasoned Action (TRA) is a psychological model developed by Ajzen and Fishbein that seeks to predict and explain individuals' behavioral intentions by considering their attitudes toward a specific behavior and the subjective norms associated with that behavior (Otieno et al., 2016). The Theory of Reasoned Action (TRA) explores how individuals respond to the adoption of information technology (IT) by examining their attitudes and conformity to societal norms (Otieno et al., 2016). The theory proposes that a user's choice to embrace technology is guided by the predicted results derived from its usage. However, TRA might prove less suitable when considering its application to big data technology adoption research due to certain inherent limitations. TRA predominantly focuses on individual attitudes and subjective norms, which might not fully encapsulate the complexity of factors influencing organizational-level decisions, such as in the context of adopting big data technologies. In big data adoption, the decision-making process is often influenced by intricate technical, organizational, and environmental factors, extending beyond the scope of individual attitudes and social norms. Furthermore, the study questions and the questionnaire were constructed to identify the technical, environmental, and organizational constraints influencing the organization's decision-making process regarding the adoption of big data technology. Given that the TRA model assumed users would act as they intended without considering various influencing factors, it was deemed unsuitable for use in this research study.

3.2.2 The Theory of Planned Behaviour (TPB)

The Theory of Planned Behaviour (TPB) expands on the concepts introduced in the Theory of Reasoned Action (TRA). It aims to provide a more comprehensive framework for understanding and predicting human behavior. TPB proposes that an individual's intention to engage in a particular behavior is influenced by three key factors: attitudes toward the behavior, subjective norms, and perceived behavioral intent or control (Bosnjak et al., 2020). The behavioral intention is a unique addition to TPB. It accounts for the individual's perception of their ability to perform the behavior successfully, considering factors such as skills, resources, and external constraints (Bosnjak et al., 2020). Although the TPB framework introduced certain elements not previously addressed in other technology adoption models, it remained unsuitable for the current study. TPB overlooked external factors beyond the organizational realm and their potential influence on technology acceptance and user experience with using the technology (Bosnjak et al., 2020). Big data adoption often involves intricate interplays between organizational factors, including technological readiness, financial resources, leadership support, and compatibility with existing systems. TPB's emphasis on individual perceptions of control might not adequately account for these broader factors that shape decision-making processes at the organizational level.

3.2.3 Technology Acceptance Model 2 (TAM2)

The Technology Acceptance Model (TAM) is a widely recognized theoretical framework for predicting and explaining users' technology acceptance. Developed by Davis in the 1980s, TAM proposes that users' intention to use technology is influenced by two main factors: perceived ease of use and perceived usefulness. These factors, in turn, impact their actual usage behavior. The Technology Acceptance Model 2 (TAM2) extends the original TAM by introducing additional variables to better explain technology acceptance and usage. Developed by Venkatesh and Davis, TAM2 incorporates more factors such as subjective norm, image, job relevance, output quality, result demonstrability, and voluntariness of use (Khoa et al., 2020). It recognizes the role of social and organizational contexts in shaping users' perceptions and intentions toward technology adoption (Khoa et al., 2020).

The technology acceptance framework (TAM2) was not utilized in this research project due to its focus on analyzing user behavior concerning a particular technology. The determination of whether to embrace or reject the technology was primarily contingent upon the user's feelings toward that specific technology. While TAM2 considers more diverse factors, the complexity of big data technology adoption involves not only individual perceptions and social influences but also facilitating conditions such as organizational and technical support provided to users to make the adoption and usage of a technology smoother. For this study, although grasping user emotions could have provided valuable insights, comprehending the factors influencing technology adoption, utilization of the technology, and the contextual circumstances surrounding its usage held greater significance. Evaluating the usefulness of big data was contingent upon numerous factors, several of which existed beyond the organizational boundaries and had no direct connection to the user, and as a result, it would have been difficult for this study to investigate some of those difficulties with this framework thoroughly.

3.2.4 Unified Theory of Acceptance and Use of Technology (UTAUT)

UTAUT is a widely accepted theoretical framework that explains how and why users adopt and use technology (Wang et al., 2022). By adopting the UTAUT framework, HEIs can evaluate the potential benefits and identify barriers to adopting big data technology. In this study, the UTAUT serves as a framework for examining the performance expectancy of adopting big data, the perceived effort required to use it, the social factors that influence it, and the facilitating conditions that can impact big data adoption. Wang et al. (2022) highlighted the significance and widespread application of the UTAUT framework in studying user acceptance of technology. This theory stands out due to its comprehensive integration of vital elements from eight prominent technology acceptance theories, consolidating them into a single framework. Furthermore, a comprehensive analysis of existing literature by Al-Qaysi et al. (2020) revealed that UTAUT is one of the most prevalent frameworks employed in investigating the acceptance of new technologies in higher education contexts. According to

Venkatesh et al. (2003), four unswerving predictors determine users' adoption and intent to utilize technology, as depicted in Figure 3.1 below.

Performance expectancy (PE) refers to the user's perception of the usefulness of the technology (Venkatesh et al., 2003). It refers to an individual's belief that adopting and utilizing a particular technology can boost their performance and enable them to achieve their desired outcomes or goals more effectively (Williams et al., 2015). In the context of this study, performance expectancy (PE) refers to the user's perception of how big data analytics (BDA) can improve their academic performance or institutional outcomes. It also pertains to the extent to which stakeholders in higher education perceive that the utilization of big data technology can substantially contribute to attaining teaching and learning goals, thereby signifying a valuable gain. For instance, educators may perceive that big data analytics platforms can provide better insights into student learning and progress tracking, support more targeted recommendations, and identify learning gaps more effectively than traditional learning assessment methods. On the other hand, students may perceive that big data analytics platforms can provide personalized learning experiences and adaptive learning, leading to better academic results.

According to Venkatesh et al. (2003), effort expectancy (EE) represents the user's perception of the ease of using a particular technology. In the context of this study, effort expectancy (EE) reflects the degree of ease or difficulty a user expects when using big data technology (Gautam et al., 2021). If users perceive that big data tools are easy to use and require less cognitive and physical effort, they will be more likely to adopt and use them. On the other hand, if users perceive that big data tools or applications are challenging to use or require a significant amount of effort to understand and apply, they may be less likely to adopt and use them. It also relates to the extent to which stakeholders in higher education perceive the adoption and usage of big data technology as effortless. It encompasses the ease of using BDA for tasks such as measuring and tracking student performances, visualizing data, and other related activities.

Social influence (SI), according to Venkatesh et al. (2003), can be referred to the extent to which the opinions and behaviors of others influence an individual's perception of the technology. In this context, social influence (SI) can include the views and recommendations of colleagues, superiors, experts, and influencers in the higher education sector (Williams et al., 2015). Similarly, Brata and Amalia (2018) asserted that social influence could be the most critical component in a person's usage of a novel system or technology because the support of colleagues around such a person impacts it. In simpler terms, if a respected colleague or expert speaks highly about big data tools or applications, it may influence other individuals to perceive them as applicable and relatively easy to use. Conversely, opposing opinions from peers and experts could have the opposite effect of dissuading a person from adopting and using big data technologies, tools, or techniques.

According to Liebenberg et al. (2018), Facilitating conditions (FC) can be referred to as the availability of resources and support for the use of the technology. It encompasses the presence of organizational and technological infrastructure that enables the application or usage of a particular technology. Facilitating conditions plays a crucial role in adopting and implementing big data by providing the resources and support necessary to use the technology successfully (Liebenberg et al., 2018). In the context of this study, facilitating conditions (FC) can include access to appropriate hardware and software, training programs, technical support, and adequate funding. Facilitating conditions (FC) also pertain to the availability of sufficient funding to secure the essential resources needed for acquiring the hardware and software necessary to analyze and interpret big data or technical support in addressing any technological issues that might occur when using big data technology, or infrastructures that lecturers feel may promote or hamper the adoption of big data technology for teaching and learning. Figure 3.1 below depicts the UTAUT framework.

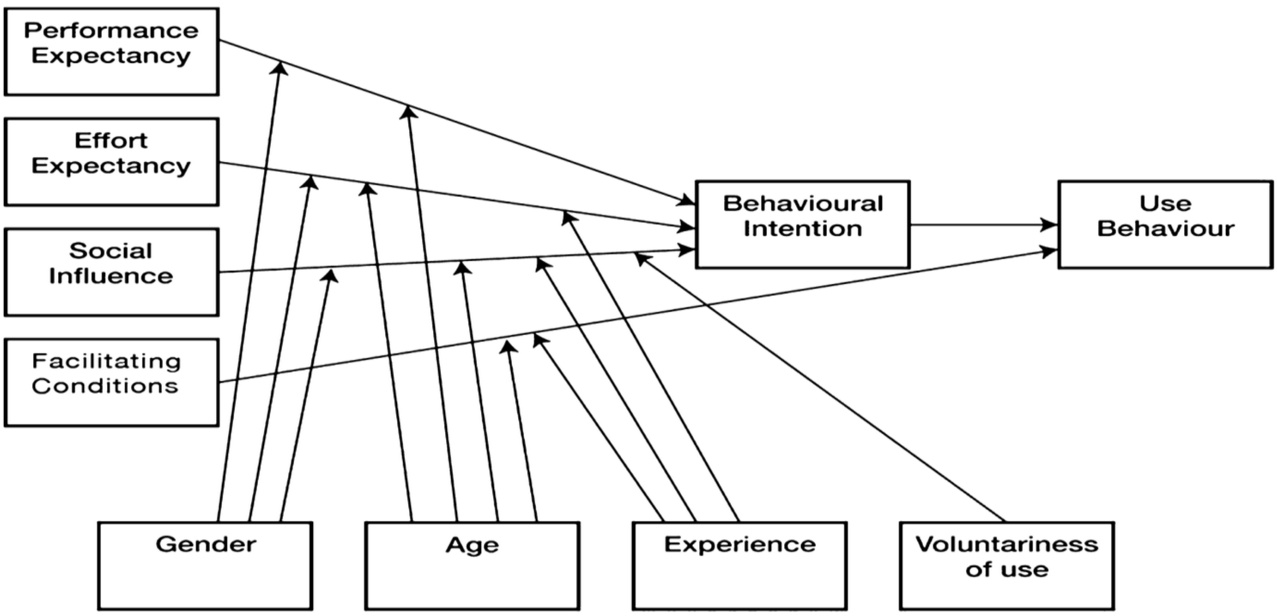

Figure 3.1. Unified Theory of Acceptance and Use of Technology (UTAUT)

Source: Venkatesh et al. (2003)

As shown in the figure above, the strength of determinants on intention is defined by the moderating effects of age, gender, experience, and voluntariness of use. Age serves as a moderator for all four determinants, influencing their outcomes. Gender moderates the relationships between effort expectancy, performance expectancy, and social influence. Experience moderates the strength of the relationships between effort expectancy, social influence, and Facilitating conditions. Voluntariness of use only mediates the relationship between social impact and behavioral intention (Venkatesh et al., 2003).

In the context of big data technology adoption in higher education, gender may influence the perception and acceptance of the technology. For example, gender-related differences in attitudes, beliefs, or prior experiences could influence the willingness to adopt and use big data solutions (Khechine & Augier, 2019). It is essential to consider potential gender differences when implementing big data initiatives in higher education to ensure equal chances and inclusivity. Furthermore, age also impacts the readiness to accept and use big data technologies (Khechine & Augier, 2019). The link between effort expectation and behavioral intention shrinks with the increase in age. Younger faculty and students might be more open to adopting and leveraging big data technologies for educational purposes. At the same time, older individuals might require additional support, training, and assurances to overcome potential resistance or hesitancy (Liebenberg et al., 2018).

In the context of big data technology adoption in higher education, individuals with prior experience in using analytics tools or working with large datasets may be more inclined to adopt and utilize big data solutions. Their familiarity with related technologies can reduce perceived complexity and increase confidence in using big data tools for educational purposes. On the other hand, individuals lacking experience in data analytics may require more support and training to embrace big data solutions (Liebenberg et al., 2018). According to Parameswaran et al. (2015), individuals' previous experience with technology usage can influence their frame of reference. Individuals with substantial technology experience are less swayed by the opinions of others, while those with limited technology exposure are more likely to conform to social influence. Furthermore, the UTAUT framework also recognizes voluntariness as a key factor influencing technology acceptance. If the adoption of big data solutions is mandatory or strongly encouraged, the perceived usefulness and ease of use become critical factors in driving acceptance. On the other hand, when the adoption of big data solutions is voluntary, individuals' motivations, perceived benefits, and perceived effort required become more influential factors in their decision-making process for adopting and utilizing big data solutions (Khechine & Augier, 2019).

3.3 Justification for Proposed Theoretical Framework

According to Wang et al. (2022), the UTAUT framework has gained widespread recognition and is significantly applied in technology acceptance research. It has been used in various studies to understand the adoption and usage of technology in different domains, including education, because it incorporates aspects controlled by eight prominent technology acceptance theories into one theory (Wang et al., 2022). Additionally, previous research conducted by Williams et al. (2015) and El-Masri and Tarhini (2017) has shown the applicability of the UTAUT framework in various educational contexts. Using UTAUT as a guiding framework, the researcher can identify and comprehend elements that drive the adoption and usage of big data technologies in a South African higher education context. For example, HEIs can assess the performance expectation of big data technology by evaluating its potential to improve student outcomes and enhance the learning experience. Institutions can also evaluate the effort expectancy of big data technology by assessing its ease of use and the user's ability to navigate it effectively. Furthermore, the UTAUT served as the framework to shape the study's questions and objectives. The correlation between the study questions, objectives, and the open-ended survey questions with the UTAUT framework is depicted in Appendix A. Overall, the UTAUT framework's well-established nature, comprehensive coverage of relevant constructs, proven effectiveness in technology acceptance research, and flexibility in accounting for individual and contextual factors justify its selection as the theoretical framework for examining big data adoption in a higher education context.

3.4 Summary of Chapter Three

The chapter focused on the UTAUT framework adopted in the study and the rationale for using it. UTAUT proves to be an adequate theoretical framework for identifying elements that drive the adoption and usage of big data technologies in a South African higher education context, and its application to the South African context highlights the urgent need to explore and address possible hindrances to adoption. The subsequent chapter (Chapter Four) will delve into the research methodologies employed in the study.

CHAPTER FOUR: RESEARCH METHODOLOGY

4.1 Introduction

Research methodology is the systematic approach or strategy researchers use to conduct a study and gather relevant data to address study questions or test hypotheses (Saunders et al., 2015). This chapter presents the research methodology employed in investigating the problem statement and addressing the study questions highlighted in Chapter One. The chapter discussed the research onion and its layers in connection to the study. The chapter also covered the data collection method, sampling strategy, data analysis techniques, and ethical considerations considered during the research process.

4.2 Research Onion

The significance of the "Research Onion" lies in its applicability to practically any research type, as Saunders et al. (2019) noted. The research onion comprises several phases or layers, each representing a distinct aspect of the research process. It was developed to guide researchers through the various research design and methodology stages. It helps researchers make informed decisions about the appropriate methods and procedures to use in their study (Saunders et al., 2019). The phases (shown in Figure 4.1 below) were thoroughly discussed in connection with the investigation.

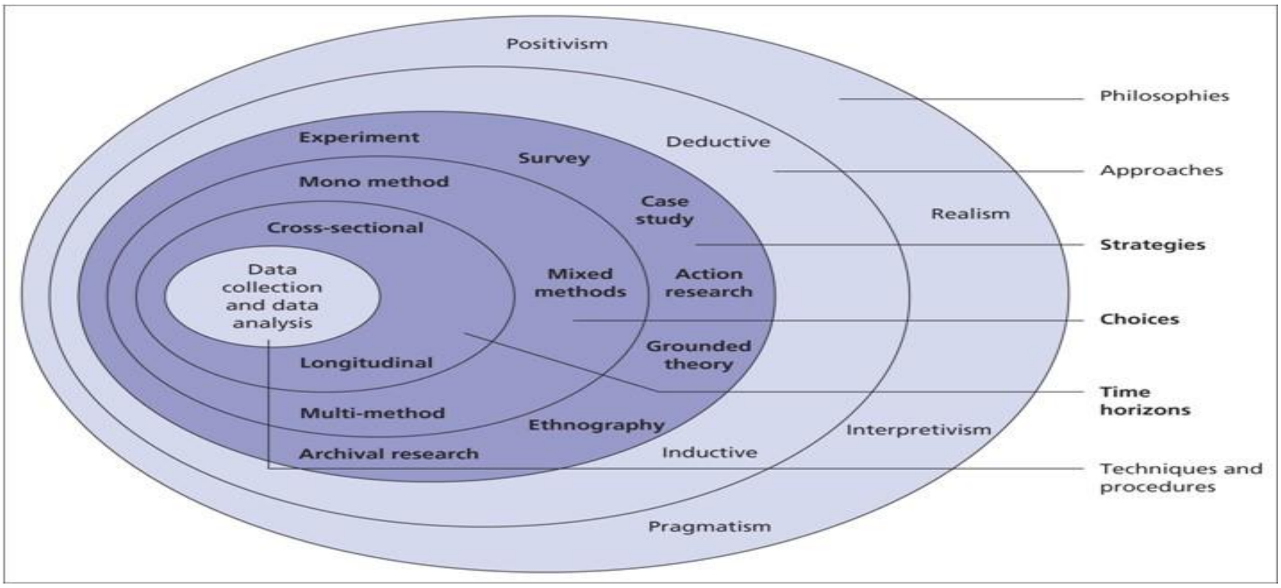

Figure 4.1. The Research Onion

4.3 Research Philosophy

A research philosophy justifies a study's approach and, as such, should be guided by the nature of the events being examined (Hürlimann, 2019). According to Saunders et al. (2015), Interpretivism is one of the five research philosophies based on naturalistic data-gathering methods. According to Hürlimann (2019), the interpretivism method proposes that researchers examine disparities in participants' interpretation of the idea under investigation rather than presuming that all participants share the same view. In this study, an interpretive approach was employed to understand the perspectives and viewpoints of participants regarding various aspects of big data's impact on teaching and learning. These aspects include the participants' expectations of performance when utilizing big data, their perceptions of the effort involved in utilizing it for improving the teaching and learning experience, the social influences affecting the adoption of big data methods in higher education, and the essential enabling factors for a successful implementation of big data in the higher education sector.

4.4 Research Reasoning

According to Saunders et al. (2019), inductive and deductive reasoning are two approaches to theory development. "Inductive" reasoning seeks to elicit beneficial information or insights from collected data to identify patterns and relationships that may be used to form a theory (Saunders et al., 2019). It is also based on the idea that if certain specific instances or cases exhibit a particular pattern or characteristic, the same pattern or characteristic is likely to apply to other similar scenarios or the broader population (Saunders et al., 2019). Inductive reasoning in theory development is instrumental in exploratory research, qualitative studies, and areas with limited prior theory or knowledge. It allows researchers to derive novel theories or hypotheses from specific observations, which can be further tested, refined, and integrated with existing knowledge to advance understanding of the phenomenon under study (Woiceshyn & Daellenbach, 2018).

On the other hand, "deductive" reasoning suggests that the fundamental source of conducting research studies is using pre-established theories and models through which the proposal is developed and then empirically tested (Saunders et al., 2019). However, it is vital to emphasize that deductive reasoning relies heavily on the accuracy of the initial theory and the assumptions made during the deductive inference process (Woiceshyn & Daellenbach, 2018). Therefore, both inductive and deductive research reasoning were used in this study. Furthermore, the UTAUT served as the framework to shape the study's questions and objectives. The correlation between the study questions, objectives, and the open-ended survey questions with the UTAUT framework is depicted in Appendix A.

