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Digital Technologies and Analytics:
An Investigation on University Academic Staff Perceptions of the Role 'Big Data and Analytics' might play in Teaching and Learning.

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Abstract

This thesis investigates variation in how academics account for Big Data (BD) in teaching and learning in higher education from a single institution in the United Kingdom (UK).

The study adopted a phenomenographic research approach in order to elicit and give a detailed qualitatively different ways in which academic staff experienced Big Data and Analytics in teaching and learning. These phenomenographic results were based on a purposive sample of thirty-six academic staff as participants who ranged from gender, age, academic positions, and careers across the nine schools in the university. Semi structured interviews were used for data gathering in this study and these were subjected to a rigorous phenomenographic analysis. In this study the analysis revealed qualitative differences in academic staff accounts of their experience with Big Data which constituted five hierarchical descriptions of categories in the role that Big Data emerges which included *(1) no knowledge, (2) large amount of data, (3) evidence of student support, (4) structured information, (5) evidence of professional development.* These findings highlighted the fact that academic staff hold on views about Big Data to an extent that has not always been acknowledged in existing literature in teaching and learning in higher education.

This research gives a more comprehensive picture of the way academic staff experience the role that Big Data plays in teaching and learning, however the research also revealed the incompleteness of this world picture and suggests the need to carry out further research on the topic to enhance the existing knowledge.

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Abbreviated Terms

AI-Artificial Intelligence

BD-Big Data

BDA-Big Data Analytics

GAI-Generative Artificial Intelligence (Chat GPT, Chatbot)

GDPR-General Data Protection Regulation under Data Protection Act 2018

HE-Higher Education (University studies)

LA-Learning Analytics

LMS-Learning Management System

ML-Machine Learning (Deep Learning)

JIT-Just in Time

SEM-Student Engagement Monitoring System (MyProgress)

TEL -Technology Enhanced Learning

TL -Teaching and Learning

VLE -Virtual Learning Environment

7Vs -Volume, Velocity, Variety, Variability, Veracity, and Visualisation (Daniel, 2017)

NL -Networked Learning

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List of Figures and Tables

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Completed Taught Work on Doctoral Programmes

The research papers below were submitted as part of the requirements of the e-Research and Technology Enhanced Learning Doctoral Programme with a total of 25,000 words and with a credit passed successfully.

- **Module 1 (ED. S821) "**To what extent do Teaching Academics have Autonomy in Technology Enhanced Learning (TEL) Policies and Practices?": A Grounded Theory approach.

- Module 2 (ED. S822) "An investigation on indicators of learner experience with Technology in Networked Learning: Learner and Educator perceptions of connectivity with technology": A Literature Review approach. To submit to the Information Systems Journal 20/21.

- **Module 3 (ED. S823) "**To investigate the collective variation in perception, experience, or opinion of academic staff about Teaching Excellence in TEF in school of computing": A Phenomenographic approach. ***Presented the methodology to the post doc workshop in LBU and to submit a paper to the Information Systems Journal 20/21.***

- **Module 4 (ED. S824) "**A Theory Practice Gap between Networked Learning (NL) and Big Data (BD): Why Big Data has not been widely discussed in Networked Learning in Higher Education: The absence of theory": A Document Analysis approach. ***Presented at HEA workshop 2018. The research paper for module 4 was presented at HEA conference Neural-Pathway Enhanced Learning Framework (NPL) for Teaching Advanced Software Engineering Course 2017/18.***

- **Module 5 (ED. S825) "**A Critical Analysis of Barriers from Interculturality, Globalisation, Multiculturalism and Culture that impact on Technology Enhanced Learning adoption and Developments for academic staff in Higher Education": A Theoretical Study approach.

- **Module 6 (ED. S826)** "Academic Staff Perceptions of the Role 'Big Data and Analytics' might play in Teaching and Learning". ***Presented the Topic and Poster at the 2018 Intellectual Summer Conference.*** Lancaster's Intellectual Party/Summer Conference is a fantastic opportunity to meet with research students from around the world, discuss your work in a friendly and encouraging environment and engage with some of Lancaster's renowned academic staff. The Intellectual Party is more than just another conference – it combines academic challenge with a lot of fun as well!

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My respects to COVID-19 for the tsunami revolution to normal times and disrupting my studies but I took a no stance to ‘surrender’!

Author's declaration: Candidates must make a declaration that the thesis is their own work and has not been submitted in substantially the same form for the award of a higher degree elsewhere. Any sections of the thesis which have been published, or submitted for a higher degree elsewhere, shall be clearly identified. If the thesis is the result of joint research, a statement indicating the nature of the candidate's contribution to that research, confirmed by the supervisor(s), shall be included.

Signature: Margaret Chawawa

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Chapter One: Introduction

1.0 Introduction

In the last decade the world has witnessed tremendous social and technological developments in the use of technology in teaching and learning and these are becoming a '*must'* as opposed to being in a state of '*enablers'* in pedagogy (Mercader, & Gairín, 2020; Guggemos & Seufert, 2020; Ellis & Goodyear, 2013). Their individual research further argues that teaching in modern universities is very difficult to sustain as a solo activity in the present climate in associated activities such as assessment, planning programs, management, and mapping graduate attributes (Daniel, 2017; Arnold, Ham, Pappas, & Rehrey, 2020). It is argued that it is rare to find an individual academic staff who has all the knowledge and experience needed to make the best choices among learning tasks, technologies, and ways of organising students, and to make sure that these choices are aligned efficiently (Kirkwood & Price 2013; Ellis and Goodyear, 2013). According to Daniel, (2015; 2017; 2019) Big Data is an emergent field of research which is dominating in higher educational circles and environments which, includes supporting data generated from networked learning environments. Daniel further states that networked learning and Big Data is extending the horizon of opportunities that can be ceased upon in higher education. Williamson (2017, p. 28) concurs by adding a voice of 'neglect' in educational digital data, although he does not delineate in terms of tertiary, secondary or higher education but presents a term that is true and common across these educational classifications. There are still pockets of challenges existing in higher education in relation to the myth that information age groups are moving into higher education (Deepwell & Malik, 2008) who are deemed to be digitally literate and will demand more in technological hierarchy of needs in their curriculum. This digital information age group interact more with technology and producing more raw data for Big Data Analytics in higher education for opportunities and challenges. This adds to the already complex scenario that university teaching and learning falls in, which has direct links to Big Data in managing communication, flexibility in learning. The integration of distance networked technologies (Goodyear, 2005) in higher educational curricula of the time did not visualise the current use and such demands as ‘complex learning spaces’fast-changing world (Goodyear, 2020) including natural disasters like Coronavirus. It is anticipated that complexity in Big Data will grow faster alongside the overwhelming technological acceptance and growth within higher education as Big Data is becoming a key part of the educational landscape in this century (Williamson, 2017).

1.1 Background to the Research Study

The aim of the research study reported in this thesis is to investigate variation in university academic staff perceptions of the role of ‘Big Data’ in teaching and learning and how they experience it. This follows many years of working as an academic staff and in outlining the background to this research study I consider:

- My research background as a researcher and practitioner, to be aspects that are driving, and motivating factors for this current research.
- The research participants to be an integral part of the research in their individual capacity generating research data which heavily contributes to the research outcome Space.
- The research participants to be an integral part of the research in their individual capacity in using Big Data analytics.

This research study was triggered and the motivation for conducting it, stemmed from an earlier research paper, I carried out in the taught module four in the aspect of this PhD on ‘*Networked*

Learning' and inspired by Goodyear, (2005) and Goodyear & Retalis, (2010) in which he highlighted the complexities of data from networked learning. In addition, my teaching in coding and information systems strategies in computing with Big Data being a concern in a few highlighted topical issues (Daniel, 2015) and finally the Big Data study which was carried out by Chaurasia & Rosin, (2017) in teaching and learning in higher education. During the course of the networked learning research paper, it became apparent that academic staffs' understanding, or views on Big Data and Analytics have not been considered in any related research at the time and yet academic staff significantly use a number of technologies that generate Big Data and Analytics in that environment. I continued to observe the lack of examination of academic staff's experiences of Big Data Analytics (BDA), which continued to be noted as the voices from Networked Learning (NL) and BDA links to higher education started to become louder and louder (Daniel, 2015). In all these processes, whilst addressing paper requirements or teaching, I felt the increasing need to understand more clearly how fellow academic staff experienced Big Data. In order for academic staff to deliver pedagogy effectively today, it is necessary to engage with technologies in todays higher educational institutions as advances are tremendous in teaching and learning. COVID-19 has just added to the central role of supporting teaching and learning using existing technological advances that surround us. Therefore, in order to deliver pedagogy effectively and understand their learners within the pedagogical sphere, it is paramount that one understands/hears the experience academic staff hold on role that Big Data and Big Data Analytics support in higher education. This is the departure point for this research study, however, it is anticipated that the understanding of academic staff's experiences will have relevance to management and other parties in higher education other than educators. It is anticipated that understanding their perceptions and variations will help the sector to do more with technology.

In understanding of Big Data and Analytics experiences in higher education, it is crucially impotant that the gathering of data should explicitly utilise Marton & Booth, (1997) approach in using phenomenographic approach when trying to investigate and understand how academic staff experience the situation in higher education. A thorough review of the literature on academic perceptions of Big Data (google, journals and books) study reveals that there are significant gaps in knowledge of the topical issue. However, the number of publications is steadily growing. Such publications include the research of Williamson (2017) on digital data that enhances educational improvements, Chaurasia & Rosin, (2017), Johnson, (2014) on Ethics of Big Data in higher education; Cope, (2002), Siemens & Long, (2005, 2011) and Daniel, (2015, 2017) all show that there is variation in the way academic staff in higher education experience Big Data, although these studies do not fully consider the academic staff experience of the phenomenon of Big Data. Kollom et.al, (2020) in their research on academic staff expectations about learning analytics in higher education, reveals similarity to my research findings, though it falls short of the second level order of peoples experiences as discussed in the categories. A number of these studies exist and have investigated broader issues on Big Data in higher education with Williamson (2017) Siemens & Long, (2005, 2011) 'intelligent decision-making' and on analytics in learning. In addition, Chaurasia & Rosin, (2017) examine the impact of Big Data whilst Daniel, (2019; 2015) articulates the opportunities and challenges for educational research presented by Big Data. However, these fail short of distinctive research on academics in higher education, on their perceptions and experiences of Big Data.

In order to set the current research in context of literature review of a number of key publications in relation to teaching & learning in higher education and the phenomenon under the lens were reviewed as literature appendage to the nature of information on Big Data and Analytics in this community.

Personally through this research study, I have discovered quite a few things about myself which include but list not exhausted:

- The research reflects the values, beliefs, and perspectives of the researcher in a community of practice (Anderson, 1998) and in higher education. I am simultaneously a teaching academic staff in computing school within the information systems domain, in which this research is supported amongest other schools.
- The doctoral process was a period of self-discovery and transformation in thinking process on ontological, espistemological within the research paradigm (Cohen, Manion and Morrison, 2007, 2000). This has enhanced my confidence about admitting and accepting uncertainty, not only ontologically but also epistemologically. In addition, acceptance in the world of research has sunk in on the understanding that different kinds of research approaches can produce different types of knowledge about the same phenomenon under study (Blaxter, Hughes and Tight, 2010).
- The entire process has taught me greater strength is pursuing a research regardless of the hard life huddles and given me greater strength as researcher at PhD level with resilience and perseverence.

1.2 Purpose of the Research Study and Motivation

The landscape of higher education sector globally is under 'technological pressure' to transform its operational structure in teaching and learning to accommodate new blended ways by integrating learning technology in the classrooms (Chen, 2020) for the Tec-Savvy students and the digital landslides (Williamson, Bayne, & Shay, 2020) as an indispensable component in higher education (Janse van Vuuren, 2020). The phenomenon of Big Data in higher education is still in its early stages (Halloway, 2020) and its conceptual relevance is largely unknown (Chaurasia & Rosin, 2017; Chad, Corey John, 2017), even more so in relation to pedagogy (Daniel, 2019). Big Data and Analytics have the potential to enable institutions to thoroughly examine their present challenges (Daniel, 2019; Chen, 2020; Williamson, Bayne & Shay, 2020), identify ways to address them as well as predict possible future outcomes and this was a source of motivation in embarking on this research to add knowledge to the existing gap. The understanding of 'Tec-Savvy student', technology, teaching & learning sums up the call to research into academic staff, so we understand their experience in order to further understand the benefits of technology and datafication in higher education (Selwyn, & Gasevic, 2020; Kirkwood & Price, 2014).

The world is operating in digital times and more so in western countries today with tremendous leaps in technology advancements (Goodyear, 2020; Kirkwood & Price, 2013; Deepwell, 2008;) and universities are no different in this requirement. This merits consideration in order to support academic staff. They have no choice but to accept Big Data as part of their everyday dealings in teaching and learning in institutions, as it comes with pressure from management and peers. Conceptions of Big Data Analytics imply what information embedded in these, collectively mean to academics or the ways in which academic staff view or conceptualise the phenomenon of it in pedagogy. In empirical sciences, 'a way of seeing them & experiencing', 'a way of knowing & understanding' 'and conceptualisation can be used interchangeably, all of which can be synonyms for the notion of conception.

1.3 Significance of the Study

The significance of this study is in the fact that the thesis had undertaken an in-depth analysis of variation in academic staff perceptions of Big Data Analysis in relation to teaching and learning. In line with the existing literature on Big Data in higher education, this study adds knowledge in understanding the essential aspects of innovation which has recently gained major attention of Big Data Analytics and its use in teaching and learning. This is considering the importance of the higher education sector, and the tendency is moving towards the role that Big Data in different domains for various reasons and this should include that of the academic staff.

The purpose of this study is to identify how academic staff perceive and experience the Big Data phenomenon and the variation that exists between their experiences. In executing this research study, the research findings will provide academic staff with an enriched understanding of the role that Big Data might play in their pedagogy and how this supports teaching and learning in their specific professional subject areas. This will further enable them to devise ways that they can use to understand the significant aspects of the phenomenon of Big Data thereby potentially changing their holistic understanding of it.

According to Daniel, (2015) Big Data in institutions of higher education is known for having increasingly complex and competitive environments. These institutions should be able to identify contemporary challenges and explore the potential of Big Data and its challenges. Decision making power derived from Big Data in higher education is well known whilst recurring behavioural patterns and meaningful trends are fully explored. What this research adds to the voice of limited research into Big Data in higher education despite growing interests that has been shown (Daniel, 2015; 2017) in unlocking the values. This research will add contributions of academic understanding of conceptual, theoretical understanding of Big Data Analytics perceptions and experiences they hold.

Halloway, (2020) posits that data gathered through learning analytics can offer some conclusions on supporting students whilst rendering power and authority to those interpretation the data. This research through its findings will help to affirm this in higher education through the birds' eye of the academics in their collective experiences.

In higher education sector, the only close proximity similar research has come close to Daniel, (2017) and Chaurasia & Rosin, (2017). Even though I managed to locate several recent journals and books, (Baig, Shuib, & Yadegaridehkordi, 2020) on large volume of data in education; whilst Williamson, 2017, on digital data in education; Åkerlind, 2008 on academic understaning in higher education), none of these have investigated the voices of academics on Big Data phenomenon. Åkerlind, (2005d) used phenomenographic aproach to investigate academic growth and development as a research on academics in the university, a research close to my current research. This gives my research study some distinct aspects such as exploring individual lived experiences & perceptions held, using phenomenographic approach with academic staff on their perceptions and experiences. The work of Daniel gives us a general understanding of the role of Big Data and Analytics in higher education and the benefits it holds if utilised to its full potential, however this is removed from the phenomenon under invistigation and my research focus are also different. I turn the research study lens on the variation of experiences of academic staff's perceptions in my phenominographic stance on the Big Data phenomenon. The phenomonography is reinforced by (Marton, 1986) in identifying different understanding of 'reality' and 'constant' as commonality in different participants experiences, a method to be used in gathering such data. In my phenomenographic approach I was closely trying to elicit the underlying deep meanings and intentions of the phenomenon in this community beyond just a descriptive surface that academic staff might hold on Big Data, exploring the variation and understanding the staff perceptions. To paint a worldview picture of academic staff experiencing chen as an awareness on a critical focal point in their community relationships as opposed to Daniels assumptions of objective reality.

1.4 Contribution to New Knowledge

This research study considers the answers to the research question that I set out as the first holistic portrayals of the experience of Big Data in this institution of higher education and whilst adding new knowledge to the limited higher educational institutional research (Daniel, 2015). The originality of my research work that I am presenting, incorporates the distinct voices of academic staff at different levels of their professional career in an institution of higher education in Leeds Beckett University (UK). The existing literature highlights the lack of documented similar research focused on understanding academic staff's perceptions of Big Data. The role that Big Data Analytics plays in higher education as experienced by academic staff as discovered from this research, contributes to new knowledge in the sector.

This study is the first on academic staff perceptions of Big Data in teaching and learning in the higher educational institution that has focused on *staff development*-requirements, building on the work of Åkerlind, (2008) and Trigwell (2006), Prosser, (2004) on teaching and learning. The five categories that emerged from this study form a 'niche finding' in higher education and will offer a first step in a platform for secondary research in similar studies to come in future. These emerging hierarchically five categories of description describe experiences of the phenomenon on a colective level which is in line with (Limberg, 2000) and (Åkerlind, 2005) authoritative research theories.

1.5 Structure of the Thesis

In the following chapters, ***Chapter One*** of the thesis is an introduction, in which the background and purpose of the research study are outlined, and research question are established. The research approach employed is that of phenomenography and a summary of the research design is presented. The significance of the research study is discussed within it.

Chapter Two examines the literature relevant to the research in order to provide a research context for the study. This presents reviews on Big Data and provides an examination of Big Data Analytics in higher education related to uses of it and challenges.

Chapter Three gives a detailed discussion of the methodology and the research study process. In this chapter phenomenography is presented as the research study approach employed to conduct the study with a rationale. The rationale for employing phenomenography is justified within other methodologies that were considered in the discussion. The chapter further describes the philosophical underpinnings of the research study approach, together with a detailed presentation of a description of the data collection and analysis methods. This chapter concludes by addressing the issues relating to the validity and reliability of the research study.

Chapter Four presents the findings which include the outcome space of the phenomenographic analysis containing a finite set of categories of description that outline the qualitatively different ways in which academic staff experience the role of Big Data and Analytics. This chapter has been divided into Part 1, Part 2 and Part 3 detailing findings relating to academic staff experience; presentation of perceptions in categories; Big Data Analytics in pedagogy and BDA academic variation respectively. The five categories of description that emerged from the data analysis of the research are described and the relationships between them are detailed in the outcome space. ***Chapter Five***, details discussions of the main research study outcomes and in relationship to Big Data Analytics in relation to the existing literature. The discussions are based on the findings provided from this research study. ***Chapter Six*** ensues a discussion on findings. Lastly ***Chapter Seven*** provides the conclusions, implications, and recommendations of this research study. The final section of this chapter presents future areas of research to increase the research body of Big Data in higher education from the academic staff foci (birds' eye).

1.6 Main Research Question

The main research question entails, '***In what different ways do Academic Staff perceive the role of Big Data in Teaching and Learning in Higher Education?'*** This was broken down into a further question below which was addressed in the research study: *(1) In what different ways do academic staff understand and describe their processes of experiencing Big Data in higher education? (2) What are the qualitatively ways academic staff experience Big Data in teaching and learning? (3) In what different ways do academic staff experience the role of Big Data in pedagogy to support teaching and learning with technology? (4) In what different ways do academic staff understand and describe their processes of experiencing existing Big Data Analytics generated from the Big Data in virtual learning environments higher education.* These fed into the main research question (focus of the study) in the data analysis and findings chapter and these two sections describes the research study findings in depth.

1.7 Summary

In summary this chapter has introduced the research study into "An investigation on university academic staff perceptions of the role 'Big Data and Analytics' might play in teaching and learning". The research background, research question and research study design have been fully outlined and discussed. This has allowed for the significance of the research study to be fully established with an overview of the structure of the thesis presented. Chapter Two below presents a detailed review of the literature that sets the research study in context.

Chapter Two: Literature Review: Part 1: Academic Staff's Experiences of Big Data Benefits, Contrasts & Conflicts

2.0 Introduction

My research work was set out to answer questions on the qualitative differences in Higher Education (HE) academic staff's experiences and perceptions of the role Big Data might play in teaching and learning. This research considered their individual perceptions as the main contributors to this experience and with this I set out to clarify how this research addresses the gap in the existing body of knowledge on Big Data in teaching and learning in higher education environment.

2.1 Presence of Big Data in Higher Education

Educational Big Data is about extracting meaning from the data for smart education of the 21st century and beyond (Chen, et. al. 2020) which is encapsulated in countemporary education. According to Chen, et.al. contemporary education, is at all levels now in educational environments and it is unbounded by time, space and learning can occur both in physical and virtual environments and with the assistance of countless (learning management systems-LMS in HEI, Baker, 2018) technologies like Google, Adobe, Moodle & blackboard. These have highly used pedagogical gadgets encapsulated, like videos, audios, live chats in teams, ChatGPT, Adobe and skype for business with list not exhaustive. This results in an overwhelming volume of data sources and formats that are behind the concept of Educational Big Data (EBD) also referred to as Learning Data which is being tackled by google and blackboard for analytics (Munshi and Alhindi, 2021). In the 21st century most educational institutions are producing huge amounts of educational data and equally facing the common challenge in finding an effective method to harness and analyse their data for continuously delivering enhanced educational experience (Daniel, 2017; Munshi and Alhindi, 2021). Enhanced educational experience has included new curriculum being innovatively developed, supported, and shared in data science signature pedagogy (Crowther, 2013) in various institutions as a benefit whilst causing analytical cup storms in understanding and interpretation.

As the volume of data generated by education increases, more solutions for data management are required by university top management for financial projection and preparedness towards purchases of these teaching and learning technological tools, whilst on the other hand academic staff seek smart data from them. Given the richness of the data that is collected in instructional settings, a growing number of educational institutions are increasingly using EBD for strategic planning (i.e. at university level in open days, course level & faculty level) and decision-making by academic staff, investment by top management. EBD enables institutions to access data that is scattered in different sources; to respond more swiftly to the constant changes in the education sector (recruitment patterns) ; to make informed decisions based on data (learning); to gain real-time insight into their students' behaviour patterns and recommend solutions (for academic staff in teaching and learning) ; to use predictive tools to enhance their students' learning results (academic staff in engagement & retention); and to support at-risk students (academic staff and registrar management) EBD can be used by institutions to inform the development of educational policies by resorting to data-based decision-making (Picciano, 2012).

Chen, et. al. (2020) argue that data is constantly being generated in higher education, and that it is available as a priceless resource. However, most tools are bringing in with them embedded analytics to present the unstructured data. These tools include Hadoop, Google Analytics, Blackboard Analytics and Tableau Data Visualisation for Business Intelligence in universities and any other organisation. Big Data exists firstly in an unstructured format, therefore, the claims that its significance depends on the capacity of reducing its multidimensional complexity into simpler relationships that can be used to improve the education system.

Authors such as Crawford in computer science, Data Science, bio-informaticists, political scientists, sociologists, bio medics are clamouring for access to the massive quantities of information produced by and about people, things, and their interactions (Boyd and Crawford, 2012). The many diverse groups argue about the potential benefits and costs of analysing genetic sequences, student and staff records, social media interactions, health records, phone logs, government records, and other digital traces left behind by people whilst interacting with technology (Ball and Grimaldi, 2019, 2021). Significant questions emerge based on these theories and inclusively similar theories are asked within the higher education sector, in an attempt to understand fully the implications in teaching and learning. Such inquisitive searching questions include will large-scale search data help us create better tools, services, and systems in higher education? This begs further questions like will it usher in a new wave of privacy incursions (GDPR compliance requirements in HE) and invasive ways of thinking and delivery of higher education in local communities and will data analytics help higher education to understand online communities and educational political movements? Crucially, will it be used to track engagement and retention of students in higher education and what role will this play in teaching and learning? Given the rise of Big Data as a socio-technical phenomenon, it can be argued that it is necessary to critically interrogate its' assumptions and biases in higher education in teaching and Learning. These questions prompted this research in search of answers that could be helpful to the educational wider community.

In order to achieve this, in my research, a thorough review of literature relating to academic staff, Big Data, Teaching and Learning Analytics was undertaken in order to address some of the questions around higher education. This then called for provision of the backdrop research, attention focusing on exploring various facets of academic staff's perceptions, experience, and variation of the role of Big Data in their Teaching and Learning Analytics. This research highlights the missing lived experience facet of academic staff perceptions of the role that Big Data might play in teaching and learning as indicated in the previous chapter that this is scarce hence the instigation of this research. However, several authors have tackled several issues on the related topic in higher education with Daniel, (2019) examining educational critical views on use of Big Data with a focus on the six V's (Daniel, (2017) giving a pictorial view on Big Data big picture. Daniel, (2015) and Shah, (2018), on Big Data furthers his focus on how beneficial Big Data is in management decision making based on the analytical analysis that follows. Williamson, Bayne, & Shay, (2020) examine how datafication and learning analytics create the heavy traffic that is pouring into higher educational silos. Williamson, (2017, 2018) focuses on the future of learning in higher education with all this Big Data that is generated from a variety of platforms and systems, such as learning management systems, student information systems and online learning platforms, educational institutions gather enormous volumes of data in teaching and learning. Goodyear, & Retalis, (2010) examine the technological tools that are being used in higher education. Guggemos & Seufert, (2020) focus on teaching with technology as academics on pedagogy. This further bring onboard success as articulated by Sclater & Peasgood, (2016) on learning analytics and student success, concuring with Janse Van Vuuren and the work of learning anlytics power & authority (Halloway, 2020) that it offers academic staff in this process. Janse Van Vuuren, (2020) adds his voice on Data Anaytics on student success and factors related thereto. Student success includes retention and progress in order for success to prevail. Other research in the same vein has emerged around the role of Big Data in higher education depicting its role in responding to global trends and competitive intelligence in areas of recruitment and retention (Daniel, 2015) within the digital learning exponential technology growth. A number of recent studies on Big Data in higher education suggest nascent research body that exists such as 'student experience with blended learning' which again is scarce. The big picture that is emerging from this body of knowledge is a rather fuzzy and chaotic picture of academic staff's lived experiences of Big Data and its role that it might play in teaching and learning mediated by the fast emerging technologies that are being adopted across the HE sector. The following chapter is subdivided into three main sections as outlined below in exploring literature review on the related topical issues.

According to Thomas, Fabienne, and Steffen, (2018) misleading patterns are found in the data that are erroneously interpreted as causal relationships (see also McAfee and Brynjolfsson 2012; Lazer *et al.*, 2014). Starting from such data patterns found with Big Data analytics, decisions without potential for improvement or even unwise decisions can be made. That is why the use of Big Data analytics may not guarantee sustainable, positive effects on firm performance, as in the predicted *'Big Gains'*. The grey areas with respect to privacy, data protection, the regulatory environment, or an insufficient internet connection are viewed as the other main barriers to the diffusion of Big Data and related practices. Despite these challenges associated with Big Data, a widely shared expectation is that the ongoing changes in how data is being generated and made relevant for firms can help to increase business value through profitable use of data, that previously had even been used to be produced as 'waste' product of business activity before the surge of Big Data technologies. New data information practices and better-informed decision-making can be particularly advantageous for firms' innovation processes, which often involve high uncertainty and risk. In this vein, mining of consumption patterns or social network and consumer sentiment analysis, for instance, might improve the adoption and market success of new products.

2.2 Big Data Perceptions in Teaching and Learning in Higher Education

Daniel, (2017) states that the global landscape of the higher education is under increasing pressure to transform its operational and governing structures in order to accommodate the increasing pressure in tranforming its new economics, social and cultural agendas to support its regional, national and international demands. Universities are responding to this pressure and demand by constantly searching for actionable insights from their data such as *enrolment, engagement, rention, progress attendance* and *standards* to generate strategies to use to meet the recruitment and new demands in teaching and learning. The new demands extend to increased student recruitments, reduced funding, massification and marketisation of higher education on governing and operational new demands.

Over the last decade the higher education sector has been witnessing a pervasive exponetial growth in the number of learning technologies (Daniel, 2016) in almost all the areas of teaching and learning, creating both excitement and concerns amongest academic staff and the university as a whole. The prevalence of emergent forms of technology enhanced learning environments that were seen at one point as disruptive innovation in teaching that challenged beliefs about teaching effectiveness, beliefs and cultures in higher education (Rodriguez, 2012; Yuan, Powell & Cetis, 2013).

Enhancing these challenges is the increasing adoption of various forms of tablets, mobile and ubiquitous technologies by academic staff and students such as Twitter, Apps, Facetimes, Collaborating ultra, Teams, Skype for business which provide greater flexibility in teaching and learning with more timely access to learning materials which contests with the traditional deliveries i.e. lectures and seminars, tutorial and even laboratory sessions on campus (Daniel, 2017). These foremetioned technologies generate volumes of Big Data as they are being used in the new pedagogies such as flipped classroom which encourages Open Educational Resources such as video streaming, audious and voice over powerpoint adding to the classroom transformation in higher education in lectures, tutorials, seminar and laboratory sessions. All these bring with them some crucial blackboard based analytics holding embedded (Williamson, 2017) intelligence for (Siemens and Bake, 2012) decision making in various parts of the university but crucially here in teaching and learning.

Information has surrounded us for decades and in today's society there has been a proliferation of this information that has formed a new trend known as Big Data and Analytics, as this information is now coming in large *Volume* with *Velocity, Veracity, Variety, Verification* and *Value* (Daniel, 2017) also known as six V's. In the information age, this data existed, was known, and operated comfortably in silos known as Data Mining (Sin and Muthu, 2015) and therefore it is not entirely a new concept. The large volumes has been a result of the rapid growth in technological developments with advancements in strategic alignment in order to strengthen the institutional capabilities in facing new challenges (Tulasi, 2013) in higher education. Higher education has access to realms of data which can be used to improve decision making at several spines. The use of Big Data and Analytics in higher education is relatively new but fast growing in usage within teaching and learning. However, the relevance of analytics is profoundly seen in many areas (Daniel, 2015) and higher education is no different. My research is to explore this relevance in the understanding of academic staff and their perceptions.

Individuals are demanding access to vast amounts of information in *'Just In Time'* mode in different business requirements which include competitons, innovation, productivity, opportunities and enhanced by the advances in educational technological gadgets in the century. Higher education is no exception (Tulasi, 2013; Manyika, et.al 2011). The sector has followed suit and gone further in using this information coming from Big Data in several domains including teaching and learning (Arnold, et.al 2020; Siemens, n.d.) using the Internet, blackboard and MOOC's platforms (Romero & Ventura, 2017).

Daniel, (2015) examines the managerial challenges and opportunies that can be harnessed for management decision making in higher education. Big Data Analytics comprises of '*Descriptive'*, *'Diagnostic'*, *'Predictive'* and '*Prescribes'* which poses questions of '*What'* and *'Why'* in answering to the embedded information in graphs and dashboards on root causes of a pattern (Riahi & Riahi, 2018) emerging, which can be studied further for interpretation. Big Data Analytics refers to processed Big Data using technological software such as Blackboard Analytics, Yet Analytics, Wooclap, Bright Bytes, Clever, Knewton, Tableu and Hadoop (list not exhaustive) to give pictorial dashboards or graphs for optimising learning environments for student success.

In the following sections, I will discuss Technology Enhanced Learning in Teaching and Learning in higher education.

2.3 Big Data Learning Analytics (LA) Landscape in Higher Education

The integration of digital technology in higher education has influenced both teaching and learning practices by allowing access to vast amounts of data from the online learning portals which can improve student learning. Viberg, et. al, (2018) state that learning analytics improves practices by bringing along transformation in ways that support learning processes. These learning processes include online learning facilitation of asynchronous, synchronous, interaction and communication within a given virture portal environments which have become a key partner in becoming an integral part of the higher education, and this should focus on the *'quality'* aspect of these learning analytics (Viberg, et.al., 2018). The work of Viberg et.al, reviewed 252 papers on learning analytics in higher education published between 2012 and 2018 and concluded that there is a shift towards deeper understanding of students' learning experience but not that of the academic staff. It is in this vein that my research explored the understanding of the accademic staff experience. The academic staff in the institution contribute heavily to student learning experience with some of it coming from the Big Data in learning analytics that they deploy in use day in and out as they deliver pedagogy. According to Tulasi, (2013,) the use of Big Data and analytics in higher education was relatively a new practice and projected that it is one of the future areas of research. Heeks et. al (2019 p82); Albanna & Heeks, (2018) and Wilder-James, (2012) identified the addition to the *'Knowledge Gap'* in Big Data and on the *'implementation slow pace'* whilst acknowledging that Big Data is spreading fast in all sectors and that Big Data is facilitating a *shift in power* in all sectors including higher education from the existing stakeholders such as '*students, academic staff, IT Staff and top management'*. Heeks et.al (2019) further highlights the implementation challenges facing such systems in big organisations. Since the work of Daniel, (2015, 2017), Hilbert, (2016) and Heeks, et. al (2019) all still concur on that , 't*o date there have been relatively few analysis of the real -world experiences'* of what they call *Big Data Datafication* in organisations and calls for further research into it. These calls are also echoed by Williamson, Bayne & Shay, (2020) as they still call for future research into Big Data, so that it could be understood in higher educational or organisations alike. This supports the reason why my research explores academic staff's experiences of Big Data in order to add to narrowing the 'k*nowledge gap.*

It is worth noting that Learning Analytics (LA) and Technology Enhanced Learning (TEL) are emerging as a fast-growing multi-disciplinary areas in higher education as both these use virtual/online environments which gets feeders from Big Data silos in higher education-part of the datafiction. From the LA and TEL portals, the gathered information about learners and learning environments is used to predict, elicit, access, analyse for further modelling for prediction and optimisation of learning processes. This data is instantly analysed and models can be presented as soon as the 'data collection' is completed (example includes processing access of information). Some of these portals have very good and fast processing capabilities built in the online environments like blackboard with blackboard analytics.

On the other hand, LA's can be based on academics to support the institutional operational, and financial decision-making processes in order to understand how students learn and those "*at risk*", which academics are always interested in (Lawson,et. al 2016) and this adds to the overall student experience. Based on the analysis of large-scale educational data, LA tends to also support research and practice in education, however this is a topic for another dimension and discussion.

2.4 Importance of Big Data and Limitations in Higher Education

There have been significant technological advances in higher education in recent years with Big Data Analytics being captured in various portals that depict learners retention, engagement, progress, ethics, and student learning (Ahmed, et. al, 2017, Daniel, 2017, Chen, & Zhu, 2019; Arnold, et. al 2020). Academic staff are continuously engaging technology in pedagogy in offering students learning, access and submission flexibility in the comfort of their choice (Daniel, 2014). There has been an increase in management supporting the technological investments to enhance these capabilities in the higher education sector and moreso following the recent COVID-19 pandemic (Rosenberg, & Staudt Willet 2021). This has further highlighted the importance of the power of technology in supporting delivery of online sessions as universities, were forced by the government to close their campuses in order to control the pendamic (govt.uk, 2020). Similar moves by governments across the world have pushed the issue of Big Data and Analytics into the limelight once more in teaching and learning. Rosenberg, & Staudt Willet (2021) extend this approach with a call to educational technology scholars to meet the challenges of learning with a focus on disruptions and ethics of learning with technology and the privancy issues. In order to capture these challenges, learning analytics will need to be available and examined for academic staff who can share these data whilst protecting the privacy of students.(Pargman, et.al. 2021).

