Title: Supporting student experience management with learning analytics in the UK higher education sector

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SUPPORTING STUDENT EXPERIENCE MANAGEMENT WITH LEARNING ANALYTICS IN THE UK HIGHER EDUCATION SECTOR

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SUPPORTING STUDENT EXPERIENCE MANAGEMENT WITH LEARNING ANALYTICS IN THE UK HIGHER EDUCATION SECTOR

by

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DECLARATION

I declare that this thesis is my own unaided work. It is being submitted for the degree of Doctor of Philosophy at the University of Bedfordshire.

It has not been submitted before for any degree or examination in any other University

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ABSTRACT

While some UK Higher Education Institutes (HEIs) are very successful at harnessing the benefits of Learning Analytics, many others are not actually engaged in making effective use of it. There is a knowledge gap concerning understanding how Learning Analytics is being used and what the impacts are in UK HEIs. This study addresses this gap. More specifically, this study attempts to understand the challenges in utilising data effectively for student experience management (SEM) in the era of Big Data and Learning Analytics; to examine how Learning Analytics is being used for SEM; to identify the key factors affecting the use and impact of Learning Analytics; and to provide a systematic overview on the use and impact of Learning Analytics on SEM in HEIs by developing a conceptual framework. To achieve the research objectives, a qualitative research method is used. The data collection process firstly involves an exploratory case study in a UK university to gain a preliminary insight into the current status on the use of Big Data and Learning Analytics and their impact, and to determine the main focuses for the main study. The research then undertakes an extensive main study involving 30 semi-structured interviews with participants in different UK universities to develop more in-depth knowledge and to present systematically the key findings using a theoretical framework underpinned by relevant theories.

Based on the evidence collected from the exploratory case study and interviews, the study identifies the key challenges in utilising data and Learning Analytics in the era of Big Data. These include issues related to data quality, data consistency, data reliability, data analysis, data integration, data and information overload, lack of data, information availability and problems with systems. A series of critical factors affecting the use of Learning Analytics is emerged and mapped out from a technology-organisation-environment-people (TOE+P) perspective. The technology-related factors include Usability, Affordability, Complexity and System integration. The organisation-related factors cover Resource, Data Driven Culture,

Senior management support and Strategic IT alignment. The environment-related factors include Competitive pressure, Regulatory environment and External support. Most importantly, the findings emphasise the importance of the people-related factor in addition to TOE factors. The people-related factors include People's engagement with using data and Learning Analytics, People's awareness of Data Protection and Privacy and Digital Literacy. The impacts of the Learning Analytics are also identified and analysed using organisational absorptive capacity theory. The findings are integrated in the final theoretical framework and demonstrate that the HEIs' capabilities in terms of data acquisition, assimilation, transformation and exploitation supported by Learning Analytics enable them to improve student experience management. This study makes new contributions to research and theory by providing a theoretical framework on understanding the use and impact of Learning Analytics in UK HEIs. It also makes important practical contributions by offering valuable guidelines to HEI managers and policy makers on understanding the value of Learning Analytics and know how to maximise the impact of Big Data and Learning Analytics in their organisations.

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List of Abbreviations

.rtf	Rich Text Format
ACAP	Absorptive Capacity
AI	Artificial Intelligence
AIS	Academic Information System
APTT	Academic Progression & Tracking Tool
BA	Business Analytics
BI & A	Business Intelligence & Analytics
CAQDAS	Computer Aided Qualitative Data Analysis Software
CMS	Content Management System
CRM	Customer Relationship Management
DA	Discourse Analysis
DLHE	Destination of Leavers from Higher Education
DOI	Diffusion of Innovation
EDM	Electronic Data Mining
ERP	Enterprise Resource Planning
ESD	Electronic Service Desk
FE	Further Education
GPA	Grade Point Average
HE	Higher Education
HEDIIP	Higher Education Data and Information Improvement Programme
HEA	Higher Education Academy
HEAT	Higher Education Access Tracker
HEI	Higher Education Institution
HEIDI	Higher Education Information Database for Institutions
HeLF	Heads of E-Learning Forum
HESA	Higher Education Statistics Agency
HOD	Head of department
HR	Human Resources
ICT	Information and Communication Technologies
IS	Information System