4.5 Research Strategy

A research strategy refers to the approach or methods researchers employ to effectively address their study objectives and answer their study questions (Saunders et al., 2019). These strategies can be categorized into various types, including experimental, action, case study, grounded theory, survey, and archival research strategies. The grounded theory strategy was adopted in this study. As Abdel-Fattah (2015) described, grounded theory involves systematically collecting and analyzing data to develop or uncover theories using comparative methods. In grounded theory research, researchers aim to generate a theory "grounded" in the data collected rather than testing pre-existing hypotheses. Holton and Walsh (2016) added that researchers using this approach must possess an intellectual interest and familiarity with the domain literature but do not have to create or test hypotheses. Instead, a theory emerges through a thorough exploration of the collected data. According to Mayes (2020), grounded theory is beneficial for exploring areas that have received limited research attention, where existing research is insufficient, or where fresh perspectives on established themes are required. In South Africa, incorporating big data technology within higher education is a relatively new concept, which has led to a scarcity of literature from a South African standpoint regarding the adoption and utilization of big data for educational and training purposes in higher learning institutions. To address this void, the present study investigated the potential benefits and concerns allied with the adoption of big data analytics (BDA) in the sphere of teaching and learning within South African higher education.

4.6 Methodological choice: Research Design Method

According to Saunders et al. (2019) and Chih-Pei and Chang (2017), there are three research methodological choices which are qualitative, quantitative, and mixed methods.

4.6.1 Quantitative research

According to Chih-Pei and Chang (2017), quantitative research is a systematic empirical approach to investigating phenomena by obtaining and examining numerical data. This research method aims to provide objective and generalizable findings by focusing on measurable variables and employing statistical techniques for data analysis.

4.6.2 Qualitative Research

According to Hennink et al. (2020), the qualitative research method allows for various investigative instruments such as case studies, interviews, and open-ended questionnaires to collect and analyze non-numerical data, to uncover rich and detailed insights into the research subject. It can be utilized to provide in-depth insights into research concerns that include the study population's opinions and the context in which they live (Hennink et al., 2020). Qualitative research provides a holistic and in-depth understanding of human experiences and social phenomena, allowing for rich insights and nuanced interpretations (Basias & Pollalis, 2018). Furthermore, according to Chih-Pei and Chang (2017), researchers often use qualitative research to explore complex social phenomena, understand individuals' perspectives, examine cultural practices, or investigate topics where limited prior research exists. Hence, a qualitative research method was used in the study to get a thorough knowledge and understanding of the potential adoption and usage of big data to advance teaching and learning in South African higher education.

4.6.3 Mixed Method Research

Mixed-methods research is a comprehensive approach integrating qualitative and quantitative research methods within a single study (Chih-Pei & Chang, 2017). Chih-Pei and Chang (2017) claimed that using multiple forms of data collection aids in producing enough evidence to adequate evidence to address the study objectives and questions. Mixed-methods research proves highly valuable when investigating research questions requiring a deeper understanding of the phenomenon while exploring patterns, relationships, or generalizability (Edmonds & Kennedy, 2016) (Saunders et al., 2019). However, as noted above, the qualitative research method was employed in this study.

4.7 Time Horizon

From the research onion framework, the time horizon can be referred to as the extent of time over which the research is conducted or the duration for which data is obtained and examined

(Saunders et al., 2019). It represents the temporal scope of the study and helps determine the timeframe within which the research is situated (Geoffrey, 2019). The Research Onion specifies the cross-sectional and longitudinal periods. According to Geoffrey (2019), cross-sectional studies are conducted at a specific time or over a relatively short period. They provide a snapshot of the phenomena under investigation at a specific period, allowing researchers to simultaneously capture data from a diverse sample or multiple sources. On the other hand, longitudinal studies involve gathering data over an extended period, allowing researchers to observe changes, patterns, or turns over time. In this study, the cross-sectional approach was adopted since the data was acquired during a specific period.

4.8 Data Collection

The study utilized both primary and secondary data sources. Primary data was collected directly from research participants, allowing for first-hand insights and perspectives. Secondary data, on the other hand, was obtained from prior academic papers, books, and articles, which served as valuable resources to enhance the researcher's knowledge and comprehension of the topic under investigation. By combining these data sources, the study sought to present a well-rounded and informed analysis of the subject matter.

4.8.1 Research site

A research site is where research activities occur, or data is collected for a specific research study. This study collected data from the UKZN College of Law and Management Studies at the Westville and Pietermaritzburg campuses in KwaZulu-Natal. The College is split into four schools: the Graduate School of Business and Leadership; the School of Accounting, Economics, and Finance; the School of Law; and the School of Management, Information Technology, and Governance. The researcher collected data from the School of Management, IT, and Governance. This school was selected over others because the researcher was based or enrolled there for the duration of the data collection. As a result, collecting data from the school was timely and convenient for the researcher.

4.8.2 Sampling Method

According to Etikan and Bala (2017), there are two sampling techniques: probability and non-probability. Probability sampling is a method based on randomization, ensuring everyone has an equal opportunity to be included (Etikan & Bala, 2017). Probability sampling allows researchers to draw statistical inferences and extend their findings with a measurable level of confidence to the broader population (Etikan & Bala, 2017). On the other hand, non-probability sampling does not use random selection and does not give every population member an equal chance of being included. Participants are chosen depending on the researcher's perception, convenience, or availability (Etikan & Bala, 2017). Non-probability sampling is generally used in exploratory or qualitative research, focusing on understanding specific cases or phenomena rather than statistical generalizations about the broader population (Vehovar et al., 2016). The purposive sampling technique is one of the types of non-probability sampling and was adopted in this study.

According to Palinkas et al. (2015), purposive sampling is a form of non-probability sampling that involves intentionally choosing units based on specific characteristics or criteria deemed relevant to the research study. Purposive sampling is instrumental in qualitative research, where the focus is often on obtaining in-depth and rich information from a select group of participants (Vehovar et al., 2016). To create a purposive sample, the researcher specifically targeted academic staff and/or postgraduate students affiliated with the UKZN School of Management, Information Technology, and Governance (SMIG), primarily from the discipline of Information Systems and Technology due to its notable emphasis on various IT areas, including big data analytics (BDA). The purposive sampling approach was employed to judiciously choose individuals who could provide valuable insights, elucidations, and justifications about the probable applications of big data in advancing teaching and learning experiences within South African higher education. The researcher aimed to gather detailed and meaningful data regarding the subject under investigation.

4.8.3 Sample Size

The sample size can be referred to as the individuals chosen from the populace to participate in a particular study (Saunders et al., 2019). According to Rahi et al. (2019), the sample size is crucial in quantitative research in proving the credibility of the research's outcomes. As a result, in quantitative analysis, large sample sizes frequently give reliable results (Rahi et al., 2019). However, according to Mocănașu (2020), the sample size is less important in qualitative research as there is no consensus on the precise scope of a suitable sample size, and the notion of representativeness is not a reliable criterion or yardstick. According to Malterud et al. (2016), qualitative study usually involves a lesser sample size compared to quantitative study.

Additionally, Rahi et al. (2019) and Mocănașu (2020) highlighted that qualitative research is characterized by its in-depth nature, which means that the sample size needed for data analysis is typically moderate and carefully chosen.

4.8.4 Sampling Process

The researcher visited the UKZN official website to retrieve a list of academic staff members affiliated with the School of Management, IT, and Governance (SMIG). After thoroughly examining the list, individuals who did not meet the specific inclusion criteria were excluded from being part of the study. The study employed the purposive sampling method, with a particular interest in academic staff and/or postgraduate students from the SMIG, primarily from the discipline of Information Systems and Technology, because big data analytics (BDA) is one of the discipline's primary focus areas, among others. Out of the academic staff members within the SMIG, a total of eighteen (18) individuals satisfied the inclusion criteria and were invited to respond to an open-ended questionnaire or survey. However, the researcher received a total of fourteen (14) responses, which were detailed and deemed sufficient for the study.

4.8.5 Data Collection Method (Research Instrument)

The research instrument is determined by the research approach utilized in a particular study (Saunders et al., 2015). An open-ended questionnaire (survey) was used for data collection in this study. As described in the literature, open-ended questionnaires provide greater flexibility than closed-ended surveys since they enable respondents to articulate their views and thoughts using their own words (based on their experiences, knowledge, and understanding) rather than being constrained by the researcher's predetermined categories (Paradis et al., 2016). This makes capturing the diversity and complexity of participants' perspectives and experiences easier, which is especially important when investigating complex or sensitive topics (Paradis et al., 2016). Furthermore, open-ended questionnaires (surveys) allow respondents to provide detailed and descriptive responses to queries, providing a comprehensive view of the studied phenomena. This data can reveal nuances and complexities in respondents' experiences and perspectives, which may be lost in more structured survey designs (Lenzner & Neuert, 2017). Data was gathered via an online open-ended questionnaire or survey created using Google forms. Data was collected anonymously in the hopes of encouraging respondents to be more genuine in their responses. Anonymity implies that the respondent's identity was not disclosed to create a safe and non-threatening environment, which l believe led to more sincere answers or responses.

4.9 Data Analysis

Thematic data analysis was adopted and used in this study to understand the collected data comprehensively. Thematic data analysis involves organizing and categorizing data into meaningful themes, which are then analyzed and interpreted in relation to the study questions and objectives (Vaismoradi et al., 2016). This analysis method typically involves multiple stages, including becoming familiar with the data, coding, developing themes, and interpreting (Clarke et al., 2015). Furthermore, Vaismoradi et al. (2016) claim that thematic analysis is an appropriate technique for analyzing qualitative data since it reveals themes, trends, and patterns, allowing the researcher to acquire profound knowledge and insight into the data obtained. Researchers categorize and organize the data into themes based on shared meanings and patterns from participants' responses (Swart, 2019). As a result, thematic analysis was used to examine the data obtained through the research instrument (open-ended questionnaire or survey) used in this study.

“NVivo” was used by the researcher in this study to analyze the obtained data by categorizing it into subjects or themes, examining it, and discussing it in light of the existing literature. According to Yeager (2019), NVivo is a software application that is used explicitly for text, audio, video, and picture data processing, including (but not restricted to) interviews, focus groups, and surveys (Yeager, 2019). The software streamlines the qualitative research process and enhances the researcher's ability to make evidence-based conclusions and interpretations from the data. NVivo allows researchers to visualize the data, explore relationships between themes, and facilitate interpreting and reporting findings (Jackson & Bazeley, 2019). Figure 4.2 below illustrates the data analysis process, representing only a portion of one respondent's data. To conduct the analysis, the researcher transcribed and imported the responses from each participant into the NVivo system. Subsequently, the researcher identified the themes that appeared most frequently and established corresponding nodes. The researcher then established parameters based on the most recurring subjects or themes. The participants' responses were then examined to determine the alignment of the themes with the UTAUT framework, leading to the creation of sub-themes during this iterative process.

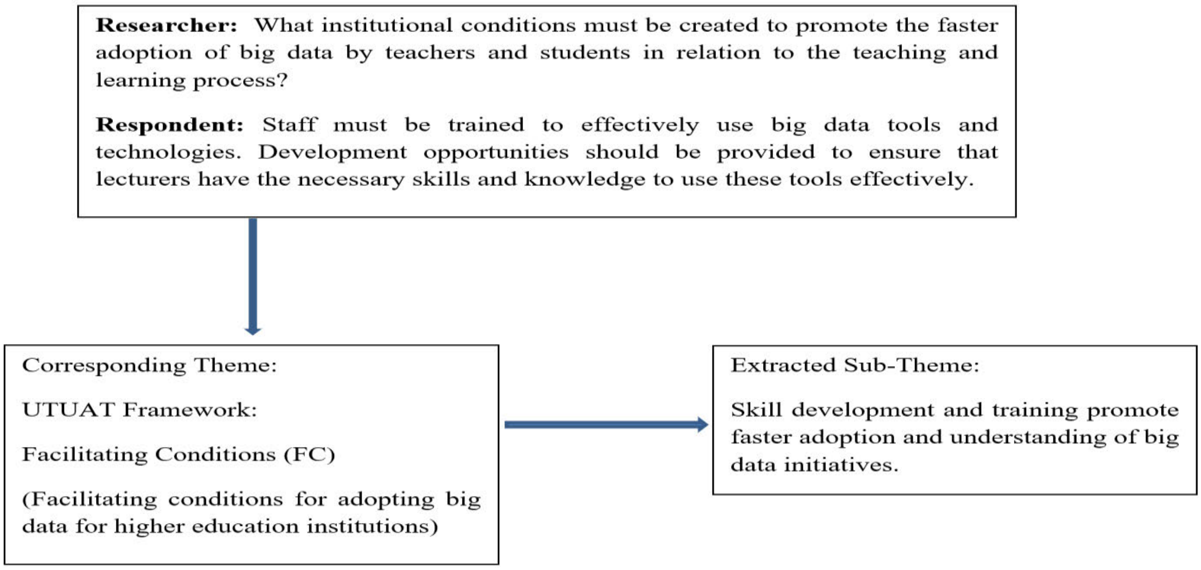

Figure 4.2. Excerpt of the Data Analysis Process

4.10 Data Quality Control

Data quality control in a qualitative study entails ensuring the credibility, transferability, dependability, and confirmability of the data collected (Daniel, 2019), (Johnson et al., 2020), (Noble & Smith, 2015). According to Daniel (2019), the credibility criteria ensure that the data collected in qualitative research is trustworthy, reliable, and accurately represents the phenomenon under investigation. To ensure credibility, researchers must use rigorous data collection and analysis methods, such as triangulation, member checking, audit trail, and peer review (Daniel, 2019). In this study, the researcher maintained a detailed record of the research process, including data collection procedures, data analysis techniques, and interpretations.

According to Johnson et al. (2020), the transferability criteria refers to the extent to which the research results can be used in different contexts or situations. To ensure transferability, the researcher provided deep and detailed descriptions of the research context, participants, and the phenomena under investigation. This ensures that other researchers can evaluate the rigor and appropriateness of the research process and judge its applicability to different contexts.

According to Noble and Smith (2015), the dependability criteria refers to the uniformity and reliability of the findings across time. In this study, the researcher used clear and well-documented data collection and analysis procedures and ensured the alignment of research findings with the study's questions and objectives.

According to Johnson et al. (2020), the confirmability criteria refers to the objectivity and neutrality of the results. It is suggested that researchers use an audit trail to document their research process and decision-making, which can be used to verify the accuracy and reliability of the findings (Johnson et al., 2020). The researcher performed a data audit at the end of the study to evaluate the data-gathering processes by sending the transcribed texts to the research respondents to validate their submitted responses. The data audit confirmed that the data gathered was not altered.

4.11 Ethical Considerations

According to Roberts and Allen (2015), ethical considerations in research extend beyond simply obtaining ethical permission before initiating the study. It is essential to acknowledge that ethical issues encompass more than procedural ethics and involve safeguarding the well-being and integrity of participants. The researcher sought ethical clearance from the UKZN Humanities and Social Sciences Research Ethics Committee in this study. The ethical approval (protocol reference number: HSSREC/00004618/2022) was granted on 12 October 2022 (refer to Appendix 2: Ethical Clearance Letter) before data collection began. The study adhered to confidentiality and anonymity as ethical criteria. Data were collected anonymously. The names or personal information of the respondents were not included in any part of the study. Furthermore, rigorous measures were implemented to ensure data security. All copies of data were securely stored throughout the study period and will be archived for five years in compliance with data retention protocols. After this designated period, all data will be appropriately and securely disposed of.

4.12 Summary of Chapter Four

This chapter comprehensively explored the research methodology, guided by the Research Onion Framework. It encompasses the data collection method, sampling strategy, data analysis techniques, data quality control, the ethical considerations considered during the research process, and more. The subsequent chapter (Chapter Five) thoroughly discussed the study findings and outcomes, examining the results obtained. This further contributed to understanding the research's implications and significance.

CHAPTER FIVE: ANALYSIS, FINDINGS, AND DISCUSSION

5.1 Introduction

This chapter presents a detailed analysis and discussion of the study's findings, highlighting how the results address the research questions and objectives initially highlighted in Chapter One. Data analysis is crucial in research by contributing to the final research outcome. This chapter involves examining and interpreting the data collected during a research survey, enabling the presentation of meaningful results. The data collected were subjected to thematic analysis to explore experiences and perceptions regarding the subject matter being investigated.

5.2 Rate of Response

The purposive sampling technique was employed because it enabled the researcher to choose respondents that possess the desired qualities or experiences necessary to achieve the study objectives. To create a purposive sample, the researcher specifically targeted academic staff and/or postgraduate students affiliated with the UKZN School of Management, Information Technology, and Governance (SMIG), primarily from the discipline of Information Systems and Technology (IST) because one of the discipline’s focus areas is endorsing big data analytics, among others. Out of the academic staff members within the SMIG, a total of eighteen (18) individuals satisfied the inclusion criteria and were invited to respond to an open-ended questionnaire (survey). However, the researcher received a total of fourteen (14) responses, representing 77.8% of the response rate. The responses were detailed and deemed sufficient for the study.

The study’s questionnaire (Appendix B) comprised three major sections. The sections present are Section A: Demographic Questions, SECTION B: Main Questions, and Section C: Final Thoughts. The questionnaire has ten open-ended questions in Total. The other sections of the questionnaire covered the specifics of the researcher and the study, the importance of participation, and the agreement to participate.

5.3 Definitions of Qualitative Techniques Used

a) Word Clouds

A word cloud is an effective visualization method to illustrate the frequency or significance of words within a text data set. It accomplishes this by displaying the words in different sizes and colors. The larger the size and the brighter the color of a word or comment, the more prominent it is within the data set. This technique facilitates the identification of key areas and themes within the data (Al-Kindi & Al-Khanjari, 2020).

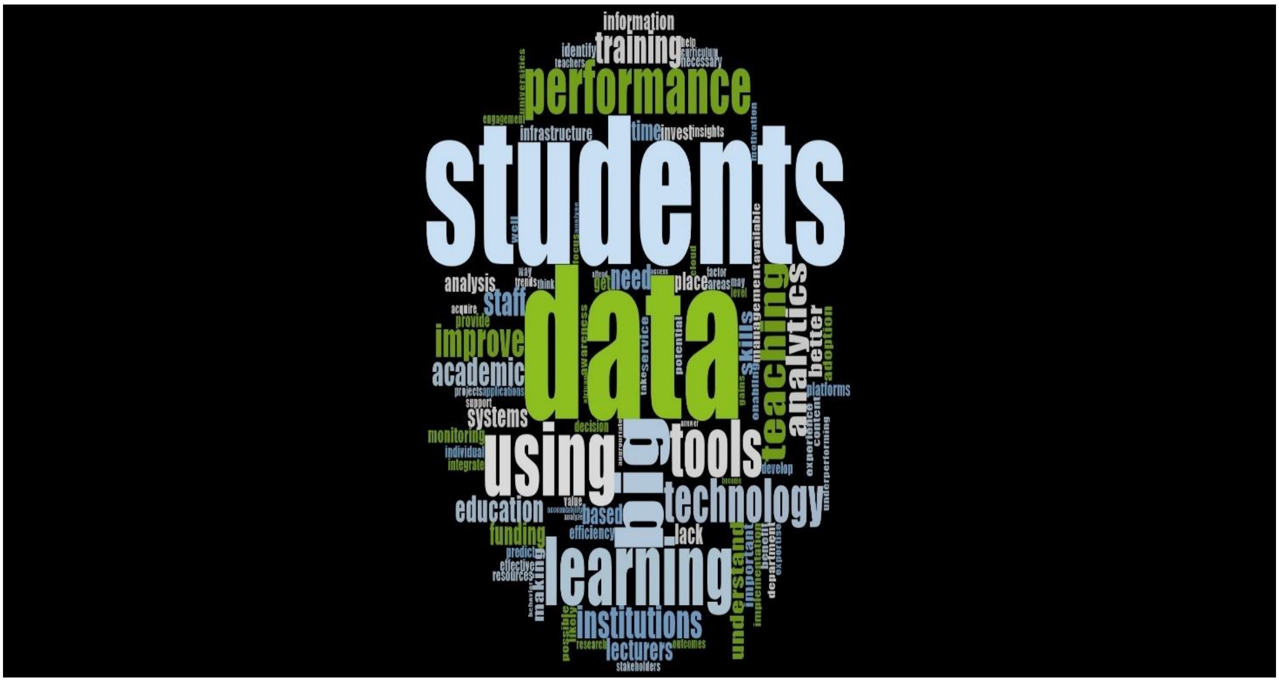

Figure 5.1. Word Cloud of all Survey Data

b) Tree Maps

A tree map is a graphical depiction of hierarchical data, employing nested rectangles to represent each node within the hierarchy. The size of each rectangle correlates with the value or significance of its corresponding node. They visually display the data, particularly frequently used words, by varying the size of the blocks. As a result, larger blocks indicate the predominantly utilized words (Jackson & Bazeley, 2019).