Williamson, (2020, pg. 21-22) highlights the significance of Big Data as a new source of knowledge in which embedded are evidence of data driven decision making, realisation of benefits of greater bound, making the organisational process transparent and the analytics, to increase the efficiency for greater accountability. He further states that there is need to explore this data further as many institutions fail to make efficient use of the huge amount of data available. He further calls for the analysis of Big Data and in order to add value this data needs interpretation by users so that it could be understood.

2.5 Learning Analytics Supporting Teaching and Learning

Learning Analytics (LA) refers to the collection, analysis and gaining intelligence on learners in their learning environment in higher educational institutions (Sclater & Peasgood, 2016). Research of (Sclater & Peasgood, 2016) highlights the emerging uses of LA in higher education through their case studies with overwhelming evidence of LA impacting on teaching and learning with the current focus on teaching *excellence* (willia, Shukla & Passey, 2021 p 3) and the enormous potential opportunities (Wong, 2017; Kumar, 2018) it has for many institutions in improving student experience and their achievements at the university as institutions also move more and more into blended and online teaching, which is on the increase (Sclater & Mullan, 2016). Big Data which produces learning analytics has further potential for improving performance and teaching quality, due to the many digital learning platforms (Siemens & Long, 2011) that are widely being used to collect educational data on staff and students (Yang, Chen & Ogata, 2021). Chen, et. al (2020) highlight the pervasiveness of technology, online learning, and Big Data in the context of education, which extends to higher educational institutions, which are experiencing exponential growth in Big Data derived from students' interaction with technology, their personal and academic profile. Furthermore, EBD is increasingly becoming a critical central concern of educational institutions, as its value becomes increasingly visible and as a new body of evidence of its benefits becomes gradually published and disclosed among researchers and practitioners (Chen, et. al 2020). Governments are also looking to use EBD to make educational improvements. As in other sectors, in education one of the dominant conundrums is how to extract meaning from the data that is collected. While some agreement occurs in terms of the best instruments and techniques, governments, institutions, and academic staff are still left with the question of how to understand, interpret and derive meaningful meanings form educational Big Data. This means that there is a challenge around how to effectively use Big Data in higher education. As the volume of data generated by digital technologies increases, more solutions for data management are required and therefore the need for academic staff perceptions understanding. Learning Analytics help academic staff to have a clear understanding of their students in various academic interactions.

My research contributes to this knowledge through this research as it will add a voice from academic staff that heavily contribute to teaching and learning on their perceptions of BD by exploring its understanding and experiences gained. The full picture of BDA supporting teaching and learning is still in its infant stage and more research is required to show explicitly the gains that academic staff and teaching and learning can benefit from it (Chen, et. al 2020; Siemens & Long, 2011). However, through this research, in viewing the analytics embedded in teaching technologies indicate an interesting pattern that is emerging and supporting the claims of Diebold et.al. (2012) on utilisation of knowledge, skills, and techniques of Big Data (Chen, et. al 2020). He further claims that data analytics are providing new opportunities to improve management decision-making. Therefore, I ask through my research question how academic staff are experiencing Big Data in higher education as this will tap into how this extends to teaching and learning. It is acceptable to speculate that with such large amounts of data being gathered in teaching and learning technologies, that this will do good to this sector especially towards student behaviour, retention, engagement, performance, attainment just like it has done to management on decision making and financial expenses (Shah, 2018). He further argues that large datasets are available in universities for predicting future direction and can generate actionable information from it.

2.6 Summary

This chapter has provided Big Data review in higher education and its usage which is underpinned by some recurring themes. These themes include the academic importance and potential that it holds for enhancing the teaching and learning in higher education. This highlights how academic work is centred on the notion of autonomy and freedom on usage within exploration of the raw data that is generated in teaching and learning. This also highlights the impact that Big Data is bound to have as part of the academic pedagogical activities now and in future.

Furthermore, factors such as enhanced ongoing technological advances, access and privacy issues are likely to influence the experiences and perceptions of academic staff. This is however a rather restricted view of academic work as it is managed by other non-academic staff but impacts on heavily on academic staff duties. Academic Staffs' constructions of the central meaning of Big Data perceptions and the variation in this meaning, in addition to the systematic exploration of the impact of Big Data has received less attention in higher education, so far. This research will aim to gain raw data from academic staff experience of it and the perceptions that they may hold in the current dispensation.

Part 2: Big Data Analytics in Teaching and Learning: Academic Staff Experience - Benefits, Contrasts and Conflicts

2.7 Introduction

Chen, et. al. (2020) argued that recently Big Data have become mainstream in many research filelds as the concept and phenomenon whose size is beyond the ability of databases and data warehousing in supporting teaching and learning, today. Chen et al. (2020) refer to this mainstream as Educational Big Data that would support pedagogy whilst presenting unstructured values. For decision-making, predicting students' grades, academic performance and engagement using Educational Big Data and learning analytics. To benefit these the focus on the capacity of learning analytics to identify students who are at risk and suggest an opportune intervention based on the results of their behaviour analysis in teaching and learning would be crucial and this could be achieved through understanding of embedded analytics in the 'educational tools'. Chen et. al. (2020) posits that when deploying machine learning to train risk-identifying models, the factors that influence the performance of those models is overlooked and academic staff left behind in understanding.

2.8 The Chaotic Picture of Teaching and Learning with Big Data Analytics

The work of Chaurasia & Rosin, (2017) highlighted the chaotic scenario presented on Big Data and Analytics. It is acknowledged that it quickly gained much acceptance in higher education since 2009 but it's implementation is rather slow and it is understood in different ways. Much of the impetus for using Big Data and Analytics also comes from gradually strained university budgets, greater awareness on appropriate fees spending and collection (Chaurasia & Rosin, 2017) and analysis of data related to the advancement of learners and the perspectives in which learning takes place (Daniel, 2015) in higher education. It is possible to solve this chaotic scenario, if technology addresses the scales of diversity and lessens the pressures on demand in, higher education with the arm of signature pedagogy (Crowther, 2013) and the academics as the drivers (Laurillard, 2008) in this change.

Many authors (for example Gutierrez, Tasmin, Muhammad Nda, Nor Aziati, 2020 Williamson, 2017; Matsebula and Mnkandla, 2017; Tulasi, 2013) argue that Big Data can be transformative for higher education by altering the existing processes including teaching and learning. They further posit the notion of analytics from Big Data to bring innovation in improving existing systems. Innovation would create a new view in the current processes in the existing systems in order to address the growing needs of academic staff in higher education. The crucial aspect related to this research would be the changed view towards traditional pedagogy in courses which would lead to a network of relations between knowledge and skills. In recent years it can be observed that there has been an increasing involvement of analytics elsewhere and higher education has not been exempted which has brought reform activities and improving teaching and learning processes. There is a call for more research to understand the impact that Big Data has in higher education hence this research to help on an understanding aspect.

2.9 The Big Data and Analytics and shifted Pedagogical Approach

Big Data and Analytics in higher education is a pedagogical paradigm shift from the traditional classroom teacher-oriented approaches to a blended learning approach (Nurasma and Kaur, 2020). This trend is on the increase as technology advances in higher educational institutions and as more analytical tools are being embedded into signature pedagogy. Crowther, (2013) enhances this notion of being able to understand the opportunities for its technological enhancement against a range of delivery modes and technological media forms in pedagogy.

Seufert, Meier, Soellner, *et al.*, (2019) in their paper pedagogical perspective on Big Data and Learning Analytics (LA) highlight the increase prevalance of learner-centred forms of learning as well as the increased devices in streaming of learning data from digital platforms. From this data they indicate that LA can enable, teachers, learners and their institutions to better understand, predict learning and performance. However, they indicate the the shortage of research on pedagogical perspective and matters of learning design as being underrepresented. The underrepresentation is echoed across the higher education sector and searches in many journals reveal the same pattern. My research question in my research study sets the scenery as I seek to understand the pedagogical viewpoints of academic staff from their lived experience and own their account. This effort is reflected in this main question where I set myself to explore in my research study and sub questions in appendix F1.

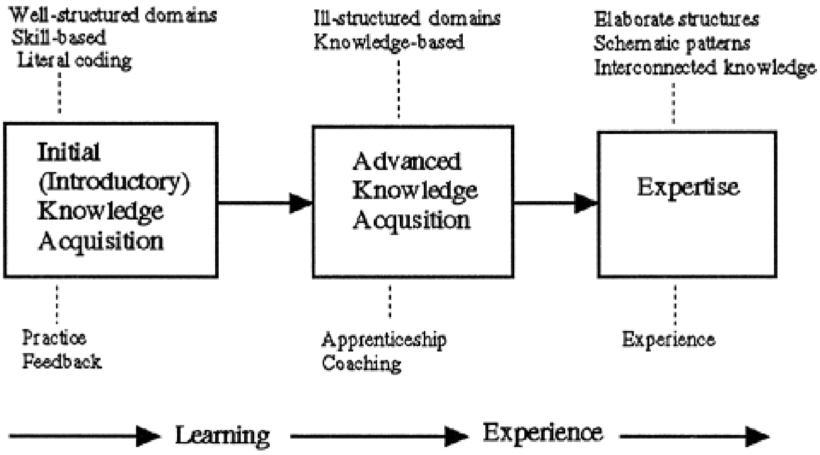
2.10 Understanding of Perceptions embedded in Higher Educational Environment

Venkatesh, Croteau, Rabah (2014) highlight the perceptions of effective technologies used in higher education using the web 2.0. Initially, the perceptions were around '*distance learning'* only, which later started forming trends towards '*blended learning'* for students on campus. It is the academic staff and student on campus interactions with technologies that supports and enhances teaching that really increased the role of Big Data in higher education. This really qualifies Big Data in higher education as there are approximately 122,360 students and 217,065 academic staff in 169 higher educational institutions in the UK based on Higher Education Statistics Agency (HESA, 2019) figures. These HESA figures encapsulate the activities around the six Vs of *Volume, Velocity, Veracity, Variety, Verification* and *Value* (Daniel, 2015) from which Big Data and Analytics emerge from. The data within these V's can be presented for research exploration in finding hidden vital information for development, innovation, competition, research, retention, 'learning behaviours' *etc.* Perception means the ability to see and hear the way in which some things are being understood and interpreted (Venkatesh, Croteau, Rabah, (2014).

It is anticipated that higher education perceptions and expectations around technology will increase in teaching and learning as the decades go by. It is further expected that academic staff in institutions will be expected to prepare and support students to meet the demands of an increasingly technological environment in higher education (Ashour, 2020). Ashour in the research of 2020 contradictory highlights that 'collected data' at the time of their research indicated that 'digital age is not 'transforming' the nature of universities, but this is debatable and may highlight the different needs in different subject areas. According to (Yukiko, 2007) universities will have to cross the digital divide as technology starts to contribute towards the notion of multiple paths to learning, a perception that is held by many academic staff including implementation challenges with diverse student body. Here the picture emerging in higher education is that of a dominated technological advancement as technology expands in every sphere. Increase in technological advancements will increase Big Data silos that will require more analytical tools to give pictorial visualisation that could led to intelligence that can be harnessed.

2.11 Manifesto for constructive approach on uses of Technologies in Higher Education

Jonassen, et.al (1983) take a constructive approach to technologies. They illustrates this constructive approach by applying the diagram in Fig 1 below with three distinctive steps. This could be true of Big Data and Analytics growth in HE, today. It can be assumed that gaining understanding and expertise in academic staff goes through these steps in a similar process.



2.0 Jonassen, et.al. (1993) Continuum of Knowledge Acquisition

It is only after knowledge acquisition from Big Data and Analytics that they can make up the claims by Gibson (2012) on making use of this data in communication, curriculum and learning more about students behaviours for pedagogical benefits in higher education from the digital learning. Gibson (2012) coins this as the 'game changers for transformating learning environment' such as those in higher education. My research question four explores this knowledge acquisition and expertise through learning the surrounding supporting *teaching technologies* and *experience* gained, as these add to Big Data and Analytics in higher education. Mostly academic staff are underpinned by a constructivist approach which is similar to phenomenography (Straub and Maynes, 2021), whereby they construct their own knowledge and understanding of the academic world through *experience* rather than direct instruction (Dewey, et.al. 2013), this study was informed by the phenomenographic methodology. Straub and Maynes, (2021) highlights that constructivist research and phenomenography as having the potential to lead its researchers to understand and discover nature of students conceptions in order to influence pedagogical activities that include Big Data and its tools in teaching and learning. This is crucially important as both approaches tend to have similar goal on ability to combine new and complex knowledge in enhancing use of Big Data Analytics in higher education.

2.12 Big Data Analytics Technology and Networked Learning

A good number of studies, focus on management and students' use of Big Data technologies, gains for 'learning' and for 'leadership management use' with findings from quantative methods (Manyika *et al.*, 2011; Ahmed, *et al.*, 2017 & Chad *et al.*, 2017). Kirkwood and Price (2013, 2014), focus on technology enhanced learning with enhanced capabilities of modern smartphones in teaching and learning that offer new potential design tools that would offer new learning experience to students including geospatial thinking (Price, *et al.*, 2014).

This literature has also considered the extent to which students can be considered digital natives'. Prensky, (2001) on altered learners mind, (Stoerger, 2009) making a distinction on the 'Net Generation' with skills and those without; whilst (Dede, 2005a & 2005b) discusses 'neomillennial' learning styles in which learners are assumed to be tech-savvy young people. Some of these claims can be challenged as the stereotyped declarations could be misleading.

However, what they do emphasise is the salient awareness of pre-university students coming into higher education with some tech savvy technical capabilities and at the same time not to make sweeping statements on use of teaching & learning technologies. It is in this vain that these capabilities and understanding that my research explores on academic staff in understanding the enhancement BDA has in teaching and learning. In todays technological advancement, networked learning (Goodyear, *et al.*, 2010) is on the increase for students in higher education and in addition to their personal use such as in social sphere. Deepwell and Malik (2008) home in on self-directed learning (SDL) time and more academic guidance by lecturers in facilitating students' use of technology and lecturers' engagement with technology, which is required in enhanced technological learning environments, today. This unfolding intertwined situation raises questions on what variations exists in academic staffs' experience of Big Data in teaching and learning and is of interest finding out the perceptions being held.

In 2005 in United Kingdom a research paper indicated that 95% of higher education were supported by a Virtual Learning Environment which included the term 'blended learning' that implies integration of traditional face-to-face and online learning in higher education, enhancing student experience both on and off campus (Deepwell & Malik, 2008). The notion is supported by many scholars (Oliver, 2006, Sharpe *et al.*, 2006, Creanor, *et al*., 2006, p23 etc.) on understanding pedagogy; 'learning activity management systems and narrative accounts of learners' experiences respectively. Of interest is the finding that VLE and blended learning strongly reinforces the need for lecturer/instructor /academic staff (terms used interchangeably) playing a critical role in learning in this environment. However, it has to be noted that jury is still out on known facts on how Big Data has impacted desired learning outcome (Shamsuddin & Kaur, 2020). I personally, find this to be true regardless of the tech-savvy generation of today and this has also been consistent with the generations before.

2.13 Academic Staff Ways of experiencing Big Data: Data, Information and Knowledge

In relation to academic staff's way of experiences of Big Data, Laurillard, (2008) examines the 'pressure from technology', which demands lecturers cope with knowledge in subject area as well as technology know how in use and handling of Information Communication Technology (ICT). Through ICT raw data is collected, which then gets processed into information from which knowledge is gained (Johnson, 2014; Nonaka & Takeuchi, 1995). In this century, technology enhancements in higher education have increased significantly and this has demanded higher processing software and cloud storage spaces. When discussing Big Data in higher education, it is pertinent to consider the relationship between data, information and knowledge (Johnson, 2014, pg 4) which have continuously played a part in higher education. From the wide range of resources available it is apparent many scholars claim these words having a range of meanings attributed to them in different contents. With this knowledge in mind, for this thesis, I will adopt Zin's approach.

Zins, (2007) articulates that data, information, and knowledge are part of a sequential order and that *data* are the '*raw material'* for information, and *information* is the raw material that has been processed to give meaning and for knowledge to be derived.

A number of scholars claim that data, information, and knowledge are part of a sequential order as per Nonaka & Takeuchi, (1995) and Polanyi, (1962) adds Personal knowledge to experience and wisdom in which Big Data (Daniel, 2014 pg 3-4) and this research taps into, in order to understand academic perceptions. According to Zins, (2007) he states that if this is the case, then *Information Science* should explore data (information's building blocks) and information, but not knowledge, which is an entity of a higher order. Nevertheless, it seems that information science does explore knowledge because it includes the two subfields, knowledge organization, and knowledge management, which can be confusing (Nonaka & Takeuchi, 1995). However, it is in knowledge that one finds explicit and implicit knowledge that academic staff can recall from time to time or build blocks on it (Nonaka & Takeuchi, 1995). Zins poses critical thinking on data, information and knowledge on the sequential order as to whether we should go to the extremes of excluding the two subfields of knowledge organization and knowledge management from information science, but this is for another research topic.

2.14 Academic Perceptions of Big Data in Higher Education and Implications for Practice and Policy

Largely, academic staff's perceptions of Big Data and analytics is missing in the body of literature from books and journals as a library discovery search engine reveals in this subject area. However, perceptions on Big Data Analytics in universities has a larger publication in the body of knowledge to include Smart Campus Big Data Analytics (Osuwa, Katende, & Osuwa, 2019) relating to GPS, staff and student ID cards, Mobile phones, Wireless Fidelity (Wi-Fi) with list not exhausted. Osuwa, *et al.*, (2019) advocate for the notion of a smart campus as technology that exists across universities that will enhance the process of learning and research because they are deemed crucial tools, which will help researchers and academicians in conducting research and finding alternative solution in problem solving. They extend this supposition to include Smart Campus technology adoption by universities will be significantly advantageous to both universities staff and students in conducting research and learning. However, this doesn't include academic tools that they use apart from electronic cards and Wi-Fi on this list. Therefore, my research here dives deeper into actual learning tools that assist in teaching and learning such tools include Blackboard, Moodle, Databases, SEMs and now SEAtS. The work of (Ruiz-Palmero, et.al., 2020) advocates for perceptions on training advisors of teacher training centres on application of Big Data in education whilst (Fosso, et.al., 2015) advocates for how Big Data can make big impact.

Academic staff perceptions are such that they are expected to develop the data-driven tools that can cope with the advanced Big Data influx in research and development within institutions. In addition, developing learner's mindset through teaching and learning that will enable them as the future workforce to anticipate their customer needs, provide more intelligent services and products, and achieve desired business outcomes as an expectation of academic higher institutions.

Practice and Policy in higher education is in a juxtaposition as the two major stakeholders have to operate together for success. This means that higher educational institutions have to operate within the government defined parameters with policies including quality assurance, funding and economical contribution with list not exhaustive, here (Atherton, Lewis and Bolton, 2023). However, embedded in these polices and that impact on academic staff and on use of Big Data daily is the pressing General Data Protection Regulation (GDPR). This regulation impacts directly on Big Data Analytics with its legal framework on collecting and processing of personal information within higher educational institutions.

2.15 Learning Analytics, Datafication and Big Data links

The field of learning analytics is rapidly growing in all facets of its research, application into practice and theoretical contributions as the modern landscape in higher education is being shaped by several critical drivers. These include meeting the needs of the 'diverse group of students', promoting learning with technology, promoting 'lifelong learning', enhancing student learning experience and widening participation (Siemens, Gašević, and Dawson, 2015). As early as 2005, Goldstein and Katz reviewed how higher education institutions made use of data for decision making in USA institutions. This indicates that Big Data Analytics is not a new phenomenon but just an extension of visualisation of data for several purposes in higher education. Whilst Siemens, Gašević, and Dawson, (2015) argue there is much interest surrounding learning analytics, the vast majority of institutions that are yet to exploit the full use of learner and organisational data to address institutional and educational challenges as cited in (Colvin et.al, 2015; Tsai *et al.*, 2018); Tsai and Gašević, (2017). Brown, (2012) discusses broadly on that learning analytics is comprised of three major themes namely '*predictors* and *indicators*, *visualisations*, and *interventions*. This is closely linked to the theories that Big Data Analytics stands for too in dealing with data in higher education. Daniel, (2017) highlights the decision making embedded in educational data which forms patterns that are derived from Big Data. This is concured by Siemens, Gašević, and Dawson, (2015) who further articulate learning analytics as focusing on the deployment of learning intervention or on how learning enviroments are shaped to improve student experience. These initiatives explore how interventions can be included as an additional element in a learning design and the interaction with the rest of the design components (Lockyer *et al.*, (2013). The recent trend is to provide personalized feedback at scale that combines the power of analytics with pedagogical knowledge to empower the teachers (Pardo *et al.*, 2018; Fincham *et al.*, 2019). Pardo *et al.*, (2019) add to this voice by stating that the intended result of any designed intervention is to provide for improvements in student outcomes and satisfaction. All these authoritative authors can be summarised as supporting the notion of data being vital in higher education in usage towards retention, engagement, innovative teaching, intervention, and student experience.

For decades information has been considered a fundamental building block of reality in many organisations with higher educational institutions alike. Datafication aligns with the trend of data which is subsequently transferred into information (Manyika, *et al*., 2011).

2.16 The future of Big Data Analytics with Machine Learning (ML) and Artificial Intelligence (AI)

Artificial Intelligence (AI) has the potential to address some of the biggest challenges in education today, innovate teaching and learning practices (Goksel & Bozkurt, 2019). However, rapid technological developments inevitably bring multiple risks and challenges, which have so far outpaced policy debates and regulatory frameworks. There is a need for a human-centred approach to AI (Collins, 2018) in order to harness the power of Machine Learning that can be made to think and make sense of the world in a similar manner like humans would do and in the process capturing the Big Data that helps to give that world view. It aims to shift the conversation to include AI's role in addressing current inequalities regarding access to knowledge, research, and the diversity of cultural expressions and to ensure AI does not widen the technological divides within and between countries. The promise of "AI for all" must be that everyone can take advantage of the technological revolution under way and access its fruits, notably in terms of innovation and knowledge (Mueller and Massaron, 2022). Research is still in infant stages in interested in leveraging emerging technologies like AI to bolster the education sector in capturing live image Big Data as interactions take place. However, in higher education the future of deep learning is heavily embedded in the relatively new technologies in the realm of machine learning which involves the complex attempt to unravel human levels of perception and cognition. Shaikh, (2017) and Goksel & Bozkurt, (2019) articulate that Deep Learning (DL) breakthrough such as 'personal & digital learning' are fuelling the drive of Artificial Intelligence boom, today in natural language processing. Therefore, with the rapid growth and adoption of DL, a human level of accuracy has been reached through neural networks that use Big Data collection, which in higher education with further research could become a backbone of knowledge in solving various issues in teaching and learning. The future of AI, ML and DL is bright for higher educational institutions to utilise the intelligence captured in Big Data for its progressive development in use of technologies in teaching and learning (Mueller and Massaron, 2022).

In higher education, AI has begun producing new teaching and learning solutions that are embedded in Big Data Analytics and being put into use in different contexts (Collins, 2018; Goksel, and Bozkurt, 2019). For AI to work successfully and support teaching and learning, it requires advanced infrastructures and an ecosystem of thriving innovators such as academic staff who are advancing in technology capabilities as well as in developing new innovative curriculum for a digital and AI powered world for this century and for the higher education of the future. This usage of AI (Mueller & Massaron, 2022) and ML (Chee-Kit Looi et, c2005) extends into supporting innovative creation of new curriculum for a digital powered generation. This further empowers the academic staff in seeking research funding that prepares learners to thrive with relevant skills in an AI market which explores the different means by which governments and educational institutions are rethinking and reworking educational programmes to prepare learners for the increasing presence of AI in all aspects of human activity whilst cutting down costs. The world of AI research includes 'Robotics, machine learning, artificial neural network, natural language processing (Chatbot and ChatGPT), artificial intelligence, evolutionary computation, expert systems to mention but a few. In higher education Copilot, Chatbot and ChatGPT (Benichou and OpenAI, 2023) has brought unexpected results for academic staff as in how students apply it. Chatbot refers to software that mimics human conversation whilst ChatGPT which follows instructions (Recurrent Neural

Network (RNN) in a prompt and provides detailed responses, which students copy and paste in their academic work and classified as plagiarism in higher education. Both these tools can be used to support learning if intelligently applied as assistive tools. The Big Data Analytics analyses how AI can be used to improve learning outcomes. It presents examples of how AI technology can help educational systems in using gathered data to improve educational equity and quality in the developing personalisation, better learning outcomes, collaborative environments, intelligent lecturing, laboratory, tutoring systems and policies that can support academic staff. Mayer-Schönberger, & Cukier, (2014) presents the challenge in developing quality and inclusive data systems in education as we head towards the datafication of education, the quality of data should be the chief concern in institutions. Therefore, it is essential to develop capabilities to improve data collection and systematisation within the environments and AI developments should be an opportunity to increase the importance of data in educational system management by senior management. In this age of Big Data, individual academic staff and student information footprints are left behind in educational portals, resulting in an abundance of data, allowing human and societal behaviour to be objectively quantified and therefore, easily tracked, modelled and, to a certain extent, predicted using embedded blackboard and google analytics. These Big Data Analytics forms part of the historical records in educational silos for future usage whilst improving learning outcomes and teaching experiences. This phenomenon surrounding information footprints is referred to as 'datafication' (Mayer-Schönberger & Cukier, 2014) and also affects the education sector alike. While datafication certainly raises some ethical concerns, which also require a concerted policy response, it also brings a world of possibilities in terms of individualising learning and education governance. All these technologies end up supporting Computational Thinking (CT) that has emerged as one of the key competencies (Denning, 2012) to enable learners to thrive in an AI-powered society of today. Academic staff are aiming on graduating students from higher educational institutions with problem solving capabilities (Kong, 2019; 2022) to fill the needs of the outer world.

2.17 Big Data Security Issues of concern in Higher Education

The following sections 2.17 to 2.19 are sections that do not directly impact on this study. However, as the research deals with Big Data in teaching and learning in higher education, issues of data privacy, quality and security are important to be carried on board in discussions around Big Data and hence the coverage in here.

The six V's (Daniel, 2016) are intertwined and from this research findings they contribute to several issues that impact on academic experience as data security. Large amounts of complex data is cultivated which requires time for analysis to give the full meaning in order for academic staff to use it intelligently in pedagogy. Big Data faces intrusion detection challenges, as the system captures both staff and students' activities around the portal giving the *Big Brother* atmosphere. Although many security monitoring systems have been developed to improve data security, intrusion detection is still challenging virtual learning environment, in cloud computing, in the virtual & physical Servers etc. extending to isolated systems in the university. The issues include how to store large quantities of data safely and compliance to the GPD requirements, how to maintain data security in teaching and learning, and how to track data that flows quickly from different sources in the various university systems.

2.18 Data Privacy Issues of concern in Higher Education

According to academic staff gathering data from students might lead to privacy challenges where the gathering process may cause the data context and semantics to be modified, leading to faulty and inefficient policies (Ali *et al.*, 2016) in such data as attendance, engagement, performance, and progression. This is concurred by (Zhang, Huang, & Bompard, 2018; Lv, *et al.*, 2017a pg4; 2018b) who showed that one potential problem in Big Data is data security and privacy, as Big Data applications often contain sensitive information such as student confidential data (identities) and engagement in various portals which are not appropriate for normal data transmission protocols (Campus money card, printing, and engagement). Data security and privacy must thus be considered before the adoption of any protocol for sharing information or using this in pedagogy. The challenges caused by the inclusion of sensitive information and the requirements for access control or certification are generally well known; however, secured certification mechanisms remain challenging to implement, and anonymisation approaches decrease data confidence (Wang *et al*., 2016). Big Data privacy contains two aspects: the first is that the personal data privacy should be protected during data gaining such as personal data & residential data, which plays a role in learning and used by academic staff in retention. The second aspect is that the personal privacy data might discharge during storage, transmission, and usage, even if it gained with the user permission.

2.19 Data Quality, Data Capture and Data Storage concern in Higher Education

Capturing valuable data is only done at a high cost of time according to academic staff (Chen *et al*., 2014) as they are increasingly faced with data sets that are increasingly growing, challenging and complex in presentation in analytics for teaching and learning for the posited gains. Qiu *et al*., (2016) and Oussous *et al*., (2018) discussed Big Data characteristics in terms of it being processed by many analytical tools and visualisations, which is a true reality of the university data as found in this research in blackboard, SEMS and other data silos. The Big Data platforms layer and its components and technologies are rarely explained for academic staff and a number of the voices on 'self-learning' as a way of understanding what they view in front of these analytics. In term of capabilities, different technologies were compared, and Big Data systems categorised according to their features and the services provided to academic staff such as student progress & completion with list not exhaustive. This highlights that Big Data usage in higher education still has many technical issues that need to be studied and polished in order to fully support academic staff. The Big Data computing systems' challenges, examining difficulties on various different levels 'including data capture, storage, searching, sharing, analysis, management and visualisation' Qiu *et al.*, (2016). This included examining security and privacy issues as already discussed above. The size of Big Data is increasing exponentially, and this makes the current technology unable to handle such Big Datasets that are really meaningful to academic in various activities of teaching and learning. Modern Big Data challenges thus include Big Data management where the challenge lies in collecting, integrating, and storing data with minimal requirements (hardware and software), although this affected more of the IT Services than academic staff as per this research study. Most academic staff found Big Data analytics challenges lie in the complex data analysis required to understand the relationships among data features (**large amount of Information**). The challenge with Big Data analytics mainly arises due to the '*Volume, Variety, Velocity, Value and Veracity'* (also known as 5V's of Big Data) and their effects on learning for Big Data trends in dataset performance as also supported by (Qiu *et al.*, 2016, pp3&14).

2.20 Data Analysis and Visualisation Challenges in Higher Education

Data analysis challenges arise from data complexity, which in turn comes from the data's complex types and structures. Standard data analysis techniques face difficulties in handling such Big Data as it is more difficult to understand the distribution laws of Big Data (Wang *et al*., 2016). Big Data visualisation challenges come from the data's high dimensions and size from the portals. The main goal of data visualisation is to explain knowledge effectively by using diagrams; in order to transfer information easily to the user, hidden knowledge in the complex and large-scale data sets is rendered visible. For more accurate data analysis, however, abstracting information in schematic formats, including features or variables representing units of information is valuable. Nevertheless, because of the large size and high dimensions of Big Data, it can also be difficult to manage data visualisation in Big Data applications and academic staff difficulties of interpretation of these large data sets lies in here, too.

Günther *et al.,* (2017) noted that some empirical studies and some old ideas have characterised much of the Big Data value realisation in which a study examined six debates identified in terms of "how organisations realise social and economic value from Big Data that require attention for future research" Günther *et al*., (2017). Two additional features of Big Data were also identified, portability and interconnectivity, and those features were utilised to show the effect of Big Data value realisation in the university.

2.21 Data for Decision Making in Higher Education

Generally, decision making occurs at the stage of each Big Data procedure, including data storage, data cleaning, data analysis, data visualisation, and prediction. However, it is sometimes difficult to achieve a suitable solution for each procedure, and many technologies and techniques can be used for decision making in Big Data work. Some decision making requires input from many disciplines, including data mining, statistics, machine learning, visualisation, and social network analysis.

Despite certain challenges, decision making is supported by advanced technologies and tools in each phase of processing and applying Big Data, and the use of Big Data now plays an important role in many decisions making (Marr, 2015, 2016b) and forecasting domains such as in healthcare where it has unlocked new opening (Patil and Seshadri, 2014) on health records storage and communication.

Big Data use requires decision support mechanism, in higher education as articulated by Daniel, (2017) in his six V's as universities are operating under enonomous pressure to tranform the educational research using the volumes of Big Data that institutions generate. Academic staff could use such generated data to enhance analysing and presenting data from surveys, interviews in teaching and learning for value, validity and verification that would enhance innovation in informing pedagogical practices (Lockyer, Heathcote, & Dawson, 2013). They further argue that pedagogical actions include understanding concepts of learning analytics which embedd collection, analysis and reporting data from big data assiciated with student learning behaviour and learning design of teaching practice. This is concured by Taylor-Sakyi, (2016) as he articulates the importance of transformation from traditional analytics to Big Data analytics necessity, which maximises computation power and algorithmic accuracy that further unblock vulnerability, volatility, viability, veracity and visualisation in teaching and learning data. The decision maker must identify the values required and focus on finding methodologies, technologies, and tools that allow them to select the best decision; this process thus relies on the assumption that the decision maker is sensible and reasonable.

2.22 Summary

In summary in this chapter, I reviewed the existing body of literature on academic staff perceptions of Big Data and Analytics in teaching and learning in order to give the present research context. This has been done by organising the chapter into three sections which are intertwined and support the exploration of the research question. The literature review has revealed a spectrum of interpretations in various sections. The research being carried out here, will be significant in determining the experience of staff and should be able to position the findings in close proximity to the findings of other authors on Big Data and Analytics (Williamson, 2017; Chaurasia & Rosin, 2017; Daniel, 2015) or to totally open up new insights in higher education. The work of the aforementioned authors is recommendable in this research either from a topical point or methodology adoption, however nothing explicitly highlighted the academic experience with Big Data and Analytics that fully aligned with higher education. Therefore, the proposed research study will seek to build on this higher education work already covered and that articulates distinctively the academic staff perceptions on the role that Big Data might play in teaching and learning. This should highlight their varied experiences and the environment that they operate from. The chapter also captures in detail the pedagogical approach with Big Data Analytics in industry and the university, with a commonality in the intelligence derived for different benefits.

In addition, the beauty of examining the existing literature review is that it provides context in which to set the present research by understanding what has taken place before and future projections. The review has provided the researcher with a number of challenging thoughts and questions, which have led to the articulated research question in my research. It is anticipated that in the process of the research some of the questions will be addressed through the main core research question.

The literature review has highlighted the direct scarcity of research into academic staff experience of Big Data Analytics in the 21st century. This is rather shocking considering the advances in technological capabilities but hypothetically, if such research existed it would have only tapped into technology and not the Big Data phenomenon as the latter only bubbled up in the late 21st Century (2014 to the current state). Furthermore, the state of technological capabilities in higher education has been going through a revolution at a faster rate, therefore before 2014, the use of technology was very different to the one present today. Therefore, the research is timely and provides full justification for pursuing an investigation into academic staff and Big Data in higher education. **Terminological Tangles**, it was viewed as good scholarly practice to untangle the terminology tangles within this emerging field of **Big Data**, where we have Big Data Analytics and Learning Analytics in existence around Higher Education to give a focal point to these related concepts. Big Data refers to significant growth and volume that is used in HE which requires large storage and processing software (Daniel, 2016). Once processed then it unveils patterns and generates useful insights for decision making. **Big Data Analytics** on the other hand is a byproduct of BD once processed and involves enormous and complex datasets which include structured (Fig 5.1 pg. 119), unstructured (Pages 182-183), and semi-structured (Fig 5.2 pg. 122) data as captured in appendices, too. These as demonstrated in figures they offer patterns that can be intellectually interpreted for purposeful information for decision making in pedagogy (Daniel, 2015). **Descriptive Analytics**: historical data and provides insights into what has happened. **Predictive Analytics**: which uses historical data to predict future outcomes (Satpathy & Mohanty, 2020). **Prescriptive Analytics**: Recommends actions based on data analysis. **Cognitive Analytics:** Involves machine learning and artificial intelligence to enhance decision-making (Satpathy & Mohanty, 2020). This research has utilised these analytics from various sources within HE which are highly intertwined to BD. Whilst **Learning Analytics** entails analytical techniques to educational datasets. It discovers hidden patterns and uses the analysis outcomes for actions such as prediction, intervention, recommendation, personalization, and reflection in educational contexts. All these intertwined terminologies play crucial roles in understanding patterns, making informed decisions, and driving advancements. There exist high similarities in their theoretical definitions and what they provide has a common theme running through them, with a keyword "interpretation". It is this interpretation that can be used to improve practice in strategic planning, course development, teaching pedagogy and student assessments in higher educational institutions (Lester, et. al., 2018).