ISS	Information Systems Success
JISC	(formerly the Joint Information Systems Committee)
KPI	Key Performance Indicator
KPP	Key Performance Parameters
LA	Learning Analytics
LACE	Learning Analytics Community Exchange
LMS	Learning Management System
MOOC	Massively Open Online Course
NSS	National Student Survey
PEOU	Perceived ease of use
PU	Perceived usefulness
RFID	Radio Frequency Identification
SEM	Student Experience Management
SES	Student Engagement System
SID	Student Information Desk
SIMS	Student Information Management System
SIS	Student Information System
SLA	Social Learning Analytics
SLC	Student Loans Company / Student Life Cycle
SLRM	Student Lifecycle Relationship Management
SMS	Student Management System
SNA	Social Network Analysis
SNAPP	Social Networks Adapting Pedagogical Practice
SRS	Student Records System
STEMM	Science, Technology, Engineering, Medicine and Mathematics
TAM	Technology Acceptance Model
TOE	Technology-Organisation-Environment Framework
TQA	Thematic Qualitative Analysis
UA	Unit of Analysis
UCAS	Universities Colleges & Admissions Service
UKVI	UK Visas & Immigration
VLE	Virtual Learning Environment

Research Publications to date

- Kika, C., Duan, Y., & Cao, G. (2015), 'Supporting Student Management with Business Analytics in the UK Higher Education sector' (Abstract and presentation): UK Academy for Information Systems (UKAIS) Consortium, 17 March 2015, University of Oxford, Oxford.
- Kika, C., Duan, Y., & Cao, G. (2015), Supporting Student Management with Business Analytics in the UK Higher Education sector – an exploratory case study (Full paper and presentation): International Conference on Intellectual Capital, Knowledge Management and Organisational Learning (ICICKM) 5-6 November, 2015, University of Bangkok, Bangkok – *Awarded joint 2nd prize for best PhD paper.*
- Kika, C., Duan, Y., Cao, G. (2016), 'Understanding the use and impact of Learning Analytics on Student Experience Management' (Poster) – Pacific Asia Conference on Information Systems (PACIS), 27- June 1 July, 2016, Taiwan.
- Kika, C., Duan, Y., & Cao, G. (2017), 'The Use and Critical Success Factors of Learning Analytics: An Organisational Absorptive Capacity Analysis' – Americas Conference on Information Systems (AMCIS), 10-12 August, 2017, Boston, MA.
- Kika, C., Duan, Y., & Cao, G. (2017), 'Understanding the factors affecting the use of Learning Analytics in the UK Higher Education Sector' – European Association for Research on Learning and Instruction (EARLI), 28 August - 2 September, 2017, Tampere, Finland.

Chapter 1: Introduction

1.0 Overview

This chapter gives an overall idea of the research. It covers the research background, the rationale behind the study, and the aim and objectives, the key terms for the study and the research process.

1.1 Introduction

This PhD research is founded on the examination of the use and impact of Learning Analytics for Higher Education Institution (HEI) organisations in the UK. The working definition used for this research is adopted from the 1st International Conference on Learning Analytics and Knowledge (Siemens and Long, 2011, p34), which defines Learning Analytics as '*the measurement, collection, analysis and reporting of data about learners and their contexts, for the purposes of understanding and optimising learning and the environments in which it occurs.*' This research is conducted in the context of Big Data and Analytics in the area of SEM

1.2 Research Background

Driven by the need to improve success, retention, and learning experience, Learning Analytics is a rapidly growing area of interest in educational institutions worldwide (Sclater, 2014a). Over the years Learning Analytics has been defined in several ways: for example, Sclater (2014a, p4) define it as '*a way of enhancing teaching and helping to build better relationships between students and staff'*. Cooper (2012, p3), on the other hand, draws language from business intelligence and refers to Learning Analytics *as* '*the process of developing actionable insights through problem definition and the application of statistical* *models and analysis against existing and/or simulated future data*'. In the same vein, Campbell and Oblinger (2007, p42) identify Learning Analytics as '*marrying large data sets, statistical techniques, and predictive modelling. It could be thought of as the practice of mining institutional data to produce 'actionable intelligence.*'

Learning Analytics has been widely used in extant literature, for example, Shum and Ferguson (2012, p3) offer the concept of Social Learning Analytics (SLA); they propose that it is '*a distinctive subset of Learning Analytics that draws on the substantial body of work demonstrating that new skills and ideas are not solely individual achievements, but are developed, carried forward, and passed on through interaction and collaboration*'.

Campbell and Oblinger (2007, p8) exploit the Big Data aspect of analytics through the concept of academic analytics, which is referred to as '*an engine to make decisions or guide actions. That engine consists of five steps: capture, report, predict, act, and refine.*' Haythornthwaite et al. (2013) argue that Learning Analytics is impelled by changes in social practices due to the increase in participatory culture which has led to several changes in how teaching and learning happen. Examples include transformative learning, e-learning, online courses and degree programmes to the developing trend of massively open online courses (MOOCs). According to Haythornthwaite et al. (2013), Learning Analytics supports the following: teachers wanting to comprehend the impact on interaction, student learning or other outcomes of their assignments and learners who wish to comprehend their learning experience against people who are current learners or even past learners, e.g. fellow learners in a MOOC. The use of Learning Analytics dashboards, according to Few (2006), give graphical depictions of the present state of a learner or a course to allow decision making which is flexible. For example, Verbert et al. (2013) examine the area of dashboard applications and argue that numerous dashboard applications have been made in order to support teaching and learning.