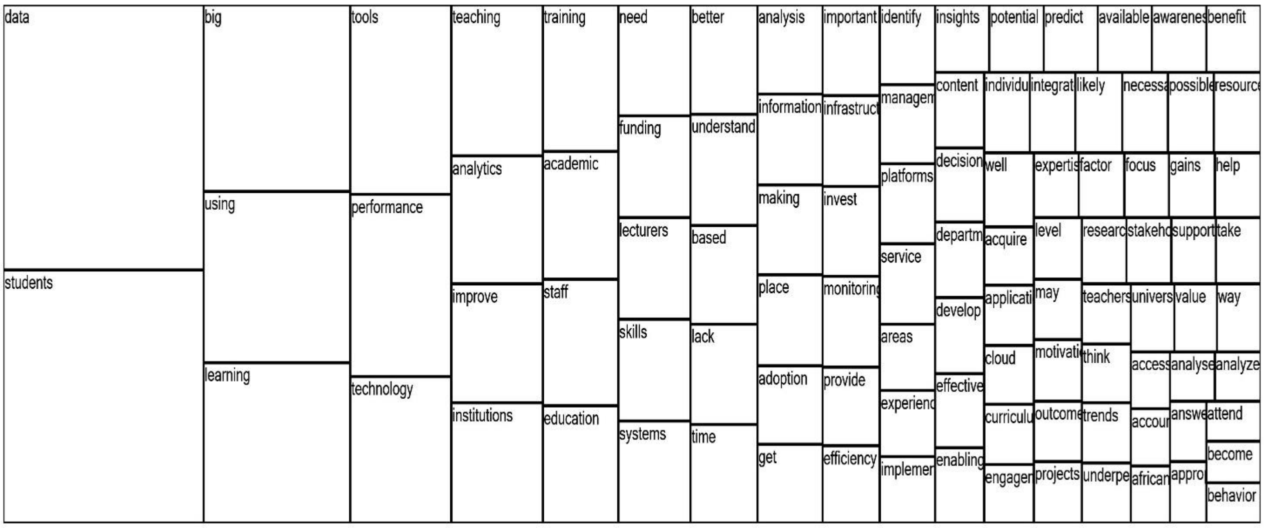

Figure 5.2. Tree Map of all Survey Data

c) Hierarchy Charts

The size of the nodes in these charts directly represents their volume of responses. Larger sizes indicate a more significant amount of data within that specific area. Hierarchy charts are employed in qualitative analysis to organize, summarize effectively, and depict data in a manner that is easily comprehendible and communicated (Thompson, 2021).

Figure 5.3. Hierarchy Chart of all Survey Data

d) Word Trees

A word tree is a visualization technique that represents the relationships between words by displaying them as branches of a tree-like structure. The central concept is depicted at the tree's root, while the stems and leaves represent associated ideas or concepts. They enable a deeper understanding of the semantic relationships within the text and assist in uncovering hidden insights or trends within a qualitative dataset (Jackson & Bazeley, 2019).

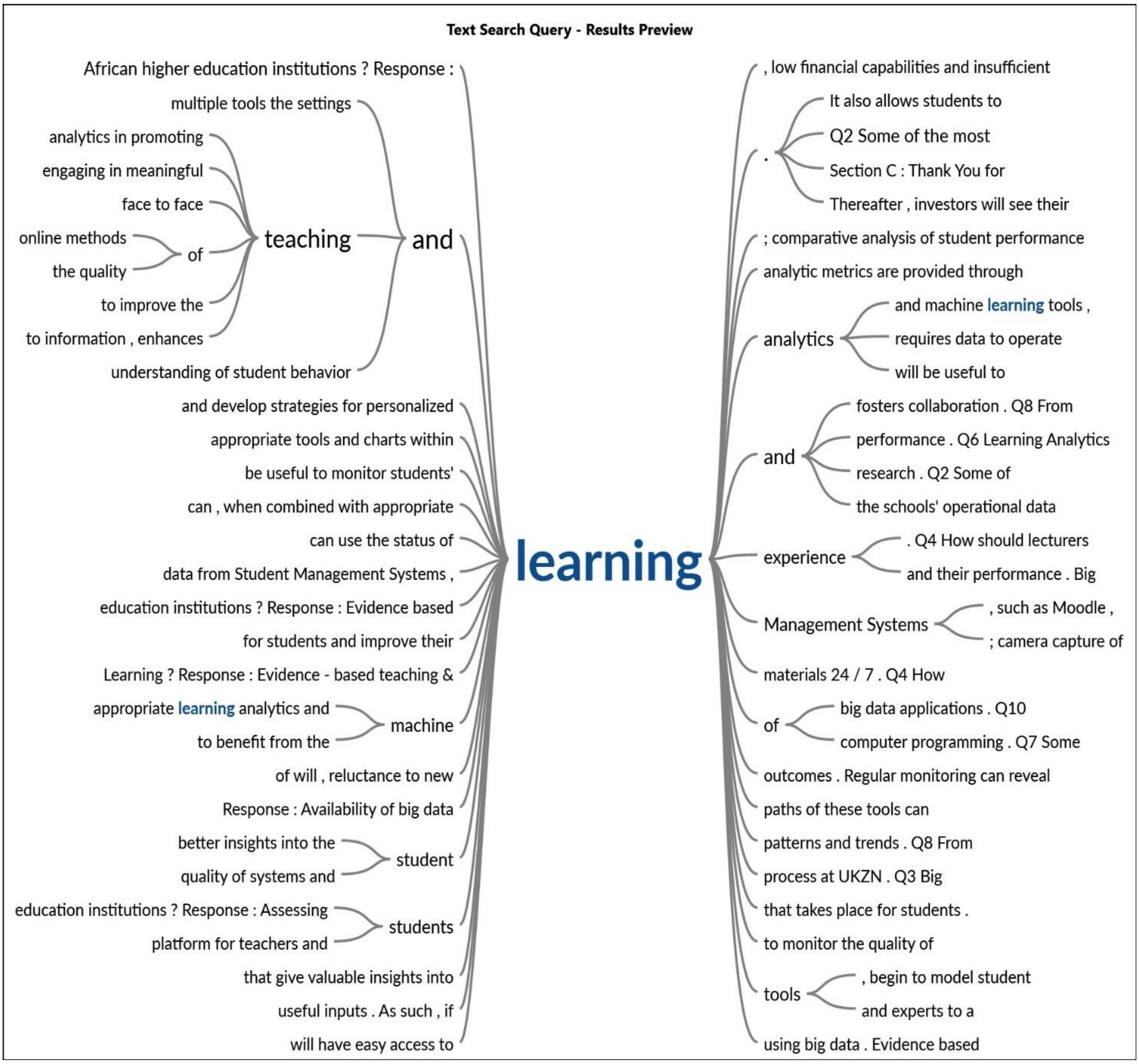

Figure 5.4. Word Tree of all Survey Data

e) Cluster Analysis

This technique is often utilized in qualitative data analysis to discover patterns and trends in data sets. These diagrams visually depict the data, specifically keywords, as "bubbles." Each bubble's size corresponds to the occurrence rate of the associated word or reference. Additionally, the proximity or closeness of the bubbles indicates a relationship between the respective words or terms, further enhancing the understanding of the interconnections within the data (Thompson, 2021).

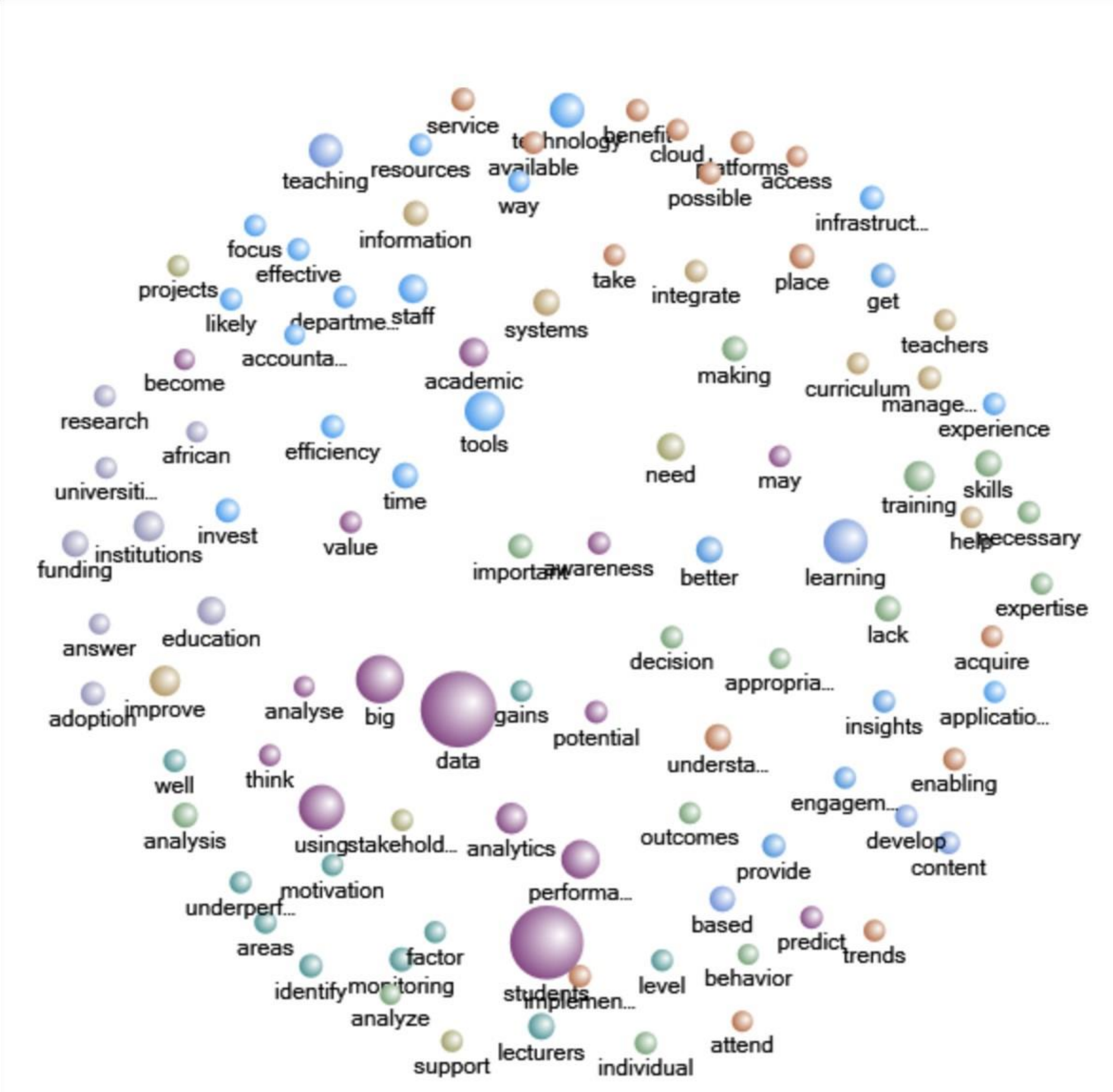

Figure 5.5. Cluster Analysis of all Survey Data

5.4 Demographics

Table 5.1. Demography

Grouping	Items	Percentage
Age	18-24	0%
	25-34	7.14%
	35 and above	92.86%
Gender	Male	50%
	Female	50%
Ethnicity	African	57.14%
	White	7.14%
	Indian	35.71%
	Colored	0%
Education Level	Degree	0%
	Postgraduate Diploma	0%
	Honors	0%
	Masters	21.43%
	PhD	78.57%
Campus	Westville	78.57%
	PMB	21.43%

Graphical Representation from one of the Groupings: Education Level

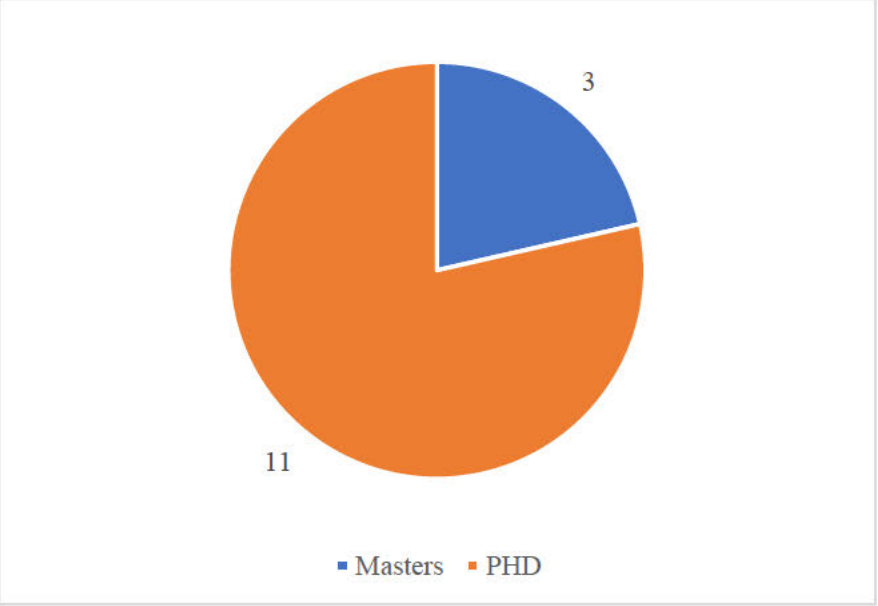

Figure 5.6. Education Level

Most respondents had a Ph.D. qualification, indicating the highest levels of education and potential research exposure.