In conclusion, I have examined the existing body of knowledge from existing literature which contribute to my enquiry on the perceptions of the role Big Data and Analytics might play in teaching and learning. The literature examination has revealed an abundance of rich literature on use of Big Data and analytics in higher education through the use of artificial intelligence in teaching and learning, painting the contrasts and conflicts within the technological advances in the area of research and around the research question outline in table 4.0 below.

The following Chapter Four will comprehensively address the phenomenographic research approach methodology that has supported this research study. I consider the following work to be significant in shaping a holistic approach for the research in contemplating academic staffs' experiences. The questions that have arisen in the What and how will be bracketed as in the data corrected to respond to but more so this will be vital in responding to the discussion of the findings in chapter four. In conclusion the discussion in this chapter has strongly supported the main research question in how my research responds to the various sections of "In what different ways do Academic Staff perceive the role of Big Data and Analytics might play in Teaching and Learning" and the embedded four questions.

Chapter Three: Research Methodology

3.1 Introduction

My research had set out to find the variation in perceptions on the role that Big Data might play in teaching and learning in higher education as experienced by academic staff, with a focus on how individuals experiences might contribute to pedagogy. The purpose of this research was to investigate experiences and document the variation in the perceptions that academic staff might hold on to the role that Big Data might play in teaching and learning. This outlined purpose determined the methodology to be used and outlined below. The main research question entails, '***In what different ways do Academic Staff perceive the role of Big Data in Teaching and Learning in Higher Education?'.***

This section describes the research study strategy to answer the research question which aim to understand the academic staffs' experience with Big Data within higher educational settings in pedagogy and experience current Big Data Analytics features (Appendix A1) and indicators (figure 5.1) derived from multiple analyses on BDA's. By exploring the academic staff's requirements and beliefs about Big Data and Analytics helps researchers to understand what academic staffs expect from Big Data and how BDA can provide value to academic staffs' and higher education.

Therefore, in this Chapter Three, I seek to outline the qualitative phenomenographic research method that was adopted to aid the efforts towards this research. This section will, therefore, firstly outline the method that was used to *collect (bring a number of things)* and *generate (produce & create)* the required data as preferred descriptive terminologies, with participants acknowledgement of their role in influencing this research process. This will be followed by a second section that will outline and map out the methods used to analyse the collected data towards my specific research objectives. In both these sections, I will clearly outline the trajectory that my research followed through collection, generation and analysis of data in the main before progressing to some critical aspects of the research process.

In the third section, I will discuss quality issues with regards to the research undertaking, with a particular focus on ethical conduct, *validity* and *reliability* (Åkerlind, 2005). I use these two terms respectively in my research to acknowledge the position (*stance*) that phenomenography shares much in commnon with assumptions uderlaying other qualitative research traditional methods (Åkerlind, 2005). According to Åkerlind, these draws on practices with differences that necessitate its own practices and this supports my research emphasis on similarities to qualitative research that is not inferior to its quantitative counterpart or that it escaped the rigorous scrutiny (Åkerlind, 2005 pp329-330; Kvale and Brinkmann, 2008).

3.2 Theoretical Underpinnings and Perspective of the Research Study

Phenomenography was adopted as a rigorous way of answering my research question as it offered research procedures on conducting a thorough and systemic phenomenographic study (Han, & Ellis, 2019) (Åkerlind, 2005b). This included sampling that was done before the main data collection, fitting in with a phenomenographic data analysis stage in building the categories that developed from the analysis which communicated key findings of my research. The phenomenographic *second-order perspective* which helped in tackling the contemporary challenges in science education in higher education by describing the academic staff's collective experience of the world and variations in that collective experience that my research was exploring with use of Big Data and Analytics. This was of crucial importance in understanding why Big Data plays a vital role in pedagogy and how all may experience the same Big Data but have different individual experiences which can develop into a collective theme. The phenomenographic second order perspective was able to bring out the understanding that another person can see things differently in one physical space and indicative the organisation of that other person's point of their worldview (Trigwell, 2006). In order to provide academic staff in science education (Tight, 2016, pp 319-338) an appreciation of the phenomenographic method and capacity to implement the findings of my research into practice including the ontological & epistemological assumptions in the second-order perspective as further discussed in the methodology and data analysis chapters (Han & Ellis, 2019).

A theoretical perspective describes the stance behind the chosen methodology that is to direct the research in question (Crotty, 1998). The theoretical perspective and philosophical position, taken in order to fully address the research study was that of an interpretive (Crotty, 1998, pp 67-68). According to Crotty, the interpretive stance is contrasting to that of the positivists stand with the former looking for culturally derived and historically situated interpretations of the real-world view. However, this comes at a cost of encountering difficulties in convincing mainstream audiences that the findings are as much a contribution to knowledge as those of their positivist-oriented disciplines (Hogg and Maclaran, 2008). Interpretivists believe that the focus of study for social scientists like the one being undertaken here i.e., academic staff and their institution is essentially different from the focus of the study by natural scientists who focus on predictions and descriptions. Therefore, interpretivists researchers believe that social phenomena exist in the minds of people in the community of study and in general attempt to understand phenomena through the meaning that people give them. Meanwhile positivists hold the view that phenomena can be defined objectively. According to (Bryman, 2004) interpretivists hold the views that social phenomena have to be defined subjectively. Interestingly, positivism tends to reject the idea of detached individualism, objective observer who can apply natural sciences to the study of social reality. These tend to understand that the social world is fundamentally different from understanding the natural world (Cohen, Manion and Morrison, 2007 p200) with concepts of realibility at the forefront. According to (Cleaver, Lintern, & McLinden, 2014) they state that:

> …Interpretivist fundamentally underpins the wish to understand social phenomena within their particular context. For this reason one doesn't/ not attempt to research the phenomena in objective way but rather recognises that accounts of the phenomena necessarily needs to take their settings into account. Cohen et.al, succienctily captures it as interpretations of understanding of individuals intepretations of the worls around them has to come from the inside and not outside.

From an interpretivist view point the theoretical perspetive is a way of looking at the world and being able to derive sense out of it in its current state. Many assumptions could be inevitable that can be brought to a methodology chosen, namely phenomenography. In light of this it is therefore considered a good research practice to reflect on some of the assumptions. These will be stated and discussed in the following sections (3.5 and 3.5.4) within the methothodology chapter. I therefore put forward an argument that it would not have been appropriate to adopt a positivist stance in the research exploring academic staff perceptions and how they experience Big Data and the role it might play in teaching and learning. This is suitable considering that the focus is drawn from 'individual understanding of reality' in their perceptions and interpretations of the academic world' (Cohen, Manion and Morrison, 2000 p200). In view of the research study the theoretical stance taken and deemed fitting was therefore the 'iterpretive' which was adopted. In view of this section, it is logical to look into qualitative research.

3.3 Qualitative Research Strategy

At this stage it is pertinent to address quantitative and qualitative research strategies briefly, in order to describe why the adoption of qualitative research strategy was appropriate through this research study in recognition of the phenomenography as part of the qualitative research (Marton, 1986). This is concurred on by Kvale and Brinkmann, (2008) who puts emphasis on the fact that phenomenography uses qualitative interviews in data gathering. According to (Kelle, 2006 p69) qualitative research strategy is 'derived from the humanities with an emphasiss on holistic and qualitative information analyses by means of computing.

3.4 The Choice of Phenomenographic Research Approach

Phenomenography is a well-established qualitative research approach which is widely used in HE to understand students' experiences in order to uncover pattens and trends of variation (Marton, 1986; Marton & Booth, 1997; Bowden & Walsh, 2000) in individuals' personal worldview. To arrive at adopting qualitative phenomenographic research included an extensive literature review on methodologies on my part including the competitor 'grounded theory' (Bryant & Charmaz, 2007) approach. Phenomenography in this research helped the researcher to identify a participants' prior knowledge, including its relative accuracy and immature conceptions about various concepts of Big Data and Analytics as the research focus.

Phenomenography is highly associated with research that has an interest in higher education practice, such as this study, particularly in exploring experiences and in seeking to understand a phenomenon by way of encouragement of deeper rather than shallow experiences and variations in Big Data (Marton, 2000 and Tight, 2016). Considering that I have worked in higher education for twenty three years not only do I take pride in our own research design but moreso it congruently fits the reseach study to be undertaken, in this study (Tight, 2016). This research design if conducted well, yields practically useful findings (Tight, 2016) and it is anticipated that this will be the case in this study. It is a well thought out qualitative research held in high esteem with the sector, and it is supported by a stronger qualitative interview in its' research design.

Several methodologies were reviewed, and only phenomenography covered the needs in my research aim and answered the '*What and How'* questions that I had set in exploring academic staff experiences (Trem, 2017). Marton, (1986, p31) articulates phenomenography as a research method for mapping qualitively different ways of peoples '*experiences'* and with Åkerlind (2005) articulation on peoples' '*variation'*, phenomenography gained more acceptance as a research approach in academic staff in HE in this research. According to Tesch, (1990 pp. 60-69) constructs a different model of qualitative research that consists of four cognitive mapping (as shown below) which comprised of twenty six types of research. The following four stands out and aligns with my research question.

1. *Research that studies the characteristics of language,*
2. *Research that aims at the discovery of regularities,*
3. *Research that seeks to discern meaning,*
4. *Research that is based on reflection.*

(Tesch, 1990 pp 60-69)

It is in view of these core undertaking those different ways of experiencing the phenomenon can be logically captured and commonality be identified as echoed by Marton & Booth, (1997); Bowden & Walsh, (2000) which in phenomenography provides an upper stand on contrasts and conflicts by provisding less judgement on classification of high or low experience. My research study aimed at exploring academic staffs' Perceptions of the Role 'Big Data and Analytics' might play in Teaching and Learning.

3.4.1 Consideration of Alternative Research Methodology

Consideration was given to two other approaches, namely Grounded Theory (GT) and Phenomenology. GT provides a rigorous approach to qualitative research and its purpose is similar to that of phenomenography in revealing and grouping issues into categories (Bryant & Charmaz, 2019). In phenomenography categories or themes emerge from the analysis of the transcripts as opposed to forcing data to fit a predetermined model (Åkerlind, 2005 & Marton, 1986) and GT could be argued that it would not be an appropriate methodology to deploy in this research. GT tends to have inductive approach and have emphasis on exploring themes raised by participants which is viable, but phenomenography had an edge over this as it tackles core ways of a groups' experience on a known phenomenon and how it seeks different qualitatively relationships with each other (Bryant & Charmaz, 2019).

3.4.2 Comparison of Phenomenography to Phenomenology

It is logical to discuss the relationship between phenomenography and phenomenology as it is important not to confuse the two as they both share the term "phenomenon" which means to "bring to light" (Larsson & Holmström, 2007). Phenomenography and phenomenology offer further a few more similarities as they are both qualitative research approaches and they both use interviews in exploring interests in "human", "experiences" and "awareness" of a specific phenomenon (Tight, 2016; Marton & Booth, 1997 and Larsson & Holmström, 2007). These two research approaches mirror each other with high similarities but with distinctive differences at the same time. Marton & Booth, (1997, p117) articulates that these two have a qualitative different way of experiencing a phenomenon which is "finite but not closed" as science continues to develop new ways of seeing any phenomenon in question. However, Marton distinctively states that:

"Phenomenography and phenomenology do share the object of their research in as much as both aim to reveal the nature of human experience and awareness".

He further calls these legitimates of "child" of the other and "cousin-by-marriage" but not to be confused as an 'offspring' of phenomenography. I chose phenomenography over phenomenology for the reason that the former doesn't draw a line between "prereflective experience and conceptual thought (Marton & Booth, 1997, p116)", meaning not having awareness before doing any reflecting on ones' experience in Big Data. The choice was further reinforced by its known stance in education, where it is understood that it was developed as an educational framework. The research approach further denotes a research approach aiming at describing the different ways a group of people on how they understand a phenomenon. This aspect would assist on understanding Big Data within the academic staff in higher education.
According to Larsson & Holmström, (2007) phenomenography offers a "second order perspective" that offers an orientation towards people's ideas about the world views and experiences. Whilst phenomenology offers a "first order perspective" which describes the world as it is. Phenomenography puts its emphasis on reflective experience and collective meaning whilst emphasis in phenomenology is on prereflective experience and individual meaning of the phenomenon (Marton & Booth, 1997, pp 116-117 and Brinkhamann & Kvale,

2015, pp 30-31). Marton, further states that phenomenography extends its wing to include capturing richness of variation in individuals' experiences, the fullness in which those individuals experience and describe the phenomenon of interest.

Another differentiating aspect between the two research approaches is their stance on ontological difference. Phenomenology takes a dualistic ontology, which stipulates that the "object" and "subject" are viewed separately and independently. Phenomenography has its principles in that the nature of reality is defined as non-dualistic with the subject and object are inseparable (Åkerlind, 2005).

3.5 Engaging with Phenomenography in this research.

Phenomenography is based on beliefs and doesn't make assumptions about its actors or objects of its study on their conception and experience as discussed in the section above. The challenge to those engaging in a phenomenographic research lays in clarifying and justifying what their research involves ontologically, epistemologically, and methodologically and the following sections will aim to tackle these.

3.5.1 Ontological and Epistemological position – Avoiding Dualism Ontological Issues.

According to Maykut & Morehouse, (1994) ontology is about the nature of reality and concerned with nature of existence, whilst Uljens, (1996) states that the issue of ontology in phenomenography refers to the relation between consciousness and reality both concuring on 'reality'. One describes the world the way one experiences and creates ones knowledge about it and therefore reality.

In ontological terms a basic tenet of phenomenography is that the nature of reality is defined as non-dualistic. This implies that the subject and object are inseparable:

> From a non-dualistic ontological perspective there are not two worlds: a real, objective world, on the one hand, and subjective world of representations on the other. There is only one world, a really existing world, which is experienced and understood in different ways by human beings. It is simultaneously objective and subjective. An experience is a relationship between object and subject, encompassing both. The experience is as much an aspect of the object as it is of the subject (Marton 2000, p.105).

3.5.2 Different ways of Awareness

According to Marton & Booth, (1997, p107) in phenomenography, to experience somethig is to be aware of something, "the totality of our experiences we call awareness". He further draws on Gurwitsch's (1964) ideas about the structure of awareness (p.98):

Awareness is not seen in terms of the dichotomous nature in order to avoid simplification fifure-ground, thematised-unthematised, explicit -implicit, but being characterised by an infinitely differentiated figure-ground structure (Marton 1997, p98). There are different degrees of how figurial things or aspects are in our awareness.

Marton (2000, p110) discusses in more detail on figure-ground structure, as he articulates certain things coming to the fore, they are fugural and thematised while other things recede to the ground which are tacit and unthematised. This highlights the factual underpinning that there are different levels of awareness in individuals as they can all be aware of everything at the same time but not in the same way. Hence awareness is structured in a particular way that gives meaning to an individuals conception of an object and this makes individuals to be able to hold certain things in the foreground of their awareness. These are presented at the next level , further away at an outer level, on the fringe, are yet other things. Normally individuals are not always consciously aware of most things but only when they become relevant they enter the foreground of an individual's awareness. This then suggests that individuals can hold explicitly and implicitly their group as opposed to isolated awareness and experiences are always embedded in a context.

In summary, Marton & Booth, (1997 p111) describe:

> Phenomenography is not a method in itself, although there are methodical elements assosicate with it, nor is it a theory of experience, although there are theoretical elements to be derived form it. Phenomenography is not merely an opportune player that can assume the role needed for the moment, it is rather a way of-an approach to -identifying, formulating and tackling certain sorts of research question, a specialisation that is particularly aimed at questions of relevance to learning and understanding in an educational setting.

Phenomenography is used not just as a method of analysis but as a holistic research approach, which has been adopted in this research study.

In summary, experiencing a phenomenon has two aspects a referential aspect which holds meaning and a structural aspect comprising an internal and external horizon. Therefore, referential aspect is derived from the related aspects of the phenomenon in the internal horizon and the relationship between the two horizons. The two aspects, referencial & structural are intertwined and occur simultaneously when an individual experiences something.

3.6 Research Approach-Researcher and Practitioner Boundaries

Monitoring the balance of power between the researcher and the participant in this research study was necessary and was given priority. I adopted the guidelines of Marton & Booth, (1997) by treading carefully around the fragile relationship, especially one during times of reflection requiring the researcher when asking probing questions. This included not being too demanding whilst at the same time not appearing indifferent. As a researcher I had to step aside the scenerio which is very familiar to me and I kept reminding myself that conducting phenomenographic research is a challenging activity in a number of respects which includes:

- Observing the prime objective of phenomenographic research as being to see the world from the participants perspective and experience.
- I was always aware of the power balance between myself and the participants.
- To be able to be a keen listener with listening skills during interviews whilst being alert to new lines of thought that participants could introduce and be ready to follow the participant's course of reflection.
- Being able to empathise with periods of participants silence during the interviews as they critically reflected on their responses.
- To be able to seek diversity during my data analysis and recognise the significance of all categories that emerges from the research question.

Ashworth & Lucas, (2010, p.299) *"The researcher and researched must begin with some kind of shared topic, verbalised in terms which they both recognise as meaningful".* With this in mind, when considering how to start the interviews, I decided to discuss with the participants to reveal how they understood, 'Big Data and Analytics' and to discuss the first thing that comes to their minds when they heard the word. In doing this each interview was in effect uniformally started on the participants own terms and not those of the researcher as stipulated by Marton.

3.6.1 Marton's Framework: Origins, Experience and Awareness in Phenomenographic Research

The Origins of phenomenography are deeply rooted to the Göteborg (Gothernburg) university studies of the 1970's which suggested the approaches to learning framework. In particular this was led by Ference Marton in developing this as a separate research approach with his influential articles that commenced in the 1980's (Marton, 1982, 1986) and his popular book with Shirley Booth (Marton & Booth, 1997) which articulated in more depth the underlying philosophies. Ference's main research work is firmly focused on a frameswork within the field of educational research as an approach that he proposes as being useful for examining both the content and process of learning (Marton, 1981) which contributes well to my research study. Marton & Booth (1997) state that the unit of analysis in phenomenography is a way of experiencing something and the object of the research is the variation in the ways of experiencing. In his further research work, Marton went on to clarify that the unit of analysis was a 'conception' which he considered analogous to ways of experiencing , understanding and apprehending (Marton & Pong, 2005) etc. this conception occurs when an individual discerns something from the broader context within which it disseminates both its structures, key features and meaning. Hence these two aspects of the conception(structure and referencial) are intertwined and tend to occur simultaneously. This is true of us as humans that we can not be aware of all aspects around us and therefore our awareness can only be structural, in which we foreground certain aspects of things and allow others to recede (Marton & Booth, 1997). The key element of phenomenography is further embedded in the fact that individual people may experience a phenomenon differently as they encounter them in 'qualititively limited different ways' (Marton & Booth, 1997, pp 110-112), which is linked to the argument of a structure of awareness. Again, as humans we can not possibly be aware of all aspects of everything at once, discern or foreground certain things in order to be ble to give them meaning. Marton and Booth link this to 'limited capacity' for simultaneous focal awareness in us (p101) on a phenomenon that we are constrained into with a limited number of qualitatively different ways of experiencing it in its existing abundance.When these limited numbers of differential ways of experiencing emerge from data analysis, they form categories that we refer to as 'categories of description' which build a hierarchy based on the level of complexity or inclusiveness of the description. This line of thought is justified in the educational context there Marton's framework approach was developed. According to Marton & Booth, 1997 (p101, p126) they state that it is an educational norm to have a reasonable assumption on a 'particular way of experiencing' a phenomenon that is to be preferred over others and 'educational efforts' are designed to 'foster' this aspect. This line of thought is central to my understanding of the hierarchial structure of the categories of descriptions of phenomenographical outcomes of my research study and I will revisit in chapter four. When the final set of categories of descriptions related to each other in a hierarchical structure is reached after many iterations, it is known as the '*outcome space'*. This outcome space comprises of descriptions of variations in ways of experiencing the phenomenon at a collective level. At this juncture the voices of individuals have been lost in an effort to arrive at what Marton describes, "a stripped description in which structure and meaning of the differing ways of experiencing the phenomenon are retained" (p114).

Therefore, the outcome space documents the relationship between the categories of description:

> The outcome space is the complex of categories of description comprising distinct groupings of aspects of the phenomenon and the relationship between them (Marton & Booth 1997, p126).

Usually, categories of description are logically related to one another (intertwined) but not always, this relationship is a hierarchically inclusive relationship with some categories being more advanced and complex than others in the same study. The outcome space therefore represents the variety of ways in which a given population experiences a phenomenon. In my research study this population exists in higher education with academic staff across all the existing schools\faculties. I will come back to discuss outcome space later.

3.6.2 Object of Phenomenographic Research

Phenomenography involves elements of knowledge based on some ontological assumptions and therefore it will form part of an epistemological assumption in the research by default. Phenomenographic deep interviews and analysis was chosen as a fitting theoretical framework based on developments by (Marton, 1986). Marton further states the encapsulation of 'hermeneutics' in the methodology and this aspect will give this educational research 'interpretation of knowledge' on academic staff experience and variation or indicate gaps that exists. It is hoped that in applying phenomena on understanding 'Big Data' in higher education, we can gather a careful understanding of staff experiences with different ways in a survey of thirty-six participants in Leeds Beckett University perceive it. Therefore, this Phenomenographic data and information about conceptions of Big Data phenomenon will be helpful to academics and management in the university who can further use this to understand aspects of technological pressure and management of it in order to be able to understand it from academic staff perspective. Phenomenography research approach helped my research by giving it a focus which was based on an understanding that the investigation was not directed at the Big Data phenomenon as such, but at the experience, understanding and variation in people's ways of understanding the phenomenon (Larsson & Holmström, 2007 p56), fitting in with the "second order perspective".

3.6.3 Outcome of Phenomenographic

In a phenomenographic research study the "outcome space" is derived from the data analysis that sorts the perceptions which emerge as categories of descriptions that collectively they express the variety of the ways in which a particular phenomenon is experienced by a group of individuals in a given context. He further state that the unit of phenomenographic research study is a way of experiencing something and the object of the research is to find variation in ways of experiencing something as discussed in sections above (Marton & Booth, 1997, p111). As the unit of analysis of phenomenography are the qualitatively different variety of ways in which a phenomenon can be experienced with the outcome not being accounts of the experiences of individuals. The outcome space requires a pool of experiences collected and the collective variation is extracted and presented.

3.6.4 Categories of Description

Categories of description describe the variation in ways of experiencing a phenomenon at a collective level. Categories of description are not formulated prior to data collection or analysis as they tend to emerge from the researcher's interpretive analysis of the data. These describe the variety of ways in which individuals and collectively in a specific context experience. These categories are formulated through examining the qualitative variation in meaning in academic staff accounts, by a process of formed and reformed by moving between the categories with the aim of constituting a hierarchy of empirically grounded and logically consistent categories of description of the different ways in which academic staff described Big Data. However, it should be stated that even if only one participant describes a category, it is still valid. An individual participant category does not constitute the phenomenon itself but represents a unique way of experiencing the phenomenon being investigated. The category name given to a category of description is intended to convey the embedded meaning of the category and each category name is unique, shows what is distinct about the category in relation to other categories. I will use quotes from the data, and these will be used to demonstrate the important feature of each category.

As mentioned in the discussion above in section 3.5.4, the set of categories should fully represent the collective views of experience of the population under investigation. The collective view should be understood to be reasonably stable in the population and context, however, they cannot claim to be exhaustive given the limited number of people studied within the fulfilment of the recommended phenomenographic range. Marton & Booth, (1997 p125) state that a set of categories of description should be able to satisfy three criteria and namely:

1. Individual category should each stand in clear relation and in distinct about a particular way of experiencing the phenomenon.

2. Categories have to stand in a logical relationship within a commonly hierarchical between the categories.
3. The system outcome space should be parsimonious as possible for capturing the critical variation in the data.

3.6.5 Outcome Space

As discussed above, Therefore the outcome space documents the relationship between the categories of description:

> The outcome space is the complex of categories of description comprising distinct groupings of aspects of the phenomenon and the relationship between them (Marton & Booth 1997, p125).

The categories of description are logically related to one another, and the relationship is normally a hierarchically (not a norm) inclusive one with some categories being more advanced and complex than others. These collectively offer the variation that as a group would experience and shines a light into the context under investigation.

3.7 The Phenomenographic Research Design

Both Research Ethics Committee's approved the study as meeting the University requirements for a post graduate research.

3.7.1 Ethical Consideration

The ethical approval involved both institutions, Leedsbeckett University where the investigations were taking place and Lancaster University where the course runs from as per the validated program requirements set. Leeds Beckett University's Research Ethics Approval

Committee and Lancaster Research Ethics Committee stipulates that when conducting research involving human participants, requires full adherence to:

- All participants received full information about the nature, confidentiality, objective, withdrawal, and duration of the research in 'Participation Information Sheet'.
- Consent was sought from participants and 'Consent Form' was emailed in advance and signed during the interviews.
- All participants were assured of confidentiality of the data being collected during the interviews in this research study. All participants in this study are known by pseudonym comprising of a letter and number *(see Appendix D2)* which held all their data. This made participants untraceable and respecting their confidentiality and privacy.
- All documentation for participants has been kept in accordance with both university guidelines.
- All participants were informed of data storage arrangements and given an opportunity to ask questions or voice concerns regarding the research before embarking on the interviews.

3.7.2 Selecting a Research Study Sample

Potential participants in the study included academic staff from all faculties across the Leeds Beckett University in England. The selection only focused on academic staff in teaching and learning with no less than 6 hours teaching allocation and with a maximum of 18 hours contact time with students. These participants are highly exposed to technologies that impact in their teaching and will have used tools that hold Big Data in this institution. Therefore, this sample was ideal for responding to the research question. Big Data can be experienced through shared drives, databases, cloud computing facilities, SEMs and Blackboard (Blackboard analytics). As an academic myself, I was aware that this community is likely to experience two or more of these technologies in teaching.

3.7.3 Selecting Participants

According to Marton & Booth (1997) it is relatively easy to get interviewees to describe their strategies, however, it is much more difficult to get them to discuss their intentions underlying their strategies and their conceptions of phenomena. (Prosser, 2000, p. 44). In order to approach the participant's conceptions, I considered phenomenographic interviews as a suiting qualitative methodology. They further state that interviews take place on two levels: the interpersonal contact between the interviewer and the participant and at a metacognitive level in which the participant relates his/her awareness of an experience (Marton & Booth, 1997, p. 87). So, whilst I attempted to maintain focus on the target conception(s), I was also mindful to provide room for the participants to fully express related nuances and details of their experiences. I further took into considerations, within the context of the co-constructed interaction to share my own experiences, whilst carefully observing Bowden (Chapter 4) warnings against "leading too much" to avoid influencing the participants during the interviews. The co-construction interaction and anything that I disclosed during the interview was carefully transcribed and reported as part of the participant's dialogue *(see data analysis sections)*.

In some cases, a phenomenographic interview might seem to revolve tediously around the same question repeatedly. This was partially true in application in this research as similar questions in different ways were asked, to elicit a number of different views on the phenomenon (Kvale & Brinkmann, 2008). A set of questions were typically used to help with the provision views of each conception from several angles in order to make the description of the conception as rich as possible (Trem, 2017 & Åkerlind , 2008).

3.7.4 Main and Pilot Interviews Limitations

3.7.4.1 Pilot Interviews

Prior to the interviews taking place a pilot interviews were carried out with an aim of testing the clarity of questions, time required to conduct an interview, check objections and omissions on any questions. All the three pilot interviews were recorded and thematically transcribed to gain insight into how well this had been achieved. The pilot study here helped to increase the likelihood of success in the main study. This will further support feasibility, valuable insights and potential practical problems into the questions and see if any modification is required before main study (Brinkhamann and Kvale, 2015).

I had used phenomenographic study in paper EDS283 which gave insight into requirements of utilising qualitative semi-structured interviews in a study sample. Even with this experience, I did position myself as a novice in using the phenomenographic research approach and therefore it was in order to conduct a pilot interview to examine and be able to refine my skills (Åkerlind, 2005b). The pilot study was deemed essential too, as limitations and lessons gained from the earlier paper assisted in making the pilot study essential. Bowden (2005, p19) states that pilot interviews should be undertaken with people individuals similar to the intended research sample. This prompted me to select a sample of three academic staff from the largest participating schools within the existing twelve, namely the Built Environments, Engineering & Computing, Business and Education.

The pilot study was conducted within LBU in line with Bowden's thinking and these were invited to attend the interview individually, at a location of their choice and at their convenient times. The key research question was prepared to examine their thoughts, experience and variation in Big Data Analytics. Indeed, the questions for interviews should be kept as open-ended as possible to allow participants to choose the dimension they intend to answer. Marton (1986, p.42) argues that dimensions chosen are an important source of data because they reveal an aspect of the individual's relevance structure. The open-ended questions were further supported by the *probing questions*, that helped to explore deeper answers in order to bring about depth and breadth in the interview results. Such questions included:

- *Could you talk me through a particular experience you have had with Big Data and Data Analytics from the VLE?*
- *Can you tell me about one incident from which at a particular time, when you had to seek this information for pedagogical practice from Big Data or Big Data Analytics information that supports teaching and learning?*

The interviews on average were arranged to last for 25-45 minutes, the same length of time applied to the pilot study. On average most interviews lasted for

45 minutes with participants being encouraged to explore Entwistle's remembered instances, in which a concept has been experienced (a perceived concept or perception) in order to determine the conceptions held by participants of the phenomenon (Entwistle, 1997).

3.7.4.2 Pilot Study Summary: Lessons Learnt

In summary, carrying out a pilot study interviews demonstrated the importance of putting myself and participants at ease by providing a comfortable environment. Pilot studies also demonstrated the value of spending time talking to participants about life outside our "click phenomenon". These allowed for discussions around internal politics to ensue in order to create, within them, an appropriate frame of mind and confidentiality about their experiences within schools across the higher educational environment.

The pilot study offered room for 'Reflection' in a phenomenographic interviews, which helped to uncover thoughts not previously recognised to the researcher as I spent time reflecting on each pilot interview, the questioning style and the emphasis its significance and consequently the importance on the use of probing questions. By the time I got to the pilot study three, it was found that repetition on my part was reducing significantly, use of prompting repeated words increased to encourage participants on their line of thought. The pilot study interview findings helped to shape the main interviews for the phenomenographic interviews in the main study.

3.8 The Phenomenographic Interview Preparation

It was important that I prepare myself for these interviews and the order that the questions will take in the interview. Therefore, I explored my research question which allowed academic staff to talk about their experience and perceptions of Big Data in teaching and learning. In asking academic staff to talk about their experiences of the phenomenon was part of working with them, in bringing forth their awareness of undertaking the task, a state of meta-awareness" (Marton & Booth, 1997, p 130).

Interviews were scheduled to take place in individuals offices or quite meeting rooms as per the choice of the individuals across the schools and all took place in between the four campuses of the university. At the outset, all necessary assurances and confidentiality documents (information sheet, consent forms-appendix B1-2) were given to academic staff. Each academic staff member had the interview briefing and if happy they proceeded to signing the 'consent form'. All these efforts made participants to feel comfortable and contributed fully to the research study.

I spent quite some time on the narrative in the structure interviews and this meant using open-ended probing questions for clarification. The free narrative was was elicited by using props like, 'please describe', 'kindly expand', in as much detail as possible in relating to their experience with Big Data silos in the university in their teaching and learning (Colwell, Hiscock, & Memon, 2002).

In addition, I further spent quite some time on reflecting on my own position as an academic staff and the environment. On my position as an academic staff had the advantage and I was guided by the use of 'Statement Validity Analysis (SVA) which is based on differentiating *memory for a real event that will differ from fabrication in structure, content and quality* (Colwell, Hiscock & Memon, 2002) as I aimed to gain an insight into the real experiences and perceptions of my participants. As I was in search of credible qualitative research, being part of the community of practice did really help not only in articulating the probing questions but also in avoiding the pitfalls of SVA.

3.8.1 Bracketing of Researcher's Presuppositions

I was guided by Tufford and Newman, (2010) in applying 'bracketing' on preconceptions that may have tainted the research process from literature or my personal experiences in the university. This was justified to adopt considering that qualitative methodology harnesses and explores the lived experiences of the participants, whilst recognising that though conversational encounters afford unique opportunities to construct understanding from the perspective of the particpant, also mark an inherrently subjective endeavor. This subjective endeavour entails the inevitable transmission of assumptions, values, interests, emotions and theories, collectively known as preconceptions, within and across the research project. I was mindful that these preconceptions can influence how my data are gathered, interpreted, and presented (Tufford and Newman, 2010). This brought to the forefront areas for me where I had potentially strong opinions or experience (Big Data Analytics, the student, university, pedagogy, learning, Big Data) which could be activated during the interview in order to increase the rigor in my research study. This was the case considering the close proximity between my position and the research topic that may both precede and develop during the process of qualitative research interviews. Bracketing here was applied as a method to protect against the cumulative effects of examining what may be emotionally challenging material in Big Data Analytics. According to Ashworth & Lucas, bracketing helps to understand the participants' experience and it is important for the researcher to bracket a presupposition (Ashworth & Lucas, 2010). When analysing the pilot study interviews, in one of the interviews the following instance of an assumption on the part of the researcher was noted and valuable skill on building up an awareness of the need for constant vigilance was enhanced.

***Interviewer**: ...therefore I presume that you were not aware of this Big Data embedded in Blackboard until today, right and you have not opened these statistics before?*

***Interviwee**: all this Big Data is in its inmature state on multiple levels…if I decide to create my own Blackboard and deposit my own folders, no data is collected from those silos…therefore we are going back to the fact that data in university systems is not mature enough and can not produce reliable data.*

3.8.2 Understanding and Sequencing of Questions

Most participants understood the research question that were asked and however, at times they demonstrated that it was not always easy, given that the Big Data phenomenon is relatively new in HE, and to talk about it. Therefore, when a participant was finding it difficult to continue talking about a situation, probing questions were found to be useful to put a question to them based in a specific context.

During the qualitative semi structured interview, the sequence of questions was not rigid, as participants were encouraged to discuss all information systems that they experienced as these were part of the systems that contributed to their experiences in the university. This was in line with the pilot study results as it indicated working well then and this confirmed that the phenomenographic interviews were given enough consideration and worked well. This further concurred with Marton (1986, p.42) where he states that "though we have a set question at the start of the interview, different interviews may follow somewhat different courses". As the interviews used open ended questions, some participants chose to respond to their initial questions about what they understood of Big Data and Big Data Analytics experienced of it in their environment. In aligning phenomenographic principles in conducting these interviews, adherence to these principles was of importance. This allowed participants to think specifically and let their thoughts develop freely and were encouraged to reflect deeply on them. Further into the interviews the participants were asked to think specifically about how they experienced Big Data analytics all around them in SEMS, Blackboard and databases that they are in frequent use of. Another good thing about using a pilot study interview demonstrated the importance of the researcher remaining aware and alert to what needs to be covered in an interview, which in phenomenographic research is crucial.