These dashboards are also used in modern online learning or face-to-face teaching; examples include the learning management system (LMS) Moodle and the Classroom view, which demonstrates what is happening in a classroom. Another example of Learning Analytics is predictive modelling (Clow, 2013). Predictive modelling involves developing a mathematical model which then creates estimates of likely outcomes; these are then used to report interventions intended to improve those outcomes. According to Clow (2013), the most effective application of predictive modelling to student completion in the Higher Education (HE) sector was the Course Signals project at Purdue University (Arnold, 2010).

This model involves a colour-coded system with green demonstrating a good chance of success, yellow demonstrating that there could be potential problems and red demonstrating a great chance of failure. Other historical contributions to Learning Analytics include social network analysis: this has been examined in Haythornthwaite (2002), where she investigated the impact of media type on the progression of social ties: user modelling which involves modelling users in their contact with computer systems. Fischer (2001, p70) argues that user modelling has become significant in research in human computer interactions as it aids researchers to develop better systems by recognising how users interact with the software.

In the HE sector there has been a growth of online learning (Haythornthwaite and Andrews, 2011). E-learning has helped the improvement of Learning Analytics as student data can be taken and made accessible for analysis (Siemens, 2013). However, according to Slade and Prinsloo (2013, p1511), there are ethical issues for Learning Analytics which fall into the following categories: '*the location and interpretation of the data, informed consent, privacy and deidentification of data and the management, classification and storage of data*'.

Currently, the HE sector is facing a number of challenges and increasing pressures in providing the best learning experience for students; this is due to various newer technologies that have now become readily available that deal with large volumes and varieties of data. Sarker et al. (2010) state that there has been a growing interest in identifying those challenges and also discovering ways to address them. Nowadays, HEIs are collecting a great amount of data in various areas within SEM (Bichsel, 2012).

Learning Analytics has been a rapidly growing interest in HEIs worldwide, due to the increasing competition within the HE sector in this digital age and the need to provide good educational services. However, despite new technological approaches in the field of analytics becoming increasingly important in academic communities, HEIs are still not exploring and adopting these approaches despite their huge potential benefits. The Heads of E-learning Forum (HeLF) survey report in June 2015 (Newland et al., 2015) states that Learning Analytics has not been used by almost half of UK HEIs; only one university in the survey stated that Learning Analytics has been used to its full potential and supported within the university.

Dietz-Uhler and Hurn (2013) also define Learning Analytics as improving areas such student success and increasing student retention, which has been mentioned in literature as one of the main challenges the HE sector faces (Tiropanis et al., 2009). There is also increased focus on how Learning Analytics can increase the overall student experience in HEIs (Sclater, 2014a). For example, in order to improve student retention and the motivation of students through the use of analytics (Sclater, 2014a), JISC (formerly known as the Joint Information Systems Committee) are doing what they can as an organisation to help. There is a significant need for Learning Analytics in HEIs as they can be used to help students learn more effectively and improve student recruitment and faculty performance.

Learning Analytics is relevant and important at the moment because, according to Van Harmelen and Workman (2012), Learning Analytics is not being used to its full potential in the UK HE sector. The argument that has come to the forefront is how can teachers be convinced that Learning Analytics would be very useful for their students? Van Harmelen and Workman (2012) also state that HEIs differ in analytics readiness and development and might to a larger or smaller extent be prepared for the introduction of analytics or the greater use of analytics. Zilvinskis et al. (2017) state that Learning Analytics combines a diverse range of new ways to think about approaching the learning environment. They also argue that applying Learning Analytics offers an opportunity to connect the knowledge of existing roles (Student Services and IT).

In terms of Student Experience, it is a Key Performance Indicator (KPI) in HEIs. Temple et al. (2014) refer to the student experience as the entirety of a student's dealings with an institution. They also go on to state that student experience has many meanings and the list of what it may incorporate is practically endless. It is vital to recognise that each student's set of experiences will be exclusive to that person; there also is a threat that mentioning 'the student experience' will propose a degree of consistency that cannot occur in practice (Temple et al., 2014). They also state that the management of the undergraduate student experience in the English HE sector is shifting due to a more competitive environment.

Morgan (2013) states that enhancing the student experience (from first contact with the student to when they become alumni) is vital to HE success for the student as well as the HEI. She also goes on to state that the challenges with student experience involve the increasing expenses of providing HE, the decrease in government funding and resource constraints.