5.5 Themes of the Study (Answering the study questions)

5.5.1 Impact (Perceived Usefulness) of big data in teaching and learning

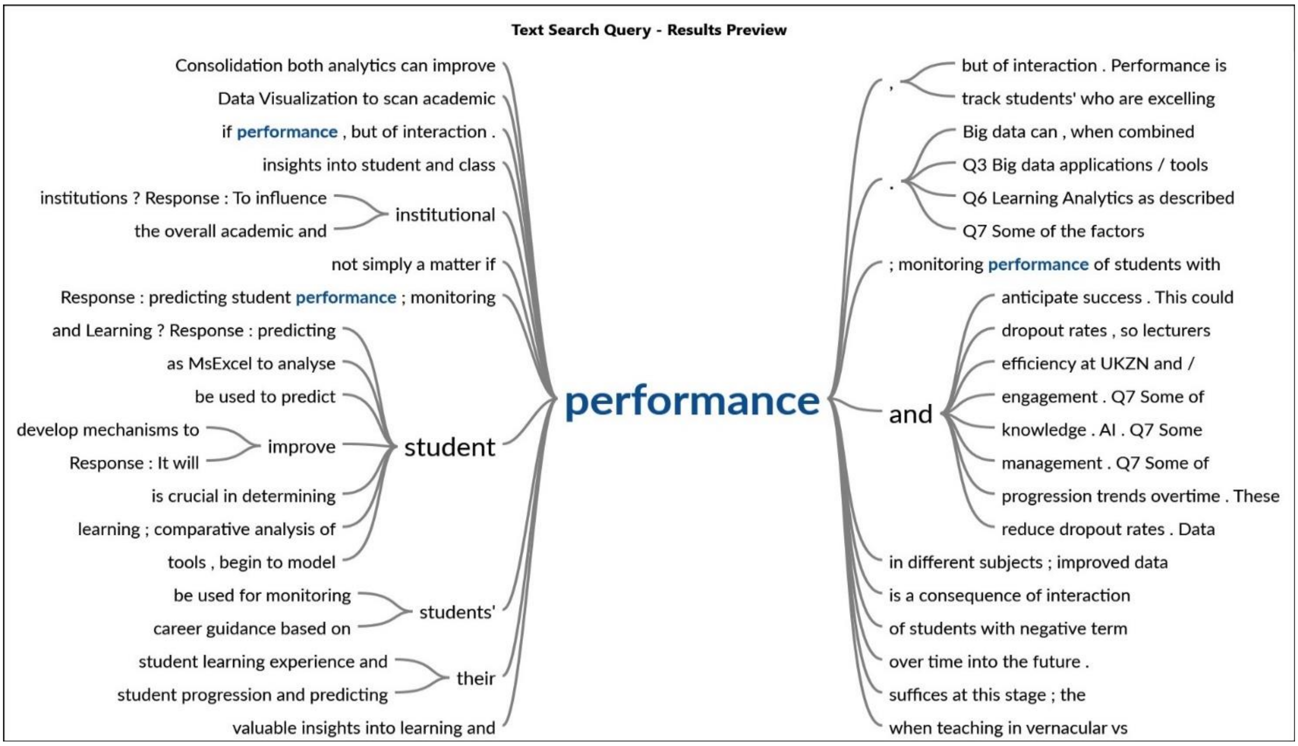

Figure 5.7. Word tree - Impact of big data in teaching and learning

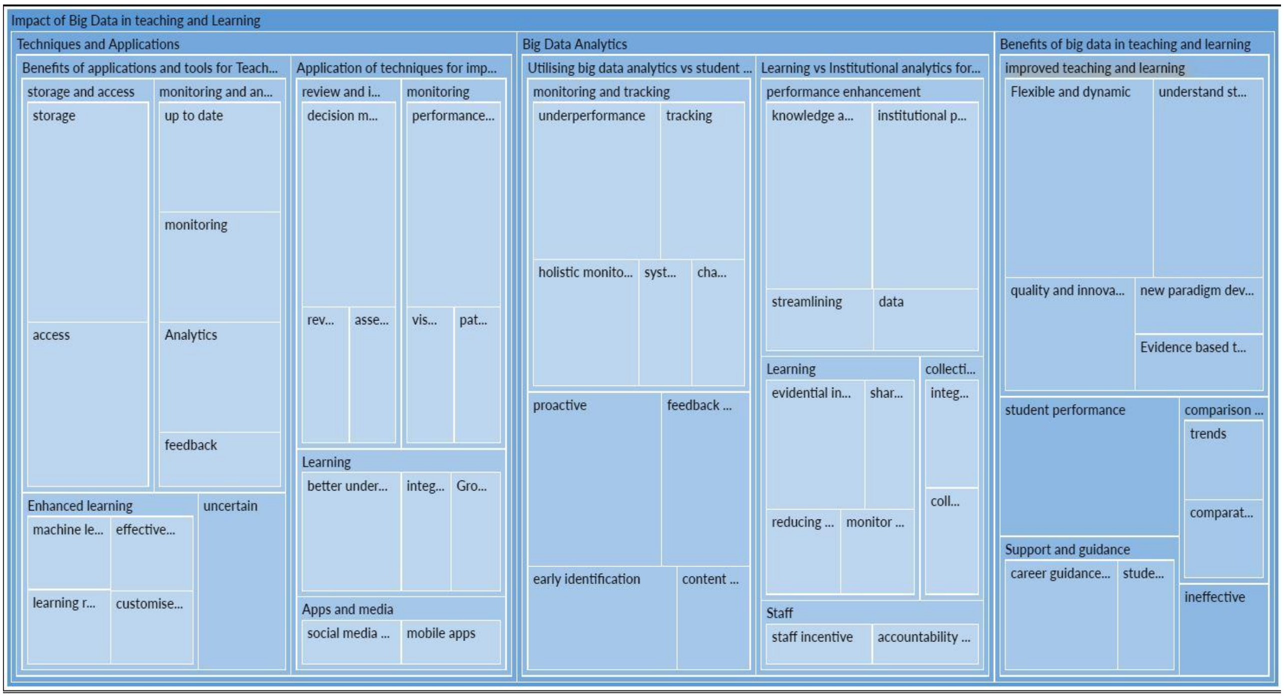

Figure 5.8. Hierarchy chart - Impact of big data in teaching and learning

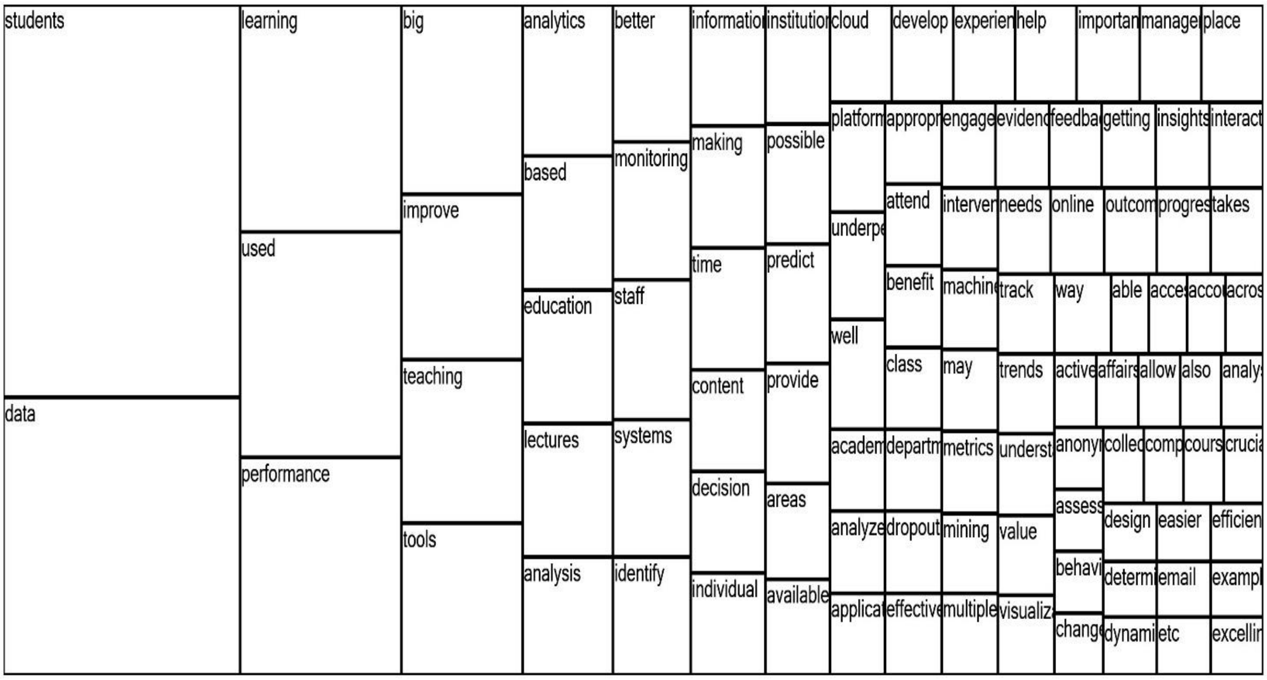

Figure 5.9. Tree map - Impact of big data in teaching and learning

This primary theme examined the impact of big data on teaching and learning. It was informed by a plethora of subthemes.

5.5.1.1 Big Data Analytics

Being the crux of the study, this primary subtheme detailed the area of big data analytics.

5.5.1.1.1 Utilizing big data analytics vs. student performances

This subtheme established lecturers' use of big data analytics to analyze student actions and performances.

5.5.1.1.2 Monitoring and tracking

Monitoring and tracking were key derivative themes that emerged. It was informed by the following.

(i) Underperformance

Underperformance was a key concern, and this was a logical argument. For retention and throughput, students cannot be underperforming. The implementation of big data analytics can therefore serve a role in analyzing student data to determine causes of underperformance and inform support actions.

<Files\\Survey_2> - § 1 reference coded [1,22% Coverage]

"Use of Big Data in identifying areas where Students are Underperforming." This is one reason I can think of why and where lecturers can utilize big data analytics to analyze student performances.

<Files\\Survey_5> - § 1 reference coded [0,78% Coverage]

Big data can be used to monitor students' performance and track students who are excelling and underperforming.

<Files\\Survey_7> - § 1 reference coded [0,83% Coverage]

The example specified is a perfect use of Big Data in identifying areas where students are underperforming or performing.

(ii) Tracking

Similarly, big data analytics can be used to track such underperformance for interventions to be made respectively.

<Files\\Survey_10> - § 1 reference coded [0,76% Coverage]

They can be used in tracking student progression and predicting their performance over time.

<Files\\Survey_5> - § 1 reference coded [0,78% Coverage]

Big data can be used to monitor students' performance and track students who are excelling and underperforming.

(iii) Holistic monitoring

There can be holistic monitoring done from different angles, be it summative or formative. Overall, conclusions can also be drawn from the data.

<Files\\Survey_3> - § 1 reference coded [0,92% Coverage]

I do not think that we will have sufficient data for individual interventions. However, gross conclusions may be drawn from class data.

<Files\\Survey_8> - § 1 reference coded [0,44% Coverage]

Apply it in analyzing student marks, formative and summative.

(iv) System quality

Monitoring of systems quality can be done via the status of learning. This can impact learning outcomes.

<Files\\Survey_11> - § 1 reference coded [0,73% Coverage]

Lecturers can use the status of learning to monitor the effectiveness of systems and student learning outcomes.

(v) Changes

Monitoring can improve student outcomes by informing student performance changes based on interventions. This can inform future interventions and decision-making.

<Files\\Survey_11> - § 1 reference coded [1,14% Coverage]

Regular monitoring can reveal changes over time in response to interventions that can be implemented to enhance student results. This process provides valuable feedback and additional data that can inform decision-making.

5.5.1.1.3 Proactive

Big data analytics can provide a proactive method of predicting student performance. Inferences can be made from the data to intercept poor performance.

<Files\\Survey_4> - § 1 reference coded [0,68% Coverage]

Intercept failing students before exams and assist in better preparation for these students.

<Files\\Survey_6> - § 1 reference coded [0,82% Coverage]

Using this, it may then be possible to model and predict student success and therefore design pre-emptively activities for students.

<Files\\Survey_8> - § 1 reference coded [0,35% Coverage]

Look at all the data points and make inferences.

5.5.1.1.4 Early identification

It can assist in promoting early detection and intervention thereof.

<Files\\Survey_14> - § 1 reference coded [0,60% Coverage]

This is very useful in identifying students at risk for early intervention and support.

<Files\\Survey_4> - § 1 reference coded [0,30% Coverage]

Identify areas of weakness for students.

5.5.1.1.5 Feedback and engagement

Interaction can become crucial through student feedback and time spent learning content via the learning management systems. This can provide key insights into performance indicators.

<Files\\Survey_13> - § 1 reference coded [0,54% Coverage]

It could be used to get feedback from students based on their learning status.

<Files\\Survey_6> - § 1 reference coded [1,92% Coverage]

It is not simply a matter of performance but of interaction. Performance is a consequence of interaction or lack thereof. Big data analytics could provide insights beyond simple screen time - a poor proxy for engagement - to potentially measure and categorize students' levels of cognitive engagement potentially.

5.5.1.1.6 Content review and improvement

Learning content can be reviewed for potential improvement.

<Files\\Survey_4> - § 1 reference coded [0,27% Coverage]

Improve content or revise content.

In relation to the sub-theme "Utilising big data analytics vs. student performances" discussed above, further studies such as Liang et al. (2016) and Khan and Alqahtani (2020) also reveal a similar argument whereby big data analytics (BDA) can be used in identifying and tracking students who are at risk of underperforming and finding ways to support and enhance their academic performance. In this context, BDA involves gathering and processing vast data in relation to learners and their academic performance. The data can be analyzed using techniques such as data mining, machine learning, and predictive analytics (Khan & Alqahtani, 2020). BDA can also provide insights into multiple aspects of student performance, such as attendance rates, grades, scores, and student engagement. Based on these insights, educators can make data-driven decisions to improve student performance by identifying areas where students are struggling, providing targeted interventions, and implementing strategies that work best for individual students (Liang et al., 2016).

5.5.1.2 Learning vs. Institutional Analytics for improving overall academic and institutional performance

This primary subtheme examined how implementing both Learning Analytics and Institutional Analytics could improve overall academic and institutional performance and efficiency at higher education institutions.

5.5.1.2.1 Performance enhancement

Performance enhancement did emerge clearly, and this was informed by the following.

(i) Knowledge and performance

The analytics can contribute to knowledge creation for the institution regarding student performance. This can inform performance measures.

<Files\\Survey_9> - § 1 reference coded [0,38% Coverage]

It will improve student performance and knowledge.

<Files\\Survey_12> - § 1 reference coded [0,39% Coverage]

Consolidation of both analytics can improve performance.

<Files\\Survey_14> - § 1 reference coded [0,58% Coverage]

And great support for the students to improve their academic performance.

(ii) Institutional performance

All necessary stakeholders can harness the power of analytics to identify institutional problems and opportunities. In addition, strengths and weaknesses, even at the school level, can be identified and addressed. This can bring about positive development.

<Files\\Survey_10> - § 1 reference coded [0,40% Coverage]

To influence institutional performance and management.

<Files\\Survey_13> - § 1 reference coded [1,20% Coverage]

Assessing students learning and the schools' operational data could expose both strengths and weaknesses of the school, which could be improved and addressed respectively.

<Files\\Survey_11> - § 1 reference coded [1,09% Coverage]

Educators, decision-makers, and stakeholders can leverage data analytics programs to identify institutional problems and spot opportunities for positive change. Data-driven decision-making also enhances resource allocation, as stakeholders can identify areas that require additional investment or improvement to optimize educational outcomes.

(iii) Streamlining

Teaching can become more streamlined.

<Files\\Survey_3> - § 1 reference coded [0,16% Coverage]

streamlining teaching

(iv) Data

The quality and relevance of the learning analytics data can be used to gain valuable insights. Relevant learning analytics data offers a deep understanding of student progress, engagement levels, and learning outcomes.

<Files\\Survey_6> - § 1 reference coded [0,87% Coverage]

Learning Analytics requires data to operate - and the more data, the better the algorithms are likely to be able to provide valuable inputs.

5.5.1.2.2 Learning

Improvement in academic performance and learning outcomes can be attained through the following approaches and strategies.

(i) Evidential intervention

Learning can now be evidence-based, informing measures based on real-time reports.

<Files\\Survey_1> - § 1 reference coded [0,58% Coverage]

Evidence-based learning using big data. Evidence-based teaching using big data.

<Files\\Survey_8> - § 1 reference coded [0,82% Coverage]

By implementing these, institutions would put in place necessary measures based on the reports from the analysis.

(ii) Monitor learning

Monitoring of learning in respective subjects can be possible.

<Files\\Survey_7> - § 1 reference coded [0,61% Coverage]

Learning analytics will help monitor students' learning of computer programming.

(iii) Reducing dropouts

Dropout rates can be mitigated, and this can improve retention and throughput.

<Files\\Survey_3> - § 1 reference coded [0,30% Coverage]

In the obvious ways of reducing dropouts,

(iv) Shared degree qualifications

It can promote shared degree qualification through collaborations. A shared degree is usually when a student can do more than one degree at a given time.

<Files\\Survey_3> - § 1 reference coded [0,55% Coverage]

And most importantly, building collaborative and shared degree qualifications.

5.5.1.2.3 Staff

However, the staff role is critical in using such analytics to improve institutional performance.

(i) Accountability needed

Staff have to be accountable for the use of analytical tools. Such tools will be ineffective if not used properly. It comes down to how good the user is. Training should be provided to staff, and they must be accountable for utilization.

<Files\\Survey_2> - § 1 reference coded [5,22% Coverage]

I don't believe it will improve the overall academic and institutional performance and efficiency at UKZN and/or other South African higher education institutions if you have staff that are not *committed and take days to respond to student emails or ignore them. I'm not suggesting that all staff are like this. In other words, you can have the best tools available, but if there is no accountability and transparency from staff, then those tools will not be used efficiently and effectively, no matter how much value the tools are designed to offer. For example, the Department of Home Affairs department spent tons of money on its information systems. However, there is still incompetency in the department of Home Affairs, not because of the information system inadequacies but because there is no staff accountability.*

(ii) Staff incentive

Incentives and rewards can also become a mechanism to encourage staff to use such tools to their full potential, which can positively impact the institution.

<Files\\Survey_2> - § 1 reference coded [1,20% Coverage]

Maybe there should be incentives in place to solve such issues and motivate staff to use the tools/IS to their full potential so that the organization can reap the returns on investment.

5.5.1.2.4 Collective efforts and integration

It will require collective efforts for effective integration.

(i) Collective efforts

Everyone will have to work collectively to bring about capabilities for implementing both learning and institutional analytics to improve overall academic and institutional performance.

<Files\\Survey_5> - § 1 reference coded [0,69% Coverage]

Each individual possesses unique capabilities, which, when combined with others, can form a powerful collective force. This synergy of talents allows for a more comprehensive and practical approach to problem-solving and achieving shared goals.

(ii) Integration and linking

There has also to be effective integration and necessary linkage of all systems. Hence, all systems linked to learning should ideally be linked so they work in synchrony. Information and analytics can then be accessed collectively.

<Files\\Survey_6> - § 1 reference coded [1,41% Coverage]

As such, if learning analytic metrics are provided through appropriate tools and charts within Learning Management Systems, such as Moodle, lecturers could gain better insights into student and class performance and engagement.

In relation to the sub-theme "Learning vs. Institutional analytics for improving overall academic and institutional performance" discussed above, further studies such as Chaurasia et al. (2018) and Mustafina et al. (2018) also reveal a similar argument whereby the adoption and implementation of both Learning and Institutional Analytics could profoundly transform the manner in which institutions approach student and institutional success. Learning analytics primarily focuses on understanding and optimizing the learning process for individual students. It involves collecting and analyzing data related to students' interactions with learning materials, assessments, and educational technologies to identify patterns and trends that can help educators personalize learning experiences and optimize instructional strategies. (Mustafina et al., 2018). On the other hand, institutional analytics takes a broader perspective, examining data on a larger scale to evaluate the performance of the entire institution. It involves analyzing data related to student registration, retention, graduation rates, resource allocation, and other institutional metrics (Chaurasia et al., 2018). This knowledge is transmitted through accurate data and trend analysis, allowing an institution to streamline its resources, processes, and goals to optimize both academic and institutional performance (Chaurasia et al., 2018). Through both types of analytics, institutions can reduce the likelihood of student dropout, identifying and intervening if necessary, resulting in much-improved retention rates. Moreover, it allows HEIs to make data-driven decisions in furtherance of student outcomes and institutional growth (Mustafina et al., 2018).

5.5.1.2 Benefits of big data in teaching and learning

This primary subtheme was influential in establishing the benefits of big data in teaching and learning. Benefits would bring about the value of big data and inform its implementation.

5.5.1.2.1 Student performance

Student performance was a highly ranked factor. This argument is logical, as teaching and learning directly affect student performance. The result implies that big data can enhance performance by predicting and monitoring student performance. Data visualization is also essential for visually representing and interpreting performance metrics, while data modeling can strongly predict student success.

<Files\\Survey_6> - § 1 reference coded [1,95% Coverage]

One of the most critical needs, primarily as more content is delivered online, is better insights into the student learning experience and performance. When combined with appropriate learning analytics and machine learning tools, big data can begin to model student performance and anticipate success.

<Files\\Survey_5> - § 1 reference coded [0,62% Coverage]

Predicting student performance; monitoring performance of students with negative-term decisions.

<Files\\Survey_6> - § 1 reference coded [1,95% Coverage]

With the vast amount of data generated in online learning environments, big data analytics can play a transformative role in analyzing student interactions, engagement levels, and learning patterns. By harnessing the power of big data and employing suitable learning analytics and machine learning tools, educational institutions can create models that predict student performance and anticipate academic success.

<Files\\Survey_7> - § 1 reference coded [0,34% Coverage]

Data Visualization to visualize and analyze academic performance.

5.5.1.2.2 Improved teaching and learning

Teaching and learning holistically can be improved through big data in the following ways.

(i) Flexible and dynamic

Learning and teaching can become more flexible. This is because interactive and personalized trends can inform teaching and learning methods. Courses can become more dynamic and flexible based on how students interact with content. This can eventually inform the entire curriculum.

<Files\\Survey_11> - § 1 reference coded [0,34% Coverage]

And develop strategies for personalized learning.

<Files\\Survey_5> - § 1 reference coded [0,42% Coverage]

Developing personalized teaching plans and methods tailored to individual student results is fundamental to student-centered education.

<Files\\Survey_6> - § 1 reference coded [0,90% Coverage]

This could allow for the development of dynamic course content that adapts to students based on their current interaction with the course content.

<Files\\Survey_9> - § 1 reference coded [0,14% Coverage]

Dynamic curriculum.

(ii) Understand Students

Student behavior and needs can be understood, allowing teachers to determine academic areas of weakness.

<Files\\Survey_10> - § 1 reference coded [0,22% Coverage]

Imperative to analyze student behavior.

<Files\\Survey_11> - § 1 reference coded [0,94% Coverage]

By conducting big data analysis, professors can identify areas where students may encounter difficulties or excel. This process allows for a deeper understanding of each student's unique needs and enables professors to tailor their approach accordingly,

<Files\\Survey_2> - § 1 reference coded [0,39% Coverage]

Lecturers would have a better understanding of their students,

(iii) Quality and innovation

The quality of teaching, learning, and research could be improved through big data. Big data can inspire innovation in teaching approaches. Educators can discover novel ways to engage students and create more impactful learning experiences.

<Files\\Survey_6> - § 1 reference coded [0,33% Coverage]

It could lead to new innovative approaches to teaching.

<Files\\Survey_8> - § 1 reference coded [0,54% Coverage]

Big data will enhance the quality of education, learning, and research.

(iv) New paradigm development

It can lead to new paradigms in teaching and learning, especially post-covid when online education became a dominant form of teaching and learning.

<Files\\Survey_2> - § 1 reference coded [1,08% Coverage]

They can develop new teaching paradigms to meet the needs of the "covid-generation" students who have become accustomed to the online methods of Teaching and Learning.

(v) Evidence-based teaching and learning

Evidence-based learning became a re-emerging factor as big data can provide analytical evidence of learning.

<Files\\Survey_1> - § 1 reference coded [0,26% Coverage]

Evidence-based teaching & learning.

5.5.1.2.3 Comparison and trends

Comparison and trends can become an added benefit in the following ways.

(i) Comparative analysis

There can be comparisons drawn between virtual and conventional teaching and learning. Thereafter respective performances can be comparatively analyzed to determine the effectiveness of either method.

<Files\\Survey_5> - § 1 reference coded [1,08% Coverage]

Comparative analysis of online vs. traditional face-to-face teaching and learning; comparative analysis of student performance when teaching in vernacular vs. English.

(ii) Trends

Through data visualization, student performance trends can be discovered.

<Files\\Survey_5> - § 1 reference coded [0,30% Coverage]

This leads to improved data visualization and trends analysis.

5.5.1.2.4 Support and guidance

Apart from academic benefits, student support can be enhanced in the following ways.

(i) Career guidance and pathing

Big data can help plot the career path of students, thereby enhancing career guidance into the right choice.

<Files\\Survey_11> - § 1 reference coded [0,39% Coverage]

It also allows students to choose their education paths.

<Files\\Survey_5> - § 1 reference coded [0,45% Coverage]

Career guidance is based on students' performance in different subjects.

(ii) Student support

Students can be supported in terms of challenges and difficulties experienced.

<Files\\Survey_6> - § 1 reference coded [0,32% Coverage]

As well as supporting students more effectively.