3.8.3 The Phenomenographic Qualitative Interview

In my efforts to fulfil the research undertaking, generating data was a key element in the research. I therefore, interviewed 36 (N=36) academic staff participants in main interview in 2019 between the month of January 2019 to September 2019 in Leeds Beckett University a listed higher educational institution in England. This excluded the first three (N=3) pilot study interviews, which were planned as part of a crucial element of the research with an aim to increase the chances of success (Kvale and Brinkmann, 2008). Two (N=2) of the interviews were spoilt and disregarded, bringing the total of participants to fourty one, a good representative number in such a big university. In total pilot and spoilt data were discarded in the main analysis of the 36 academic The research sample represents a good representative number of participants as per phenomenographic reasech approach recommendations of 10-20 individuals in order to gain representative conception and variation (Åkerlind, 2008 and Ashwin, 2006).

Once the approval was gained, invitations were sent to a simple random sample of academic staff in various schools within the faculties across the university of n=41 of the total number of academic staff employed in the university to attend. In total n=41 (see distribution diagram below) staff were invited to participant in the research study and n=36 academic staff accepted and contributed. Once the interviewees accepted, they were given an information sheet *(see appendix B1-2.)* and asked to volunteer for an interview with a deadline of the interview date to respond.

Another good lesson learnt from the pilot study, was the act of adjusting so that I skilfully avoided invitation to subjectivity and talked less, a trend that continued throughout the interview stage in the research study. Both the pilot and main interview saw each participant being interviewed for over 30 minutes with 45 minutes being the average and 90 minutes in length being one of the longest. In each interview, I took my own notes and wrote quickly short paragraph of field notes that were aimed at capturing my immediate key areas on participants.

3.8.4 Conducting the Interviews

During the pilot study, it was apparent that my agenda for the interview to explore accounts of academic staff perceptions and experiences in Big Data was sometimes at odds with the participant's agenda which was to use the opportunity to chat about Senior Management (SM) in the university and deployment of technologies that assist in learning and pedagogy or on how they view Digital Learning Services (DLS) in the university as not consulting with academic staff on matters that involve them. In order to allow academic staffs space for this, I added probing questions to pick up on these, so how do you perceive Big Data or what are your views on that? In directly some of these were somewhat linked to my research question and therefore any relevant responses were included as part of the data analysis. From both SM & DGL comments, these were summarised as important themes that were given to the faculty and shared with the faculty in meetings. The overall categories will be presented to the senior management and the responsible Deputy Vice Chancellor (DVC) responsible for teaching & learning as feedback to the university.

The n=39 accepted as discussed in the above section and below is the breakdown of the number of participants and schools that took part in the study.

Figure 4.1a **No of Interview Participants in Fourteen Schools in the Research Study 2019**

Post	School	Invited	Interviewed	Pilot	Spoiled
SL/CD/	Computing	5	4	1	0
Reader/SL	Languages	5	5	1	0
SL/L/CD/	Business	5	3	0	0
CD	Sports	5	1	0	0
SL/CD	Health Sciences	5	2	0	0
SL	Clinical Sc	6	1	0	0
SL	Law	5	1	0	0
SL	Tourism	5	2	0	0
SL	Cultural Studies	5	1	0	0
SL/CD	Education	5	4	0	1
SL/CD	Forensic& Security	5	3	0	0
SL/CD	Music & Arts	5	4	1	0
SL	Arts & Film	5	2	0	0
SL/CD	Built Environment	5	2	0	0
SL/CD	Engineering	5	5	0	1
	Teaching allocation>5hrs	75	41	3	2
Key: SL=Senior Lecturer; CD=Course Directors; Reader; Lecturer (all academic staff)					

Therefore, it was deemed that a methodology is to be considered as an imperative in the research undertaking, because it provides the philosophical underpinnings, which guides the manner in which data was collected, analysed, presented and subsequently discussed (Chaurasia & Rosin, 2017). A phenomenographic methodology further enhanced forcing respondents into open-ended discussions with the interviewer, confirming key comments by respondents in the research study. Based on this approach my research undertaking covered 36 uniform phenomenographic interviews that were conducted in higher education and solemly based on academic staff. This is a body of knowledge that can exeperience what role might Big Data play in teaching and learning as they directly interact with both activities in their daily engagements. These are known as teaching academic staff and to differenciate distictively between the variation that exists in HE such as researchers, technologists and proffessors (also known as non-teaching academics) that are academics but do not teach any students in undergraduate and postgraduate course levels.

Overall, I feel that my interviews and interviewng skills improved over time with the 41 interviews carried out in this research study. This was very otable as I allowed the academic staff to give an in depth ellaoration on questions. As the interviews progressed my own experience grew and I became very familiar with my research question and often I did not have to directly ask some questions as they were embedded in some of the answers already given. Through this process, I became better at letting the phenomenon emerge rather than focusing on individual questions. In some interviews the academic staff were often asking if their 'responses to the questions were right' and if they were offering the 'answers that I wanted'. I had to frequently reassure them that all answers were important to me and will be included in the analysis and thus when I would be aware if the answers were 'wrong' or 'right'. This explanation was given in order to encourage participants not to with hold information that may seem wrong or inccorect to them and useful for the reseach study. This could have been a result of the fact that I was one of their own in the community of practice and again reassurance had to be given.

All interviews were recorded and took place on a face-to-face basis in pre arranged office spaces which offered good conducive environment for participants to fully engage and they gave their best. The 1st spoilt data was due to a faulty recording device which had a virus which corrupted the second file. Although the participants were willing to retake the interview, I already had reached the target sample number therefore it was decided not to take up this opportunity.

Being part of the community of practice, and being known to some of the colleagues that participated in the research, this came with its own challenges that included a challenge on my epistemology which forced me to engage deeply with my own thinking about how Big Data Analytics generated and used in pedagogy. It felt hard to isolate this in the process, however I believed that the research study will give the best answer which would be shaped by a collective view of the participants in the sample. This gently removed the worry whereby undoubtedly some colleagues thought I had the powers to change ther frustrations with technologies in their teaching as they voiced strongly and aligned their feedback to me as a vehicle to transport to management. The rich data that I collected undoubtedly had no objective or truthful about Big Data, however, it is undoubtedly a construction between the interviewer and the interviwees at a particular moment in time and their presentation of the world view.

3.8.4.1 Probing Questions

In both the pilot and main interviews, probing questions that were prepared were useful with all participants. These encouraged participants to reflect deeper and into their response statements. Reflection was crucial in uncovering thoughts which might otherwise not have been articulated. I encouraged participants to follow their line of thoughts by these probing questions that gave room for reflection during the interviews.

3.9 The Phenomenographic Data Analysis

Phenomenographic data analysis aims to uncover and identify variation in ways of experiencing. However, phenomenographic research typically avoids influencing data collection, analysis and production of findings through the application of theory, phenomenography is itself grounded in constructivism. It is "sensitive to the individuality of conceptions" of research phenomena (Ashworth & Lucas 2000, p.297). Phenomenography looks at a research phenomenon from a second order perspective, which focuses on the ways of experiencing phenomena from the perspectives of the people experiencing it (Marton, 1997; Andretta, 2012), and establishes variation in the collective ways these phenomena are experienced in practice. This add to the benefit of phenomenographic approach focusing on variation and experience, different ways of thinking of a phenomenon which can be perceived as 'a powerful way of seeing' in this educational research.

Analysing data, in the early stages, I was predominantly guided by the authoritative literature of (Marton, 1986); (Åkerlind, 2005) and (Bowden, & Walsh, 2000), who have written about comparing different approaches to data analysis in phenomenography . This helped in exploring different ways of the analysis process and moved it significantly. I started gaining a better handle on carrying out a phenomenographic data analysis meandering stages which, I will revist in chapter four (Smith and McMenemy, 2016).

In this research study the data analysis used followed closely the steps as articulated below as aligned to those of Bruce (1999). According to Bruce, (1999, p. 43) states that the data analysis procedure in phenomenographic analysis should summarise the following:

- Becoming familiar with the transcripts data.

- Identifying relevant parts of the data.
- Comparing extracts to find sources of variation or agreement and grouping similar segments of data.
- Articulating preliminary categories.
- Constructing labels for the categories.
- Determining the logical relationship between the categories

Bruce (1997, p.104) states that it is important to note that although it is portrayed in a linear fashion, the actual implementation was recursive and often drew simultaneously on more than one phase of the analysis whilst using software in qualitative research.

This procedure was carried out repeatedly, as categories of description were identified and refined with several iterations. The categories of description emerged from this data iterative process and were not formulated prior to data collection and analysis. There was no attempt to fit the data into pre-determined categories. Each step of the analytical procedure was completed with the assistance of a qualitative software package ATLAS.ti (Lewins, and Silver, 2007) Each interview transcript was imported and became known as a primary data document. Each of the primary data documents were given a title bearing the code name assigned to each interview i.e., SLCD (Fig. 4.1). The ATLAS.ti software was a useful tool in facilitating the organisation of data i.e., for selecting, sorting, comparing, and grouping data. The use of the software made it easier to deal with the large volume of data in a systematic and controlled manner adding to the rigour of the research. However, it has to be noted that it also makes a lot of interpretation errors, and this required several iterations of listening and correcting chunks of sections, extending the rigour of the research.

- **Becoming familiar with the transcripts data**

During the interviews, I kept making handwritten notes of some key words or point as the participants give their elaborations. I was doing this although I was recording each interview, and this turned out to be a useful way of getting familiar with the data. This process permitted the researcher to become so familiar, intensely engaged with data and in the process becoming closer to the participants. In order to cover depth and breadth of becoming familiar with the data, all the transcripts were read no less than three to four times, and each recording was listened to in its entirety more than twice. All this undoubtedly helped in the data analysis process that ensued in identifying, comparing, grouping of the data sets.

- **Identifying relevant parts of the data**

Marton (1986, p.42) describes the first phase of the analysis as the kind of selection procedure based on criteria of relevance. He further states that utterances found to be of interest for the research question being investigated are selected and marked. This supports identification of descriptions, analysis and understanding of experiences of the phenomenographic approach which supports the identification of the relevant parts in the data. In the individual transcripts relevant parts of data were being identified which aligned with the research question posed in the interviews, which were themselves derived from the research question. In order to get through thirty-six interviews, Atlas.ti software was deemed relevant in supporting identification of segments of the data from the recorded MP3-audios. Once the transcripts were derived from the primary data, coding followed accordingly. It was important at all times during the analysis process for the researcher to maintain an open mind, to avoid any preconceived ideas of their own phenomenon in question. This approach was in support of Åkerlind (2005, p.323) who states that a researcher as far as possible should avoid any predetermined views or foreclosure in views about the nature of the categories of description.

- **Comparing extracts for sources of variation or agreement in the interview data and grouping similar segments of data**

Once the initial themes had been identified, the research activity shifted to the selected parts of the data that were taken from the individuals' transcripts and pooled. This shifted the attention from the individual to the collective meanings expressed by the entire sample group. This presented each quote to have two contexts in relation to which it had been interpreted, giving the first interview from which, it was extracted and the second that was giving the 'pool of meanings' with a belonging as articulated by (Marton, 1986). This highlights the importance of emphasising that a phenomenographic research focus is on the collective views as opposed to the individual experience. This shifts the unit of analysis from an individual as they may articulate in more than one way of experiencing a phenomenon in a phenomenographic study. In the collective approach, all of the transcripts from the individuals' interviews are combined to make up the collective data to be analysed (Marton, 1986). The software Atlas.ti assisted in grouping all the data assigned to a particular code were grouped together to form one report. The use of Atlas.ti meant that whilst reading an extract withing the pool of data, it was always possible to refer to the data in its original position within the context in which the participant had made their statement. The analysis took place and continued once the pooled data was analysed with identification of distinct ways in which individuals experienced Big Data and Analytics by comparison within the extracts whilst searching for similarities and differences. The aim was to identify the referential and structural dimensions of the ways in which academic staff experienced Big Data Analytics. The referential dimension referred to the overall meaning; the various ways academic staff experienced BD. The structural dimension referred to what academic staff focused on when experiencing BD; experiencing BDA was now considered in terms of awareness. Although identifying the referential and structural dimensions are two distinct stages in the process of analysis, they often take place in parallel with each other. Marton and Booth (1997, p.87) assert that the two dimensions occur at the same time when an individual experiences a phenomenon: Structure presupposes meaning, and at the same time meaning presupposes structure. The two aspects, meaning and structure, are dialectically intertwined and occur simultaneously when something is being experienced (Marton and Booth 1997, p.87). phenomenon.

Identifying the referential dimensions of each way of experiencing Big Data had as its aim the establishment of the essential meanings underlying the categories of description. This involved an iterative process of comparing extracts and seeking variations in the data that was collected from the thirty-six participants. As the iterative process continued the dimensions and depth of variation became apparent. These dimensions in the research methodology variation were aspects of the phenomenon of information that made a distinction between the emerging categories of description. At this stage of the data analysis the question being asked was, what is the most appropriate way, based on the emerging data that would complete the statement 'academic staffs experience of Big Data in teaching and learning…'as per Bruce 1997, p.105 outline.

In order to identify the structural dimensions of each way of experiencing big data involved exploring the participants' layers of awareness as they experienced Big Data Analytics; what they focused on, what remained in the background and what rested on the periphery.

The main question at this stage of the analysis focused on: 'What does the participant focus on, in order to experience BDA in this particular way'? (Bruce 1997, p.105). As the structural dimensions of the ways of experiencing Big Data were emerging which formed part of the five categories. As a researcher, at all times I was interpreting the participants responses in relation to the phenomenon which was central in this research study.

- **Articulating Preliminary Categories**

According to Bruce (1999) she describes this analytical stage of research as of a recursive nature with drafts of categories of description being constructed earlier in the process as they are progressively revised in the noetic and noematic elements of each conception are clarified through regular consultation with the original data transcripts. During this process the referential and structural dimensions of academic staff experiences of Big Data and Analytics were brought together and a set of emergent categories of description was constructed. The variations between each of the categories were articulated and each set of categories was furnished with illustrative quotes. Subsequent to this many reviews and reiterations of the transcripts were made before a final set of categories of description was arrived at. It is difficult to sum up the intense nature of the process of revising the emerging categories of description, as the data were scrutinised closely to refine the essential features of each category. Here, it is only possible to give a brief outline of the evolution of the categories but nevertheless the evolution outlined gives an impression of the process undertaken in full in appendix (D3) to reach this stage. For the purposes of description, the categories listed in Figure 3.1 were numbered. It should be noted that the numbering of the categories was not finalised until the outcome space was constituted. The categories emerging were listed in a bottom-up approach progressing from the lowest level in Table 3.1. The full stages of iteration process are also captured in appendix D2 & D3 and can be viewed.

Category	**Category Label**
Category- C5	Evidence of Professional Development
Category- C4	Structured Information
Category- C3	Evidence of Student Support
Category-C 2	Large amount of Data
Category- C1	No Knowledge

Table 3.1 Emerging set of Categories of Description Stage 1

As the research study analysis progressed, it was made apparent that some changes were necessary to the categories as the iterations ensued in Table 3.2 below.

Category	**Category Label**
Category- C5	*Evidence of Professional Development* -Valuable insight into module management -Module review critical spotlight -Insight tacit and explicit knowledge base.
Category- C4	*Structured Information* -Provides useful patterns, trends in performance & progress from students without a voice in sessions. -Unlock the understanding of student-learners -Supports academic staff in sporting engagement with material on topics & timings
Category- C3	*Evidence of Student Support* -Supports teaching & learning i.e., attendance, retention -Pedagogical feeds -lost in the sea & fear -disseminate mixed teaching materials
Category-C 2	*Large amount of Data* -Tracking Student assessment Progress -Engagement and attainment -Evidence in disputes and legal evidence.
Category- C1	*No Knowledge* -related to issues on tools, presentation, location, interpretation.

Table 3.2 Emerging set of Categories of Description Stage 2

The set of categories listed in Table 3.2 shows a difficult period encountered in the process of stabilising the categories of description and goes some way towards illustrating the complexity of a process which requires the researcher to surrender them self entirely to the data and consider it from every angle in order to get to the final analysis. It cannot be over emphasised that each twist and turn in the analytical process has to be made in direct relation to the raw data captured as I ensued to interpret the participants' responses in relation to the phenomenon. The process proved to be both demanding and exhausting with the utterances of participants continually clamouring to be heard and the researcher must listen to each utterance until satisfied that what the data says, its' the true interpretation and completely understood. In this process some of the points under each category were subsumed into other categories in refining and contributing to the final categories and labels in Table 3.1. When this set of categories was arrived at it was apparent to the researcher that Category C1 was particularly unstable but crucial to C5 with the data being scrutinised more closely. This generated a set of questions that needed to be addressed. The more immediate questions were: (1) Were participants experiencing Big Data and Analytics as something that was found? (2) Were participants experiencing Big Data Analytics as a source of professional development (creating a self)? (3) Were participants experiencing Big Data Analytics as a process of finding structured information value? This highlighted the instability and the changes occurring in several iterations that took place right from the start. A substantial period of time was spent reviewing the data and as a result the five new categories emerged in the end, but this took several iterations that took time to build up.

The categories presented in Table 4 were the final one's that emerged after several iterations with the data in this research study.

- **Constructing labels for the categories**

Table 3.1 above captures an individual category of description that represents one way of experiencing the phenomenon from the academic staff. Constructing labels for the categories of description was a crucial stage in the process of analysis as the label had to capture the essence of the ways in which the participants experienced Big Data and Analytics in their teaching and learning. These Labels describe academic staff experience of the phenomenon based on their individualistic linguistic expression and the researcher's interpretation of their descriptions of the phenomenon. Labels were only attached to categories of description when the researcher was content that the data had been condensed to its core meaning.

- **Determining the logical relationship between the categories**

After exhausting the iterations in category of description the research study moved on to the outcome space. The outcome space describes the structural framework housing the categories of description as articulated by Marton, (1986, p.34). Åkerlind, (2005b) describes the ultimate aim of phenomenography as the exploration of the relationships between the obtained categories of description and the subsequent derivation of a structural model of the perceptions exhibited by the participants in the study. He states that the search for meaningful structure demands identification of the distinguishing features of categories and the determination of logical and other relations between them. The logical relationships between the categories of description based on the referential and structural aspects of the phenomenon are described in the outcome space. These logical relationships were determined as the result of the in-depth scrutiny of the *meaning structure* and *awareness structure* for each category with several iterations as shown in the section above.

The main underlying principle of the phenomenographic research approach is that the different categories of description are logically related to one another, frequently in a hierarchical fashion as can be observed in fig 5.0. Marton and Booth (1997, p.125) asserts that categories have to logically establish a relationship with one another, a relationship that is frequently of a hierarchical structure and the logical relationship between conceptions is portrayed in the outcome space in numerous ways depending on understanding (Åkerlind, 2005a). Morris (2006, p.3), in her discussion of hierarchical relationships, concurs that opinions on this point are varied and open to interpretation as also stated by Åkerlind. She cites published studies using a phenomenographic approach which present a variety of outcome spaces ranging from those that assume a hierarchical relationship is necessary and establish them without a question as a feature of phenomenography but have not presented findings with such relationships for example Brew (2001, p 275.) in her four variations that captures the richness of the data as a whole and renders it meaningful. At the outset of this research study, it was not known how the categories of description would be related. However, as the data analysis ensued the logical relationship between the different categories of description in the outcome space was found to be hierarchically inclusive. At the end of the process of analysis an outcome space was constituted that illustrated the structure of the qualitative variation in the way academic staff who participated in the study experienced Big Data phenomena. The outcome space as presented in Chapter 5 (Figures 5.0 and 5.1) which captures Brew, (2001) structural illustrations and she cites the work of these based on teachers' conceptions of teaching.

3.10 Rigour of the Phenomenographic Research

According to Kvale and Brinkmann (2008 pp102, 327) they position the creteria of reliability and validity in a qualitative research as in appropriate as these tend to be based on positivist epistemological and not on an interpretativist. However, Sandbergh (1997, pp.207-208) argues that reliability and validity are both concerned with 'external' process and therefore it is inappropriate for a research justification to be based against positivist criteria. Although there exists tension on this topic, Åkerlind (2005 p.330) states that qualitative researchers are still expected to address issues of validity and reliability in their research and asserts they should be addresses in relation to the assumptions guiding the research. In this research study the reliability and validity were both addresses in accordance with the assumptions guiding phenomenographic research of Sandberg (2000, p14) which includes three criteria to justify researchers interpretations in phenomenographic studies. These include 1-communicative, 2-pragmatic validity and 3-reliability. Cope (2002) states that identification of the structure of awareness helps to strengthen ones phenomenographic data analysis and hence the validity of the results. I will come back to justification of my position as a researcher on interpretations in my research on communicative, pragmatic validity and reliability in the second stage in phenomenographic process where communicative validity is important in the analysis process, in sections to follow.

3.10.1 Communicative Validity

Communicative validity here will be seen through the eyes of (Sandberg, 2000 and (Michelini, 2017) authoritative material as they both state that communicative validity is tested by knowledge produced in communication throughout the the research process addressed by the researcher. If the claims are fulfilled, ideal situation and mutual understanding are satisfied, therefore suboptimal communicative is limited in validity violation hence Sandberg (2000, p14) proposes a three stage in the phenomenographic process communicative validity is relevant. She advocates for inclusion of communicative validity to take place in interviews, analysis and results in a research.

3.10.2 Communicative Validity in Interviews

According to Sandberg, (1997, p.14) communicative validity is to be established through ongoing dialogue between the researcher and the participants. This was duly applied in accordance with participants. Communicative validity was established quite early in the study with participants as an ongoing dialogue between the researcher and the participants. The pilot study helped me a lot in building my confidence in handling participants and prior to the interviews, start of the interviews, all participants were informed that I was interested in how they experienced Big Data in teaching and learning from their perspective only and that their accounts will not be rated in anyway. This made participants to open up more and was important in terms of developing a common understanding between us in the interview discussions. As a result, communicative validity was established by generating data through dialogue during the interviews (Sandberg, 2000). This allowed the researcher to check that participants were being correctly interpreted during the interviews as data was being collected through the research question and follow-up questions which were open ended questions to stimulate our discussion. The use of open ended questions helped to encourage academic staff to identify and describe the ways in which they experience Big Data and greatly reduced the possibility of the interviews carrying the researcher's biaseness due to her personal experience of the phenomenon. To increase the validity of the data in the research study, I used probing questions as a means to stimulate participants to elaborate and clarify their descriptions of the ways in which they experienced Big Data in higher education. Again to increase validity in the research, participants were further prompted by use of repeated statements that they had produced to give them the full opportunity to express their own reflected thoughts. This further enhanced the researchers understanding of the points and answers being given by the participants, which helped to enrich the data that was obtained.

3.10.3 Communicative Validity in Analysis

Sandberg, further states that the quality of the research depends on how the researcher interacts with the data. In this stage of the data analysis, strict adherence was given to the data as the main control of researcher's interpretations. To ensure that this was duly followed, the descriptions were faithful to the text gathered and several iterations were made to the data by constantly going back to the data as a whole and listening to the participants statements in the audio and transcripts statement in context. ATLAS.ti software facilitated this activity with a bit of ease in accessing the full transcripts.

> According to Åkerlind, (2005, p330-331), in accordance with ontological assumptions guilding phenomenographic research, an individual experience of the phenomenon is context based. If consulted at another point in time participants may not necessarily experience the same understand of that very same phenomenon that they experienced during the recent interviews. Therefore, it is assumed that participants can interprete things differently of the same phenomenon. Other qualitative research paradigms within the phenomenographic group of researchers do not seek communicative validity from participants. This has received criticism from some authors within, however, it as to be noted that in phenomenographic research interpretations are based on a collective

basis and that are based on the interviews as a holistic group view as opposed to individualism.

3.10.4 Communicative Validity in results to Professionals

Once the outcome space of a phenomenon has been discovered and revealed it, should be communicated to other professionals in a manner that other researchers could recognise the instances of the different ways of experiencing the phenomenon in question, according to Marton (1997, p.100). Sandberg adds that this involves discussing findings with other researchers and in this research study, this was achieved by chatting with fellows that were adopting the same approach in their research in the cohort. This third stage in the phenomenographic process stipulates that communicative validity is relevant when communicating ones findings to other researchers (post doc workshop, 2020) and professionals such as my supervisor. Through out the research process, checks were made with the researcher's aademic supervisor regarding all the stages including methods, interpretations and outcome space after analysis. The evolving categories in the findings were presented and discussed with fellow researchers and academic staff at the LBU Centre for Teaching and Learning conference (2020). These steps were taken to ensure that the research methods and final interpretations were regarded as appropriate by the research community concuring with Åkerlind (2005, pp330-331). All feedback from other researchers at a worksop, academic staff and my academic supervisor helped to strengthern the communicative validity of the research to professionals.

3.10.5 Pragmatic Validity

Within the validity there is Pragmatic validity which refers to the extent to which the outcomes of the research are seen as useful. The findings from my study provides an insight into the ways in which academic staff experience Big Data and provide a framework to guide pedagogic practices in higher education in relation to technologies that hold large information and their relationship with these in teaching and learning.

3.10.6 Reliability

According to Denzin (2009, 2010) & Fielding (2010) reliability refers to replicability of results in qualitative research that reflects arguments made in the ongoing discussions on evidence within the research hierarchies. In phenomenographic research terms, this would anticipate that an identical outcome space would be replicated by another researcher handling the same data at a different time. Sandbergh (1997, p207) assumes according to a phenomenographic research, states that individuals experience the world in different ways so the assumption is that researchers would experience the variation in participants' experiences of the phenomenon in different ways. Therefore replicability is neither consistent with the relational nature of the constitution of categories nor the dynamic nature of awareness (p.207-208). Marton (1986, p35) states that however, there are two issues related to the demand for replication of results. These issues include other researchers to (1) be able to establish the same categories of descriptions (2) establishment of the same conceptions as categorised by the original researcher in both points. Here Marton, acknowledges the former in recognition of 'replicability'. The issues of reliability for this research study have been fully addressed ensuring that interpretive awareness has been achieved following Sandberg (1997, p209-210) creteria outline. These criteria include:

- Suspension of researcher's theories and biases
- Accurate description of the individual's conception rather than a provision of explanation.
- Equal importance paid to all aspects of an individual's experience
- Search for structure of meaning by focusing on the relationship between the 'what' and 'how' aspects of the experience.

3.10.7 Structure of Awareness: Validity and Reliability

Cope (2002) states that identification of the structure of awareness will strengthen phenomenographic data analysis and hence the validity of the results. Cope further suggests that interview questions and analysis of data during the interview can be based on the analytical framework of a structure of awareness. This then would allow the researcher to be more likely to focus on aspects of a structure of awareness and less likely to focus on their own prior knowledge of the phenomenon being investigated. This implies that the structure of the interviewing can be justified as minimising the influence of the interviewers prior know of the phenomenon (Cope, 2002).

3.11 Intellectual Process Undertaken to derive the Outcome Space

This research study adopted the intellectual process in phenomenography by adopting (Åkerlind, G. S., 2005b) the key aspects of this model. This enabled the researcher to reach the outcome space that was derived from the subjects (in this case the academic staff) and the aspects of the world (in how the academic staff viewed the Big Data) by looking deeper into academic staff and their relationship with Big Data and Analytics. As a researcher I adhered to distancing my own experience and knowledge in the sector from the subjects and their aspect of the world. Figure 3.11 captures this process well in supporting my research activities in deriving the Variation that led into the five categories that emerged.

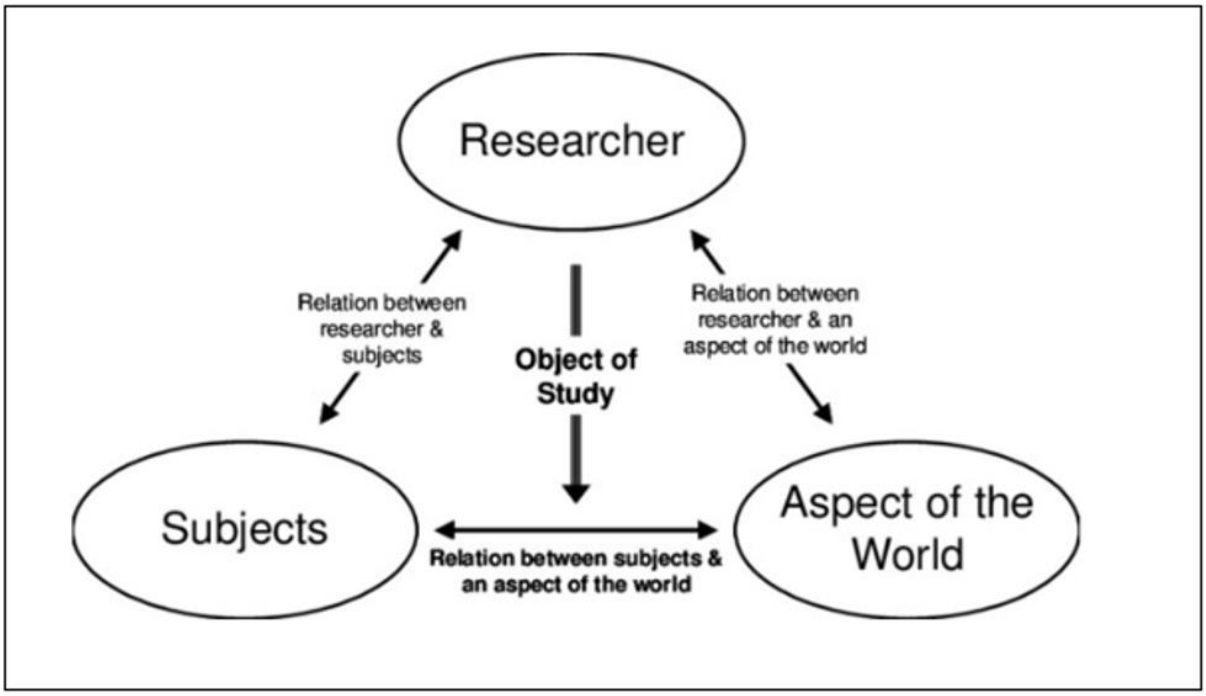


Figure3.11	Focus of Phenomenographic Research Study

The intellectual process of deriving the research outcome in here, heavily learned towards the phenomenography methodology (Marton, 1981) which aims to understand how academic staff interpret Big Data and Analytics in reality. The interviews were aimed at focusing on mapping the **qualitatively different ways** in which individual academic staff experience, conceptualise, perceive, and understand various aspects of the Big Data and Analytics world around their teaching and learning activities.

This research study outcome space consists of **categories of description** (*Figure 5.4-Referencial aspect*) that outline these different ways of experiencing. Each category within an outcome space holds **meaning** in two ways: it reflects how people understand a phenomenon *Category One, "No Knowledge"* and how they experience it ("*unwillingness to engage", "Issues with understanding tools", "Issues with presentation", "Issues with graphics* *interpretation")*, which demonstrates how academic staff understood Big Data in higher education and how they experienced it without knowledge and understanding of the terminology and visualisation. This is the case in all categories as discussed in chapter 4 above. This phenomenographic approach helped the researcher to intellectually explore diverse perspectives and uncover nuanced understandings within higher education on Big Data and Analytics. This has been particularly useful for investigating how academic staff in higher education intertwines with the original '*teachers research'*, (Åkerlind, 2005d) on conceptualising knowledge creation or other complex phenomena in education. The entire process followed the intellectual methodology process of a phenomenographic research (Marton, 1986) as comprehensively documented in chapter three.

3.12 Summary

In summary, this chapter has presented a comprehensive discussion of the research methodology selected for this research study. I have outlined the detailed description of the phenomenographic research approach employed in this research study. This in-depth detailed outline has been done through the lens of the phenomenographic qualitative research requirements, which may be different to other methodologies in qualitative research. I believe that this has tackled the possible critique based on a lack of rigour in phenomenographic qualitative research as it was felt necessary to do so. The chapter concludes by addressing the issues around validity and reliability of the research study. In the next chapter four, will outline the findings of the research study.

Chapter Four: Part 1 Findings Academic Staff Experience with Big Data and Analytics: Categories of Description

4.1 Introduction

I have articulated my understanding and experience of phenomenography in this research and beyond to support the undertaking. In addition, my research wanted to gain an understanding of the academic staff perceptions of the role that Big Data and Analytics might play in teaching & learning in the higher education institution, adding to the already existing technology enhanced learning environment. In this undertaking I was pursuing a way of transcending the contrasts construct and conflicts of academic staff lived experiences which the research continues to reveal to us from this research. In this chapter, the aim is to explore the meaning of experiencing Big Data and Analytics by academic staff and presenting the findings of this research effort. The findings represent the answer to the main research question in the table 4.0 below, positioned for convenience and each question has some sample answers that were given and make up the outcome space. This constitutes of the delineation of the referential and hierarchical structural relationships following the detailed descriptions of each category and the data generated for it. The findings of this research consist of two parts namely '**Outcome Space'** and '**Categories of Description'** and will be discussed respectively.

The previous chapter has offered a detailed description of the data generation and analysis processes that were adopted through my attempts to answer the research question in chapter one, on page 11, in relation to academic staff perceptions of the role Big Data and Analytics might play in teaching and learning in the research. This chapter will now proceed to present the '***outcome space'*** findings of this research effort based on the research question that I reiterate in Table 4.0 below for convenience.

In order to present each category comprehensively and fairly, the following are included throughout the findings chapter (Entwistle, 1997, p.132):

- Individuals extracts of interviews.
- Direct quotations from academic staff.
- Academic staff words are woven into text.
- Academic staff drawings.

The descriptions of each of the five categories that emerged from this research is presented in the following way:

- Category label.
- The diagrammatic representation of category relationship.
- Diagrammatic description with a focus of each way of category experience.
- BDA structure of awareness which establishes the essential parts of the meaning' that contributes to each category to form part of the whole.

For each question, I present the resulting outcome space together with discussion around each category with the internal relationships between the subject topic and academic staff (BDA perceptions of the role that BDA might play in teaching & learning) which constitute the whole in experiencing as described in each of the five categories, made known through a referential component and a structural component as these are intertwined parts. The referential component (**what** is being experienced?) in the phenomenon is conveyed in category label, relationships, extracts and drawing of each category description. The structure describes the essential components of the subject topic which sums up the way academic staff experience (**how** is BDA experienced) each phenomenon is conveyed in the structure of awareness.

Let it be noted that the categories of description are a representation of the collective views of academic staff and how they exemplify the characteristic of the whole of the phenomenon of Big Data and Analytics as reported by the individual participants in this research study. This supports the interest of the phenomenographic study that supports collective views as opposed to individualistic experiences and as such these representations will further be presented with codes or pseudonym names in direct quotations in discussions within the findings to comprehensively conform to phenomenographic requirements (Marton & Booth, 1997) in appendix B1.

I discuss the five shared categories of experience of academic staff and Big Data Analytics in higher education. Three of these categories were positive, namely, *"professional development", "structured information" & "evidence of student support"*. Although majority of the academic staff valued the categories, however, these did not emerge as being central to all academics in teaching and learning. Whilst the remaining two: one had a mixed outcome of positivity & nagativity, *'Large amount of Data'* and one negative category was, *"No Knowledge"* carrying the challenging aspects of the vast sea of BDA (information) and absolute lack of knowledge.

In this research, I show that there were three positive central constructions of the role that Big Data & Analytics might pray in teaching and learning in the above highlighted categories. I further advance the discussion of the variation in these including the other two categories. This has highlighted how each participant in the research constructed one of these central meanings as opposed to multiple meanings as each participant is in only one category. The critical discourse analysis of the categories indicated other strands into use of BDA in higher education …but a subject for another topic that can be explored in the future in this topical area.

Quotation in this chapter have been selected to illustrate perceptions, experiences, opinions & views held by indivudals as they construct their own world, therefore effort has been provided to present quotations that are representative of the perceptions expressed by a substantial number of academic staff only.

The findings represent an answer to the research question below which is positioned here as a referencing point and ease of reading.

In what different ways do Academic Staff perceive the role of Big Data and Analytics in Teaching and Learning in Higher Education?

Table 4.0: The Research Question.

The phenomenographic outcome space consists of the finite set of categories of description for each of the recognised ways in which academic staff experience Big Data and Analytics which outlines the structural relationships between these categories. The outcome of the phenomenographic analysis is the detailed set of categories of description which with their relationships does explain the different ways individuals experience phenomena in the world. In my research, collectively the descriptions outlined in the outcome space here present the phenomena of perceptions (information held) revealed in this research study and these are outcome of the data collection and analysis as reported in chapter three, above. In this study the outcome space is presented in the form of two main diagrams (Figure 5.3 and 5.4) which map the different ways that Big Data & Analytics is experienced by academic staff based on the variation in the structures of their responses. These two main diagrams reveal the encapsulated structural relationships between all the categories. In here, I discuss five shared perceptions of experiencing Big Data in the institution where the research took place by academic staff, which, comes through their voice of perception & experience with a collective variation in the categories, identified as:

- ***Category One: No Knowledge***
- ***Category Two: Large Amount of Data***
- ***Category Three: Evidence of Student Support***
- ***Category Four: Structured Information***
- ***Category Five: Evidence of Professional Development.***

The five categories are also presented in a diagram format below to illustrate the links between the relationships in Figure 4.1 below. These categories were valued by most participants from different academic group background and roles such as professors, researchers, senior lecturers, and lecturers with teaching activities embedded in their roles. The diagram below answers the main research question which I reiterate as well for convenience here, "***In what different ways do Academic Staff perceive the role of Big Data in Teaching and Learning in Higher Education?***" To ensure that the main character of the way of experiencing the phenomenon is made explicit in each category, Entwistle, (1997) argues that the categories of description should give a fair reflection of the participants responses and he further suggests that this can be achieved by providing sufficient numbers of interview extracts which represents each category comprehensively, succiently and fairly.

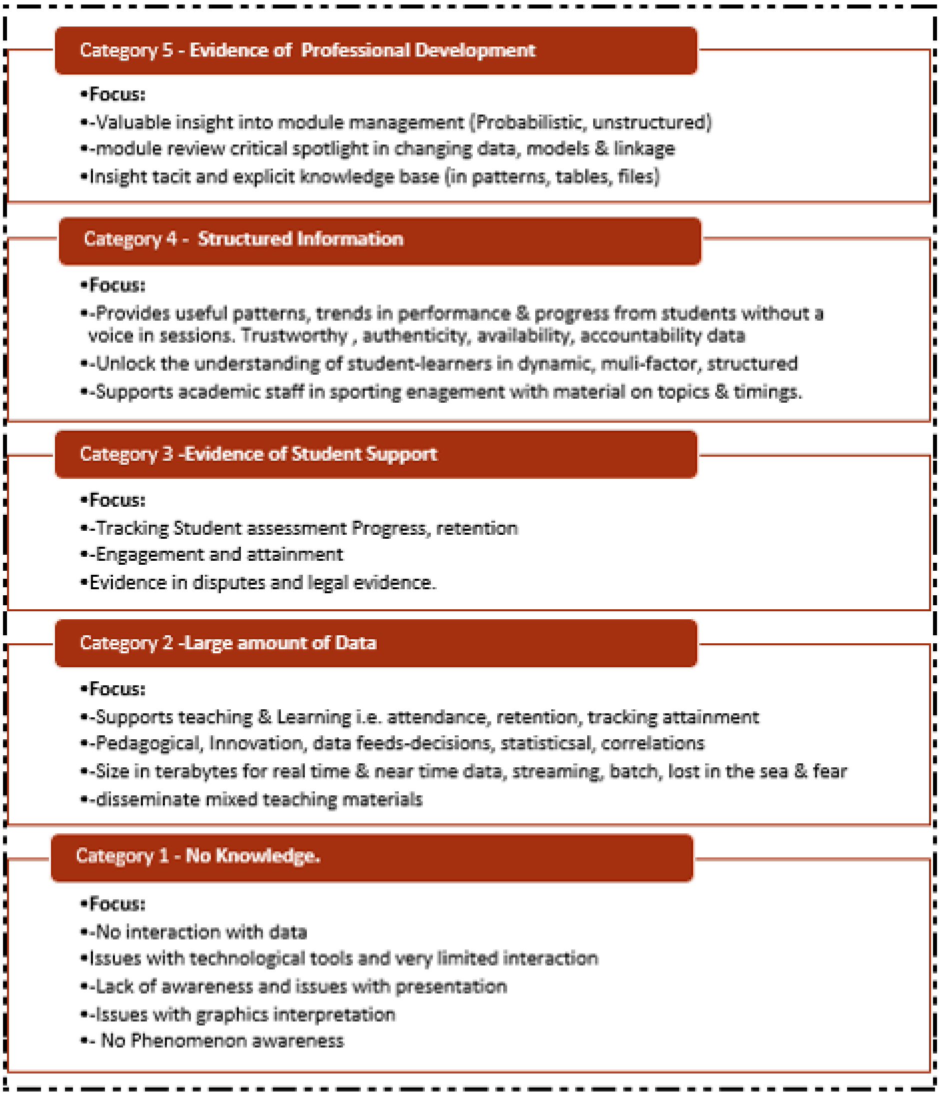


Figure 4.1 Category Focus – Original December 2022

In concurring with Entwistle, categories are synthesised through reference to the observations described in the Methodology Chapter 3. In this chapter, each category is described and discussed through a narrative that is supported by a table of the main elements that emerged in that category, and consideration of the similarity of experiences expressed as the range of coincidence of those experiences, whilst noting the variation between these experiences, too.

For each outcome space I seek to highlight the spotlight on the hierarchical inclusivity of the categories, the shifting focus in growing awareness, and increasing use of Big Data and Analytics in pedagogy as highlighted in appendix E1-E2.

During the interview's quotations were transcribed and the selected few are going to be used to illustrate experiences, opinions, views, and perceptions to give representation of the collective views from academic staff as expressed by a substantial number of them. Inclusive are individual views that indicate individual or unique minority opinions in the findings.

4.2 Shared experiences of Big Data Analytics by Academic Staff

All interviewees had one thing in common that they were all professional teaching academic staff in a specialised area with students at undergraduate and postgraduate levels with whom multiple technological resources either isolated or in conjunction are elements of an integral part of the pedagogical practice that includes course management as a fundamental aspect of the integrated process within the university. A significant number of academic staff acknowledged that they experienced use of technological resources provided in the institution that contain Big Data and Analytics within the teaching portals that they use. However, majority of these highlighted their individual use of their freedom, flexibility and autonomy in their technological capabilities and usage of the given technologies which were being extensively applied. This whole data captured is "stored", "reused", "retrieved" and "disseminated" within the institution to support teaching and learning activities.

4.3 The Categories of Description

In this section I answer the main research question and guiding questions separately in the diagram and the follow-up discussions. For each guiding question I present the outcome space together with a delineation of the referential and structural relationships with a detailed description of each category with evidence from the interviews gathered data. In each outcome space I seek to put a spotlight on the hierarchical inclusivity of the categories, the shifting focus in growing awareness within the perceptions, usage, and empowerment of Big Data and Analytics in teaching and learning in higher educational institutions. I advance looking at variation in different aspects of the academic staff's experiences of Big Data Analytics as an emergent progression of understanding BDA role in teaching and learning. In my articulation of this conceptualisation, I exercise with great ability to use discernment without excluding the possibility of seeing things from a different perspective as the foregrounding aspect of a phenomenon.

4.3.1 Variation in Experiencing Big Data and Analytics

All the thirty-six participants in the research acknowledged the existence and usage of some form of Big Data and Analytics in teaching & learning and collectively shared the broadening variation of experiences in BDA. The phenomenographic investigation carried out in this research, its outcome is captured in Figure 5.3 (pg. 127), which gives a panoramic view in which academic staff experienced different ways of experiencing BDA in teaching & learning. In figure 5.4 the categories of descriptions are considered to represent powerfully in which ways academic staff experienced BDA and this is presented as a complete pictorial view of the outcome space in the way each experienced as part of the partial portrayal in development. This is a way of seeing a holistic picture of the variation as established by this researcher from the research participants' own accounts. The given graphical representation in figure 5.4 (pg. 129-130) is a representation of a rationalisation of the variation as revealed in the participants own accounts. It is, therefore, possible that any given instance of BDA experience may not conform to one particular category of description as laid out by the mapping in figure 6.2. The hierarchically inclusive arrangement in Figure 4.1 outlines the logical understanding of the apparent disorder in the nature of experiencing BDA by academic staff, which provides some initial insight into the individual person-phenomenon relationship.

4.3.2 Structural and Referential Relationship aspects of the categories

Figure 5.4 (pg. 129-130) Structural and Referential aspects are concepts discussed by Marton and Booth (1997) in which they state that what an individual holds in the focal awareness at a particular moment there are structural (features) and referential (meaning) aspects that are intertwined. This is shown in figure 4.1 (pg.101) and this was enhanced by data analysis process used by Åkerlind (2005c) which was most appropriate for this study as he also stresses the necessity of retaining individual transcripts as units of analysis whilst taking into account the entire sample. The following data analysis depicts the five categories' themes of Academic Staff Perceptions of the role that Big Data and Analytics might play in Teaching and Learning with their constituent dimensions of variation. In considering the different ways in which academic staff experienced BDA from a referential perspective, their variation in meaning shifted from a mirror of reality to a collective meaning which contributed to relationship between words and their world view in this context.

4.3.3 Category One: No Knowledge

This category has been positioned on category level one because it is the least complex way of experiencing BDA. In this category academic staff see BD as both an internal & external entity in which they have no experience as it comes in and within the silos that it resides in, making it less complex. The central meaning of this category was being a nonexpert in a particular area of Big Data and Analytics and recognised for it as illustrated in the verbatim quotation below:

> *"I have never been exposed to Big Data anywhere, what is it"?*
>
> *"I feel I have had no training on, I started as a part time lecturer, and I have learnt to find things out for myself".*
>
> *"the stuff I have seen on MyBeckett (referring to BDA) …I will be honest with you, those things in there (BDA)…I have never seen before and never knew that they existed…and yet extremely helpful like retention centre…thus incredibly useful to me as an academic".*
>
> *"Is I did not know that it was there, and it existed in this university, so we need to raise awareness".*
>
> *"My experience with big data is that I didn't know it was there".*

Academic staff highlighted that there was no interaction with the data and subsequently no interaction with the BD phenomenon. In this instance the BDA exists within the source and technologies that academic staff use, however knowing the source and landscape of this data is problematic to academic staff that expressed this theme and category. Such issues include no idea to source or embedded analytics that exist in the silos of data that are defined as BDA. This includes missing out on reading and interpreting vital Big Data Analytics information and its characteristics is paramount. This group of academic staff could fit into the 'passive minimalist' grouping that perceives the role of Big Data and Analytics to have information literacy in which facts are obtained in dealing with simple and immediate content. These academic staff have less knowledge of the BDA role in teaching & learning, are less motivated with technology and less likely to look for new emerging patterns that develop in analytics.

> Through a variety of platforms and systems, such as learning management systems, student information systems, and online learning platforms, educational institutions gather enormous volumes of data. In recent years, technological advances have added

numerous Artificial Intelligence technologies such as AI and ML ChatGPT, that are impacting on teaching and learning experienced by academic staff in this category.

4.3.4 Category Two: Large Amount of Data

This category carries a combination of internal and external data that comes into play using different sources including from 'open source', 'emerging technology tools' in teaching & learning such as 'blackboard tools', 'videos', 'YouTube', 'Instagram to bespoke in-house-built software (learning management systems) with list not exhaustive. In these mentioned tools data is embedded in the 'volume' and 'velocity' of the six Vs of Big Data (page 28) which holds large dataset sizes and processing capacity. This data has large variety which holds value and veracity that allows it to be questioned for answers. This data further presents conflicting data messages and provides information about matters that one may not be sure on how to deal with it in offering 'truth and authenticity' in teaching and learning. The central meaning of this category was being a non-expert in a particular area of handling Big Data and Analytics volumes as recognised for it as illustrated in the verbatim quotation below:

> *"It is vast amounts of different data types that is generated at different points in universities that involves staff and students in teaching and learning".*
>
> *"It is data that is gathered through different systems in the university as I am aware of, although I question its purpose".*
>
> *"I know that it is about student attendance, retention, staff movement and I fear for this big brother watch with such large amount of information being gathered".*

These several combinations make it very complex in dealing with such data at this category level as to deal with emerging challenges created by the technology advancements in the six Vs of Big Data dimensional challenge framework, which requires immerse academic staff commitment and engagement (conflict with **allocation** hours). The challenges extend into detection of new insights into students from the BDA datasets that could provide better flexible teaching and learning skills and knowledge that benefits both the learner and the teacher. This category also highlights the skills set, capabilities and knowledgeability of academic staff in dealing with 'data mining techniques' in reading and interpreting the analytics from the web, and social media data which enables identification of the optimal practical guidelines, monitoring and identifying 'new insights' to support their pedagogical activities in this higher educational institution. Embedded in Big Data Analytics is new knowledge and intelligence, which could be used for exploring new hypothesis in teaching and learning to identifying hidden patterns for action and decision making (inclusive in analytical **dashboards**).

4.3.5 Category Three: Evidence of Student Support

This category three has been placed on level three because both contribute to the complex situation of BDA whilst it is achieving strides in embedding complex large amount of data that can be daunting to academic staff in harvesting the embedded relevant 'student support' material within it. In this categories, academic staff spent time to interact with the large sets of data to find the embedded evidence of student data from which they could draw support to offer students on attendance, progression and retention from the large amount of data in the silos. This holds the intelligent data that can be used in more than one way (supporting **'Innovative learning'**). Here, this category further describes a way of experiencing the role of BDA in which academic staff are focused on a specific goal within the category. This information is sought out, identified and applied in the context of specific student support requirements (retention, engagement, learning support etc. with list not exhaustive). This is highly achieved with a combination of developing background knowledge of the technologies which allows the academic staff to know how to address a specific need, whilst enhancing their skills and relationships with the learners. This is where Big Data Analytics plays a big role in showing patterns of data that are meaningful for academic staff as visualisation at this point draws a clear picture of the given scenario as expressed by them. The central meaning of this category was being an expert in handling Big Data and Analytics for intelligence in supporting students as recognised for it, as illustrated in the verbatim quotation below:

> *"It helps to identify gaps and give struggling students the information they need to improve their performance and progress. Sometimes this is a group of students that do not have a voice in sessions for one reason or the other".*
>
> *"It is data for tracking student's assessment progress, engagement and attainment in their learning trajectory".*
>
> *"This offers me a quick chance to recognise patterns of behaviour that might indicate successful work habits (engagement with particular week's delivery)', ineffective study patterns (no clicks at all)".*

4.3.6 Category Four: Structured Information

Categories four is placed at level four with emphasis on this data being complex with variability in presentation. Academic staff find these internal data analytics very complex but reliable if understood, can be used in a variety of ways to support learners. The support extends to student experience, decision making, developing an improved curriculum, and defending Quality Assurance Agent queries for academic purposes. This data is further complex as it is mostly presented in different structures of data-dashboards and patterns that can be constantly changing within its very same environment as the blackboard analytics keep emerging by the ongoing technological changes in teaching & learning (challenging skill to those not familiar with graph scales and statistical aspects). It is here where Big Data forms patterns that can be extremely useful in context once conceptulised using visualisation and machine learning algorithms. The knowledgeable academic staff here excels in identifying useful patterns whilst those with no knowledge tend to be baffled and confused in interpretation of this information. This follows the utilisation of Big Data and its adaptation into the higher educational learning management system. The illustrative quotations below enhance the meaning of this category.

> *"It is where you see information is nicely laid out and we can add extra information and students know where it is to access it. This saves time for both staff and students".*
>
> *"Structured engagement data is well presented in the SEMs, Registers, MyBeckett, one drive shared files, which supports engagement in individual student".*
>
> *"My experience is with information in BDA is that this data is presented extremely well and in a helpful manner".*
>
> *"Presented data in the way it is done is a good thing…the visual pictorial presentation is extremely good like in SEMs and others where it is colour coded…easy to understand".*

This information then is internalised and forms part of the knowledge base in academic staff in teaching and learning as they continue to reuse the knowledge (internalising & externalising). There is a hierarchy within this level which links it to the next category which is more complex and therefore category five is positioned higher up the hierarchical structure.

4.3.7 Category Five: Evidence of Professional Development

Category five is at the top of the hierarchy on levels. In this category the experience of BDA is more complex than in category three and four. In here BDA that has been conceptulised, internalised & externalised and it is used as a 'powerful knowledge base' for academic staff in teaching (**empowerment** in being an academic staff). The following quotation captures this academic staff empowerment:

> *"I gain insight into the university performance of students even outside my domain, which gives me an overall picture of performances in different courses and levels in their degree".*

> *"I gain valuable insight into module management and module review which feeds into so many aspects of my teaching (noticing popular topics to least enjoyed one; timing of uploading stuff to maximise student access)".*

This extends to personal professional development in short courses, self-taught courses, or those that spotlight their needs to management for support in professional development. This category level offers valuable insight into course-module management; puts a critical review spotlight and offers insight into tacit and explicit knowledge base of academic staff, who constantly reflect and innovate based on existing explicit knowledge. Academic staff indicate strong views on how Big Data and Analytics assist them in innovative new ways of approaching improvements in their pedagogical activities on curriculum innovation. The diagrammatic representation of the outcome space is given in Figures 4.1 and 5.3 showing hierarchical relationships & awareness between categories.

4.4 Summary

In summary, Part 1 has presented the outcome space of the phenomenographic analysis which is an outcome space consisting of categories of description with their relationships, explaining the different ways in which individuals experience Big Data Analytics phenomena in higher education. The focus in this part is to highlight how the research question found the categories, what they entail, how the blocks were formed, and they show how intertwined emerging data can be in a category.

Part 2 below will now discuss in depth elaborations of the outcome space in relation to academic staff experience. This part will explore how collectively academic staff aligned with each category. It is important to understand this aspect in order to establish how Big Data and Analytics might play a vital role in teaching and learning with all the data that surrounds higher education systems. This could be a panacea for higher educational institutions as they interact with the global village of technology.

> *"This is very important to me as an academic staff. It works as a benchmark within our institution but can more so do the same at national level if these analytics were to be shared".*

The central meaning of this category was being an expert in handling Big Data and Analytics for intelligence in that supports professional development for academic staff as recognised for it and as illustrated in the verbatim quotation above.

5.0 Chapter Five: Part 1 Findings on Experiencing Big Data and Analytics in Categories of Description.

The Categories of Description (Åkerlind, 2005a) presented below were derived from the transcript analysis as recommended by Åkerlind in phenomenographic research. In this section I give an elaboration of each elicited category of description as they arose from the analysis of all the thirty-six transcripts of the participants over a period of ten months in this research study. In this section I attempt to expand the perceptions of academic staff and Big Data by establishing relationships to each research question.

5.1 Category 1: Experiencing Big Data Analytics as No Knowledge (C1)

The academic staff that aligned with this category focused on the availability of data from the online sources and others struggled with the interpretation of the Big Data and the Analytics embedded in the terminology for meaningful knowledge into teaching & learning. On availability of data from online sources these academics showed lack of understanding of the location and instant access of Big Data Analytics. These academic staff had no idea of the existence of BDA that feeds into learning analytics that are used for measurement, collection, analysis and reporting on learners on their trajectory within the virtual spaces that they interact with. The academic staff in this category were aware of availability of technologies that assist teaching, used them but never explored and understood the BDA technologies (layers behind the pages) used within the various tools that they are handling in their profession (Google Sheets, SEMS, Blackboard). Academic staff voiced concerns over having to deal with several different technological tools, dashboard interpretations embedded in teaching & learning *in the thick of things* whilst coping with the influx of emerging technology that assist them. They further highlighted the issue of lack of staff development within their schools or from the IT services within. Below are some of the extracts that highlight this lack of knowledge:

> "The stuff I have seen on Blackboard (referring to BDA) …I will be honest with you, those things in there (BDA)…I have never seen before and never knew that they existed…and yet extremely helpful like retention centre…thus incredibly useful to me as an academic" (EDUC2).
>
> "I have never been exposed to Big Data anywhere, what is it?" (EEES1; FILM1; MUSC1).
>
> "I mean, through that, I'm going to be honest, I don't necessarily think my blackboard is the perfect repository for supporting academic staff. It has somany limitations with the many clicks one has to endure" (COMP1).
>
> "The information is hidden and I do not understand Big Data" (LAWS1; EEES2).
>
> "I have never heard of Big Data Analytics in our university" (HCSS1; FORC1; EDUC1).

For the academic staff who aligned to this category, focused on delivering teaching using the basic capabilities like uploading their lecture notes, students downloading, communicating to students verbally or written notes in their course in fulfilling managers' expectation.

> "Communications would be quite difficult…so if we think about it Big Data Analytics is not there as managers do not communicate, that is really troublesome" (TOUR1).
>
> "struggling with these graphics and the numbers in them, what do they stand for…I mean, especially the different types of dashboards within one report, too many and I have no time allocated to deal with such technological aspects that are added and we are expected to know or deal with them" (CUSH1).
>
> "statistical elements you come across when you're trying to use blackboard can be overwhelming to me as an individual" (EDU1).

For the academic staff who aligned to this category focused on the terminology used in their course in university, but they didn't relate to it. These Academic staff focused on availability of the information system given to them to use and thought less of the terminology around it. The flexibility to access and being able to do the basic minimal in the portals given, was an expectation academic staff in this category felt the teaching technologies should be capable of:

"I am not aware of the Big Data and Analytics Phenomenon" (BEEC1, EEES2).

In summary, after years of teaching without technology the academic staff aligning to this category suggested that BDA was not necessarily the only way to get useful data that may play a role in teaching and learning as there are other ways of doing this. These academics focused on paper-based information like registers, classroom observation for judgement, plagiarism detection and hardcopies with list not exhaustive. These academics tended to carry the view that learning technologies including those of BDA are worthy consideration as far as they assisted without highly impacting on their time resource and with easy of technology usage. They deemed traditional teaching methods to still suffice although they agreed with basic use of technological tools that aid them in teaching and supports students to learn independently with little occasional intervention from their lecturers. Academic staff aligning to this way of experiencing BDA in role of teaching & learning, particularly in view of persisting with the information age that continued to give them classroom empowerment they interpreted the BDA technology provisions of recent years as additional but not necessarily essential. To this group of academic staff, they perceived technology in teaching and learning as useful in some respects but cumbersome in dealing with issues of access and interpretation.

5.2 Category 2: Experiencing Big Data Analytics as Large Amount of Data (C2)

The academic staff aligning to this category were those that created their own time to research around given technological tools at any point without the help of IT Services or any other training. This group of lectures will quiz and question what *'more'* can I achieve with this given tool. These are academics that are mostly comfortable with technology in general. They tend to look for real time reporting data for meaningful insights in large amounts of data.

> "I like to create opportunities for myself in new things so I would investigate to learn new learning technologies from Blackboard-BDA in my module, I like to tell my colleagues, you've got to go into it to find certain things." (MUSC)
> LAWS2; LANS2; BUSB4)

> "No, I also think that I mean, in the beginning, when I arrived here a year ago, I thought you know that these were not connected? I'm it was a bit of a conundrum to find you get from one place to another"(HCSS2; EEES5).

In summary, the academic staff who aligned with this category of description saw the portals containing large amount of information that constantly floods into their teaching environment. The influx of raw data and Big Data analytics posed a conflict with their teaching & learning activities. Most expressed lack of time outside their pedagogical activities to invest in learning this new aspect in teaching and as such tended to take a route of ignoring this aspect. Academic staff aligned with this category too, expressed how the technological tools are changing constantly in Higher Education (cited timetabling, attendance, blackboard portals, SEMs etc.

5.3 Category 3: Experiencing Big Data Analytics as Evidence of Student Support (C3)

The academic staff aligning to this category, were focused on using the terminologies being used in their course to the fullest and provided in university for teaching and learning. These academic staff indicated that they used the BDA embedded in the tools to find hidden information about their learners in order to support their learning trajectory. This group of academic staff were proactive in helping their learners including intervention in withdrawal and retention which would be enhancing star students who want to perform higher. Academic staff who aligned with this category of description focused on tracking their student and had the desire to improve progression as part of their professional achievements:

> "There is lots of useful information that I can find and use from the analytics in blackboard which helps to support students by looking at what they frequently view, who has logged in into weekly folders & topics. From this data you can also make links to their other activities in SEM's i.e., attendance from previous years, which is good".
>
> "This data in clinical studies is very powerful as it could help in supporting staff in appeals".
>
> "It is vast amounts of different data types that is generated at different points in universities that involves staff and students in teaching and learning".
>
> "So if I was working for perhaps I was teaching on different courses, and I didn't know the students so well, then perhaps this could be more useful to me, then I would know, well, I don't know the students very well". I seek to see how is the student engaged. Who's doing well? who's not doing well? So in that, I mean, that's how I make use of this information from the BDA dashboard" (EEES4).

> "It is data that is gathered through different systems in the university as I am aware of, although I question its real intention or purpose in supporting student by our management".

Academic staff aligning with this category, experienced BDA as really helpful in supporting and preventing dis-engagement by contacting the learner at the earliest point of intervention.

> "Yeah…and then as I said, I may go into search (BDA data) to find in a specific students see, you know, what's available for, but most of the, you know, mostly making use of this, to contact a student" (BEEC2)
>
> "I think that as we're moving towards blended learning and online learning, they will be making use of such platforms even more in the future, our learners too. And it is quite likely that in the future, we may have online sessions with students that kind of integrated into a platform like this. So, I think it is a plan for the future in HE. With this, just the nature of you know, of how we learn these days, everybody uses using their mobile phones, by doing well to access information, you know, on the go. So we're all as you know that we are having to rely heavily on online platforms" (EEES3).

The academic staff aligning to this category investigated supporting their students using the data that existed in technological portals (i.e., Blackboard) to support and enhance student support which includes engaging with learning material, attendance, assignment submission dashboards:

> "Big Data can include all information regarding students' submissions, attendance in all around the campus university technologies (library & Wi-Fi access inclusive). The dashboards analysing students' performance, the number of times they log in to Blackboard, use the material online material, helps me to have a deeper understanding of my students, although the blackboard analytics are not easy to find" (FILM2).

> "How students really interact with my information that we're putting on modules. But you can also look at the data in different years, so you can somehow compare the data that you you've got, year by year, per module, you can compare student data" (EDUC2).

> "I would access date on my VLE, which is Blackboard. Okay, so I can look, the number of times students, for example, login or track the students on my module. I am able to track the number of times students and track each, each part that they left" (LANS2).

In summary, the academic staff who aligned with this category of description were aware of the numerous online materials and the technological tools that support these and how these support their teaching whilst also supporting the learner. They were aware of the activities that a student would engage in and know where to find the answers in BDA, which they find to be a very helpful tool. However, academic staff here, are also discerning the institution and provision of these technological resource BDA tools.

In limited awareness of the perceptions of BDA in teaching and learning, academic staff adhered to what is widely being recognized as useful technology by technologist experts in adopting and engaging these tools which are seen as essential in achieving both teaching & learning benefits. The technology offers both staff and students to access online teaching & learning resources with flexibility and to an extent offering 'Cost & Time' saving in printing materials, traveling to a campus, shareability of limited resources are all aspects of the gains that BDA offers academic staff in supporting individual students. Here academic staff are also able to determine how student learning can take place and help faculty best use all the resources available to them for the purpose of improving teaching. In the classroom, scholarship can occur on a much smaller and more intimate level using simple BDA statistical data from its tools.

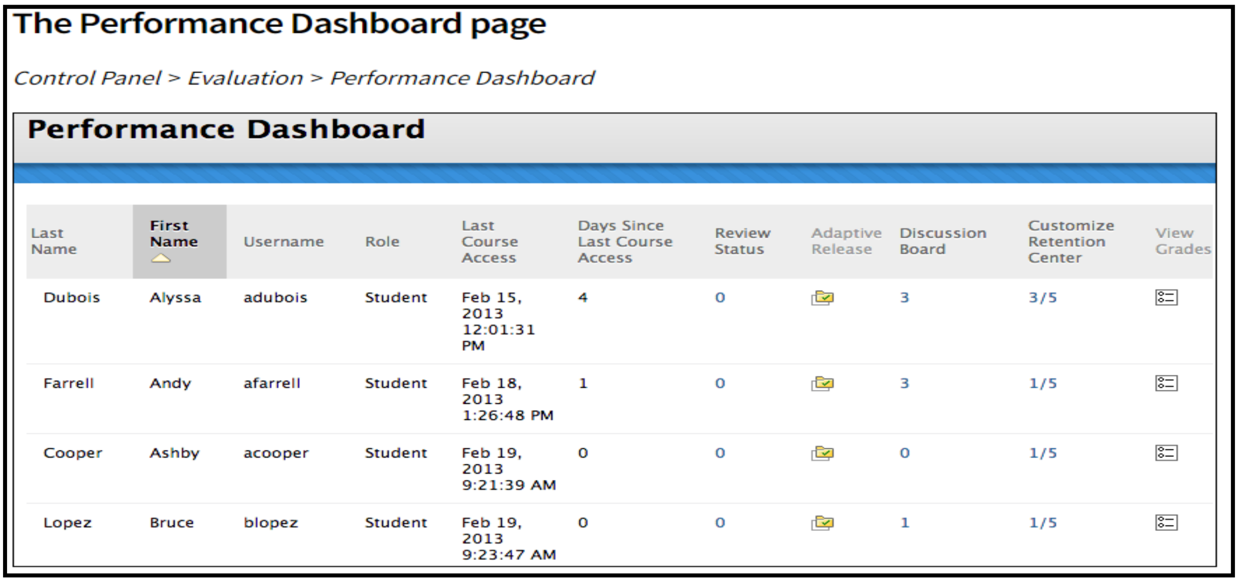
5.4 Category 4: Experiencing Big Data Analytics as Structured Information (C4)

Academic staff aligning with this category were those who were using structured information to find patterns of informative information that supports their teaching for refreshing curriculum and improving learning experience. These were able to explore BDA for improving periodical curriculum and enhancing new techniques embedded in technology that support teaching and learning.

> "The numerous dashboards in the BDA helps me to identify my students' performance in classroom as I can see who is looking at what and I then make links to their engagement in session and contributions…mostly good" (FORC2).

> Given this massive scale of Big Data in our portals, it is tempting to understand Big Data solely in terms of the six V's (Daniel, 2017). But that would be misleading in higher education for academic staff. Big Data is also characterised by the ability to render into data many aspects of the world that have never been quantified before; call it "datafication" (Chen, et. al 2020). For example, entire student movement and interaction in campus (Discussion boards, Grades, Retention, display user, course access registers, attendance, computer logs, library records, login sessions, has been "datafied", first with the invention of longitude and latitude (calculated in notepads & local DBS), and more recently with Performance Dashboard in satellite systems. Words are treated as data when computers excavate fast amounts of data worth of three years course. In current climate friendships and treadmill gym data and "likes" are datafied, via Facebook and similarly performance student data is datafied as depicted in the figures below (figures 5.0 and 5.1) are an illustration of Big Data Analytics that

academic staff would encounter, just to give a visual example of the educational real-world data.


The Performance Dashboard page

Control Panel > Evaluation > Performance Dashboard

Performance Dashboard

Last Name	First Name	Username	Role	Last Course Access	Days Since Last Course Access	Review Status	Adaptive Release	Discussion Board	Customize Retention Center	View Grades
Dubois	Alyssa	adubois	Student	Feb 15, 2013 12:01:31 PM	4	0		3	3/5	
Farrell	Andy	afarrell	Student	Feb 18, 2013 1:26:48 PM	1	0		3	1/5	
Cooper	Ashby	acooper	Student	Feb 19, 2013 9:21:39 AM	0	0		0	1/5	
Lopez	Bruce	blopez	Student	Feb 19, 2013 9:23:47 AM	0	0		1	1/5	

Figure 5.0 An illustration of Big Data Analytics in Higher Education

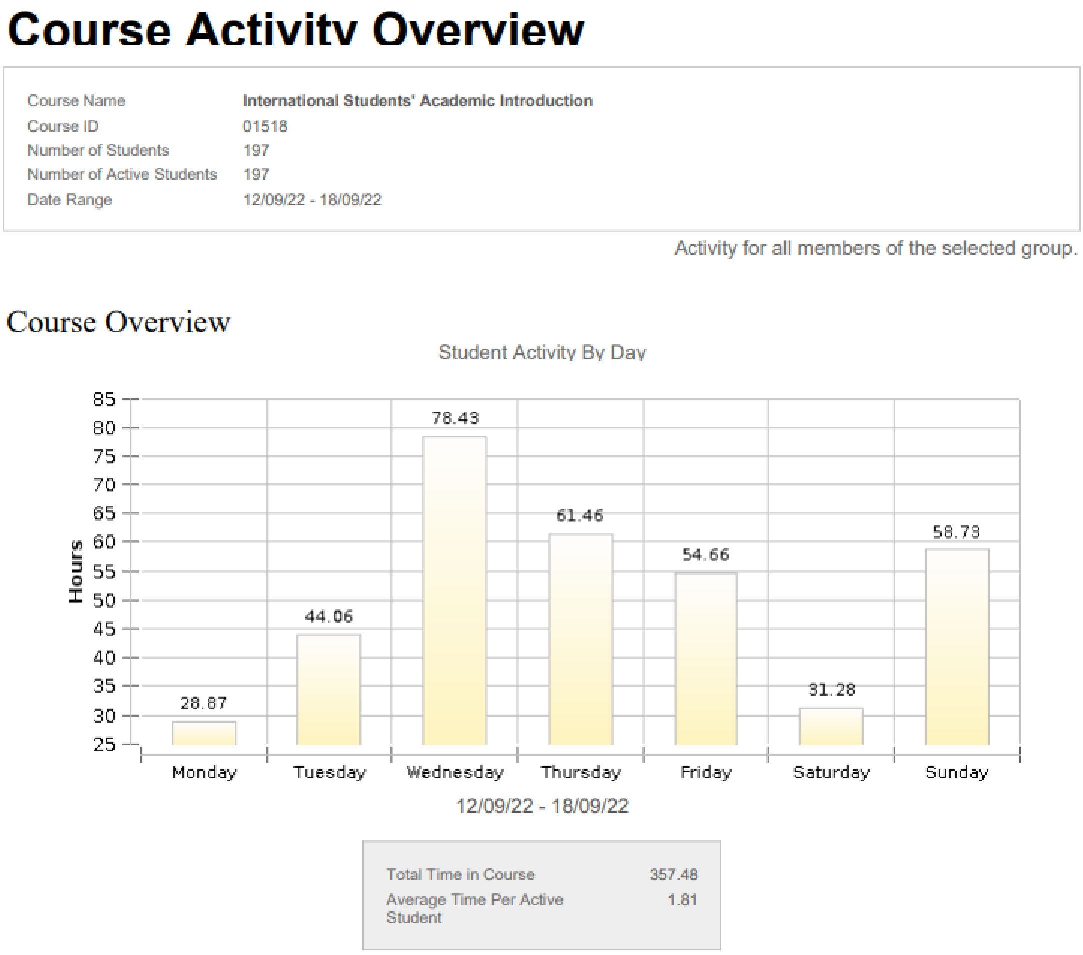


Figure 5.1 An illustration of Big Data Analytics -Patterns in Higher Education

"The new kind of data is being put into incredible new uses in higher education with expensive computer powerful processors beyond the old information that statisticians have used for years in higher education. I find crucial information embedded in the analytics that I use in pedagogy to improve the standards as well as supporting engagement and retention (KOR1)…easy to trace students engagement and progress over 3 years to form an opinion and make a decision (LAZ1),…analytics have helped to make us understand much better how students read our notes, what time they access them in terms of weeks, months and years (CD1), excellent advancement for me and cuts my time that I can invest elsewhere…it is easy once you know how to maneuver in the virtual spaces to find this data/information.