5.5.1.2.5 Ineffective

However, one respondent felt that big data would not benefit the teaching and learning process due to a lack of capacity to apply and utilize such technology appropriately.

<Files\\Survey_3> - § 1 reference coded [1,05% Coverage]

I am unsure whether there will be any value in collecting data as I am not convinced there is a capacity to utilize or analyze the data.

Further studies such as Bhadani and Jothimani (2016), Bamiah et al. (2018), Murumba and Micheni (2017), and Liebenberg et al. (2018) support the argument presented above regarding the sub-theme “benefits of big data in teaching and learning.” Using big data analytics (BDA) can help HEIs understand student learning styles better and tailor teaching methods to meet the requirements of each student (Bhadani & Jothimani, 2016). This personalized approach to teaching can lead to improved learning outcomes, increased student engagement, and higher levels of student retention. For instance, big data allows instructors to monitor student progress and gather data, such as a student's response or difficulty level with a question in real-time during the learning process (Murumba & Micheni, 2017). This information gives instructors insights into which concepts students understand and which are problematic, enabling instructors to create targeted learning activities that help fill in the gaps in the learner's understanding (Murumba & Micheni, 2017).

However, the lack of capacity to properly apply and utilize big data technology can significantly impact its adoption and usage in South African higher education institutions (HEIs). Some HEIs may not have the necessary resources to train employees to apply and utilize these new technologies, which could make it difficult to justify the cost in terms of time and budget. The successful implementation of big data technologies demands specialized skills and resources, including adequate infrastructure, resources, and personnel to implement it effectively (Bamiah et al., 2018). Therefore, for big data initiatives to be effectively adopted in higher education institutions, there needs to be a systemic and coordinated approach to building capacity among relevant stakeholders. This requires fostering a culture of data-driven decision-making in education, investing in infrastructure and resources, adequate staff training, and offering access to appropriate, user-friendly analytics tools (Liebenberg et al., 2018).

5.5.1.3 Techniques and Applications

This primary subtheme focused on big data techniques, tools, and applications to benefit teaching and learning. These tools and applications include Apache Storm, Cloud Services, Socrative, Classroom Monitor, and Civitas Learning.

5.5.1.3.1 Application of techniques for improving Teaching and Learning

The application of big data tools and techniques can improve teaching and learning in the following ways.

(i) Monitoring

Monitoring became a remerging subtheme, which plays a key role in student progress. It was informed by the following.

a. Performance predictions

Data mining is a powerful technique and can be used for students' performance predictions. This can help in the proactive development of mechanisms.

<Files\\Survey_10> - § 1 reference coded [0,65% Coverage]

Data mining is crucial in determining student performance and progression trends over time.

<Files\\Survey_12> - § 1 reference coded [0,40% Coverage]

Data mining techniques for relevant future predictions

<Files\\Survey_2> - § 1 reference coded [1,05% Coverage]

Data mining can be used to predict student performance and dropout rates, so lecturers can develop mechanisms to improve student performance and reduce dropout rates.

b. Patterns and trends

Utilizing data visualization enables tracking student attendance and participation patterns and trends. This, in turn, facilitates the development of additional strategies aimed at enhancing student engagement in the learning process.

<Files\\Survey_2> - § 1 reference coded [1,53% Coverage]

Data visualization can be used to map out the data and outliers in huge data sets so that it is easier to identify patterns in student attendance for practical and tutorial sessions and trends that attract students to attend live Zoom lectures.

c. Visual monitoring

Visual monitoring in the form of online cameras to capture student expression can be paired with relevant tools for cognitive measurement of attention and distraction. This integrated approach provides real-time insights into students' engagement and allows educators to identify specific areas where students may be struggling or losing focus.

<Files\\Survey_5> - § 1 reference coded [0,72% Coverage]

Utilizing camera technology to capture student attentiveness during lectures involves monitoring various indicators, such as facial expressions, level of distraction, etc.

(ii) Learning

Learning can be improved via the following.

a. Better understanding

Big data can assist in creating a visual presentation of learning content. This can improve the grasping and understanding of content faster and more effectively.

<Files\\Survey_14> - § 1 reference coded [1,12% Coverage]

Presentation of information concisely, pictorial, or graphical information from big data can help improve the teaching and learning process at UKZN.

<Files\\Survey_9> - § 1 reference coded [0,48% Coverage]

Visualization helps slow learners to understand concepts faster.

b. Groupwork

Groupwork can be facilitated more effectively through data clustering techniques.

<Files\\Survey_2> - § 1 reference coded [0,51% Coverage]

Data clustering can divide students into groups when doing group work. Instructors can facilitate more effective team formation by implementing data clustering in group work scenarios. This process involves grouping students with similar skills, interests, or backgrounds, which can lead to improved collaboration and ultimately enhance the overall quality of group project outcomes.

c. Integration

Integrating various systems across the institution can lead to more holistic data acquisition and analysis.

<Files\\Survey_5> - § 1 reference coded [0,61% Coverage]

Data Acquisition involves integrating data from Student Management Systems and Learning Management Systems.

(iii) Review and improvement

It can facilitate reviewing and improving teaching and learning processes such as the following.

a. Assessment methodologies

Assessment methodologies can be reviewed, nuanced, and improved based on solid analytics through the respective tools.

<Files\\Survey_3> - § 1 reference coded [0,34% Coverage]

We could also improve assessment methodologies.

b. Review and refinement of teaching methods

It can allow teaching methods to be refined on an informed basis, thus enabling maximum impact on student learning.

<Files\\Survey_3> - § 1 reference coded [0,64% Coverage]

Most importantly, to refine teaching methods so that we may have maximum impact.

c. Decision-making and policy

Big data tools can allow for better interpretation of data with real-time information, thereby enhancing decision-making and proving key indicators for policymakers.

<Files\\Survey_11> - § 1 reference coded [0,91% Coverage]

Educators can make intelligent decisions that improve student outcomes by adequately analyzing and interpreting data.

<Files\\Survey_14> - § 1 reference coded [0,57% Coverage]

Important values for timely decision-making can be extracted from big data.

<Files\\Survey_10> - § 1 reference coded [0,56% Coverage]

These are crucial indicators for policymakers in driving premier scholarship.

(iv) Apps and media

Big data tools can also be fun and creative in the form of Apps and media.

a. Mobile apps

Mobile apps and platforms can allow for the analysis of student behavior.

<Files\\Survey_5> - § 1 reference coded [0,74% Coverage]

Mobile educational application data, academic blogs, email texts, and proctoring tools to analyze student behavior. Mobile educational applications provide data on students' usage patterns, preferences, and progress in specific subjects or courses. Proctoring tools are vital in remote assessments, capturing data on students' test-taking behaviors and adherence to academic integrity guidelines. This data helps in identifying irregularities and ensuring the credibility of assessments.

b. Social media vs. Education

The current popular media, such as social media (Facebook /Twitter), can even be explored as a creative method for educational purposes, including teaching and learning.

<Files\\Survey_5> - § 1 reference coded [0,48% Coverage]

Social media data from Facebook and Twitter are used for educational purposes.

5.5.1.3.2 Benefits of applications and tools for Teaching and Learning

The benefits of applications and tools for Teaching and Learning were numerous. These are outlined below.

(i) Enhanced learning

Enhanced learning was the most highly ranked factor. This is a valid argument, as the study focused on the potential of big data to improve teaching and learning.

a. Effectiveness in the job role

Lecturers will be able to perform their job role, primarily teaching, better and more effectively.

<Files\\Survey_2> - § 1 reference coded [0,73% Coverage]

It would provide the lecturer with better tools to perform their job responsibilities more effectively.

b. Machine learning

Machine learning can take place, leading to benefits on various platforms as such platforms can access data from multiple sources, including the cloud. Hence, cloud and virtual storage can assist in this crucial process.

<Files\\Survey_6> - § 1 reference coded [1,31% Coverage]

By storing data in the cloud and possibly making anonymized metrics available across platforms, multiple platforms/tools could benefit from the machine learning that takes place for students.

c. Customized learning

Learning can be customized to fit the learning trajectory/path of the student. Hence it can break the traditional ‘one size fits all approach’ to learning.

<Files\\Survey_6> - § 1 reference coded [0,95% Coverage]

Therefore, in instances where a student needs to utilize various tools, the settings and learning pathways can be automatically tailored to suit the student's needs. This automated customization of settings and learning paths ensures students can navigate their educational journey seamlessly.

d. Learning resources

New learning resources can be created for ongoing improvement of the learning experience for students.

<Files\\Survey_8> - § 1 reference coded [0,65% Coverage]

It would be easier to curate resources for students and improve their learning experience.

(ii) Monitoring and analysis

Monitoring and analysis were recurring benefits.

a. Monitoring

Student progress and performance can be monitored, and this is not only limited to an individual but also to an entire class. This provides holistic monitoring opportunities.

<Files\\Survey_11> - § 1 reference coded [0,90% Coverage]

Teachers can use data interpretation to determine the strengths and shortcomings of an entire class as well as individual students.

<Files\\Survey_9> - § 1 reference coded [0,29% Coverage]

Monitoring students' progress.

b. Analytics

Relating to the above, analytics and statistical analyses can play a key role in monitoring.
<Files\\Survey_1> - § 1 reference coded [0,08% Coverage]

Advanced analytics.

<Files\\Survey_5> - § 1 reference coded [0,27% Coverage]

Use R or Python for statistical analysis.

c. Up to date

Investment in big data tools can allow the institution to stay updated with technology trends and obtain real-time information. This is key to enhancing the student experience.

<Files\\Survey_10> - § 1 reference coded [1,02% Coverage]

They keep the university aligned with emerging technologies and applications for better education experiences for students and teaching staff.

<Files\\Survey_14> - § 1 reference coded [0,20% Coverage]

Getting timely reports, etc.

d. Feedback

Big data tools and software can provide interactive feedback, thereby enhancing monitoring mechanisms.

<Files\\Survey_9> - § 1 reference coded [0,54% Coverage]

Some of the listed software will help with active and timely feedback.

(iii) Storage and access

Benefits relating to storage and access to data are also evident.

a. Storage

Data can be stored virtually, such as through cloud services, and this can ensure that data remains versatile, safe, and secure. Physical storage space can be reduced, saving time, money, and resources.

<Files\\Survey_13> - § 1 reference coded [0,33% Coverage]

Resources can be kept safe in the cloud for reference purposes.

<Files\\Survey_14> - § 1 reference coded [0,17% Coverage]

Storage of data

<Files\\Survey_5> - § 1 reference coded [0,36% Coverage]

Cloud services for storage and processing of big data.

b. Access

When data and information are stored virtually, then access becomes flexible. Students can access learning content from any location, thus enabling faster and more dynamic learning.

<Files\\Survey_12> - § 1 reference coded [0,68% Coverage]

Leverage cloud services for accessibility of big data technologies to students and staff.

<Files\\Survey_14> - § 1 reference coded [0,23% Coverage]

Availability of information,

<Files\\Survey_2> - § 1 reference coded [0,37% Coverage]

Students will have easy access to learning materials 24/7.

(iv) Uncertain

However, two respondents were uncertain as they had no experience with big data tools. This can imply the current deficiency of such tools at the institution.

<Files\\Survey_3> - § 1 reference coded [0,75% Coverage]

I really cannot say. I have no experience with them. However, any big data tool or system can only help if appropriately utilized.

<Files\\Survey_4> - § 1 reference coded [0,48% Coverage]

I have never used these applications, so I cannot comment on the above.

In relation to the sub-theme "Techniques and Applications" discussed above, further studies such as Sin and Muthu (2015) and Dahdouh et al. (2017), and Gómez-Espina et al. (2019) also reveal a similar argument on the usage and impact of big data techniques such as data mining, data visualization and big data platform/tools such as Socrative, Google Classroom, Apache Hadoop, Apache Storm on teaching and learning in HEIs. Data mining techniques can be used to analyze student data, such as grades and attendance records, to identify patterns and trends that inform instructional strategies (Sin & Muthu, 2015). Data visualization tools can help educators present complex data clearly and quickly, effectively communicating insights to students and other stakeholders (Sin & Muthu, 2015). Apache Storm and Apache Hadoop facilitate real-time data processing and analysis, enabling educators to quickly respond to student needs and provide personalized learning experiences (Dahdouh et al., 2017). Socrative and Civitas Learning are examples of big data learning management platforms that can track student progress, identify areas for improvement, and provide personalized feedback and support (Gómez-Espina et al., 2019). Overall, the researcher holds a firm conviction that the adoption and usage of big data technologies/platforms will lead to a transformative shift in the approach to teaching and learning. This shift will empower educators to make decisions based on data insights, fostering a more personalized and engaging experience for students.

5.5.2 Influencing Factors and Challenges

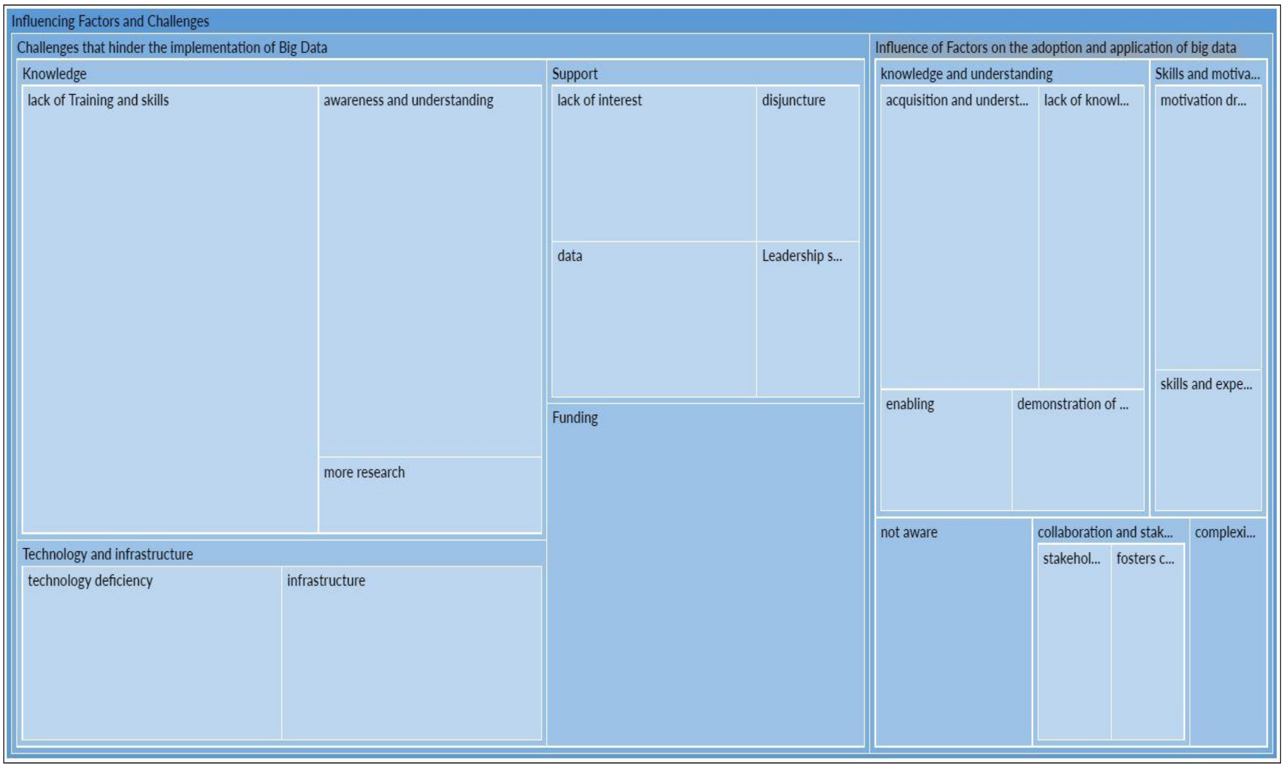

Figure 5.10. Hierarchy Chart – Influencing Factors and Challenges

Figure 5.11. Word Cloud – Influencing Factors and Challenges

This vital theme outlined the influencing Factors and Challenges to Big data adoption and application. It was informed by many related subthemes.

5.5.2.1 Influencing factors on the adoption and application of big data

Various factors influenced the adoption and application of big data. This is related to factors such as data privacy, data compatibility, institutional readiness, relative advantage, government regulations, and educational stakeholders' full cooperation and support, among others.

5.5.2.1.1 Knowledge and understanding

People, including staff and stakeholders, needed to be knowledgeable of big data and develop an understanding of its potential.

(i) Acquisition and understanding

Big data can bring about an advantage in the higher education space. However, understanding the relevant analytics is crucial in identifying patterns and trends and gaining a competitive edge.

<Files\\Survey_10> - § 1 reference coded [0,57% Coverage]

Understanding student behavior, learning patterns, and trends can significantly contribute to gaining a competitive advantage for educational institutions.

<Files\\Survey_4> - § 1 reference coded [0,56% Coverage]

Analytics cannot take place if data is challenging to acquire and understand.

<Files\\Survey_7> - § 1 reference coded [0,34% Coverage]

It enables the acquisition of relative advantage.

(ii) Enabling

The institutional readiness would have to be ascertained to enable adoption.

<Files\\Survey_5> - § 1 reference coded [0,51% Coverage]

Institutional readiness - enabling factor. However, this has to be ascertained.

(iii) Demonstration of benefits

A key factor would be the demonstration of the necessary benefits. People are visual and would want to 'see to believe' the potential of big data. Therefore, a demonstration would be encouraged.

<Files\\Survey_6> - § 1 reference coded [1,96% Coverage]

While focusing on better, more effective ways of teaching is essential, most people with limited time and resources will focus on time-saving, efficiency-enhancing tools and technologies. So, if these tools can be demonstrated to address this and enhance the teaching experience, there will likely be more uptake.

(iv) Lack of knowledge

However, some respondents felt that there was a lack of knowledge of the potential of big data. More training and development were hence needed.

<Files\\Survey_1> - § 1 reference coded [0,58% Coverage]

Many academics lack formal training in the field of big data analytics. Some of them do know these things. This knowledge gap can pose challenges.

<Files\\Survey_14> - § 1 reference coded [0,59% Coverage]

However, creating awareness and training can make people adopt the technology.

5.5.2.1.2 Skills and motivation

Skills and motivational factors were needed to promote adoption and application.

(i) Skills and expertise needed

Skills and expertise were needed to enable analytics to occur.

<Files\\Survey_4> - § 1 reference coded [0,57% Coverage]

If the technology and expertise are absent, analytics cannot be implemented.

(ii) Motivation driven

Furthermore, staff needed to be motivated to adopt such technology. Without motivation, the benefits would not be realized, and the implementation would be a wasted resource. Hence willingness and motivation, especially from lecturers, was a key factor.

<Files\\Survey_13> - § 1 reference coded [1,47% Coverage]

The institution's willingness could be a motivator or a barrier, especially with known and ensuing factors/ issues that big data could generate. It will influence their level of investment for its adoption.

<Files\\Survey_6> - § 1 reference coded [1,31% Coverage]

I would say that the most crucial factor is none of these - but rather user (lecturer) motivation. And this motivation, amid busy lives - will only come if the tools provide efficiency gains.

5.5.2.1.3 Collaboration and stakeholders

There has to be a collaborative environment with the necessary stakeholders present.

(i) Stakeholders

Support must be attained from all necessary stakeholders in the higher education space to promote adoption.

<Files\\Survey_5> - § 1 reference coded [0,59% Coverage]

Educational stakeholder support - need to specify stakeholders - potential enabling factor.

(ii) Fosters collaboration

The use of big data can also foster collaboration due to shared and easy access to information.

<Files\\Survey_8> - § 1 reference coded [0,69% Coverage]

They increase access to information, enhance teaching and learning, and fosters collaboration.

5.5.2.1.4 Complexity Tolerance vs. Adoption

One respondent made an interesting point that a key factor in adopting and implementing big data revolved around the tolerance levels for complexity at institutions. This means that they viewed the process of big data implementation as complex. Institutions may need to invest time, money, operations, resources, personnel, and related to ensure proper implementation.