Here academic staff were also able to determine how student learning took place and helped students to use the resources available to them. In the classroom, these staff indicated that scholarship could occur on a much smaller and more intimate level using simple statistical tools embedded in these technologies:

> "So, from what I have seen in Blackboard and SEMS, I'm getting a feeling that the phenomena of Big Data in higher education is something that teaching academics needs to take on board indefinitely for now and the future. And it is definitely important in teaching and informing staff in certain areas, yes. It cuts time as these tasks can be done with just a click of the finger to more than one student at a time, example announcements I mentioned" (COMP3).
>
> "I suppose it's great to have graphs, because the immediately have a visual representation of engagement, you can tell how many people are accessing things" (SPOT1).
>
> "So, it says here individual engagement rating, but again, is not quite clear, although it seems quite nice graphs presented…giving you some information, but again, it is not clear and difficult to find meaning. For me what that information…it seems that I need some sort of interpretation" (HCSS2).

In summary, academic staff who aligned with this category demonstrated an appreciation and understanding of the numerous dashboards that they would encounter both in Blackboard and SEM's technological tools. Academic staff here find this information highly organised and readily accessible. They discussed how this Big Data Analytics would have embedded structured query search that one could use to gain answers to such things as progression, retention extending to knowing your student in attendance and engagement.

5.5 Category 5: Experiencing Big Data Analytics as Evidence of Professional Development (C5)

Academic staff aligning with this category indicated that they used the data available, to give feedback to students which could be addressed and developed in a comprehensive information system. From this comprehensive data valuable insights were generated and their approach to teaching was developed through reflection on their professional career.

> "I'm also an academic advisor as part of my professional student support... as a result, I was told we have to record everything in the 1-1 student and staff meetings. I use this in professional meetings with students and I can evidence the AA professional development" (EEES5).
>
> "In appeals over an academic decision or processes, evidence is asked for on a student in question. Academic staff are able to show attendance, engagement, student access to material from Big Data Analytics supporting the marks in contestation and here analytics are helpful for such processes in HE to defend even court cases" (EDUC4; FORC2). This will require further professional development on staff with data that support this aspect.

Academic staff aligning with this category attended to such aspects as finding tacit or explicit knowledge that is embedded in BDA for enhancement of pastoral activities that support teaching & learning like 'retention rates' and building constructive discussion with students in meetings. They also found that this data could support arguments in student appeal processes. Overall, academic staff found that the Big Data Analytics offered comprehensive overviews of the student data from various sources that supported teaching and learning in monitoring, measuring, and analysing relevant data in key areas.

> "The thing I like about SEM's is the fact that all the dashboards are presented in a comprehensive manner and not just for one level of study but in all levels. This is

extremely good as an academic can understand it easily and apply it. However, I struggle in understanding the 'report specifications outline in the provided analytics.

"I am absolutely in love with this BDA as it has changed my life in saving me time to do other things like sending automated messages and seeing student engagement that they could bring into the meeting. I no longer depend on exam boards spreadsheets as I can access each learners' individual activities and performance across the course from these BDA silos and even in past years to see their performance" (FORC3). However, to get these analytics is not straightforward as it is complex to navigate and fully read some of the parameters used in these visualised analytics i.e., 'access' in the diagram figure 5.2 below.

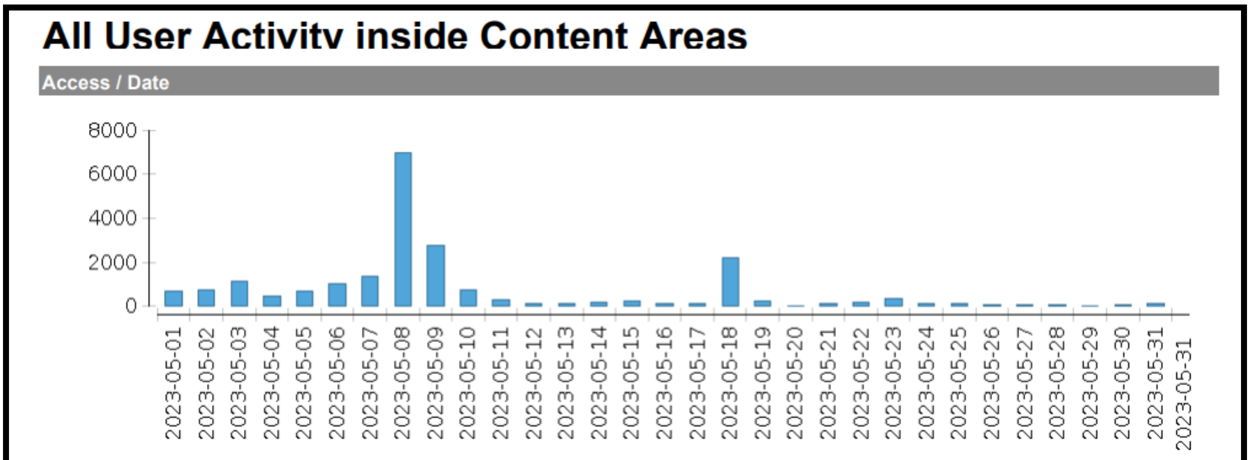


Fig 5.2: An illustration of Blackboard, 2022: All User Activity inside Areas Analytics

Academic staff aligning with this category focused on self-reflection on one's teaching experience is necessary to build teaching competency and confidence. This allows for the academic staff to recognise what skills and strengths they bring to teaching & learning that would further development their teaching practice in order to become more confident:

"So we have data that we can access on students engagement within the VLE, and materials we've got on there. And then we've got the sense that it gives us a bit more information on that, on students engagement with other other technologies in the

> university and this brings information together to me." (MUSC4) However, I need more training in understanding fully the parameters used.

Academic staff aligning with this category recognised what skills and strengths they brought to teaching and what further development their teaching practice should include in order to become more confident in use of learning analytics:

> "I have been teaching myself how to use different types of technologies over the years. I am comfortable using the technological tools given in teaching and learning. I explore them especially the analytical analysis in dashboards, sending one email to all and many more functionality" (COMP4).
>
> "I don't know if there are other things like that, that sort of feed in. I have access to some sort of systems, I don't know what they're called, where I can find out things like how many students have applied on our course, what are the university's numbers for our students who apply to come and study before they come, as part of it application here, and kind of demographics, whether their first, so profiles of the students, and what before in college, whether they've achieved the levels. So all of that sort of it informs my perception of how likely they are to be successful on the course. So those are the sorts of things where we've been using data" (COMP5).

Academic staff aligning to this category indicated how they extended their awareness in teaching and learning on giving the student a good experience with technology that can support other external academic achievements that are tied to the individual institutions. Academic staff realised that in both paper-based and technology assisted teaching & learning much information is collected on their activities and that of their students. Senior management and faculty alike use these "Big Data" or also known as "learning analytics" sets to determine institution specific Key Performance Indicators (KPIs) on academic staff and their related activities:

> "Also, we get information on things like the National Student Survey (NSS), Destination of Leavers of Higher Education (DLHE) and HE Graduate Outcome Data (HESA) and the feeder is embedded in our BDA in teaching and learning". (FILM2).

Academic staff aligning with this category focused on the help that BDA empowers them with in issues arising from student complaints in disputing marks or general complaints on module material provided in a course.

> "Most of the reports in Blackboard, I hardly ever use except only when we have a student complaining to me that they haven't seen material on teaching & learning portal. You know, the occasionally students have said something like, I've did all the quizzes, and I haven't got the answers in there. So I'll look into that." (EEES5).
>
> "In our health sciences, we have students working in live environments with patients and we schedule everything in google sheets which we share in the team. When a complaint is logged, as a course director, I first look into the BDA on the patient and student. This helps to solve problems and issues there and then with evidence" (HCSS2).

5.6 Referential Relationships Between the Categories

As shown and discussed above there is a hierarchy structure of increased complexity within the categories from 1 to 5 as experienced by academic staff in the institution. However as seen in figure 5.3, below, there is a clear hierarchy of inclusivity between categories 2 and 3 then 4 and 5 only. Category 1 is not included in the higher-level accounts as it doesn't demonstrate critical academic staff engagement in their interactions with Big Data and Analytics in teaching and learning. Category 1 is an important category and shows either an unwillingness to engage with the Big Data analytics technologies or an inability to engage in the act of learning on how to obtain vital information for feeding into categories 2 to 5. This distinction also indicates that category 1 is not inclusive of each other whilst category 2 & 3 is inclusive and then 4 & 5 are hierarchically inclusive respectively. This critical distinction between categories which do or do not engage in the act of engaging with Big Data Analytics through interaction with Big Data represents the key qualitative difference between categories established in this research outcome space.

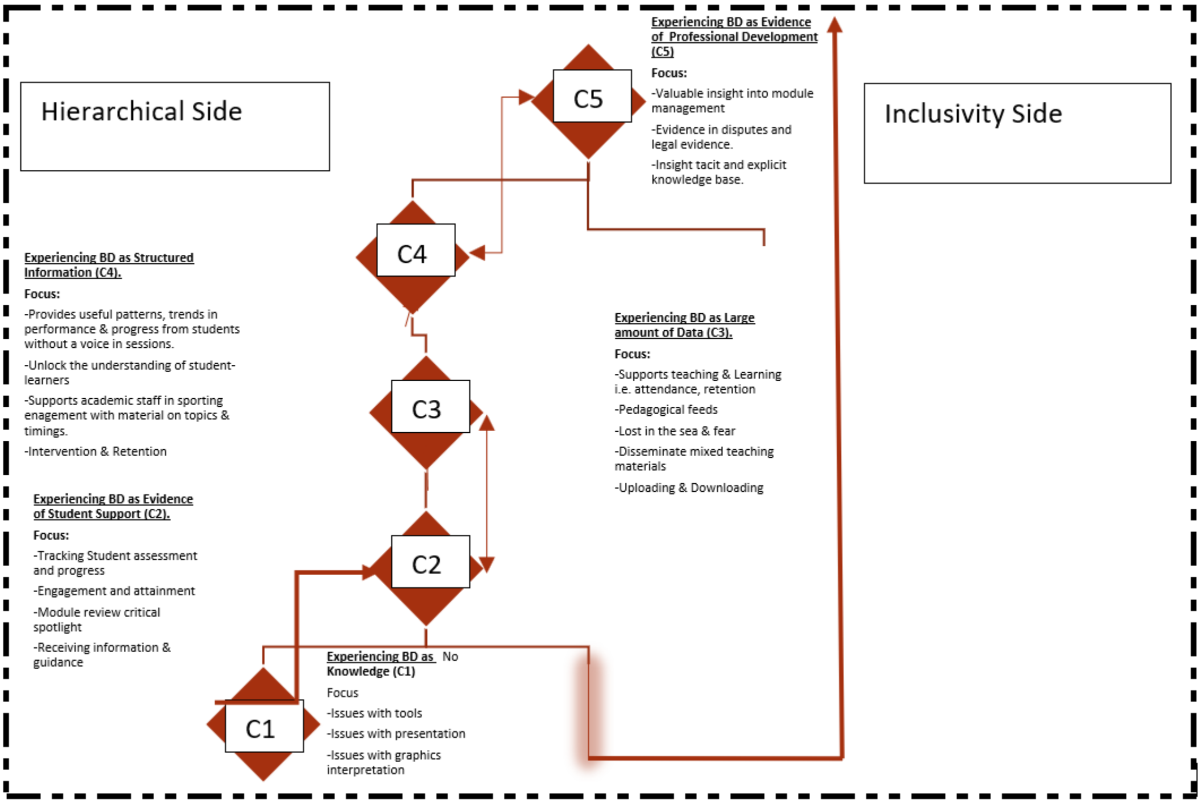


Figure 5.3: Outcome space: Big Data Analytics interactions through Academic staff.

Figure 5.3 above further demonstrates a theme of increasing complexity along the structural aspects of each category, increasing in complexity from self being foregrounded only to academic staff. This demonstrates a combination of academic staff and self-direction. The referential aspect (figure 5.3) here demonstrates the learning of BDA in teaching & learning by academic staff and further demonstrates a theme of increasing complexity from C1 to C5.

Each participant in this research constructed one of these central five categories meanings of the role that Big Data play in teaching and learning and collectively gave multiple meanings of their understanding of Big Data & Analytics in higher education, however, upon analysis, each academic staff is represented in one category only. To drill in the variation, I further discuss the variation in the meaning of experience according to participants gender, specialism, departmental and academic position where it was deemed significant.

The referential diagram 5.4 highlights the structural aspects that focuses on how the parts or the whole within a phenomenon relates to each other and sections on the issues within the categories. Further in this diagram the referential aspect pertains to what the phenomenon's content as it involves drawing an understanding behind one's experience. This enhanced the establishment and understanding on the '*how'* (arrangement of categories) and '*what'* (relationships among the categories) in my research.

Category	**Structural Aspects** What is in the Focus?	**Referential Aspects** *Process of learning BDA with academic staff are about.*	
C1-No Knowledge	-Issues with tools -Issues with presentation -Issues with graphics interpretation	unwillingness to engage	
C2-Large amount of Data	-Supports teaching & learning i.e., attendance, retention -Pedagogical feeds -Lost in the sea & fear -Disseminate mixed teaching materials -Uploading & Downloading		demonstrate critical academic staff engagement in their interactions with Big Data and Analytics in teaching and learning.
C3-Evidence of Student Support	-Tracking Student assessment and progress -Engagement and attainment -Module review critical spotlight -Receiving information & guidance		demonstrate critical academic staff engagement in their interactions with Big Data and Analytics in teaching and learning.

C4-Structured Information	-Provides useful patterns, trends in performance & progress from students without a voice in sessions. -Unlock the understanding of student-learners -Supports academic staff in sporting engagement with material -Intervention & Retention		demonstrate critical academic staff engagement in their interactions with Big Data and Analytics in teaching and learning.
C5-Evidence of Professional Development	-Valuable insight into module management -Evidence in disputes and legal evidence. -Insight tacit and explicit knowledge base. -training requirement		demonstrate critical academic staff engagement in their interactions with Big Data and Analytics in teaching and learning.

Figure 5.4: Category -Referential Aspect

5.7 Summary

In summary this chapter completes the collective picture of how Big Data and Analytics is experienced by academic staff, gathered through expression of their perceptions in this research study. The results depict the wide range of themes of expanding experience, awareness, large number of variations seem to indicate that Big Data and Analytics is a pervasive element in teaching and learning within the higher education sector. Indicators in BDA usage from this research appear to play a role in many areas of academic staff when it comes to teaching and learning as they execute their professional duties. In fact, BDA appears to play a role in various aspects of an academic staff, and it is deemed essential to improving effective practices at each level of application whilst gripped with fear embedded in new technology. This visible pervasiveness of Big Data Analytics' role, especially in evidence-based-practice, has become more widely known amongst academic staff, academia managers and the profession as a whole. It was interesting to learn how individuals quickly accepted this technological advance and embed them in pedagogy, even without formal training. The value of BDA has begun to be recognised widely and being accepted in higher education without a choice due to the emerging advanced usage of technological tools in HE that hold data and information for various uses. The chapter has presented the main findings in relation to academic staff perceptions of the role of BDA in teaching and learning which has revealed the variation of experiences within the academic staff community, namely: *No Knowledge; Evidence of Student Support; Large amount of Data; Structured Information* and *Evidence of Professional Development*. The participants tended to highlight their BDA experiences in teaching as challenging, interesting, innovative, quick learners, spotting trends & patterns, supporting the learner, and creating transferable knowledge quickly into relevant sectional needs for teaching and learning.

5.8 Chapter Five: Part 2 Findings: Phenomenographic Discussion of Big Data and Analytics: Academic Staff Variation in experiencing BDA and Perception Relationships

Here, I further advance looking at variation in different aspects of the academic staffs' experience and perceptions of BDA as an emergent progression of expanding awareness in the academia community across the boundaries in the university that participated in this research. I acknowledge the increasing expectations in incorporating technological tools to enhance teaching & learning in various courses within the institution in the data deluge era. I acknowledge the increasing discernment views in broader terms; however, I reserve the capability to see things differently in different circumstances and situations. This is the grounding aspects of a phenomenon that allows the possibility for one to foreground less aspects of the same phenomenon and acts less elaborately in another situation. Thirty-six participants in this research acknowledged the incorporation of Big Data analytics and analytics in teaching and learning in higher education. This had a collective variation in experiencing Big Data in teaching and learning as presented in figure 4.1.

5.9 Positive Experience of Big Data

Academic staff described candidly the variation in BD as its value coming from the patterns that can be derived by making connections between pieces of data especially in SEMS and Blackboard, about an individual or individuals in relation to groups of students and the structure of information itself as they are using Big Data, which supports teaching. Seeing patterns where none actually exist, simply because massive quantities of data can offer connections that radiate in all directions. Academic staff saw this as a source of both sustenance and pollution in teaching and learning in higher educational setups.

5.10 Negative Experience of Big Data

Where academic staff had negative experiences, they voiced concerns over limited access to this Big Data due to their limited knowledge of how to use Big Data. This could create a digital divide between the computer professionals and the broader scholarly community in different schools across the university. To compound this problem, not all academic staff are fully conversant with the provision of analytics nor have skills or how to read those analysed embedded dashboards.

The 'Big Data Analytics revolution' promises to ask, and help us answer, fundamental questions about individuals and collectives. However, who gets access to all this data we are provided with through our increasingly networked and digital lives around the institutions becomes problematic and scary on big brother watch syndrome on academic staff. This further limited access to Big Data Analytics was collectively viewed as creating a new digital divide between "the Big Data rich and the Big Data poor" in the institution.

5.11 Summary

In summary in this chapter, I presented a detailed account of the outcome of the phenomenographic study which has consisted of a finite set of categories of description in the outcome space, which with their relationships, explain candidly the different ways in which individual academic staff experience phenomena in the world. Chapter five has presented the findings of a phenomenographic investigation into the different ways academic staff in higher education experience Big Data Analytics. The outcome space has been presented in the two diagrams which mapped the different ways academic staff experienced Big Data & Analytics based on meaning structure and structure of awareness. Distinctive Five Categories of description emerged from the collected and analysed data with each category described in detail with its relation to the research question. The descriptions included the quotes, words, extracts from the interviews from the participants woven into the text in this chapter. This chapter will now feed into a discussion of the research findings which will form Chapter Six of my research thesis.

Chapter Six: Discussion

6.0 Introduction

The purpose of this research study was to contribute to the knowledge and understanding of the perceptions of the role of big data and analytics might play in teaching and learning. As outlined in chapter one the aim of the study was to investigate and document the findings on the variety of ways in which academic staff perceive the role of Big Data and Analytics might play in teaching & learning in higher education. The main research question addressed this and reiterated below for convenience:

"In what different ways do Academic Staff perceive the role of Big Data in Teaching and Learning in Higher Education?".

In the previous chapter I have presented the findings of my phenomenographic analysis, which led to the five outcome spaces answering the main research question and the follow-up four hierarchically inclusive research question as set out in the methodology chapter 4 at the start of the research study. The study used a phenomenographic research approach which allowed the process of experiences to emerge from the data gathered and the different ways in which this experience presented a logical pattern in relation. The different ways of experiencing the phenomenon have been logically presented in related categories of description in the given outcome space. The five categories of description addressed the main research question. The outcome space presented the essential parts of the meaning structure and structure of awareness of each experience of the process of experiencing Big Data in higher education and outlined their relationships with each other. The outcome space together with the description provided answers to the research question.

In this chapter consideration will be focused onto what the findings reveal about academic staff, on perceptions of Big Data and Big Data Analytics in pedagogy, teaching and learning experiences relate to the ideas and issues in the literature review discussed earlier in the thesis in chapter 2.

This research study found that academic staff's perceptions of the role of Big Data and Analytics might play a role in teaching and learning in five different ways. In each category academic staff described in detail how they experienced the phenomenon of Big Data. Here each of these categories will now be discussed individually with consideration and emphasis given to what we learn from each outcome. The understanding of the relationships between the categories is an important element in comprehending how academic staff perceptions of Big Data can be understood and facilitate better ways of presenting the analytics more efficiently by technologist for teaching and learning gains.

6.1 Outcome Discussion of Perception of Big Data as No Knowledge Category

This is a finding that academic staff stated as having *'No Knowledge'* and reported having no awareness of Big Data and Analytics existing in higher education. This is a finding that technologists could address in light of the study by Bowker, (2005 p.183-184) where they found that having technology is neither good or bad but data should be cooked with care for the intended audience to derive the intended meaning with ease in understanding the embedded patterns that Big data supports student on *improve student result*, *progression* and *retention* in teaching and learning. For example, Big Data is increasingly becoming critical & crucial in higher education that one can equate to digital air which can be a source of pollution for academics as they struggle to understand and derive meaning for several reasons including technological challenges in use of the tools that are given. At this point academic staff with *No Knowledge* would likely miss the overall idea of leveraging big data within the educational system in order to improve the student results as a measurement of their performance and reduce dropouts. According to Daniel, (2017) states that although Big Data is a new phenomenon and challenges the higher education and its conceptual relevance,opportunites and limitations are still unknown. However, he presents possible opportunities as well as limitations associated with unlocking its value of opportunities and limitations in Big Data in higher education.

6.2 Outcome Discussion of Perception of Big Data as Large Amount of Data

Big Data Analytics in higher education is likely to offer numerous benefits to academic staff, students, and the educational institution itself (Baig, Shuib, & Yadegaridehkordi, 2020). These benefits in this research study are referred to by academic staff as 'Large Amount of Data' that they experienced. Academic staff in this study were found to relate to the information through the technologies that held the data silos and held the perceptions that the opportunities for academic staff included informing next innovation, value creation (Baker, 2018); (Manyika, *et al.*, 2011) and advance educational research in their displines (Siemens, 2011) as the large data sets are obtained with meaning from the large amount of data in this research study. Academic staff in this study seemed alinged with with Manyika at al (2011) in that Big Data will become a key basis of competition in higher education if the large amounts of data are smartly processed and making information transparent and usable at much higher frequency. In the smart processing academic staff will be utilising the embedded values that can be realised from the ten V's as contextualised below to the categories that had emerged and presented in the outcome space. These V's below hold the information that support a particular category and linked to the literature review discussion.

'*Volume'* as in how much data is there to work with in higher education as captured in category 2 in figure 4.1. currently this agrees with higher education as it is experiencing rapid proliferation of data. Embedded in category 2 is data that could support students at risk, enhance retention, and attract engagement with '***Pre-Student, Student*** and ***Post -Student***' stages (Ekowo and Palmer , 2016; Ekowo and Palmer, 2017).

'*Velocity'* as in how quickly the data is being created, moved or accessed in higher education (Attaran, Stark and Stotler, 2018) as captured in category 2 in figure 4.1 as data analytics which is rapidly advancing as the technological tools pace advances, too.

'*Variety'* which can be the spice in teaching as in how many different types of sources are there, where this data is generated and stored as captured in category 4 in figure 4.1. The indicative results in the category 4 show that there is variation in higher education data which is utilised and underutilised in higher education in efficiency, decision making, enrolment etc, (Attaran, Stark and Stotler, 2018).

'Veracity' which surrounds the issues of trust around the data and confidentiality for teachers and learners as captured in category 2 and 4 in figure 4.1. '*Veracity'* further locks in a constant struggle with issues around the recent data governance in higher education, General Data Protection Regulation (GDPR) under Data Protection Act 2018 regulations, integrity, and quality as captured in category 3 and 5 in figure 4.1.

'*Validity'* in questioning the data accuracy and correctness within the technologies that generate and stores it for value identification by academic staff as presented in category 4 (supporting) in figure 4.1. '*Viability'* as in understanding which elements of the data are actually linked to predicting or measuring a desired outcome in order to produce trust worth results that can either be used in academic disputes and appeals amongst other aspects as revealed in category 4 in figure 4.1 unlocking understanding and patterns (Ekowo and Palmer, 2017).

'*Volatility'* as in how often the data changes including the metrics used within the analytical technologies that support analysis (Attaran, Stark and Stotler, 2018). As the volume of data increases in teaching and learning on a daily basis, academic staff decision making will increasingly be important and need to be timely in interventions, innovation, and creativity, utilising as category 5 presentation. Attaran, concurs that data has a tendency to quickly become stale and (2018 p1) also can limit progress in accumulating the extremely rich data that flow through higher education systems for the purpose of acquiring usable information for various activities in the sector.

'*Vulnerability'* would be a great concern as in keeping this data secure in todays' climate of high cyber security hacktivism in higher educational institutions with increasingly large-scale attacks. This data could also be vulnerable to all network and firewall attacks from unlawful usage by outsiders.

'*Visualisation'* as in how this data is best presented to the user-academic staff, who are constantly struggling mightily with the usability of their electronic analysed record interfaces such as blackboard analytics, complaining about too many clicks, too many alerts, and not enough time to get everything done in one teaching day. Adding to this huddle is the complexity of processed information that is part of every academic staff daily workflow. When Big Data analytics presents dense and hard-to-understand reports will only sour potential use of IT by academics who were finding IT already overwhelming and adding to their overloaded allocation tasks. The concerns on technology adoption rates on a local a scale is indicative of a pattern that can easily image if this type of research was conducted on a national level.

'*Value'* which is the icing on the cake, relates to how can this data produce a meaningful return on investment in higher education to include extraction of some sort of value (category 4 & 5) for specific activities and practices better outcomes, improved business efficiencies, or smarter strategic decision-making, higher institutions cannot afford to ignore the big question about big data (Daniel, 2015): what has it done for me in teaching and learning? The value is there for those who adhere to strong data governance principles, proactive with robust institutional IT infrastructure and take a creative approach to disseminating insights to inform their own teaching and learning innovation (Attaran, Stark and Stotler, 2018).

Beyond this research study, there may be even more Vs to come as the future of higher education big data analytics unfolds, but there is little doubt that *value* will remain the most important metric to monitor when engaging in any and all data-driven decision making (Daniel, 2017). This value will be taking higher education into the next frontier for innovation, competition and productivity in teaching and learning research and development in implementing focused curriculum in the century as Big Data becomes the key basis of competition underpinning new waves of productivity, innovation with the right policies and enablers in place by managerial staff (Manyika, et.al, 2011).

6.3 Outcome Discussion of Perception of Big Data as Evidence of Student Support

Overall, the vast majority of the academic staff acknowledge the potential of Big Data analytic dashboard to help them improve their teaching practices and students' learning process. The respondent in this category indicates that Big Data Analytics dashboards could provide academic staff with additional insights into the learning process of students using the analytics that would highlight when students access their material and duration of their engagement on the task. Academic staff preferred features and indicators related to the results of students and the comprehensibility of the course content. Action-related indicators such as time-spent, day accessed and number of pages viewed were also rated rather positive, but multiple academic staff stated that the value remains unclear, and this requires further exploration in the tools used for analysis. Thus, Big Data Analytics dashboards could provide academic staff with new insights about the student's learning process and the quality of the course to some higher extent. This research highlights the need for well-designed dashboards, including more detailed indicators about the performance of students and the comprehensibility of the course content. Academic staff indicated that rich datasets about learners are required to generate useful reports in the future to enhance full capabilities of higher education on teaching and learning. This category highlighted how more research is needed to increase the value proposition of Big Data Analytics and the accurateness of the data representing the student's learning process. Bringing analytics in a contextualised format is another challenge, taking the context of both the learner and the type of the course into account in teaching and learning would further help those in category 1 to become knowledgeable.

6.4 Outcome Discussion of Perception of Big Data as Structured Information

According to Lawson, et. al., (2016) articulates technological advances in digital teaching and learning has increased trends towards Baer and Norris, (2015) information arising from the the generation, sharing, and dissemination of educational data, via use of online learning resources (both in traditional on-campus and online educational approaches) alongside the use of Learning Management Systems (LMS) between teachers and students has certainly reiterated the need to harnessing such deluge of data availability for improving decision making. The findings of this research have concurred with views of Lawson and Baer that structured information emerges from these digital silos which supports teaching and learning in customising, leveraging higher educational systems in improving the student overall results. The research findings further unveil enhancements needed in higher educational analytical tools and techniques to handle some of these collected data in order to improve the academic interpretation in order to provide relevant analytical reports to help in teaching (including by embracing innovation in online) and learning (student to enhance mobile teaching and adaptive learning) make strategic and informed decisions records. Information is a vital asset in higher education just like it is anywhere else in supporting the core competences of higher educational institutions and as this research reveals that Big Data is crucial to teaching and learning in higher education.

6.5 Outcome Discussion of perception of Big Data as Evidence of Professional Development

One of the main challenges that academic staff highlighted in data analytics is the collected analysed data from the multiple sources they use in teaching and the challenges faced in interpreted these combined sources together so that they can make meaningful unified way. When combining different Big Data sources in higher education, often a fundamental problem is identifying which pieces of this data gives information that describes the same real-world entity or gives the worldview picture that exists in this environment. Gibson (2012) as cited in Veitch, Strehlow and Boyd (2018) state the challenges for staff and students are often the social interactions with Gibson (2012) arguing for a socio-cultural process approach to higher education, and a focus on the learning environment as various social relations, in order to advance 'the very real complexities and challenges of inclusion 'which still prevails today. This research extends by highlighting the complexities and inclusion challenges in using Big Data embedded information and not being sure on how it can offer insightful critical spotlight, tacit and explicit knowledge base in several pedagogical practices.

6.6 Further Research Study Comments

The constructed configuration from this research study based on academic staff experiences explicitly spotlights what is seen from the authoritative authors eyes on how they perceive Big Data and Analytics in higher education which complements the findings in this study. (Baker, 2018) extends the narrative that Big Data repositories from online learning platforms for universities presents unprecedented opportunity to advance research on education at the scale and impact of a global population of learners on home and away campuses. This could enhance production of published paper offering insights into student behaviour whilst teaching and learning is on the increase. This could also enhance innovative curriculum development to fit teaching and learning with technology into the next century.

6.7 The possible suggestion of the research study variation

The research study here has highlighted a crucial aspect of how Digital Technologies in pedagogy are transforming higher education in more than one area as depicted in the diagram below. This concurs with the authoritative authors such as Williamson, (2017) on Learning Machines, Prendes, et.al.,(2016) on future professionals in digital personal learning and

Castañeda, and Selwyn, (2018) making sense of ongoing digitisation of higher education with list not exhaustive here.

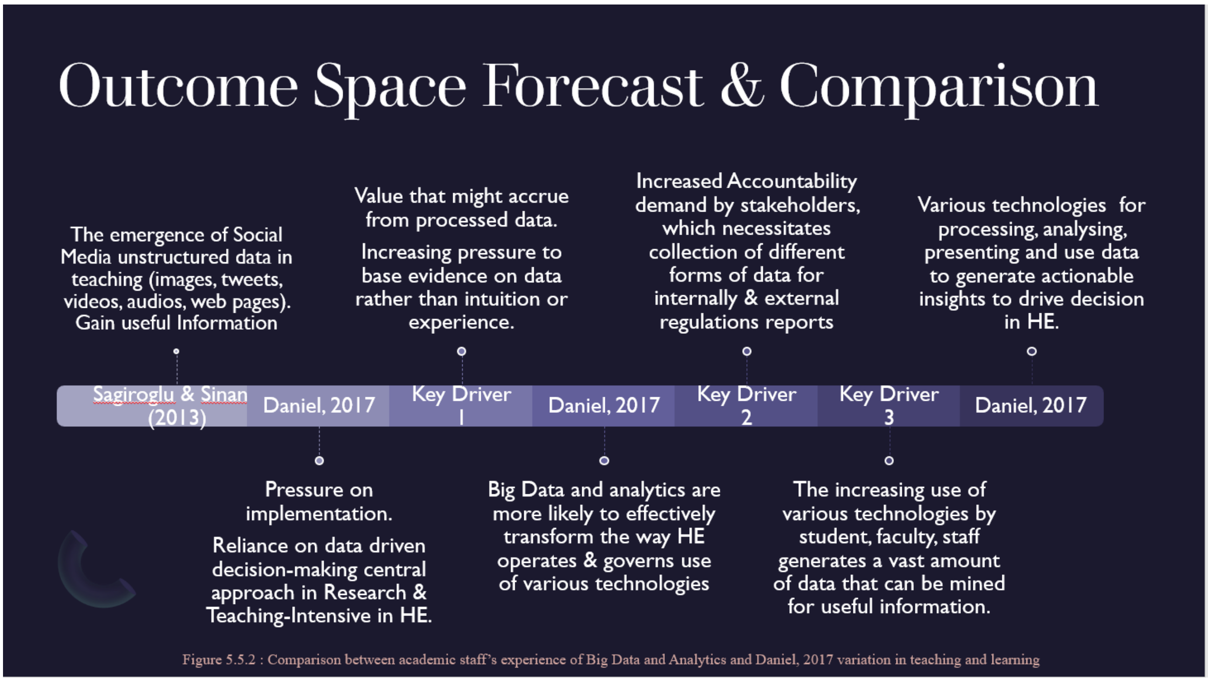


Figure 6.1 Outcome Space Forecast & Comparison - Chawawa, (2022)

6.8 Big Data Analytics in Pedagogy Supporting Teaching and Learning with Technology

For this research question on the experiences of academic staff of the role of Big Data in pedagogy. 'Pedagogy' in this research is the study of different teaching methods and for this question it is relating to the role that technologies play in supporting teaching & learning in Big Data environment as experienced by academic staff. Big Data here in higher education offers unprecedented opportunities for academic staff to reach out and instruct their students in new ways of acquiring new knowledge. This highlighted how academic staff gained deeper understanding of their learners' (students') experience and thereby helped them to evaluate their ways whilst understanding that what worked yesterday may not work in tomorrows' system. This has been the academic staff experience with the six and seven V's framework (Daniel, 2019 and Faroukh, *et al.*, 2020) in *improving student results, customizing academic programs, unlock meaningful academic values, and ensure strategic decision-making, enhancing innovation, enhance retention whilst reducing withdraws, targeted home & international recruitment.* These experiences reside in the vast amount of data generated daily through various and heterogeneous sources around teaching technologies in higher education and especially captured in the following V's and related to the research question as articulated below.

Volume: According to academic staff on Big Data in this research, universities are collecting and analysing data in ways that are greater than the databases we used a few years ago. This Big Data movement in higher education has been fueled by the fact that more data is being generating on everything in teaching (timetabling, attendance, progress, assessments with list not exhaustive) with the technological improved ability to store and analyse these huge volumes of any type of data. Academic staff found that vast amounts of innovative.

Velocity: The speed at which the data is generated is overwhelming with the use of social media, YouTube and supporting teaching technologies like blackboard. These can have the ability to integrate innovative ways of teaching and learning that enhance student experience, which academic staff found useful encapsulated in the V's.

Variety: Academic staff stated that with Big Data in higher education, it is now possible to easily monitor student engagement & actions taken on provided material, such as how long they take to answer a question, how long they looked at material, duration, what time & date, which sources they used for exam preparation, which questions did they skip, etc. These and many more similar other academic questions could be answered automatically and instantly, giving each student instant feedback even though institution holds lakhs of students. In addition, the varieties presented in the information was useful in teaching and learning as it is able to offer different solutions to different situations that academic staff face every day.

Veracity: According to this research study, academic staff highlighted the speed at which the data is generated within modules and courses on both home and international student's' activities. This Big data in higher education offers benefits like revolutionising the way higher educational institution are doing in supporting learners through the learning process through face-to-face as well as online (a blended or hybrid approach). Traditional educational institutions are facing substantial challenges in transitioning towards hybrid and online learning portals in supporting students in their learning trajectory, which are adding to the data silos.