<Files\\Survey_11> - § 1 reference coded [0,73% Coverage]

Higher institutions with a high tolerance for complexity are likelier to adopt big data analytics.

5.5.2.1.5 Not aware

However, two respondents were unaware of factors that influence adoption and application as they had related experiences.

<Files\\Survey_2> - § 1 reference coded [0,28% Coverage]

Have no idea. What does the literature say?

<Files\\Survey_3> - § 1 reference coded [0,28% Coverage]

I have no experience in this to comment.

In relation to the sub-theme "Influencing factors on the adoption and application of big data" discussed above, further studies such as Sam and Chatwin (2018), Baig et al. (2021), Tasmin and Huey (2020) and Chong and Olesen (2017) also support the same argument and reveals more information. These studies highlight the significant impact of various factors, including leadership influence, cost of big data, firm size, and in-house IT expertise, in driving the adoption of big data. According to Sam and Chatwin (2018), a proficient in-house IT (data specialist) team is a significant factor influencing big data adoption. HEIs with a robust internal IT (data specialist) team would have the knowledge, expertise, and capabilities to effectively incorporate and adapt big data analytics systems within their IT infrastructure. They would understand the complexities of data architecture, database management, and data integration, enabling them to seamlessly incorporate big data solutions (Sam & Chatwin, 2018).

Furthermore, Chong and Olesen (2017) stated that leadership influence/support is a critical determinant of big data adoption. The endorsement and commitment of senior leaders within HEIs are crucial for driving the adoption and successful implementation of big data analytics (BDA) and overcoming potential obstacles (Chong & Olesen, 2017). Their support ensures that big data initiatives receive the necessary resources, including funding, infrastructure, and human capital. Top-level executives and management can communicate the worth and potential benefits of big data analytics (BDA) to various stakeholders, such as faculty, staff, and students, thereby fostering engagement and collaboration. Additionally, they can establish policies and guidelines that promote data governance, protect privacy, and ensure ethical use of sensitive data (Chong & Olesen, 2017).

5.5.2.2 Challenges that hinder the adoption and implementation of Big Data

It was imperative to ascertain the challenges hindering big data implementation so these could be addressed.

5.5.2.2.1 Knowledge

The knowledge aspect was a highly ranked challenge. There seemed to be a deficiency of such. This was due to the following.

(i) Lack of Training and skills

There was a current lack of training and skills development for staff in the area of big data. This was the most highly ranked factor. The lack of technical expertise was evident.

<Files\\Survey_1> - § 1 reference coded [0,13% Coverage]

Lack of training.

<Files\\Survey_11> - § 1 reference coded [0,25% Coverage]

Lack of data science professionals,

<Files\\Survey_12> - § 1 reference coded [0,15% Coverage]

Technical Expertise

<Files\\Survey_14> - § 1 reference coded [0,16% Coverage]

Training is necessary.

<Files\\Survey_3> - § 1 reference coded [0,06% Coverage]

Data skills

<Files\\Survey_4> - § 1 reference coded [0,12% Coverage]

Skills expertise,

<Files\\Survey_5> - § 1 reference coded [0,11% Coverage]

Lack of training.

<Files\\Survey_8> - § 1 reference coded [0,20% Coverage]

Shortage of relevant skills.

(ii) Awareness and understanding

Similarly, a noticeable lack of awareness and comprehension regarding the potential of big data was evident. People tend to be apprehensive about what they don't fully understand, which could hinder the adoption of big data. Therefore, increasing awareness was deemed essential.

<Files\\Survey_1> - § 1 reference coded [0,34% Coverage]

Lack of understanding or awareness of big data.

<Files\\Survey_13> - § 1 reference coded [0,50% Coverage]

And insufficient knowledge of the big data's beneficial potential.

<Files\\Survey_14> - § 1 reference coded [0,06% Coverage]

Awareness

<Files\\Survey_6> - § 1 reference coded [1,08% Coverage]

Not only is there a lack of understanding of the tools and potential, but as already stated, there is unlikely to be a desire to use them if there are no efficiency gains.

<Files\\Survey_7> - § 1 reference coded [1,14% Coverage]

The actual worth of big data analytics has not been established as yet; the use of simple tools such as MS Excel to analyze student performance suffices at this stage.

(iii) More research

One respondent felt that more research into the challenges faced by other HE institutions would be able to determine the key challenges to big data implementation at Higher Education institutions.

<Files\\Survey_2> - § 1 reference coded [1,22% Coverage]

This question is best answered if the South African universities are interviewed to determine their ACTUAL challenges/barriers that hinder the adoption/implementation of Big Data.

5.5.2.2.2 Funding

As with most technology investments, funding and resource naturally became key challenges. More funding needed to be allocated to ensure an effective system could be acquired to cater to institutional needs.

<Files\\Survey_12> - § 1 reference coded [0,07% Coverage]

And Cost.

<Files\\Survey_13> - § 1 reference coded [0,19% Coverage]

Low financial capabilities

<Files\\Survey_3> - § 1 reference coded [0,06% Coverage]

Funding,

<Files\\Survey_5> - § 1 reference coded [0,10% Coverage]

Lack of funds,

<Files\\Survey_8> - § 1 reference coded [0,06% Coverage]

Funding,

<Files\\Survey_9> - § 1 reference coded [0,13% Coverage]
Government funds.

5.5.2.2.3 Technology and infrastructure

Technology and infrastructure resources were an added challenge. This was due to the following:

(i) Technology deficiency

There seems to be a deficiency of big data and related technologies. Current technology seems outdated and not compatible with big data. This needed to be changed immediately. Higher education was still behind compared to the industry.

<Files\\Survey_5> - § 1 reference coded [0,14% Coverage]

Lack of tools and technologies.

<Files\\Survey_7> - § 1 reference coded [2,41% Coverage]

The technology to integrate analysis with big data sources is still very primitive - industry stakeholders pioneer the use of big data tools, and the academic sector will always play catch-up because academics do not have a clue as to what big data entails, nor do they have the skills or resources to become experts at big data analytics.

<Files\\Survey_8> - § 1 reference coded [0,09% Coverage]

Poor systems.

(ii) Infrastructure

Similarly, the current infrastructure to house new technology needed to be upgraded. For instance, older servers cannot effectively run advanced big data technologies. This infrastructure upgrade is essential to ensure that new technologies can operate optimally, delivering the expected performance and scalability required for tasks like processing large volumes of data in real-time or conducting complex analytical tasks.

<Files\\Survey_1> - § 1 reference coded [0,26% Coverage]

Lack of or limited infrastructure.

<Files\\Survey_4> - § 1 reference coded [0,21% Coverage]

Technological infrastructure,

<Files\\Survey_9> - § 1 reference coded [0,22% Coverage]

Technological infrastructure.

5.5.2.2.4 Support

As with any new technology implementation, support was necessary. Currently, there is a lack of support in the following ways.

(i) Lack of interest

There seemed to be an overall lack of interest institutionally in terms of big data. This brought about reluctance to adopt.

<Files\\Survey_10> - § 1 reference coded [0,76% Coverage]

Institutional inertia and disinterest in embracing emerging technologies to improve educational outcomes.

<Files\\Survey_13> - § 1 reference coded [0,31% Coverage]

Absence of will, reluctance to new learning.

(ii) Leadership support

Leadership plays a crucial role in driving alignment. However, one respondent felt that the current administration was not fully committed nor supportive of big data.

<Files\\Survey_5> - § 1 reference coded [0,49% Coverage]

Top management is not committed to nor supportive of Big Data implementation.

(iii) Data

Data quality was an issue, especially when data was fragmented and coming from different sources at the institution. The standardization and consistency of data is needed.

<Files\\Survey_11> - § 2 references coded [0,53% Coverage]

Reference 1 - 0,09% Coverage

data quality,

Reference 2 - 0,44% Coverage

Gathering and verifying data from diverse sources presents a challenge. Addressing this challenge is critical because the quality and reliability of data play a pivotal role in decision-making processes and the accuracy of analyses.

(iv) Disjuncture

There was also a disjuncture between the academic staff and IT departments. Both needed to be aligned toward the goal of big data. The IT department would serve in acquisition and implementation, while the academic staff would be the primary users.

<Files\\Survey_6> - § 1 reference coded [0,90% Coverage]
There is typically a disconnect between IT service departments that understand and acquire this technology and academic staff who are teaching.

In relation to the sub-theme “Challenges that hinder the implementation of Big Data” discussed above, further studies such as Nasser and Tariq (2015), Drachsler and Greller (2016), and Bamiah et al. (2018) also reveal that while the adoption of big data in higher education has the potential to transform teaching and learning experience, there are several challenges that hinder its implementation. One major challenge is the shortage of competent data specialists. Big data requires specialized data science and programming skills, which many academic staff may not have. This can make collecting, examining, and interpreting data difficult (Bamiah et al., 2018). Additionally, there may be ethical considerations when using big data in higher education (Drachsler & Greller, 2016). South African HEIs must establish well-defined policies and guidelines to guarantee the ethical gathering and utilization of student data, as there is a potential for privacy infringements or adverse outcomes due to mismanagement or misuse. It is crucial to prioritize protecting student data and prevent unauthorized or inappropriate handling of this information (Drachsler & Greller, 2016). Furthermore, there may be resistance to change and reluctance to adopt new technologies among staff that are used to traditional methods of teaching. This can result in a lack of buy-in and support for big data initiatives, making it difficult to effectively implement them (Nasser & Tariq, 2015).

5.5.3 Recommendations for adoption and implementation

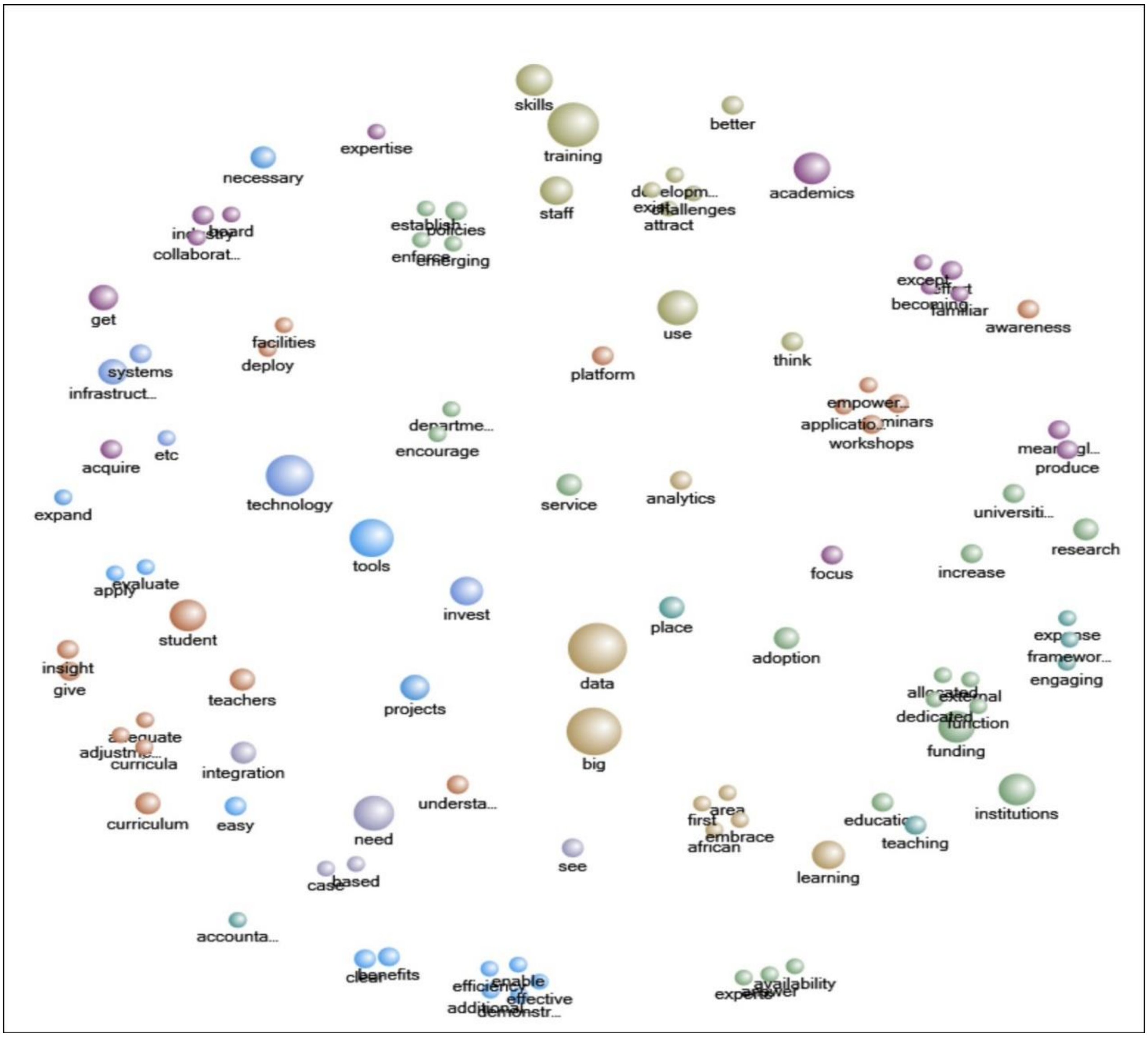

Figure 5.12. Cluster Analysis – Adoption and Implementation Recommendations

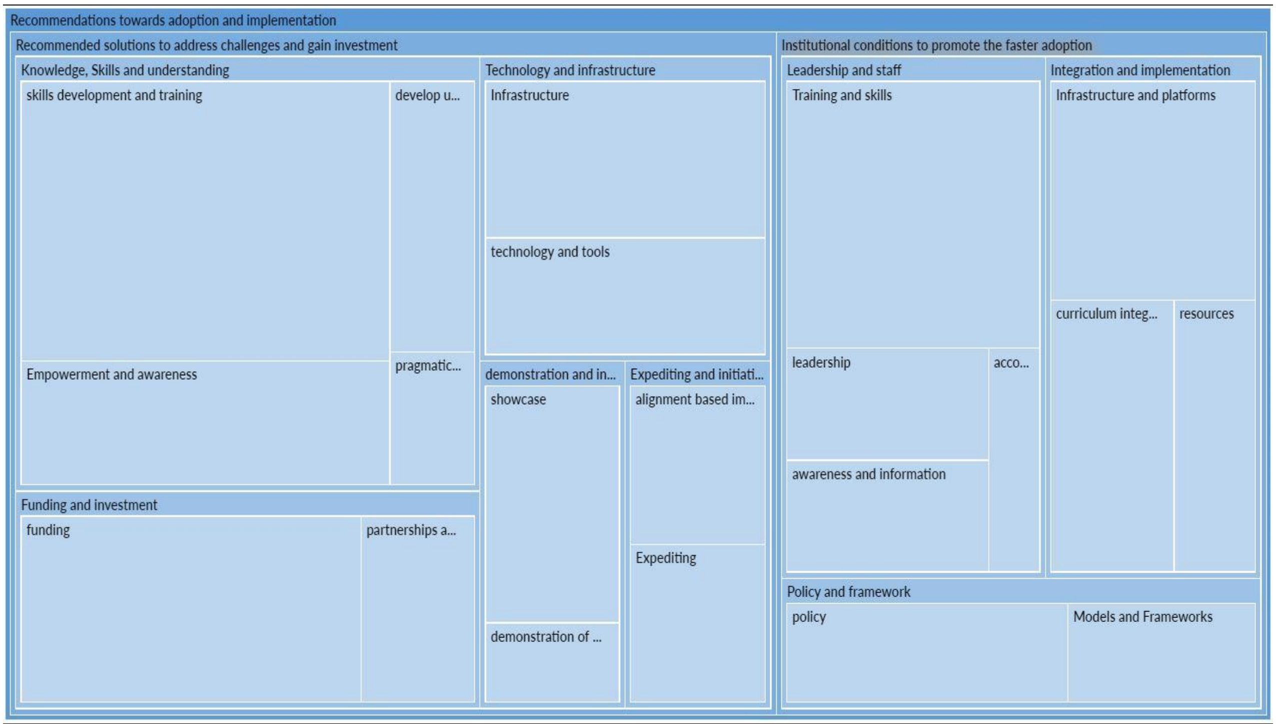

Figure 5.13. Hierarchy Chart – Adoption and Implementation Recommendations

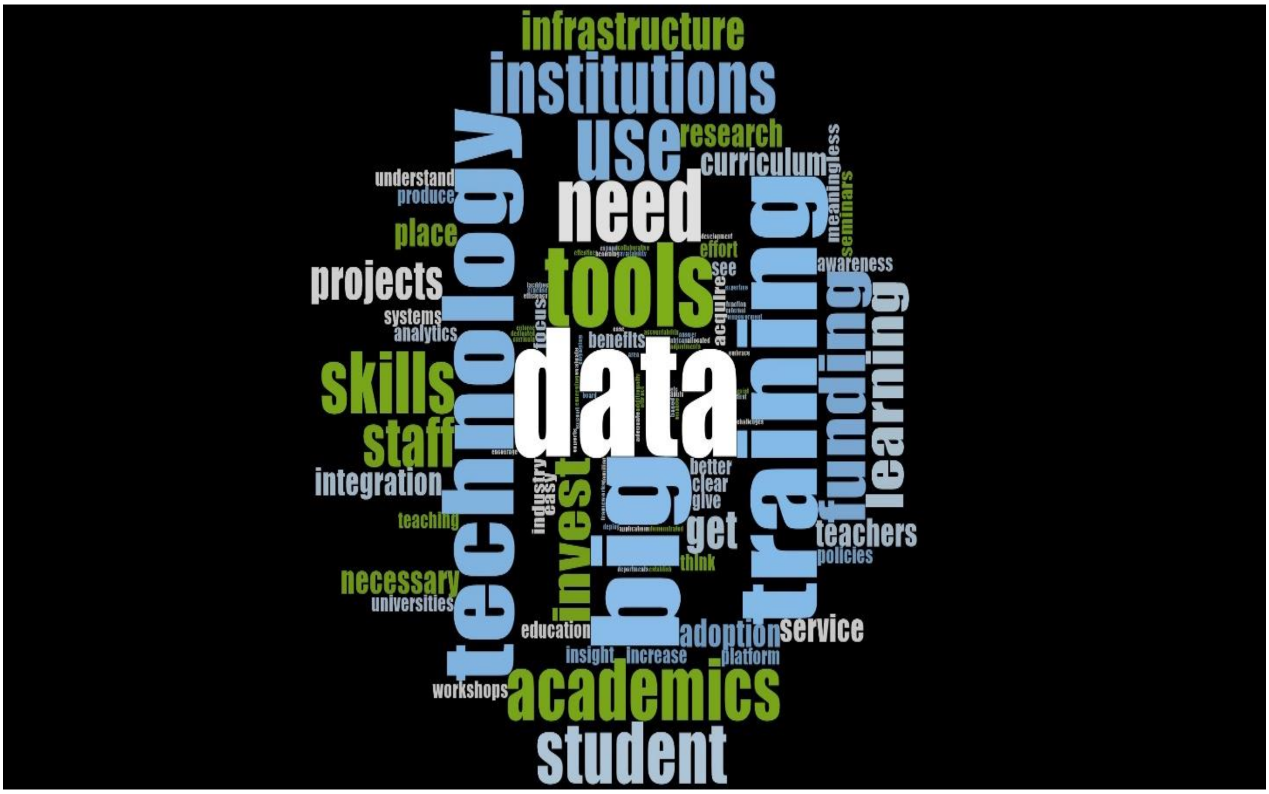

Figure 5.14. Word Cloud – Adoption and Implementation Recommendations

This primary theme recommended addressing implementation challenges and determining the institutional condition necessary for big data implementation.

5.5.3.1 Recommended solutions to address challenges and gain investment

This primary subtheme provided potential recommendations to address challenges and gain investment for big data.

5.5.3.1.1 Knowledge, skills, and understanding

It was first imperative to build knowledge and understanding of big data for staff. This should be complemented by necessary skills development.

(i) Skills development and training

This factor received the highest ranking, which is a logical outcome considering the previous themes highlighted a deficiency in big data-related skills development. Therefore, there was strong agreement on the importance of developing the skills required to successfully implement and utilize big data. Consequently, substantial investment in training is necessary. There must be a high investment in training.

<Files\\Survey_1> - § 3 references coded [0,27% Coverage]

Reference 1 - 0,12% Coverage

Train academics.

Reference 2 - 0,07% Coverage

Training,

Reference 3 - 0,08% Coverage

Upskilling,

<Files\\Survey_11> - § 1 reference coded [0,25% Coverage]

Recruitment of skilled professionals.

<Files\\Survey_14> - § 1 reference coded [0,38% Coverage]

Train people (employees) on the use of technologies or tools.

<Files\\Survey_2> - § 1 reference coded [0,71% Coverage]

Whatever challenges may exist, they can be reduced if the staff are trained to use big data analytics.

<Files\\Survey_4> - § 1 reference coded [0,40% Coverage]

Training of staff on better use of data is important.

<Files\\Survey_5> - § 1 reference coded [0,13% Coverage]

skills development,

<Files\\Survey_8> - § 1 reference coded [0,12% Coverage]

Attract talent,

(ii) Develop understanding

Understanding of big data must be promoted. Once accomplished, the institution can fully embrace big data, opening the doors to potential investors and various opportunities for growth and development.

<Files\\Survey_11> - § 1 reference coded [1,34% Coverage]

South African Institutions should first embrace using big data analytics to promote teaching and learning. Subsequently, investors will see their seriousness and be willing to invest.

<Files\\Survey_4> - § 1 reference coded [0,40% Coverage]

Understand the area of Big Data in education and focus.

(iii) Empowerment and awareness

Building understanding, empowerment, and awareness is crucial. This awareness and empowerment can be achieved by organizing workshops and seminars on big data.

<Files\\Survey_1> - § 2 references coded [0,26% Coverage]

Reference 1 - 0,16% Coverage

Seminars, Workshops,

Reference 2 - 0,10% Coverage

Empowerment,

<Files\\Survey_13> - § 1 reference coded [0,76% Coverage]

Increasing the schools' awareness and platform for teachers' and students' learning of big data applications.

<Files\\Survey_5> - § 1 reference coded [0,14% Coverage]

seminars, workshops.

(iv) Pragmatic efforts vs. theory

One respondent made a vital point about the difference between theory and practice. Higher Education institutions were highly theoretical in research and needed to invest more time in learning more of the practical component of big data technology.

<Files\\Survey_7> - § 1 reference coded [2,03% Coverage]

Universities and academics should invest time and effort in becoming familiar with the technology - using tools such as Python and R - rather than focus on producing meaningless research efforts that are highly theoretical and serve no interest to society except to the academics themselves.

5.5.3.1.2 Technology and infrastructure

Implementing technology and the essential supporting infrastructure is an exquisite and necessary recommendation. In the rapidly evolving landscape of education, integrating technology into various aspects of the institution is vital to stay competitive and delivering a modern and efficient learning experience.

(i) Technology and tools

Big data technologies and tools must be acquired. Tools must be evaluated to ensure that they are adequate and significant to meet the institutional goals of enhanced teaching and learning as well as performance thereof.

<Files\\Survey_13> - § 1 reference coded [0,41% Coverage]

They should get more tools and evaluate their significance.

<Files\\Survey_5> - § 1 reference coded [0,19% Coverage]

Acquire big data technologies.

<Files\\Survey_6> - § 1 reference coded [0,88% Coverage]

So, at a student or lecturer level, there need to be easy-to-apply tools that give valuable insights into learning and performance.

(ii) Infrastructure

As such, infrastructure investment is crucial to ensure that modern technology can work seamlessly**.**

<Files\\Survey_1> - § 2 references coded [0,30% Coverage]

Reference 1 - 0,18% Coverage

Invest in infrastructure.

Reference 2 - 0,12% Coverage

Infrastructure.

<Files\\Survey_8> - § 1 reference coded [0,28% Coverage]

Get modern technology and systems, etc.

<Files\\Survey_9> - § 1 reference coded [0,23% Coverage]

Invest in the right technology.

5.5.3.1.3 Funding and investment

The lack of funding was a key challenge (as mentioned in the challenge theme). Hence the acquisition of funding also became a key recommendation.

(i) Funding

Funding allocations to higher education for big data must be increased. To effectively adopt big data efforts, higher education institutions' budget allocations must be increased expressly for big data projects. Within the universities, more funding must be allocated to the units such as Teaching and Learning, IT, and other dedicated teams that will be the key role players in big data implementation. Moreover, seeking external funding becomes imperative to support these endeavors if internal funding is insufficient.

<Files\\Survey_10> - § 1 reference coded [0,62% Coverage]

Increase funding allocated to higher education institutions and research institutions.

<Files\\Survey_12> - § 1 reference coded [0,30% Coverage]

Release of funding to service the same.

<Files\\Survey_13> - § 1 reference coded [0,25% Coverage]

More funding towards its adoption,

<Files\\Survey_3> - § 1 reference coded [0,49% Coverage]

Funding of dedicated units within the T&L function of the university.

<Files\\Survey_5> - § 1 reference coded [0,26% Coverage]

Source external funding for BD projects,

<Files\\Survey_8> - § 1 reference coded [0,13% Coverage]

Look for adequate funding,

(ii) Partnerships and sponsorships

There should also be partnerships between the institution and industry for more funding and skills development investment.

<Files\\Survey_2> - § 1 reference coded [0,33% Coverage]

Have more industry partnerships to get sponsorships.

<Files\\Survey_5> - § 1 reference coded [0,52% Coverage]

Get industry and academic collaborative partners on board for skills transfer.

5.5.3.1.4 Expediting and initiating

However, the institutions must play a role in starting the implementation processes.

(i) Expediting

The Institutions can expedite big data projects by starting with smaller projects and then expanding as and when necessary.

<Files\\Survey_4> - § 1 reference coded [0,37% Coverage]

Start with small projects and expand when necessary.

<Files\\Survey_5> - § 1 reference coded [0,14% Coverage]

Initiate BD projects.

(ii) Alignment based implementation

There should be an alignment-based implementation whereby there must be integration between respective IT and academic departments. In addition, the institution must collectively encourage the use of such technologies.

<Files\\Survey_12> - § 1 reference coded [0,52% Coverage]

Encourage the use of big data tools and services by students and staff.

<Files\\Survey_6> - § 1 reference coded [0,53% Coverage]

There needs to be more integration between IT service departments and academic staff.

5.5.3.1.5 Demonstration and initiation

Demonstration and initiation can be done in the following ways.

(i) Showcase

Showcasing big data projects can serve to gain support, investment, and trust in the process. Hence, methods to showcase big data, such as roadshows, demos, virtual realities, and related data, must be explored.

<Files\\Survey_6> - § 1 reference coded [1,11% Coverage]

Like most things, money is spent where results are seen. If more investment is to be made in the technologies related to big data, the benefits will need to be clear and easy to see.

<Files\\Survey_8> - § 1 reference coded [0,61% Coverage]

Showcase the projects based on big data and integrate them into the curriculum.

<Files\\Survey_9> - § 1 reference coded [0,19% Coverage]

Propose the need for it.

(ii) Demonstration of benefits

Relating to showcasing, the actual tangible benefits must be demonstrated. This can justify to stakeholders how/why the technologies are needed.

<Files\\Survey_6> - § 1 reference coded [1,06% Coverage]

Additionally, there must be clear and demonstrated benefits as to why the tools/technologies should be used and how they will enable effective and efficient gains.

Further studies such as Martin and Thawabieh (2017), Manohar et al. (2016), Al-Shiakhli (2019), and Ang et al. (2020) also reveal some recommended solutions to address big data challenges and gain investment. According to Ang et al. (2020), higher education institutions (HEIs) should prioritize training and development for staff and faculty to ensure they have the essential skills and knowledge to use and interpret big data effectively. This includes providing training on data analytics tools and techniques and promoting data literacy and critical thinking skills. Al-Shiakhli (2019) states HEIs should prioritize data security and privacy considerations. This involves implementing appropriate data governance and security policies to protect student and institutional data. This can help build trust and confidence in using big data and minimize the risk of data breaches or privacy violations (Al-Shiakhli, 2019). Additionally, HEIs can seek out funding opportunities and partnerships with industry and government to support their big data initiatives. This can involve applying for grants or funding opportunities and building relationships with industry partners to develop new research and innovation projects (Martin & Thawabieh, 2017).

5.5.3.2 Institutional conditions to promote the faster adoption

This subtheme outlines the institutional conditions needed to promote faster adoption of big data technologies.

5.5.3.2.1 Integration and implementation

There must be conditions provided for seamless integration for implementation.

(i) Infrastructure and platforms

As also mentioned in previous themes, infrastructure remains crucial. The proper infrastructural conditions must be fulfilled to ensure that big data technology can work optimally.

<Files\\Survey_1> - § 1 reference coded [0,21% Coverage]

Infrastructures to be set up.

<Files\\Survey_12> - § 1 reference coded [0,26% Coverage]

Provisioning of relevant facilities.

<Files\\Survey_4> - § 1 reference coded [0,21% Coverage]

Technological infrastructure,

<Files\\Survey_8> - § 1 reference coded [0,73% Coverage]

Deploy the necessary tools to implement these techniques. Have platforms, systems, and software in place.

(ii) Curriculum integration

Besides technology infrastructure, big data should be included in the curriculum to make it inclusive of teaching and learning. With the fourth industrial revolution in the current epoch, big data integration in the curriculum can equip students with all the necessary knowledge.

<Files\\Survey_11> - § 1 reference coded [0,78% Coverage]

Giving teachers insight into specific adjustments they can make to the curricula to improve student understanding.

<Files\\Survey_13> - § 1 reference coded [0,64% Coverage]

Including them in the curriculum after adequate sensitization of the teachers and students.

<Files\\Survey_8> - § 1 reference coded [0,23% Coverage]

Integration into the curriculum.

(iii) Resources

Resources must also be readily available to support adoption and navigate difficulties.

<Files\\Survey_13> - § 1 reference coded [0,82% Coverage]

Availability of a big data knowledge base and experts to answer questions related to big data adoption and implementation.

<Files\\Survey_4> - § 1 reference coded [0,08% Coverage]

Big data infrastructures.

5.5.3.2.2 Policy and framework

The institution should also provide conditions at the legislation and governance levels.

(i) Models and Frameworks

There needs to be more model and framework development that instil big data. Currently, intuitions are too ingrained in 'research-based' models. These existing models must be critically evaluated to evolve towards a big data-oriented approach.

<Files\\Survey_1> - § 1 reference coded [0,36% Coverage]

Big Data Models/Frameworks need to be in place.

<Files\\Survey_7> - § 1 reference coded [1,07% Coverage]
I think the imperative handcuffs institutions to produce meaningless research at the expense of engaging in meaningful teaching and learning.

(ii) Policy

Policies and other related guidelines should be developed regarding big data technology adoption and other modern technologies. These policies serve as a framework for institutions to navigate the integration of cutting-edge technologies into their operations effectively. They can encompass aspects like data privacy, security, ethical considerations, and best practices, ensuring that the adoption process aligns with established standards and objectives while minimizing potential risks.

<Files\\Survey_1> - § 1 reference coded [0,13% Coverage]

Big Data Policies

<Files\\Survey_10> - § 1 reference coded [0,63% Coverage]

Establish institutional guidelines for adopting emerging technologies and enforce them.

<Files\\Survey_2> - § 1 reference coded [0,13% Coverage]

Policies, procedures

5.5.3.2.3 Leadership and staff

Big data will also be dependent on leadership and staff conditions.

(i) Leadership

Leadership must create an environment and organizational culture toward big data adoption. They must also be knowledgeable about big data.

<Files\\Survey_10> - § 1 reference coded [0,18% Coverage]

Institutional leadership.

<Files\\Survey_3> - § 1 reference coded [0,17% Coverage]

And skilled management.

(ii) Training and skills

Training must become a strong part of big data conditions for staff to build skills, knowledge, and understanding.

<Files\\Survey_1> - § 1 reference coded [0,34% Coverage]

Academics need to be trained to acquire skills.

<Files\\Survey_14> - § 1 reference coded [0,09% Coverage]

And training.

<Files\\Survey_2> - § 1 reference coded [0,25% Coverage]

Student and staff training is necessary.

<Files\\Survey_4> - § 2 references coded [0,18% Coverage]

Reference 1 - 0,12% Coverage
skills expertise

Reference 2 - 0,06% Coverage
training.
<Files\\Survey_5> - § 1 reference coded [0,06% Coverage]
training.

(iii) Awareness and information

Awareness and more information will allow staff and stakeholders to be better informed about big data developments.

<Files\\Survey_14> - § 1 reference coded [0,07% Coverage]
Awareness

<Files\\Survey_3> - § 1 reference coded [0,11% Coverage]
Better informed

(iv) Accountability

Lastly, there must be accountability by all relevant stakeholders. This can be factored into the job roles and performance management frameworks to drive a culture of responsibility and commitment. Big data implementation will not be realized if this is not in place. Accountability also extends to the institution as a whole. Establishing benchmarks and key performance indicators (KPIs) related to big data implementation allows the institution to track progress and measure the impact of data-driven strategies.

<Files\\Survey_2> - § 1 reference coded [0,20% Coverage]

Accountability must be in place. Accountability creates transparency and encourages open communication around the use of data.

In relation to the sub-theme “Institutional conditions to promote faster adoption” discussed above, additional studies such as Vassakis et al. (2018) and Veldkamp et al. (2021) also reveal a similar argument that big data adoption in higher education necessitates some institutional conditions to promote the faster adoption. According to Veldkamp et al. (2021), strong leadership and support from institutional leaders are crucial to drive the adoption of big data. HEIs top-level management should champion the value of big data analytics (BDA), allocate resources, and create a culture that values data-informed decision-making (Veldkamp et al., 2021). Another crucial condition, according to Vassakis et al. (2018), is fostering collaboration. Big data initiatives require collaboration across different departments and stakeholders in the institution. Institutions should foster a culture of collaboration and provide platforms, tools that facilitate collaboration (Vassakis et al., 2018).

5.6 Summary of Chapter Five

This chapter examined and discussed the respondents’ responses in relation to the study questions, as well as the literature review and UTUAT framework adopted in the study. The vast majority of respondents viewed big data as a valuable asset to improve teaching and learning. Furthermore, they believed that integrating big data tools and technologies would be straightforward, provided appropriate interventions, such as skill development and training, were in place. Additionally, respondents noted that their peers' influence could persuade them to embrace and use big data tools/technologies/platforms to advance their teaching methods. Furthermore, the chapter addressed the big data adoption concerns identified in this context and recommended potential solutions to facilitate the adoption and implementation of big data in South African HEIs.

CHAPTER SIX: SUMMARY, CONCLUSION, AND RECOMMENDATIONS

6.1 Introduction

This final chapter summarizes the study's key findings and results, leading to actionable recommendations and comprehensive conclusions. This chapter also presents recommendations for adopting and integrating big data analytics (BDA) within the South African higher education system. The chapter concludes with suggestions for future research to expand knowledge in the field and fill any gaps revealed via the current study, promoting continuing advancement and growth in this research area.

6.2 Summary of the Study

The study commenced by presenting an overview of the big data paradigm. Subsequently, it emphasized the existing condition of South African HEIs, shedding light on the difficulties these institutions and educators face in delivering high-quality education. The study recognized the potential of big data approaches as a transformative solution to overcome these challenges and improve educational outcomes. Based on the literature review conducted in Chapter Two, various studies have emphasized the potential benefits of utilizing big data for teaching, training, and learning purposes in higher education. The UTAUT framework was adopted in this study to investigate the key factors influencing the adoption and integration of big data to advance teaching and learning experiences. By leveraging the UTAUT framework, which is widely recognized for its applicability in technology acceptance research, the study sought to gain valuable insights into the perceptions and attitudes of individuals towards embracing big data solutions in the higher education landscape. Understanding these factors was vital, as it directly affects the successful implementation of new technology solutions.

Furthermore, the study utilized a qualitative research design by using open-ended questionnaires (surveys) to collect detailed and contextual information. Thematic analysis was employed to examine the data gathered from these open-ended questionnaires, which entails identifying and categorizing key themes and patterns within the data. The investigation uncovered common perceptions, experiences, and concerns related to the adoption of big data approaches within the South African higher education context. The findings of this qualitative study unveiled several themes that provide insights into adopting big data approaches in South African higher education. These themes included the potential of big data to inform personalized learning experiences, enhance student engagement, and support evidence-based decision-making by educators. The study findings also highlight several issues, including the limited availability of competent data experts, concerns surrounding data privacy and security, and the need for sufficient funding. The study suggests that implementing targeted approaches and interventions, such as enhancing infrastructure, fostering collaborative partnerships with technology-centric industries, establishing professional development initiatives, and providing training programs, are crucial to promoting big data solutions in educational settings. Finally, this research study serves as a groundwork for future investigations in the field. It offers valuable insights and guidance to institutions aiming to enhance teaching and learning by adopting and utilizing big data.

6.3 Limitations of the Study

Limitations of any study can be referred to as possible shortcomings that are typically outside the investigator's control but have an influence on the research findings and are primarily associated with the study design, sample limits, financial constraints, data collection, and presentation methods used (Theofanidis & Fountouki, 2018). Some limitations of this study must be acknowledged. Firstly, the option to conduct full-scale field (primary) research was hampered by COVID-19 and social distancing restrictions. As a result, secondary research resources such as academic papers and books were used in this study to assist the researcher in understanding the subject matter under examination. Secondly, the literature review reveals specific research gaps that offer potential avenues for future exploration. The study's reliance on only qualitative data collection methods may also limit the depth of the analysis in some areas. Therefore, further study with a larger sample size might be needed to ensure a holistic understanding of the subject matter. Finally, exploring the ethical implications of adopting and using big data in education could not be extensively addressed due to time and resource constraints. Ethical considerations in the context of big data are complex and multifaceted, warranting careful examination in future research endeavors. Despite these limitations, the study provides crucial insights into big data adoption and implementation.

6.4 Recommendation

Consistent with prior UTAUT studies, the main findings emphasize the significance of performance expectancy, effort expectancy, social influence, and facilitating conditions in shaping employees' intentions to adopt big data. This indicates that employees who anticipate performance-related benefits from utilizing big data and perceive management's support and recognition for their efforts are more inclined to adopt big data compared to those who perceive fewer performance benefits and limited management involvement. Practitioners can significantly benefit from these valuable findings as they provide empirically supported insights for designing effective big data intervention plans. Numerous recommendations have been identified to facilitate the adoption and integration of big data analytics (BDA) within the South African higher education system:

(1) HEIs in South Africa should focus on fostering strong leadership engagement. This involves developing a clear vision for incorporating big data approaches in teaching and learning. A well-defined strategy that aligns with institutional goals and priorities should be developed, outlining the specific objectives, expected outcomes, and implementation steps (Veldkamp et al., 2021).

(2) It is crucial for institutions to effectively communicate the performance benefits that arise from using big data. The acceptance of big data can be enhanced by establishing a common understanding of how its utilization enables employees to gain performance advantages in their job-related tasks.

(3) To ensure the successful adoption of big data, HEIs should focus on fostering strong leadership engagement. This involves actively motivating employees to leverage big data in various ways. One approach is building data literacy among employees. South African HEIs should establish training programs, workshops, and partnerships with industry experts to upskill faculty and staff in data analysis, data visualization, machine learning, and other relevant areas. This will ensure that there are skilled professionals who can effectively utilize big data analytics tools (Ang et al., 2020). Furthermore, establishing data-driven mindsets among employees through ongoing support and guidance can contribute to a culture that embraces big data for informed decision-making.