Value: This research study highlighted that this aspect of Big Data and Analytics in higher education was the direct link to the benefits that academic staff could see directly how it impacted on their teaching and learning. The benefits highlighted included support on retention, innovation, insightful, trends that support teaching and learning activities. Academic staff further stated that the value-added element could also be seen in supporting students in academic advisory capacity, which reduced dropouts by giving early intervention.

Variability:

Big Data through this research provides a process for bringing all key stakeholders (Management, Academic staff and Students in teaching and learning environments) together to thoroughly identify, validate, vet, value and prioritise the analytical dashboards that are key to the university business and operational success. Academic staff highlighted issues of Data security and privacy which are discussed below in relation to teaching and learning (Q3).

Visualisation: From the research finding in category 5 and relating to Q3, it was found that academic staff need to understand the transformation of the immense scale of Big Data into something easily comprehensible to support actionable activities. Such as dashboards in 3 dimensional visualisations could support them if they properly show meaningful data to them. Academic staff struggled with understanding and interpreting several dashboards like the one in appendix E1-A whilst dashboards like E1-B give out meaningful actionable data. Academic staff experienced multitudes of spatial, temporal parameters and missing relationship between the visualised dashboard into understood visual messages. The views carried around these visualised data were that whilst they are able to deliver on certain aspects like, student engagement, course performance, attendance successfully, they actually do fall short of congruently putting a complete solution forward in data that is difficult to digest visually (see example appendix E2).

In the V's, academic staff were aware that Big Data usually requires 'specific forms of processing' (not to do with them) that enables enhanced teaching and learning decision making, insight discovery, and optimisation of several processes in higher education. There were issues around vulnerability when accessing the visualisations that offered insightful patterns and trends which contributed to the *no knowledge category.*

Below is a 3D diagram that underpins the outcome space to the 10V's of Big Data and Analytics that are mapped to the outcome space of the five categories from this research highlighting how each Vs supports a category.

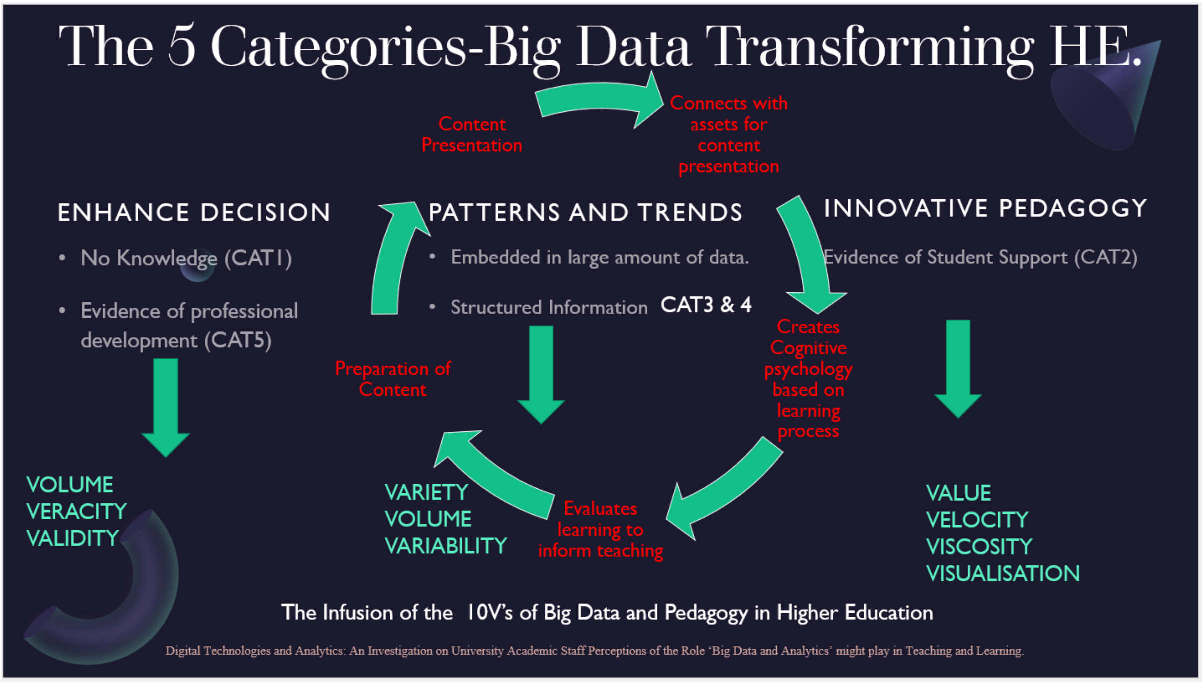


Figure 6.2 Outcome space Mapping around the 10 Vs of Big Data (Manyika, et al, 2011).

The above figure 6.0 supports the claims that Data has swept into every higher educational institution as an important resource and this is a fact depicted by this university which is a representative of the one hundred- and thirty-one-Times Higher Education ranked institution (Ross, 2022). Big Data indicative results from this research is that it will be the next frontier for innovation and productivity in higher education. This supports the discussion offered by Castañeda and Selwyn, (2018) on important digital technologies in higher education that impacts on transformation in HE. However, this digital technologies in HE may not work better for all (Prendes, et. al., 2016) academic staff in teaching and learning.

6.14 Summary

According to the results from this research, the majority of the respondents in the academic sample that was carried out had variations of little or no experience with using the statistics from blackboard analytics, SEMs and other cloud-computing silos of statistics within their range. A significant group of academic staff in category 1, used other types of analytics to evaluate the learners by applying old paper-based approach. Another section of the academic staff proactively used own designed quizzes, occasionally or always, during the teaching & learning to assist in decision making. This aspect didn't remove the traditional interim tests analysis that traditionally have helped in evaluating in teaching and learning for decades, checking the progress of students, and raise awareness for students to understand where they are at. The research findings indicate that there was a split on usage of Big Data Analytics in teaching and learning as the categories highlighted above. Some of the academic staff mentioned the daunting graphs presented in the analytics as not being able to provide any understandable instant valuable statistics, whilst other respondents explained they do not know where to find them or the value embedded was not clear for them. Overall, this highlighted the average experience of the academic staff using Big Data and analytics nowadays to be considered little, whilst Big Data is exponentially growing in higher education. Future Big Data and Analytics research could try to understand which indicators are relevant to academic staff that can help to develop and evaluate future big data analytics dashboards that are fully supportive to enhance higher education. This research also highlights the crucial elements academic staff might prefer different indicators because of their experience with big data analytics, experience in teaching, or their background. Further exploring the requirements and expectations of Big Data Analytics in the form of indicators is needed to present useful visualisations to academic staff.

The value of Big Data in higher education comes from the patterns that can be derived by making connections between pieces of data that form meaningful information, about an individual, about individuals in relation to others, about groups of people, or simply about the structure of information presented. The growing interest in Big Data mining is spurred, in part, by the increasing quantity of data available to higher education academic staff and academic researchers from transactional databases, online operations, and data warehousing (Johnson, 2014). Baker (2014) suggests four areas of application: building student models to individualise instruction, mapping learning domains, evaluating the pedagogical support from learning management systems, and scientific discovery about learners. Kumar and Chadha, (2011) suggest using data mining in organising curriculum, predicting registration, predicting student performance, detecting cheating in submissions and online exams, and identifying abnormal or erroneous data. More recent applications have embraced such suggestions, exploring course recommendation systems, retention, student performance, use of ChatGPT and assessment pattern recognition etc., which concurs with Johnson, Baker, Kumar & Chadha whilst extending support to the phenomenon of Big Data in higher education.

Chapter Seven: Conclusions

7.1 Introduction

My research study set out to investigate university academic staff Perceptions of the Role 'Big Data and Analytics' might play in Teaching and Learning. I was inspired to take up this research activity seeing how progressively in computing subject areas and the entire university has rapidly evolved in higher educational context suggesting the increasing importance of using enhanced technologies in pedagogy. Research on academic staff perceptions, understanding and experiencing of Big Data and Analytics can help inform teaching and learning designs. The impetus to focus on academic staff was further infused by the extensively increasing usage of the many technologies in teaching and learning in higher educational institution today. Information technologies are progressively growing, and the data-driven technology is becoming an integral aspect ('huge footprint') in teaching and learning in educational systems in this century highly depicted in literature reviews and during the recent covid pandemic era. Big Data is fast becoming a fast-growing new phenomenon in higher education, its conceptual relevance, as well as the opportunities and limitations it might bring, is still unknown and this research study has contributed to opening up some of the unknowns as listed in the categories above.

Adopting the phenomenography research led me to describe the different ways in which academic staff experienced the Big Data and Analytics in their world view. This empirical study led to discovery of the qualitatively different ways in which academic staff were experiencing, conceptualising, realising and understand the various aspects of Big Data around their environment.

Following this research study and its outcome space a more comprehensive picture of academic staff perceptions of Big Data experience has been revealed, however the research also revealed the incompleteness of this picture and how academic staff decipher. The emerging leapfrogging of the discourse on Big Data to more popular higher educational outlets implies that a coherent understanding of the concept and its nomenclature needs developing further. For instance, there is little consensus around the fundamental question of how Big Data and Analytics impacts academic staff in published material. Thus, there exists the need to document in higher education journals the evolution of it in the higher education educational environment of academic staff.

7.2 The Implications that Emerged out of this Current Research Study

Golfarelli and Rizzi (2009), in data warehousing stated that there is need for Advanced IT analytical tools to be used in order to maximise potential of decision making. This is highlighted in category 1-3 where academic staff whilst appreciating the technological analytical tools and the data they were using; they further highlighted the need to have clear analytics that did not pose a challenge to interpret the information embedded in it. It is estimated that the analytics-ready structured dashboards are only a small subset of big data in the emerging picture "across the piece" (Gandomi and Haider, 2015) with more to come in the near future. The unstructured data, especially data in video format, is the largest component of big data that is only partially archived.

This research study highlights the need for improved embedded software analytical tools that can easily be understood and interpreted by academic staff for a much quicker response and engagement themselves before they move to support pedagogy and learners. Here there appeared to be a bone of contestation between no knowledge (category 1) and evidence of professional development (category 5) on how this factor has been ignored by top management in the institution on investing in learning management systems.

It is estimated that the analytics-ready structured data dashboards are only a small subset of Big Data in the emerging picture "across the piece" (Gandomi and Haider, 2015). The unstructured data, especially data in video format, is the largest component of Big Data that is only partially archived.

This research has enabled higher education to unpack the evolutionary nuances of a specific field of Big Data and Analytics, while shedding light on the emerging areas in that field and the potential gains and pitfalls. From this research, it is yet understood that its application in higher educational research is relatively new, and in many instances, underdeveloped. To this end, this research, also sheds light on *when* and *how* Big Data and Analytics analysis should be used vis-à-vis other similar techniques such as the embedded blackboard analytics and systematic literature reviews that requires clarity for individuals understanding to further enlighten the big gains embedded.

The higher education institutions just like primary and secondary education continues to shift toward digital teaching and learning through use of mobile phones, laptops, personal computer, tablets with remote access through remote Virtual Private Network (VPN) to the university software for accessibility, generates more Big Data. With educational institutions suddenly forced to transition to online delivery, work-from-home conditions, the internet drastically increases the amount of Big Data and *access to knowledge* embedded in it as academic staff held such strong views.

7.3 The Recommendations that Emerged out of this Current Research Study

The first and foremost recommendation is to amalgamate the meaning of Big Data Analytics, Learning Analytics, Information and datafication as they all point and hold the same meaning as per Daniel, (2017); Siemens, Gašević, and Dawson, (2015) in higher education. The literature here intertwines and unveils the same interpretation. In order to build on the established foundations laid down by this research study it would be interesting to replicate the research with higher education staffs in different contexts in order to enhance the outcome space achieved in this research.

The outcome space highlights the confusion springing out amongst academic staff around scalability data analysis and subsequently the analytics that need to be understood uniformly in order to exploit the gains that Big Data Analytics can improve decision making, understanding of student learning; student experience; academic staff innovation in pedagogy from these datasets. It is recommended that further research be carried out on the confusion that exists to iron out and improve decision making.

The research outcome highlights the perils of Big Data, such as spurious correlation, between Big Data and Big Data analytics in higher education which is still underutilised and under researched in the academic press. Big Data is growing exponentially (José, Edward, and Wolfgang, 2016) in higher education equally, with use of namely large volumes of scientific data, text, audio, video, and social media in pedagogy. This research concludes by highlighting in the research outcome category one the expected developments to realise in the near future in Big Data and Big Data Analytics for academic staff in higher education to be seriously taken onboard.

A bigger research sample with academic staff, middle & top management, academic researchers, technologist across the entire university, which are closely linked to supporting teaching activities is recommended. This will harness this research outcome data as possible about what is being studied and provide a preamble to the bigger picture to emerge in, higher education institutions.

The leapfrogging of the discourse on Big Data to more popular outlets implies that a coherent understanding of the concept and its nomenclature is yet to develop. For instance, there is little consensus around the fundamental question of how big the data has to be to qualify as 'Big Data' and this calls for a recommendation into higher education further research.

7.4 Concluding Research Remarks

In this research study, I have argued that the perceptions that academic staff have on the role that Big Data and Analytics might have played in teaching and learning by presenting their variation which have been discussed in categories and themes in the previous discussion chapter that adds to new knowledge in literature review.

With this research study, I pursued my inner growing interest in Big Data and Analytics in higher education for pedagogical practices' deeper understanding. This interest and passion steamed from my career experience that has been focused on higher education for over thirty years in computing subject matters, with a '*higher order thinking'* within my lecturing commitment, namely *transfer (promoting retention)*, *critical thinking (my reasonable reflective thinking…what to do)* and *problem solving (using non memorising solution…strategising)* (Brookhart, 2019).

Through this research I have also persued the interest to explore phenomenographic research approach in computing aspects and for a deeper understanding of it having learnt it in the methods module during my PhD course. After reviewing several methods including grounded theory, I recognised phenomenographic as an appropriate method for my purposes in gaining a wider understanding of the different ways of experiencing the perceptions of Big Data Analytics away from the notions of contrasts and conflicts. This research study experience has brought about an appreciation of the phenomenographic perspective in its alignment to the theoretical underpinnings of Big Data and Analytics in higher education, favouring the outcome space of the practice existing within.

7.5 Contribution to New Knowledge

Through this research study, insights into new knowledge have been added through the discovery of a variety and a range of perceptions that academic staff hold over use of Big Data Analytics in teaching and learning including decision-making with 'real-time-data driver', identification of patterns in students activities in learning, improving teaching material and curriculum, using real-time-data for personalisation.

This research advances the understanding of new knowledge on improving decision-making using Big Data and Analytics which provide academic staff with real-time insights allowing them to make timely informed data-driven decisions in teaching and learning. According to staff who participated in this research study highlight such activities like 'instant academic student support' 'student intervention', 'innovative courses & cirriculum', and 'innovative teaching styles' i.e., blended learning and hybrid delivery amongest many other data driven decisions.

Academic Staff happily shared the ease with which they identified trends and patterns in students and their fellow academics in a module. Big Data Analytics made it possible to identify these trends that would normally have gone unnoticed in the tradional practices such as attendance and engagement in reading or accessing educational material.

The research study also highlighted the aspects of personalisation in teaching as Big Data Analytics can help organisations create personalised experiences for their learning behaviour and preferences. This aspect may be enhanced with predictive modeling that can help higher education to predict future outcomes based on student and staff historical data and trends, an aspect that is not taking place at the moment.

Through this research study, the position of learning mangement systems (Baker, 2018), challenges & opportunities (Daniel, 2015) analytics penetration (Siemens and Long, 2005, & 2011) is further supported in the findings that include collection of Big Data that is useful in pinpointng strengths and weaknesses of Big Data Analytics in supporting course activities, student participation in teaching and learning. This adds to the Higher Educational Instituitonal goal to improve and optimise student learning behaviours in order to be more successful as an institution whilst highlighting some shortfalls.

This thesis has contributed to the knowledge and understanding of academic staff perceptions of the role Big Data and Analytics experience in pedagogy. By adapting for mapping the qualitatatively different ways in which academic staff experience, concetualises, perceives and understand (Marton, 1986, p.31) various aspects of Big Data.

By adapting phenomenography in this research approach the study described the qualitatively different ways academic staff experienced Big Data role in the context of their daily lives in teaching and learning and the kind of variation that exists between their experiences. The findings from this research study has provided an important insight into the undrstanding of academic staff relationship with Big Data and Analytics which is important knowledge to the sector.

The empirical study of the different ways in which academic staff think of the Big Data and Analytics world was discovered through qualitatively different ways academic staff experience, conceptualise, realise and understand the aspects of the Big Data phenomena in the world around them. Their world view is seen through the outcome space of the five categories as discussed on page 102-108 of this thesis, which are ground breaking in the institution where this research took place. The lack of literature review in higher education on these five categories can be indicative of the wider academic staff experience in other institutions, too. The discovery of category one within the local context where this research took place is highly revealing of embedded discourse of pockets of Big Data phenomenon in the technological era that exists today that needs support itself through category five.

Through this research, I have extended the body of literature on academic staff understanding and perceptions of the role Big Data and Analytics building on understanding the link between Big Data and analytics in teaching and learning in higher education. Such a research is missing published materials in local higher education to align with that of Daniel, (2014, 2017) literature.

I advance an alternative understanding on variation in experiencing Big Data and analytics not as a set of contrasting and conflicting possibilities but as a constitutive view suggesting an emergent progression of awareness by way of the phenomenographic pespective wherein to different degrees a person is aware of certain aspects of a given phenomenon at a particular moment in time in a particular setting. I further advance a constitutive view, that suggests an emergent progression of awarenessof how higher education academic staff perceives role of Big Data and Analytics as contributors to teaching and learning (underpinning learners knowledge, empowerment in decision making, learners focus, retention and communication) in this environment.

This research study throws light into how complex the Big Data Analytics could be for intepretation for academic staff and vital messages could be lost in the process, which will require a second school of thought.

Through this research I extend the insights embedded in Big Data and Analytics that academic staff hold in their perceptions (reality on the ground) in teaching and learning, as the whole world is going gaga about Big Data in technologies that support Machine Learning, Artificial Intelligence, Datafication and Computational Thinking in seeking visualisation, trends and future predictions. The future of Big Data is massive in future direction in Higher Education (Baig, Shuib, Yadegaridehkordi, 2020) (Kirkwood, & Price, 2013) opportunities and challenges (Daniel, 2014, 2017).

Through this research I contribute to new knowledge on complexity in intepreting Big Data analytics visualisation data (category 1) that is crucial for academic staff in pedagogy, in order to extend the utilisation of the potential of technology enhanced learning in post compulsory sector.

Through this research I have a thorough understanding of policy and practice in relation to the implementation of technology enhanced learning in higher education, where this study took place, especially relating to academic staff experiences of Technology Enhanced Learning (TEL) in their individual & collective subject area delivery. This research has reinforced the position that academic staff are a branch of university stakeholders who reasonably have high exoectations of their university education and these expectations have challenged on how to respond to ways that are evidence-based (progression, retension and engagement) and future-facing to students (stakeholder) requirements and enhancements.

7.6 Implications on Findings and Reflections

The research study highlights the embedded implications on academic staff understanding the data sets that are delived from various systems to support their pedagogical activities as this data can be very complex in the format that presents it. A further implications arises as the ongoing Internet of Things (IoT) is fast developing and more Big Data is being generated in higher education to improve the accuracy and efficiency of the learners and academic staff which adds to further implications in the categories established in this research. The implications of Artificial Intelligence and Machine Learning for higher education is raising as observed since this research was invoked and this will widen the digital literacy gap in ademic staff community as it generates higher volumes of Big Data.

The research work presented has contributed to the existing knowledge on the role that Big Data and Analytics plays in teaching and learning through academic staff lived experiences as highlighted in the five categories. The findings as presented in the outcome space has provided an important insight into the understanding of Big Data and Analytics in higher education, which will serve as a preamble to future research in Big Data in teaching and learning. With this research outcome space having set as the stepping stone to future research, I draw this work to a close with all the four questions answered.

7.7 Limitations of My Research Study

This research study had a number of limitations which may need to be addressed in follow up research in the near future. The application and justification of the phenomenography methodology rationale was fitting taking into consideration that this research study was set in a higher educational institution. However, there were some limitations in my research sample as only thirty-six participants views are held which is not representative of all UK academic staff in the higher educational institution. All the participants were from a single university and although I had ambitions to carry out this research on more than one campus, the research ethics application between universities became a challenge. It is not claimed that this research findings are generalisable as they are based in the North. It is acknowledged that different outcomes might have been described if it had been possible to do this research in more than one institution. Nevertheless, the research sample do provide a basis for future studies.

Chapter Four of this thesis describes careful deliberations, as the phenomenography research approach was considered and adopted as the most appropriate to answer the research question. Adopting a single approach is known for excluding understanding that other approaches could have provided, and this was another constrain in this research. Timetabling, course management activity constraints on staff was a limiting factor as it limited recruitment of a bigger research sample as others declined the invitation. The full appendix D1 shows all those invited and who declined due to busy timetabling issues in the institution. Whilst forty-one participants were a sufficient number for a satisfactory representation in phenomenography, the views of all ninety-three could have enhanced the representation.

7.8 Similar Past Research in line with this Research Study

The present research study contributes to existing literature on academic staff perceptions of Big Data Analytics which extends the work of Chaurasia & Rosin, (2017) Most of the work on Big Data have tended to define this from a learning analytics (Daniel, 2016) (Baker, 2018) and paid little research to the experiences of academic staff. Previous studies on Big Data academic work tended to give a focus on digital tools for analysing analytics (Blackboard analytics, PowerBi, MongoDB, Cassandra, Tableau, Hardoop, etc.,) and learning analytics proliferation of web tracking tools in educational research in Big Data and Metrics for improving student retention, instant feedback, personalised experience for learners(blackboard tools) with little explicit research on perceptions of academic staff in that environment. These digital tools are helping in analysing data from multiple sources to give a comprehensive view of the current information assests in higher education which needs to be presented in the manner that academic staff can delive useful insights for academic purposes. Therefore, there has been a delineation of studies and their focus in higher education on Big Data with a few studies that have considered the views of academic staff. To my knowledge there is no research that indicates that the relationship between the role of Big Data in teaching and learning, perceptions of academic staff, key stakeholders in this symbiotic relationship has been explored. It must be acknowledged that a large amount of literature has focused on Big Data tools in higher education nationally with generic research (Chaurasia, & Rosin, 2017) whilst Daniel, (2015) highlights the opportunities and challenges that can be experienced in higher education. This enhances the current study in contributing to filling the existing knowledge gap on the specific institution of higher education and setting a base for more future research as higher education experiences more of the BDA and management systems (i.e., **S**tudent **E**ngagement and **A**ttendance **S**ystem -SEAtS) tools. It is therefore important to acknowledge and value the variation in notions of their work, interaction, and dimensions as this may offer one way to begin to acknowledge Big Data role in teaching and learning. This will then further offer management to understand from this research the perceptions academic staff and the role that Big Data might play in teaching & learning and its contributions to the Teaching Excellence Flamework (TEF) in higher education and its links to tuition fees.

The findings from my research draw attention to three main constructions of being an academic staff, and variation in the meanings of Big Data; Big Data Analytics constructions of perceptions; and multiple ways in which academic staff might experience the role that it might play in teaching and learning. With a larger and a more diverse sample from many institutions, future research could explore whether Big Data has further roles and relations that exist with a wider population; and a larger sample may reveal additional constructions of the perceptions academic staff hold of the role it plays in teaching & learning. This follows the consideration that technology is still on the increase in usage in Teaching & Learning as I submit this thesis!

7.9 Future of Big Data and Analytics with Artificial Intelligence and Machine Learning

The future of Big Data is very promising as the technological advances are increasing with exponential increase in data generational tools across the world. In view of this new advances in technology, Big Data is going to play even more significant role in shaping educational services. Some of the potential trends that can be expected in the future of Big Data will include the computing cutting edge 'Internet of Things (IoT)' devices that are increasingly being used in as part of the integral part of Big Data processing and visualisation (Ashok, et. al, (2023). The IoT connectivity of physical things that make connectivity of devices in teaching and learning that contribute to Big Data. In future, these have the potential of processing data themselves and sending the relevant information to cloud computing for further analysis. Artificial Intelligence and Machine Learning (ML) is already proving to be important in analysing Big Data in various fields with a promise of becoming even more prominent in automating data processing and decision making.

Generative Artificial Intelligence and Google Bard has taken it to a higher level with a storm in terms of their new discovery and application of the ChatGPT & Chatbot (Aljanabi, et. al.2023) for students and GenText ai (Charles, 2023) for academic professional research. In addition the storm covers the technological progress that can be used to create new content based on large volumes of data for models that can benefit academic staff in 'freeing up academic staffs' time' and reduce workload across the education sector. Artificial Intelligence for higher education, which will contribute to Big Data Analytics with the massive student interactions, and this will impact on teaching (dilemma) and learning (tool excellency) as these technologies could safely and effectively deliver excellent education that prepares students to contribute to future society workplaces. The embedded AI in ChatGPT (Generative Pre-Trained Transformer) which is powering a number of technological apps (TEACHERMATIC, NOVA with list not exhaustive) that used in higher education and especially with students on writing essays. Overall, the future of Big Data looks promising as a new trends and advancements help bring efficiency and success to higher education and organisations alike.

Big Data Analytics has a promising impact and further research in **T**PACK (Koehler, *et al.*, 2014) and the Pedagogical Wheel which both generate data whilst being used as technology that supports teaching and learning. The growth of technological tools being used in higher education in teaching and learning is phenomenal as these are being highly used in higher education context. This will impact on Mobile Learning (personal, spontaneous, informal, pervasive, situated, context-aware, opportunistic) and Flipped Learning (viewing digitised lectures pre-class) where Big Data Analytics can really give academic staff inside world picture in teaching and learning through the technological knowledge, pedagogical in TPACK model (Koehler, *et. al.*, 2011).

The datafication in higher education from rendering of social and natural worlds in machine readable digital format, MA, google & blackboard analytics has most clearly manifested in the teaching and learning with active online teaching, use of social media (Facebook, Instagram, YouTube, Twitter) in teaching, and Google analytics for various activities in higher education for the benefit of advancing higher education as the upskilling intensifies so does the datafication of education (Williamson, Bayne & Shay, 2020).

The data driven policing threatens human freedom in higher education as academic staff and students will be put on the growing web of surveillance may threaten the associational freedom, collaborative, organisational politics and expectations of privacy. This may come across as the big brother control whilst it delivers the full benefits of Big Data.

The time to respond to the threat of big-data policies is now in higher education. Academic staff and student as concerned stakeholders should have formal written policies in place detailing the approved use of new big-data policing technologies. These should be educated about the dangers to privacy, liberty, and the imbalance of power that surveillance technologies bring by management, and this will enhance category-C1. Every faculty and department should engage impacted in the risks and rewards of new predictive technologies from Big Data Analytics with official management provided answers to concerns about literacy, transparency, racial bias, accountability, and constitutional rights that can benefit teaching and learning. Education, empowerment, and engagement are the only protections against an encroaching data-driven surveillance in HE with the use and potential misuse of new Big-Data technologies and General Data Protection Regulation (GDPR) compliance in the UK (Gov.UKk, 2018). The aspect of regulatory rule is not crystal clear at the moment in higher education as per the view of the academic staff who participated in this research.

7.10 The Implications for Higher Educational Practice

As the technological world future unfolds more, it is anticipated that Big Data and Analytics volumes will create and issues of ownership, survillance and decision based actions will come into scrutiny more than before. These claims are concured by Buchanan & McPherson, (2019) who highlights the policy and technological transformation that have coalesced to usher in massive changes to educational systems over the past two technological decades. Teachers' roles, subjectivities and professional identities have been subject to sweeping changes enabled by sophisticated forms of governance. Simultaneously, students have been recast as 'learners'; like teachers, learners have become subject to new forms of governance, through technological surveillance and datafication. The impact on both the teaching and learning in terms of policy has heavily been implemented and quickly, making higher education to become fast learners and this has had impact and will continue to experience these implications in the future as Big Data continues to impact on it. Raffaghelli & Stewart, (2020) add to this voice and that of many as they articulate that . The Big Data trajectory of this future is further explored through the technoeducational models currently being developed in Silicon Valley and many other developers within Cloud Computing, Microsoft, Apple business magnets of the century. The algorithmic decision-making and data collection become pervasive in higher education, on how educators make sense of the systems that shape life, teaching and learning in the twenty-first century. Raffaghelli & Stewart, (2020) further state in their 137-paper analysis highlights the shortfall that exists showing that there is little attention on higher education teachers (C1). They also make clear that most approaches to educators' data literacy address management and technical abilities, with less emphasis on critical, ethical and personal approaches to datafication in education exists. The last two sentences support the findings in this research as highlighted in the complicated data literacy in category one. Williamson, Bayne, & Shay, (2020) highlights the controversially usage of facial recognition and predictive analytics in policing, the blackboard analytics, cloud computing, algorithmic forms of welfare allocation, automated medical diagnosis as they contribute to the datafication of higher education.

Marton, (1986) and Åkerlind, (2005) constantly reminds me that fundamentally phenomenographic results are open and partial in a research outcome as different researchers can come up with different configurations of the same subject area. This aligns with the finding of this research which are all the more partial in acknowledgement of the factual point that this research addressed a specific study on academic staff in higher education on their perceptions of Big Data and Analytics role in teaching and learning within a given timescale. However, to a greater extent this research study is considered to have shown insights in higher education for the need to understand the perceptions being held positively and negatively, which could shape the future of university student experience in more than one way by carefully applying Big data and Analytics. This ground breaking research study in this institution, meets the aims of the a phenomenographic research that should unearth the variation in experiencing, perceiving understanding and conceptulising the aspects of a phenomenon as stated by Marton, 1986 and Marton & Booth (1997). This phenomenographic research study outcome may be taken forward in changing or enabling participants mindsets, understanding and the way in which they operate in their current environment to inform their practice.

The research study outcomes in here on academic staff perceptions of Big Data and Analytics, will enable them to tackle the pervasive issues that disrupt progression and attainment in higher education based on the glimpse of this qualitatively different ways of their account. This also opens up a window for senior management to learn on these for financial injection support towards teaching and learning technological analysis activities in order to gain the embedded values. Bowden, & Walsh, (2000) states that phenomenography is not prescriptive but a means to inform a practice which in here is a teaching and learning practice.

7.11 The Research Study Conduct Considerations

There are so many experiences that were gained from this research conduct which I narrate in this section. Right from the start on engaging on this PhD research study, I anticipated that it will be difficult to manage a combination of family responsibilities, fulltime employment activities and part-time studies on which this research expedition was instigated. These were the three balls that I had to jiggle in parallel without having to drop one and that was not an option, therefore these constraints were anticipated. I went in with my strategic plan which included working on my PhD studies mostly off pedagogical activities and capitalising on weekends plus all the semester breaks. I have learnt first-hand world experience of how difficult it is to carry out all the chapters duties including the phenomenographic data collection, analysis, and discussions in each time span that I allocated. In addition, suddenly my health condition deteriorated impacting heavily on my studies and writing up. In the phenomenographic analysis, I managed to overcome this problem by scheduling the iterations into my scholarly research activities where I had three consecutive days in order to pull out the critical part of listening and reading through the thirty-six interview transcripts and analysis which produced the five categories in total. According to (Åkerlind, 2005a) taking gaps in phenomenographic makes one go back into the data analysis with a fresh outlook that can aid spoting first missed iteration, however, this was coupled with health, family and work pressure experiences as substantial obstacles in my progress. Each of these impacted on my research study and influenced my ambitions and engagement whilst executing my research and meeting my set targets, despite my best efforts in this PhD research (Åkerlind, Bowden, & Green, 2005). All this sums me up as a researcher and a person in who I am through this research journey. I cannot help but fully recognise parts of the research activities that I did not manage to pull into here on alternative view points.

7.12 Concluding Remarks

This chapter has reflected upon various aspects of the research study using the phenomenographic research on the findings of the study and how they addressed the research question. The phenomenographic research approach employed and the limitations of the study. Based on the research study findings the recommendations have been made for Big Data and Big data Analytics for academic staff in higher education and finally recommendations for further research in this area have been suggested. Future researcher could further this subject area and make base by following this up the recommendations.

In pursuing this research, the most pervasive impacts of Artificial Intelligence technologies behind Big Data Analytics have revealed to herald a new era, offering significant advances in the incorporation of technology into academic staff's lives and interactions. This research highlighted the struggles with blackboard data Analytics engagement and benefits. However, the research didn't extend to exploring struggles with mental health and AI problematic interactions as this would be research for another thesis.

In carrying out this research study, I pursued my growing passion in Big Data and Analytics application as a practitioner in higher education. This passion steamed from my focus on the growing use of technologies in teaching and learning becoming an accessible alternative in higher education by academic staff and to investigate solutions towards the problematic ongoing educational issues such as Generative Artificial Intelligence, progression and retention.

In pursuit of this research study, I also pursued my other developing interest in use of phenomenographic research approach in higher education, which was introduced in the first part of this doctoral studies. I was intrigued in its abundance use in social sciences educational and health sectors, whilst research was extremely thin on its usage in computer sciences subject areas. I recognised phenomenographic as the appropriate approach for my purposes to gain an understanding of the different ways in which academic staff experiencing Big Data and Analytics in their teaching and learning in the school in spite of the missing application of it before and I am happy this method yielded the results. Through this research study experience I have come to appreciate the phenomenographic perspective in its alignment to the theoretical underpinnings of Big Data Analytics approach as in my opinion this suggested a phenomenographic alignment as supporting academic staff research outcomes. The research findings here challenge the notions of Big Data and Analytics usage in higher education and in teaching and learning, with more could be gained if applied well.

This thesis has contributed to the knowledge and understanding of collective academic staff's experiences of Big Data in higher education. By deploying phenomenographic research approach, the study described the qualitatively different ways academic staff experience Big Data and Analytics in the context of pedagogy and exposed the kind of variation that exists between these experiences. The research study findings from the study have provided an important insight into the understanding on higher education and in academic staff relationship with technologies and Big Data Analytics.

Finally, by this research I further pursue by inference teaching datafication (Williamson, Bayne, & Shay, 2020), which is pertinent to Learning Analytics, Big Data & Analytics topic in HE. The motivation for the current study stemmed from an interest in the topic of Big Data in higher education, when the entire world is gripped in the datafication (Heeks, *et al.,* 2019) as a by-product of intensive technological advances. The impetus to focus on the meaning of Big Data and Analytics roles was further driven by literature readings that highlighted the under researched area of the relationship between these meanings for academic staff in higher education and future research should pursue this area further. Therefore, it is important that in the future research should look into these three aspects and collectively unify their meaning in higher education to support pedagogy.

We can't stop the digital revolution in this century and beyond, but we can accommodate it to harness the full potential that we can intelligently use to support higher education by indulging in elimination of category one and enhance all other four categories for the success of TEL in higher education.

Through this research I have been able to fulfil my aspirations to gain the deeper understanding of E-Research Technology Enhanced Learning (TEL) which was the course attraction. I believe through this research rigour has enhanced the chances of enhancing my own research in teaching and learning in supporting my career progression. Enrolling on this course came at a critical time of my career when I needed deeper academic understanding of e-Research TEL to advance my career progression in the research aspect of activities within the computing disciplinary. In this research journey I constantly used *Critical Thinking* to shape my progress which included constant *Research, Analysis, Explanation, Reflection Interpretation Exploration, Reasoning* and *Problem-Solving* skill sets in each chapter before progressing to the next.