(4) Before full-scale big data implementation, HEIs should consider conducting pilot projects to assess the feasibility and effectiveness of big data approaches in specific educational contexts. Rigorous evaluation should be performed to measure the impact on teaching practices, student engagement, and learning outcomes. The success of these pilot projects can generate enthusiasm and support for broader implementation.

(5) Investment in robust data infrastructure and systems is crucial for effectively harnessing the potential of big data in education. South African HEIs should invest in robust data infrastructure, including hardware, software, and networking capabilities, to support collecting, storing, and processing large volumes of data. This may involve cloud computing solutions, high-performance computing systems, and scalable storage solutions (Dahdouh et al., 2017).

(6) HEIs in South Africa should prioritize data privacy and security to maintain the trust of students, faculty, and staff. HEIs must implement strict data access controls, anonymization techniques, and encryption measures to protect sensitive information. Furthermore, HEIs must adhere to relevant data protection regulations, such as POPIA and others in South Africa (Ahmad et al., 2023).

(7) It is imperative for HEIs to establish partnerships with external organizations, such as technology-centric organizations, industry experts, technology providers, and research institutions, to leverage their expertise and technologies in implementing big data approaches. Collaborations can facilitate knowledge exchange, access to cutting-edge tools, and real-world applications (Martin & Thawabieh, 2017). Collaborative initiatives can include sharing data, research projects, and best practices, accelerating the adoption and integration of big data analytics (Murumba & Micheni, 2017).

(8) HEIs should effectively showcase the business value derived from the utilization of big data over different timeframes, including the short, medium, and long term. This entails demonstrating the tangible benefits and outcomes of harnessing big data analytics in various aspects of the institution's operations. By providing evidence of the positive impacts on key performance indicators, such as improved student outcomes, enhanced

operational efficiency, informed decision-making, and premeditated planning, higher education institutions can emphasize the value proposition of big data.

6.5 Conclusion of the Study

The study has demonstrated substantial potential for enhancing teaching and learning results within South African Higher Education Institutions (HEIs) through the application of big data analytics (BDA). However, the adoption of BDA in the South African higher education system can be hindered by the various challenges identified in Chapter Two. Despite these challenges, the study has identified several key recommendations for HEIs adopting a big data approach to teaching and learning. These include and are not limited to the need for investment in infrastructure and training, the formulation of data governance protocols, the infusion of big data concepts into the educational framework, and the need for partnerships with industry data experts and other data-driven institutions. Furthermore, this study offers valuable contributions to the UTAUT framework and the literature on big data adoption. It demonstrates that the UTAUT constructs provide a solid foundation for identifying factors influencing the intention to adopt big data.

Furthermore, this study offers a preliminary understanding of the nascent phase of big data implementation. This study takes an important step towards bridging the knowledge gap by identifying the impact of factors such as PE, EE, and SI on big data adoption intention. This study lays a foundation for further research in this area. It provides valuable insights and guidance for institutions interested in advancing teaching and learning through the application of big data. Future research could incorporate additional theories to provide a more comprehensive understanding of successful big data adoption. Finally, by addressing the challenges identified and implementing the recommendations provided above, HEIs in South Africa can leverage big data analytics (BDA) to improve student outcomes, enhance the teaching and learning experience, and contribute to the sector's advancement in the country.

6.6 Suggestions for Further Research

Due to time constraints, the researcher admits that not all factors and impediments to big data adoption in higher education were explored. As a result, the researcher suggests conducting a further comprehensive investigation to explore additional elements that might impact big data adoption in South African higher education. Further research should encompass a broader range of perspectives by including multiple educational institutions to capture the viewpoints of various stakeholders. Additionally, future studies could explore the integration of other emerging technologies, such as Artificial Intelligence (AI), Augmented Reality (AR), and Cloud Computing (CC) with big data to advance teaching and learning in the South African higher education context. Lastly, further research should include comparative analyses between adopting big data analytics in South African higher education and other developed and developing countries. This would help identify best practices and extract valuable lessons from international experiences.

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APPENDICES

Appendix A: Alignment of the theoretical framework with the study questions, objectives, and proposed open-ended survey questions.

UTAUT Constructs	Study Objectives	Research Questions	Proposed Open-Ended Survey Questions
1. Performance Expectancy	• To determine the perceived usefulness of adopting and implementing big data in advancing teaching and learning in a South African higher education context.	• What is the perceived usefulness of adopting and implementing big data in advancing teaching and learning in a South African higher education context?	a. How beneficial would big data be in the context of teaching and learning? b. How can big data be utilized to facilitate teaching and learning? c. Provide some examples of how big data could be used to improve teaching and learning?
2. Effort Expectancy	• To determine the perceived effort needed to adopt and implement big data in advancing teaching and learning in a South African higher education context.	• What is the perceived effort needed to adopt and implement big data in advancing teaching and learning in a South African higher education context?	a. Do you think it will be difficult for academic staff and students to use big data technologies to facilitate teaching and learning? b. What makes you think this way?
3. Social Influence	• To identify the key factors influencing big data adoption and implementation in	• What are the key factors influencing big data adoption and implementation in	a. What are the factors that influences big data adoption and implementation in a South African higher education context?

	advancing teaching and learning in a South African higher education context.	advancing teaching and learning in a South African higher education context?	
4. Facilitating Conditions	• To identify the opportunities and challenges to big data adoption and implementation in advancing teaching and learning in a South African higher education context. • To propose viable solutions to the identified challenges.	• What are the opportunities and challenges to big data adoption and implementation in advancing teaching and learning in a South African higher education context? • How to overcome the challenges associated with big data adoption in a South African higher education context?	a. What kinds of challenges do you foresee to the adoption and implementation of big data in a South African higher education context? Please elaborate on each type of challenge. b. What solutions would you recommend addressing the challenges?

Appendix B: Gatekeepers Approval Letter

UNIVERSITY OF KWAZULU-NATAL
INYUVESI YAKWAZULU-NATALI

12 August 2022

Oluwadamilola Samuel Obagbuwa (SN 218030337)
School of Management, IT and Governance
College of Law and Management Studies
Westville Campus UKZN
Email: 218030337@stu.ukzn.ac.za singhup@ukzn.ac.za

Dear Oluwadamilola

RE: PERMISSION TO CONDUCT RESEARCH

Gatekeeper's permission is hereby granted for you to conduct research at the University of KwaZulu-Natal (UKZN), towards your postgraduate degree, provided Ethical clearance has been obtained. We note the title of your research project is:

"The adoption of a big data approach to advance teaching and learning in the context of South African higher education."

It is noted that you will be constituting your sample by handing out questionnaires to academic staff and/or postgraduate students from the School of Management, IT and Governance (Zoom, Skype or telephone interviews recommended) at UKZN.

Please ensure that the following appears on your notice/questionnaire:

- Ethical clearance number;
- Research title and details of the research, the researcher and the supervisor;
- Consent form is attached to the notice/questionnaire and to be signed by user before he/she fills in questionnaire;
- gatekeepers approval by the Registrar.

You are not authorized to contact staff and students using the 'Microsoft Outlook' address book. Identity numbers and email addresses of individuals are not a matter of public record and are protected according to Section 14 of the South African Constitution, as well as the Protection of Public Information Act. For the release of such information over to yourself for research purposes, the University of KwaZulu-Natal will need express consent from the relevant data subjects. Data collected must be treated with due confidentiality and anonymity.

Yours sincerely

[redacted]

Dr KE CLELAND: REGISTRAR

Office of the Registrar
Postal Address: Private Bag X54001, Durban, 4000, South Africa
Telephone: +27 (0)31 260 7971 **Email:** registrar@ukzn.ac.za **Website:** www.ukzn.ac.za

Founding Campuses: Edgewood Howard College Medical School Pietermaritzburg Westville

INSPIRING GREATNESS

Appendix C: Ethical Clearance letter

UNIVERSITY OF KWAZULU-NATAL
INYUVESI YAKWAZULU-NATALI

12 October 2022

Oluwadamilola Samuel Obagbuwa (218030337)
School Of Man Info Tech & Gov
Pietermaritzburg Campus

Dear OS Obagbuwa,

Protocol reference number: HSSREC/00004618/2022
Project title: The adoption of a big data approach to advance teaching and learning in the context of South African higher education
Degree: Masters

Approval Notification – Expedited Application

This letter serves to notify you that your application received on 17 August 2022 in connection with the above, was reviewed by the Humanities and Social Sciences Research Ethics Committee (HSSREC) and the protocol has been granted **FULL APPROVAL**.

Any alteration/s to the approved research protocol i.e. Questionnaire/Interview Schedule, Informed Consent Form, Title of the Project, Location of the Study, Research Approach and Methods must be reviewed and approved through the amendment/modification prior to its implementation. In case you have further queries, please quote the above reference number. PLEASE NOTE: Research data should be securely stored in the discipline/department for a period of 5 years.

This approval is valid until 12 October 2023.
To ensure uninterrupted approval of this study beyond the approval expiry date, a progress report must be submitted to the Research Office on the appropriate form 2 - 3 months before the expiry date. A close-out report to be submitted when study is finished.

HSSREC is registered with the South African National Research Ethics Council (REC-040414-040).

Yours sincerely,

[redacted]

Professor Dipane Hlalele (Chair)

/dd

Humanities and Social Sciences Research Ethics Committee
Postal Address: Private Bag X54001, Durban, 4000, South Africa
Telephone: +27 (0)31 260 8350/4557/3587 **Email:** hssrec@ukzn.ac.za **Website:** http://research.ukzn.ac.za/Research-Ethics

Founding Campuses: Edgewood | Howard College | Medical School | Pietermaritzburg | Westville

INSPIRING GREATNESS

Appendix D: Survey (Open-ended Questionnaire)

Data was gathered via an online open-ended questionnaire or survey created using Google forms.

Evaluation of a big data approach to advance teaching and learning in the context of South African higher education

Information Sheet and Consent to Participate in Research...just a few minutes of your time please:)

* Indicates required question

Details of the Researcher and the Study

Greetings,

My name is Oluwadamilola Samuel Obagbuwa (Student No: 218030337) and I am currently studying for a Master of Commerce (M-Com) degree at the University of KwaZulu-Natal (UKZN), in the School of Management, Information Technology and Governance. My field of study is in information systems and technology (IST). The following are the contact information for myself, my supervisor, and the academic department at UKZN:

Researcher Name: Oluwadamilola Samuel Obagbuwa; e-mail: 218030337@stu.ukzn.ac.za
Supervisor Name: Dr. UG Singh; email: singhup@ukzn.ac.za
Office contact Number: 0312607955
Department of Information Systems & Technology: +27 33 260 5704; + 27 31 260 7051

You are being invited to consider participating in a study titled" The adoption of a big data approach to advance teaching and learning in the context of South African higher education". The integration of big data in higher education is an emerging concept and, as a result, there is limited literature from a South African viewpoint regarding the usage of big data for educational and training purposes in higher education. The purpose of this study is to bridge the gap in the literature from a South African viewpoint by examining the factors influencing big data adoption in the context of higher education. This exploratory study seeks to explore higher education through the lens of big data application and methods in order to enhance innovation in teaching, learning, sociality, and technology for students. The study is expected to include participants from the School of Management, Information Technology, and Governance at the Westville and Pietermaritzburg campuses of UKZN. In order to generate a purposive sample, the researcher will be primarily keen in academic staffs and/or postgraduate students from the School of Management, IT, and Governance, primarily from the Discipline of Information Systems and Technology because Big Data Analytics is one of the IST Discipline's focus areas. The study comprises of a survey-based response to questions attesting to your perspective and knowledge of big data in the context of advancing teaching and learning. The duration of your participation if you choose to participate and remain in the study is expected to be approximately 25 minutes.

Importance of your participation

The study is very relevant to the South African context because it proposes a big data framework for facilitating creative teaching - learning process in higher education. In this study, the notion of big data generates a higher standard measurement for educational achievements. Adoption of a big data approach in higher education can assist lecturers to discover areas where students underperform or excel, understand specific student needs, and develop effective and tailored teaching strategies. This research will also help researchers determine the current state of research on student progression and retention rates using big data analytics in a higher educational context.

This study has been ethically reviewed and approved by the UKZN Humanities and Social Sciences Research Ethics Committee (approval number: HSSREC/00004618/2022).

In the event of any problems or concerns/questions you may contact the researcher at (Researcher e-mail: 218030337@stu.ukzn.ac.za; cell number: 0626280798) or the UKZN Humanities & Social Sciences Research Ethics Committee, contact details as follows:

HUMANITIES & SOCIAL SCIENCES RESEARCH ETHICS ADMINISTRATION
Research Office, Westville Campus
Govan Mbeki Building
Private Bag X 54001
Durban 4000 KwaZulu-Natal, SOUTH AFRICATel: 27
31 2604557- Fax: 27 31 2604609
Email: HSSREC@ukzn.ac.za

Your participation in the study is entirely optional, and by doing so, you grant the researcher permission to utilize your responses. You may refuse to participate in or withdraw from the study at any time without penalty. Your identity will be protected by the researcher and the School of Management, Information Technology, and Governance, andyour responses will not be utilized for any reason other than this study.

During the study, all data, both electronic and hard copy, will be safely saved and archived for 5 years. All data will be erased after this time.

Please contact me or my research supervisor using the contact details mentioned above ifyou have any questions or reservations about participating in the study.

Thanks.

Agreement to Participate

I was made aware of the study titled (The adoption of a big data approach to advance teaching and learning in the context of South African higher education) by (Oluwadamilola Samuel Obagbuwa).

I understand the study's aims and objectives.

I was given the opportunity to ask questions concerning the study and received satisfactory responses.

I declare that my participation in this study is fully voluntary and that I have the right to withdraw at any time without losing any of the benefits to which I am normally entitled.

If I have any questions or concerns about my rights as a study participant, or if I am concerned about an aspect of the study or the researchers then I may contact:

HUMANITIES & SOCIAL SCIENCES RESEARCH ETHICS ADMINISTRATION
Research Office, Westville Campus
Govan Mbeki Building
Private Bag X 54001
Durban
4000
KwaZulu-Natal, SOUTH AFRICA
Tel: 27 31 2604557 - Fax: 27 31 2604609
Email: HSSREC@ukzn.ac.za

1. Do you wish to participate? *

Mark only one oval.

Yes *Skip to question 2*

No *Skip to section 5 (Declined Participation)*

Declined Participation

You have declined to participate in the survey. Thanks for your time. You may close the browser or click on the submit button below.

Section A: Demographic Questions

2. Which campus are you based at? *

Mark only one oval.

Westville

Pietermaritzburg

3. What gender do you identify as? *

Mark only one oval.

Male

Female

Prefer not to say

4. What is your age? *

Mark only one oval.

18 - 24 years

25 - 34 years

35 and above

5. Please specify your ethnicity *

Mark only one oval.

African

White

Indian

Coloured

Other

6. What is the highest degree or level of education you have completed? *

Mark only one oval.

- Degree
- Postgrad Diploma
- Honours
- Masters
- PHD or higher

SECTION B: MAIN QUESTIONS

Understanding the Big Data Paradigm

A big data approach can be defined as a strategy to manage big data from several sources or databases. With huge amounts of data created every second across the Internet, big data is a new approach in data analytics for discovery, analysis, and also to extract value from large volumes of data.

In this big data era, higher education institutions create a large quantity of data on a regular basis that may be used to provide beneficial services to its stakeholders. For instance, big data may facilitate learning by providing access to credible information sources. Hence, it can improve student engagement, interaction, and consistent content delivery. The following questions are aimed to help the researcher understand the usefulness of big data and analytics in the context of advancing teaching and learning in higher education.

7. The benefits of big data in teaching and learning as found in the literature includes (**For students:** personalizing learning, course recommendation; For **educators:** analyzing student behavior, predicting student performance, grouping and modeling students, improved data visualization; For **administrators:** organizing educational resources, enhancing educational programs, and evaluating teachers and curricula; **For course developers:** evaluating courseware, improving student learning, and constructing student and tutor models). How do you think the adoption of big data at UKZN would benefit Teaching and Learning? *

8. Some of the most beneficial techniques available for big data analytics that aid in facilitating teaching and learning in higher education includes (data acquisition, data clustering, data mining, data visualization) as found in the literature.

Data acquisition: Big data acquisition as described in the literature is the process of gathering and identifying data produced by learning systems, which may include learner information (profile, knowledge, skills, etc.), pedagogical resources of any kind (text, image, video, etc.)

Data clustering: Data clustering as described in the literature is a prominent unsupervised technique that is used for Big Data Analysis. This method divides data by grouping records based on some identical properties or uniform structure.

Data mining: Educational data mining as described in the literature can be used to categorize and predict student performance, dropouts, and educator performance. It can assist educators in tracking academic progress in order to enhance the teaching process.

Data Visualization: Data visualization as described in the literature is the process of putting information into a visual context, such as a map or graph, to make it easier for the human brain to absorb and extract insights from. The primary purpose of data visualization is to make identifying patterns, trends, and outliers in huge data sets easier.

How can these techniques be applied as a means of improving the Teaching and Learning process at UKZN?

9. Big data applications/tools that aid in facilitating the teaching and learning process in higher education includes (Apache Storm, Cloud Services, Socrative, Classroom Monitor, Civitas Learning) as found in the literature.

Apache Storm: Apache Storm as described in the literature is a free and open source distributed real-time computation system. Apache Storm makes it easy to reliably process unbounded streams of data.

Cloud Services: As found in the literature, the public cloud has emerged as an appropriate big data platform. The cloud provides resources and services that any institution may utilize on demand. As a result, the cloud makes big data technologies accessible and affordable to organizations of all sizes.

Socrative: Immediate feedback is an essential aspect of the learning process. Socrative as described in the literature provides just that for the classroom- an effective approach to monitor and assess learning that saves time for instructors while providing engaging interactions for students.

Classroom Monitor: Classroom Monitor as described in the literature provides a range of reports and analysis that can be generated from teachers' assessments and can be used to inform the next steps of learning for students.

Civitas Learning: This platform as described in the literature provides the capabilities and intelligence needed to deliver multi-faceted, data-activated student impact strategies that improve student outcomes and build sustainable institutions.

How would these applications/tools described above benefit Teaching and Learning at UKZN?

10. How should lecturers utilize big data analytics to analyze student performances? (for example, the use of Big Data in identifying areas where students are underperforming or performing) *

11. What should South African institutions of Higher Education do to gain more investment into big data analytics to promote innovative teaching and learning? *

12. Learning Analytics as described in the literature can be referred to collecting, measuring, analyzing and reporting the data regarding students and their circumstances, with the intend of understanding and improving their learning and the region in which it results. *

Institutional Analytics as described in the literature refers to analyzing operational data to support effective decision making at an institutional level like instructional analytics, assessment policy analytics and structural analytics.

How can the implementation of these two types of educational big data analytics contribute to improving overall academic and institutional performance and efficiency at UKZN and/or other South African higher education institutions?

13. Some of the factors that can influence the adoption and implementation of big data in the context of promoting quality teaching and learning in higher education includes (data privacy, data compatibility, institutional readiness, relative advantage, government regulations, educational stakeholders' full cooperation and support) as found in the literature. How do these factors influence the adoption and application of big data in the context of promoting quality teaching and learning at UKZN? Please elaborate *

14. From the literature it was discovered that "Several South African universities or colleges lack big data analytics capabilities", What do you think can be the potential challenges/barriers that hinder the adoption/implementation of Big Data in your department and/or other South African Universities? *

15. What solutions would you recommend to address the challenges mentioned above? *

16. What are the institutional conditions that must be created to promote the faster adoption of Big data by teachers and students in relation to the teaching and learning process? *

Section C: Thank You for the Time & Consideration

Your input is highly valued and will contribute to the advancement of the teaching and learning process in the context of higher education:)

17. Please provide any further suggestions that would help the researcher understand why a Big Data approach should be adopted in order to improve the quality of education in general

I really appreciate your assistance...Please click the submit button