Appendices

8.1 Appendix A1: Research Study Institutional Ethics Approval Documents

Educational Research | Lancaster University

Ethics approval (REC reference number FL17164-please quote this in all correspondence about this project)

You forwarded this message on Sat 26/05/2018 09:31

FASS and LUMS Research Ethics
To: Chawawa, Margaret <m.chawawa@lancaster.ac.uk>
Thu 24/05/2018 17:34

Dear Margaret,

Thank you for submitting your ethics application and Leeds Beckett's approval for *Digital Technologies and Analytics: An Investigation on University Staff Perceptions of the role 'Big Data' might play in Teaching and Learning.* Based on the information provided, I can confirm that the Deputy Chair of the Faculty of Arts and Social Sciences and Lancaster Management School Research Ethics Committee has approved this project.

As principal investigator your responsibilities include:

- ensuring that (where applicable) all the necessary legal and regulatory requirements in order to conduct the research are met, and the necessary licenses and approvals have been obtained;
- reporting any ethics-related issues that occur during the course of the research or arising from the research (e.g. unforeseen ethical issues, complaints about the conduct of the research, adverse reactions such as extreme distress) to the Research Ethics Officer;
- submitting details of proposed substantive amendments to the protocol to the Research Ethics Officer for approval.

Please do not hesitate to contact me if you require further information about this.

Kind regards,

Debbie

Debbie Knight
Secretary, FASS-LUMS Research Ethics Committee fass.lumsethics@lancaster.ac.uk
Phone (01524) 592605| D22 FASS Building, Lancaster University, LA1 4YT | Web: http://www.lancaster.ac.uk/arts-and-social-sciences/research/ethics-guidance-and-ethics-review-process/ & http://www.lancaster.ac.uk/lums/research/ethics/

Lancaster University

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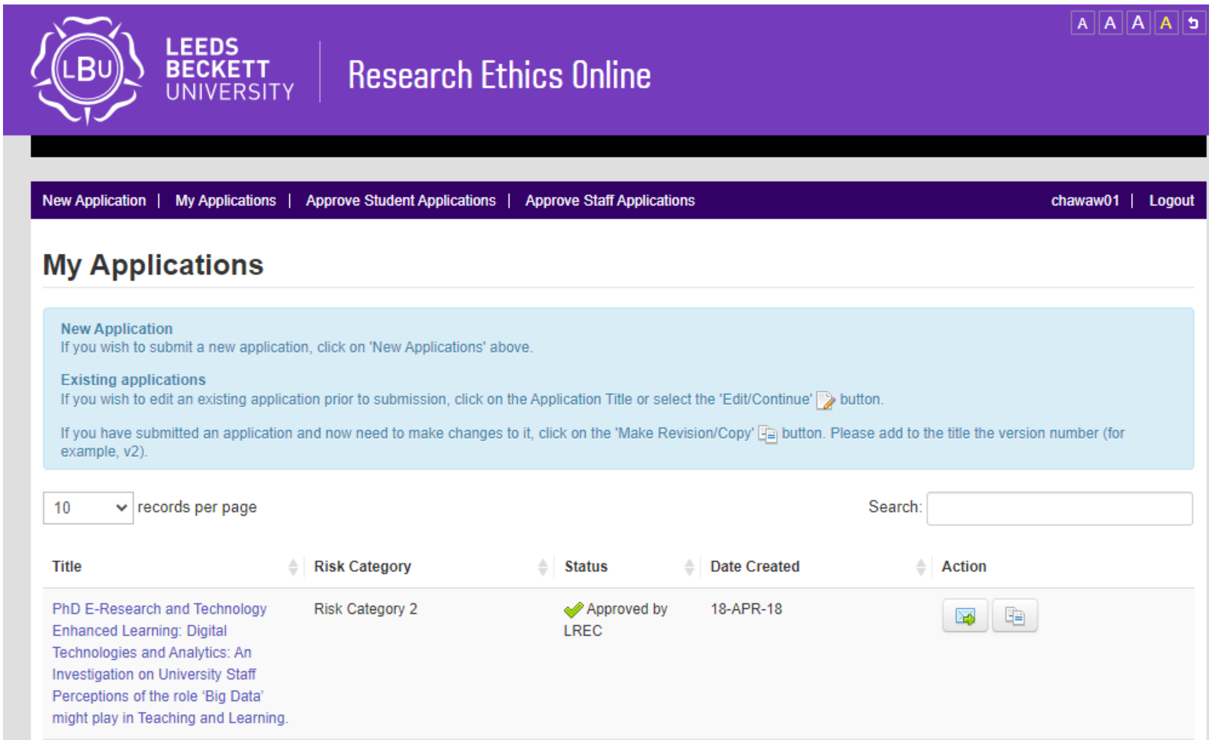
LEEDS BECKETT UNIVERSITY
Research Ethics Online
New Application | My Applications | Approve Student Applications | Approve Staff Applications
chawaw01 | Logout
My Applications
New Application
If you wish to submit a new application, click on 'New Applications' above.
Existing applications
If you wish to edit an existing application prior to submission, click on the Application Title or select the 'Edit/Continue' button.
If you have submitted an application and now need to make changes to it, click on the 'Make Revision/Copy' button. Please add to the title the version number (for example, v2).
10 records per page
Search:
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Risk Category
Status
Date Created
Action
PhD E-Research and Technology Enhanced Learning: Digital Technologies and Analytics: An Investigation on University Staff Perceptions of the role 'Big Data' might play in Teaching and Learning.
Risk Category 2
Approved by LREC
18-APR-18

8.2 Appendix B1: Research Study Ethics Forms for Interview Participant

This study has been reviewed and approved by the Faculty of Arts and Social Sciences Lancaster and Leeds Beckett Research Ethics Committees.

7th January 2019

Dear Staff

I am an academic senior lecturer in Computing School as well as a postgraduate student studying for a PhD in **E-Research and Technology Enhanced Learning** under the supervision of Professor Paul Ashwin within the Department of Educational Research at Lancaster University. As part of my degree process, I am undertaking a research study that involves conducting some in-depth research with academic staff within an educational setting in higher education.

I am writing to you to request your permission to undertake this research with your help by accepting my interview request. As you are an academic staff who uses Big Data and Analytics in your teaching and learning, I would like you to participate in the interviews whose purpose is to gain an understanding of your perceptions and experiences. My research topic is based on "*An Investigation on University Academic Staff Perceptions of the Role 'Big Data' might play in Teaching and Learning*". During the interviews we will review and discuss Big Data and Analytics from Blackboard **(includes Student Engagement (Eesysoft; Module Reports; Performance Dashboard; Retention Centre; SCORM Reports)** and **Student Engagement Systems (SEMS)**. You can access these Big Data Analytics from your MyBeckett and by clicking on your one module. Under the welcome menu, scroll down to ***'Module Management'*** then select ***'Student Engagement'*** for access to the above listed reports.

With your permission, I would, therefore like to carry out an interview on the topic in order to answer the research question. The interviews will take a less structured approach to allow for an in-depth follow-up to the answers and to offer flexibility in the approach. The interview will take approximately take 25-45 minutes and these will be recorded.

I should therefore be grateful if you would sign below indicating your willingness to consent to participating in this research.

Yours Faithfully

Margaret Chawawa
210 Caedmon Hall; Faculty of Arts Environment and Technology;
School of Computing, Creative Technologies and Engineering; Headingly Campus
Beckett Park; LS6 3QS; Tel:0113 81 27597; Email: M.Chawawa@leedsmet.ac.uk

Adopted from V25-5-18

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This study has been reviewed and approved by the Faculty of Arts and Social Sciences Lancaster and Leeds Beckett Research Ethics Committees.

CONSENT FORM

Lancaster University

Email: M.Chawawa@Lancaster.ac.uk; **Tel:** +44 (0) 1138127579

	Please tick each box
1. I confirm that I have read and understand the information sheet for the above study. I have had the opportunity to consider the information, ask questions and have had these answered satisfactorily	☑
2. I understand that my participation is voluntary and that I am free to withdraw at any time during my participation in interviews, without giving any reason. The withdraw from the study can only be applied up to **two weeks** after taking part as it is often impossible to take out data from one specific participant when this has already been anonymised or pooled together with other people's data.	☑
3. I understand that any information given by me may be used in future reports, academic articles, publications or presentations by the researcher/s, but my personal information will not be included and I will not be identifiable. Fully anonymised data (i.e. COMPX1PL, BUSMX2SL, CARNX3L) will be offered to Lancaster Library and will be made available to genuine research for re-use (secondary analysis).	☑
4. I understand that my name and my organisation's name will not appear in any reports, articles or presentation without my consent.	☑
5. I understand that all interviews will be audio-recorded and transcribed, and that data will be protected on encrypted devices and kept secure.	☑
6. I understand that data will be kept according to University guidelines for a minimum of 10 years after the end of the study.	☑
7. I agree to take part in the above study.	☑

[redacted] 12/12/19 [redacted]

Name of Participant Date Signature

I confirm that the participant was given an opportunity to ask questions about the study, and all the questions asked by the participant have been answered correctly and to the best of my ability. I confirm that the individual has not been coerced into giving consent, and the consent has been given freely and voluntarily.

This study has been reviewed and approved by the Faculty of Arts and Social Sciences Lancaster and Leeds Beckett Research Ethics Committees.

CONSENT FORM

Lancaster University

Email: M.Chawawa@Lancaster.ac.uk; **Tel:** +44 (0) 1138127579 **Please tick each box**

1. I confirm that I have read and understand the information sheet for the above study. I have had the opportunity to consider the information, ask questions and have had these answered satisfactorily	☐
2. I understand that my participation is voluntary and that I am free to withdraw at any time during my participation in interviews, without giving any reason. The withdraw from the study can only be applied up to **two weeks** after taking part as it is often impossible to take out data from one specific participant when this has already been anonymised or pooled together with other people's data.	☐
3. I understand that any information given by me may be used in future reports, academic articles, publications or presentations by the researcher/s, but my personal information will not be included and I will not be identifiable. Fully anonymised data (i.e. COMPX1PL, BUSMX2SL, CARNX3L) will be offered to Lancaster Library and will be made available to genuine research for re-use (secondary analysis).	☐
4. I understand that my name and my organisation's name will not appear in any reports, articles or presentation without my consent.	☐
5. I understand that all interviews will be audio-recorded and transcribed, and that data will be protected on encrypted devices and kept secure.	☐
6. I understand that data will be kept according to University guidelines for a minimum of 10 years after the end of the study.	☐
7. I agree to take part in the above study.	☐

________________________ ______________ ______________
Name of Participant Date Signature

I confirm that the participant was given an opportunity to ask questions about the study, and all the questions asked by the participant have been answered correctly and to the best of my ability. I confirm that the individual has not been coerced into giving consent, and the consent has been given freely and voluntarily.

Signature of Researcher /person taking the consent________________________

Date __________ Day/month/year

One copy of this form will be given to the participant and the original kept in the files of the researcher at Lancaster University

Adopted from V25-5-18

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8.3 Appendix B2: Ethics Participant Forms – Information Sheet

This study has been reviewed and approved by the Faculty of Arts and Social Sciences Lancaster and Leeds Beckett Research Ethics Committees.

Participant Information Sheet

Project Title: Digital Technologies and Analytics: An Investigation on University Academic Staff Perceptions of the Role 'Big Data' might play in Teaching and Learning.

I am PhD student at Lancaster University and I would like to invite you to take part in a research study about Digital Technologies and Analytics in Higher Education. Please, kindly take time to read the following information carefully before you decide whether or not you wish to take part.

What is the study about?

I am writing to you to request your permission to undertake this research with your help by signing attached form. My research could have potential benefits for the academic teaching staff community through its findings on understanding their perceptions of 'Big Data' from Blackboard **Virtual Learning Environment (includes Student Engagement (Eesysoft; Module Reports; Performance Dashboard; Retention Centre; SCORM Reports)** and **Student Engagement Systems (SEMS)** data that contributes to Big Data in Higher Education.

Why have I been invited?

I have approached you because you are an academic staff who uses teaching and learning technologies in your modules. I am interested in understanding how you experience, understand and conceptualise 'Big Data'. I will be interviewing a total of forty-two staff across the university in order to gather variations in experience and build a collective meaning as opposed to individual experience.

I would be very grateful if you would agree to take part in this study.

What will I be asked to do if I take part?

If you decided to take part, this would involve the following: you will take part in recorded interview with me. All of the interview data collected will be treated collectively for the purposes of analysis, such that the focus here will be on the variations in understanding across the university, as opposed to the characteristics of individuals' responses. As an academic myself, I am coming at the subject, from the perspective of an informed staff, interested in the development of Big Data research and phenomenography framework in higher education and its application to teaching and learning in pedagogy.

What are the possible benefits from taking part?

Taking part in this study will allow you to share your experiences of using data (that contributes to 'Big Data') in Blackboard and SEMS, which comes from various technologies embedded

Adopted from V25-5-18

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This study has been reviewed and approved by the Faculty of Arts and Social Sciences Lancaster and Leeds Beckett Research Ethics Committees.

herein such as Turnitin, MyBeckett and Panopto. This will richly contribute to the understanding of this phenomenon in our university and may inform new researchers on the topic in future.

What if I change my mind?

If you change your mind, you are free to withdraw at any time during your participation in the interview. If you want to withdraw after the interview, please let me know, and I will extract any ideas or information you contributed to the study and destroy them. However, it is difficult and often impossible to take out data from one specific participant when this has already been anonymised or pooled together with other people's data. Therefore, you can only withdraw up to **two weeks** after taking part in the study.

What are the possible disadvantages and risks of taking part?

Taking part will mean participating in an interview for 25-45 minutes. I will keep all personal information about you (e.g. your name and other information about you that can identify you) confidential. I will remove any personal information from the written record of your contribution and these will not feature in the published thesis.

When writing up the findings from this study, I would like to reproduce some of the views and ideas you shared with me. I will only use anonymised quotes (e.g. from my interview with you), so that although I will use your exact words, you cannot be identified in my publications. Individuals will be known in these categories and names COMPX1PL, BUSMX2SL, CARNX3L with n=42 (three in each school) in the anonymised transcripts.

Your data will be stored in encrypted files (that is no-one other than me, the researcher will be able to access them) and on password-protected computers. I will store hard copies of any data securely in locked cabinets in my office. I will keep data that can identify you separately from non-personal information (e.g. your views on a specific topic) In accordance with University guidelines, I will keep the data securely for a minimum of ten years.

If you have any queries or if you are unhappy with anything that happens concerning your participation in the study, please contact myself-: **Margaret Chawawa**, LBU-Computing School, Tel: +44(0)1138127579. If you have any concerns or complaints that you wish to discuss with a person who is not directly involved in the research, you can also contact my Supervisor: **Professor Paul Ashwin**; Department: Educational Research; Tel: +44 (0)1524 594443; **paul.ashwin@lancaster.ac.uk**

Thank you for considering your participation in this project.

Adopted from V25-5-18

For further information about how Lancaster University processes personal data for research purposes and your data rights please visit our webpage: www.lancaster.ac.uk/research/data-protection

8.4 Appendix D1: Data Collection – Interview Participants and Collective Variation page1/2.

Interview List

Gender	Post	Pseudo	CAT NO		School\Department	Sent	Accepted	Groupings	No	Done	Spoilt	Pilot	
F	SL	BUSB1	Cat1		Leeds Business School	sent	Accepted	2nd Interviews	1	Done			
F	CD	BUSB2	Cat2-5		Leeds Business School	sent							
M	CD	BUSB3	Cat2-5		Leeds Business School	Sent	**Accepted**		1	Done			
F	L	BUSB4	Cat2-4		Leeds Business School	sent	Accepted		1	Done			
F	SL	BUSB5	Cat1		Leeds Business School	sent	Accepted		1	Done			
F	SL				Leeds Business School	sent							
F	SL				Leeds Business School	sent							
M	SL				Leeds Business School								
F	SL				Leeds Business School	Sent	Accepted			Pilot		1	
M	Prof-Dean				Leeds Business School	sent	**Accepted**	Failed					
F	CD	COMP1	Cat1	Dr	School of Computing	Sent	Accepted		1	Done			
M	SL	COMP2	Cat1		School of Computing	Sent	**Accepted**		1	Done			
F	SL	COMP3	Cat2-5		School of Computing	Sent	**Accepted**		1	Done			
M		COMP4	Cat2-5		School of Computing	Sent	**Accepted**			Pilot		1	
M	Reader	LANS1	Cat1		Department Of Languages	Sent	Accepted		1	Done			
F	SL	LANS2	Cat2-4		Department Of Languages	sent	Accepted		1	Done			
F	SL				School of Sport	sent							
F	GS				School of Sport	sent							
F	SL				School of Sport	sent							
M	SL				School of Sport	sent							
F	HoS	SPOT1	Cat2-5		School of Sport	Sent	**Accepted**		1	Done			
M	SL	HCSS1	Cat1		School of Health & Community Services	sent	interviewed	4th Interviews	1	Done			
F	SL				School of Health & Community Services	sent							
F	SL				School of Health & Community Services	sent							
M	CD	HCSS2	Cat2-5		School of Health & Community Services	sent	**Accepted**		1	Done			
M	Prof				School of Health & Community Studies	sentx2		5th Interviews					
F	SL_TL				School of Clinical & Applied Sciences	sent		6th Interviews					
F	SL				School of Clinical & Applied Sciences	sent							
M	L				School of Clinical & Applied Sciences	sentx2							
F	SL	CASS1	Cat2-5		Clinical and Applied Sciences		Accepted		1	Done			
F	SL				Clinical&Applied Sciences	sent	Accepted	S2 arranged					
F	SL				Clinical&Applied Sciences								
F					Social Sciences								
F	SL	LAWS1	Cat2-4		Leeds Law School	sentx2		7th Interview	1	Done			Frust
M	GS_SL				Leeds Law School	sentx1							
M	**SL**				Tourism Hosp Management								
F	**SL**				Tourism Hosp Management								
M	**SL**	**TOUR1**	**Cat1**		Tourism Hosp Management		Accepted			Done			Frust
F	CD				Tourism Hosp Management								

Appendix D1: Data Collection – Interview Participants and Collective Variation

page2/2.

F	SL				Tourism Hosp Management							
F	SL				Tourism Hosp Management							
M	SL				Tourism Hosp Management							
F	SL				Tourism Hosp Management	Sent	Accepted			Spoilt	1	
F	SL				Tourism Hosp Management	Sent						
F	SL	CUSH1	Cat1	Dr	Cultural Studies & Humanities	sent			1	Done		
M	SL			Dr	Cultural Studies & Humanities	sent						
M	SL			Dr	Cultural Studies & Humanities	sent						
F	SL			Dr	Cultural Studies & Humanities	sent						
F	SL			Dr	Cultural Studies & Humanities	sent						
M	SL				Cultural Studies & Humanities	sent						
M	SL				Cultural Studies & Humanities	sent						
F	SL			Dr	Cultural Studies & Humanities	sent						
F	SL	EDUC1	Cat1	Dr	Carnegie Education	sent	Accepted		1	Done		
F	SL			Dr	Carnegie Education	sent						
M	SL			Dr	Carnegie Education	sent						
F	SL			Dr	Carnegie Education	sent						
F	CD	EDUC2	Cat2-5	Dr	Carnegie Education	sent	Accepted		1	Done		
M	CD	EDUC3	Cat2-5		Carnegie Education	sent	Accepted		1	Done		
M	SL			Dr	Carnegie Education	sent						
F	SL			Dr	Carnegie Education	sent						
F	SL				Carnegie Education							
F	SL	EDUC4	Cat1		Carnegie Education	sent	Accepted		1	Pilot		1
M	SL				Forenscis & Security							
M	PL				Forenscis & Security							
M	CD	FORC1	Cat2-5		Forenscis & Security	Sent	Accepted		1	Done		
F	SL	FORC2	Cat2-5		Forenscis & Security	Sent	Accepted		1	Done		
F	SL	FORC3	Cat2-5		Forenscis & Security	Sent	Accepted		1	Done		
F	SL	MUSC1	Cat1		School of Arts-Music	sent	Accepted		1	Done		
M	CD	MUSC2	Cat2-4		school of Arts-Music	sent	Accepted		1	Done		
F	SL	MUSC3	Cat2-4		School of Arts-Music	sent	Accepted		1	Done		
F	SL				School of Arts-Music	sent						
M	SL				school of Arts-Music	sent						
M	SL				school of Arts-Music	sent						
M	CD	MUSC4	Cat2-5		school of Arts-Music	sent	Accepted		1	Done		
M	CD				school of Arts-Music	sent	Accepted			Failed		
M	SL				School of Arts-Music	sent						
M	SL	FILM1	Cat2-5		Leeds Schoo of Arts-Film	Sent	Accepted		1	Done		
M	SL	FILM2	Cat2-5		Leeds Schoo of Arts-Film	Sent	Accepted		1	Done		
M	PL				Leeds Schoo of Arts-Film	Sent						
F	SL				School of Sports	sent						
F	SL				School of sports	sent						
M					Business School	Sent						
M					Business school	Sent						
M		BEEC1	Cat1		School of Built Environment	Sent	Accepted		1	Done		
F					Built environment	Sent						
M					Built environment	Sent						
M		BEEC2	Cat2-4		Built environment	Sent	Accepted		1	Done		
M					Engineering	sent	Accepted		1	Spoilt	1	
F	SL	EEES1	Cat1		Engineering	sent	Accepted		1	Done		
M	R	EEES2	Cat1		Engineering	sent	Accepted		1	Done		
F	SL	EEES3	Cat2-4		Engineering	sent	Accepted		1	Done		
M	SL	EEES4	Cat1		Engineering	sent	Accepted		1	Done		
M	SL	EEES5	Cat2-5		Engineering	sent	Accepted		1	Done		
Total Interviewed		0							36		2	3
Total Required									32			
Overal Interviewed												41
Pilot Interview												3
Overal Invited												93

8.5 Appendix D2: Data Analysis -Iterative Steps/Categories-Variation

Collectively the participants acknowledged BD in the above broadening variation and collectively accept that BD is now part & parcel of teaching and learning. Learning Analytics (LA) addresses concerns related to both teaching and learning areas. Learning analytics aims to address the following areas of education, progression, engagement, retention, and student success (etc,.) in diagram above.

Recent work has provided an overview of the motivation for data collection and analysis by universities -*Awareness on* ***No Knowledge.***

Improvement of learning design, courses, & teaching practices–*Enhance* ***Professional Development***

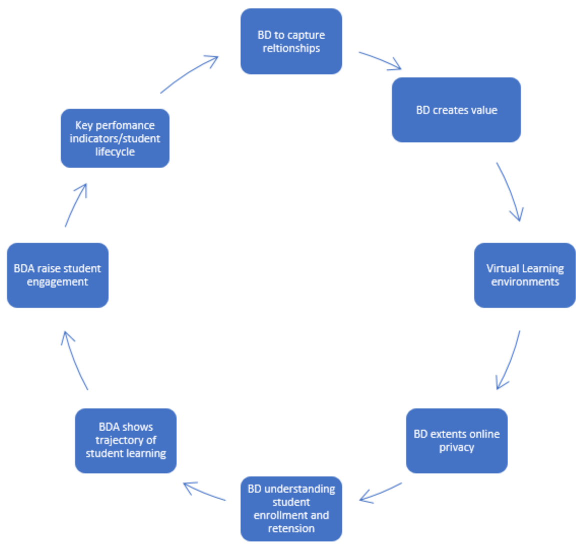
Personalised student support -*Evidence of experiencing* ***Student Support***

The full potential of learning analytics in addressing these various areas has not been reached- *experiencing* ***Large Amount of Data.***

Much of the focus to date is related to improve retention and success rates of students- *Evidence of experiencing* ***Student Support***

Learning analytics applications occur in many different forms-***Structured Information***

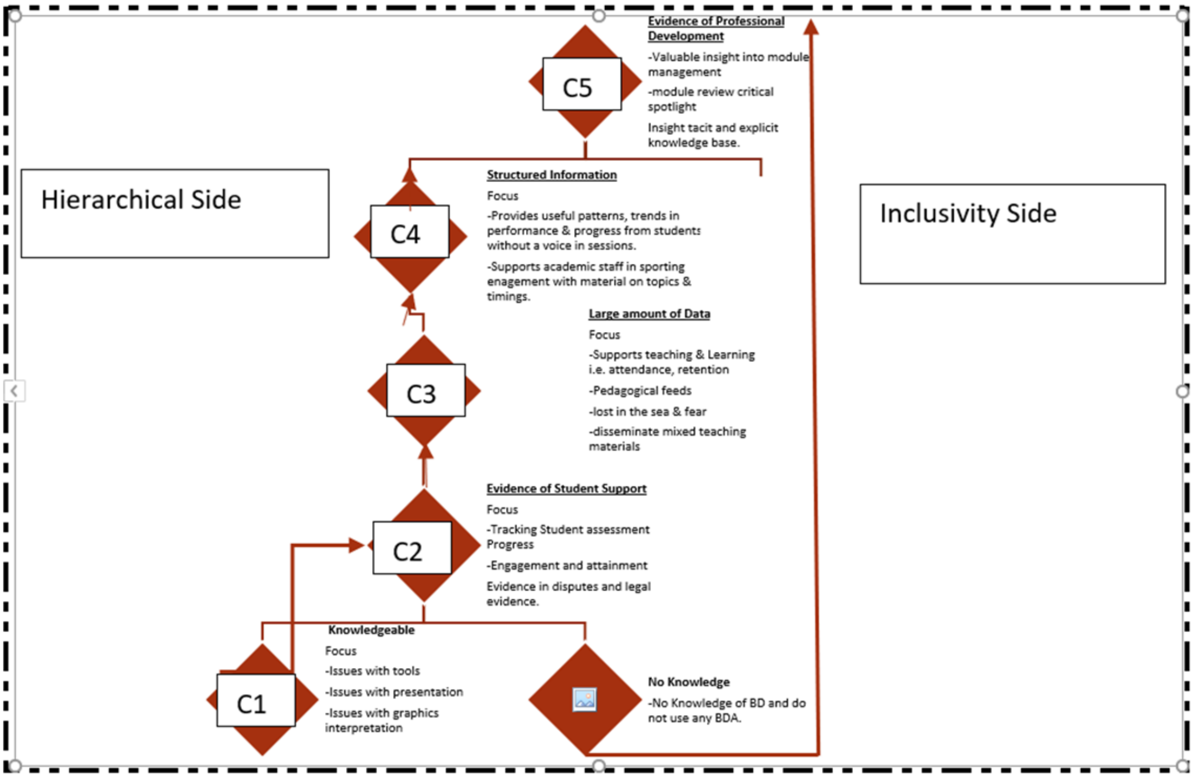
Examples of learning analytics initiatives include blackboard & google analytics dashboards, recommender systems, predictive analytics, interventions, alerts, use of statistics during and after the course by academic staff -***Professional Development***



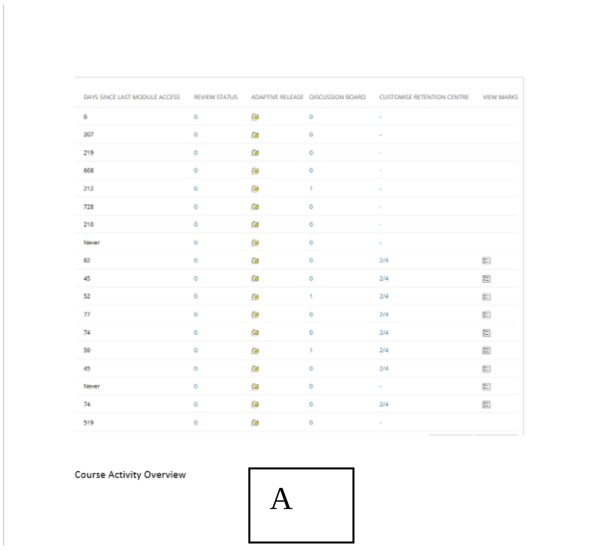
Appendix D2 : Data Analysis -Iterative Steps/Categories-Variation

Appendix D3: Data Analysis -Iterative Steps/ relationship and Structure of Categories

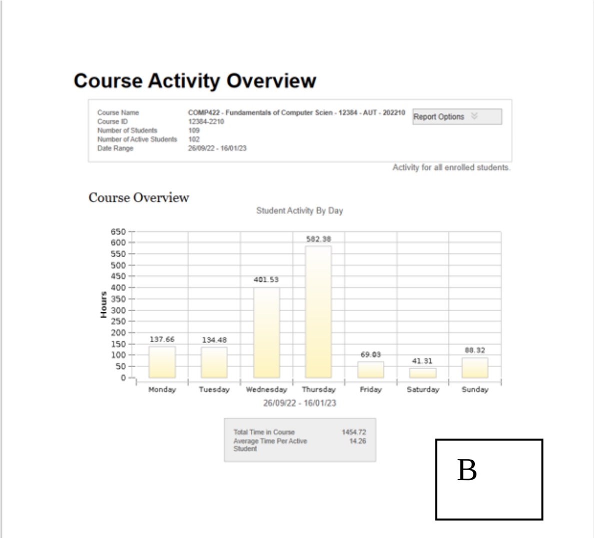
Appendix D4: Hierarchical Inclusivity of the Categories



8.6 Appendix E1-a: Blackboard Big Data Analytics -Complicated Data



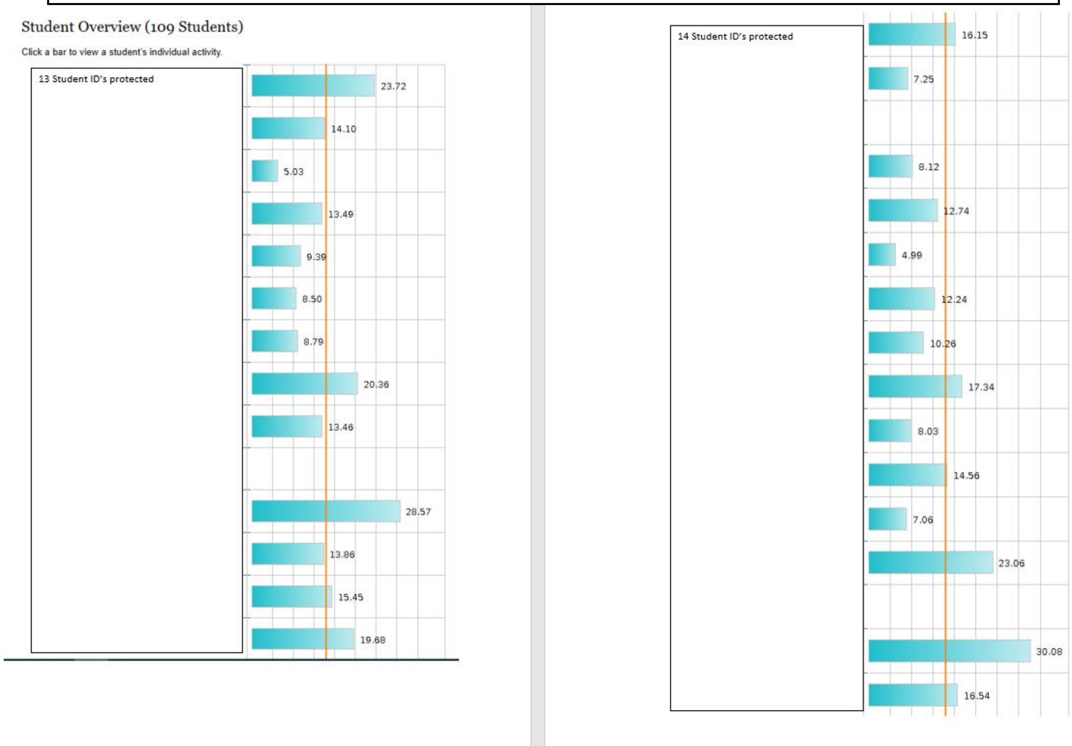
DAYS SINCE LAST MODULE ACCESS	REVIEW STATUS	ADAPTIVE RELEASE	DISCUSSION BOARD	CUSTOMISE RETENTION CENTRE	VIEW MARKS
0	0		0	-	
207	0		0	-	
219	0		0	-	
668	0		0	-	
212	0		1	-	
728	0		0	-	
210	0		0	-	
Never	0		0	-	
82	0		0	2/4	
45	0		0	2/4	
52	0		1	2/4	
77	0		0	2/4	
74	0		0	2/4	
50	0		1	2/4	
45	0		0	2/4	
Never	0		0	-	
74	0		0	2/4	
519	0		0	-	



Appendix E1-b: Blackboard Big Data Analytics -Complicated Data

Student Retention Status

Student Module Engagement



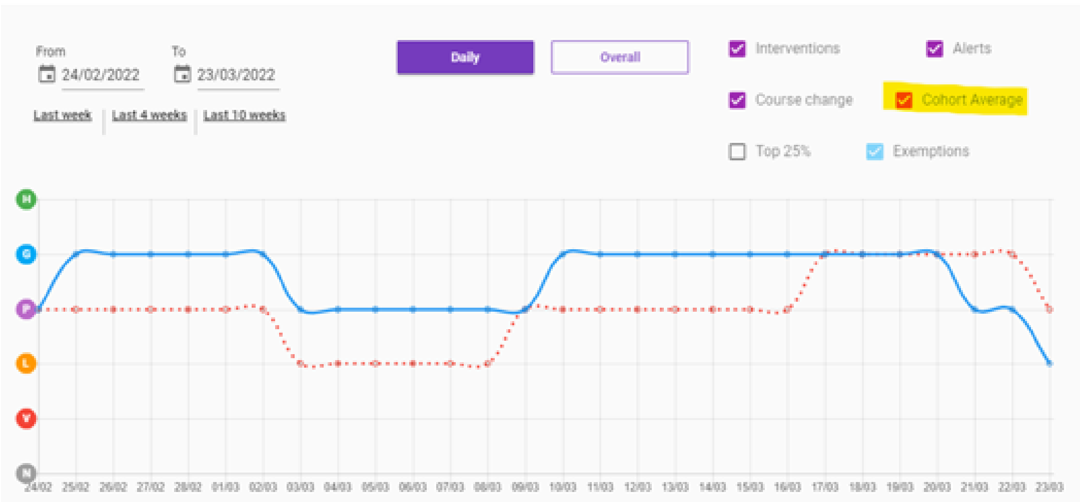
Appendix E2: Big Data Analytics – SEMS-Data leading to Decision Making Mishaps

- There was significant period when engagement data was not able to be collected (from 1st to 10th March) as the feeds into the system were 'disabled', and students had no systems access.
- Engagement scores are calculated daily by comparing engagement to the previous seven days.
- This means that the engagement data covering the period from 1st March through to 29th March is / will be inaccurate and should be exempted from any discussion with students.

- The graph below shows typical Engagement data for a student over the outage period which you will note shows a drop in engagement when systems access was unavailable.
- Note for verification, you can compare a single student engagement to the Cohort Average, which you see is following a similar pattern during this period.
- To help remind staff of the affected period, a Critical Announcement banner has been added to MyProgress. This will automatically disappear in due course.

- Unfortunately, we are still unable to process any requests for access to MyProgress. ITS colleagues are aware and are working hard to provide the team with a solution.

Student Course Engagement



Appendix F1: Main Research Question and Guiding Questions. The Guiding questions were supporting the main research question.

1. *In what different ways do academic staff understand and describe their processes of experiencing Big Data in higher education?*

2. *What are the qualitatively ways academic staff experience Big Data in teaching and learning?*

3. *In what different ways do academic staff experience the role of Big Data in pedagogy to support teaching and learning with technology?*

4. *In what different ways do academic staff understand and describe their processes of experiencing existing Big Data Analytics generated from the Big Data in virtual learning environments higher education.*

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