1.3 Research Rationale

Providing students with the best learning experience and ensuring their academic success throughout their university lifecycle has been a serious challenge for HEIs. While advances in Information and Communication Technologies (ICT) have enabled HEIs to intelligently collect more data from both internal and external sources (Bichsel, 2012, Davenport, 2013), this has led to the explosion of data and unprecedented challenges in making effective use of this formidable amount of data for effective decision making and better SEM. While there is indication that large commercial companies that use Learning Analytics perform better than those that do not in making strategic decisions and creating competitive advantages (Kiron et al., 2012), managers in HEIs are still struggling in making sense of an ever-growing amount of data and information (Tulasi, 2013).

Although a range of UK universities are increasing their Big Data and Analytics investment and starting to see the impact of it, HEIs in general are still far behind the commercial sector. The majority of HEIs are still not actively exploring and adopting Learning Analytics despite the huge potential benefits. The HE sector is a data-rich sector and universities generate and use enormous volume of data each day (Shacklock, 2016b). HEIs are starting to become aware of the large amount of data and intelligence that are available in their own systems. This can then be utilised to understand the needs of the students and the market, and to make sure that the business advantages that arise from the successful management of direct relationships with students are secure. However, a unified approach among managers and students is required for the benefits to be realised through the use of Learning Analytics.

Learning Analytics is a fast-growing area of interest because it has the potential to be enormously powerful for utilising data and improving the student experience in universities. SEM can cover all aspects of student-facing management activities from marketing, recruitment, engagement, retention, performance, to graduation and alumni relationship management. To improve student experience and ensure their success, SEM forms a critical part of HE management and is important because institutions strive to distinguish themselves from their competitors through better student services and effecting teaching and learning support. Although some HEIs are harnessing the benefit of Big Data and Analytics, the sector in general has not yet capitalised on the enormous opportunities and is lagging behind other sectors (Shacklock, 2016b). Therefore, it is important to develop appropriate knowledge and understanding on the current use of Learning Analytics and the critical factors affecting its success.

On reviewing the literature, there are a few studies that touch upon applying Learning Analytics in HEIs, but there has not been specific research on exploring the use and impact of Learning Analytics on SEM. A number of research gaps are identified below that are relevant to this study and are elaborated further in section 3.4 of Chapter 3:

1. HE is data intensive sector and various types and amounts of data are generated. However, there appears to be a lack of research on addressing the challenges in utilising data in SEM in the era of Big Data and Analytics.
2. Due to the growing importance of Learning Analytics, UK HEIs are very keen to use Learning Analytics, but there appears to be a serious lack of academic research that explores the applications and impact of Learning Analytics in HEIs, especially in the context of SEM.

1.4 Research Questions

The research questions for this study are:

- How are the UK HEIs using Learning Analytics for improving SEM?
- What are the influential factors affecting the use of Learning Analytics in the UK HEIs?

1.5 Research Aim and Objectives

The overall aim of this research is to explore the use and impact of Learning Analytics for SEM in UK HEIs. More specifically, this study attempts to achieve the following objectives:

1. To understand the challenges in utilising data effectively for SEM in the era of Big Data and Learning Analytics
2. To identify the key factors affecting the use and impact of Learning Analytics
3. To understand how Learning Analytics is being used for SEM
4. To develop a conceptual framework to provide a systematic overview on the use and impact of Learning Analytics on SEM in HEIs.

In summary, this research explores and applies the relevant theories to explain and understand the use and impact of Learning Analytics in the context of SEM

1.6 Overview of Research Methodology and Process

Since the aim of the study is to explore the use and impact of why and how the research participants are using the Learning Analytics tools for SEM in UK HEIs, a qualitative approach was adopted for this research. A qualitative approach was used as it explores the richness, depth and complexity of a phenomenon. Also, according to Bryman and Bell (2015), using a qualitative approach allows the researcher to examine the why and how of the phenomena being studied from the views of research participants and it is useful for understanding their opinions as well as experiences in particular surroundings. Bearing in the mind the description of the qualitative approach given above, this approach is most appropriate to achieve the research aim and objectives of the study and to answer the research questions. For the research method, qualitative interviewing was used which involved semi-structured interviews that were adopted in collecting empirical evidence. The data analysis on the other hand was conducted through Thematic Qualitative Analysis (TQA). TQA is mainly described as a method for identifying, analysing and reporting patterns (themes) within the data (Braun and Clarke, 2006). In terms of the inductive, data-driven approach, Braun and Clarke (2006) state that the themes developed are not formulated by previous theoretical assumptions. The inductive data-driven approach used for the data analysis allows themes to develop straight from the data which results in a through explanation of the dataset.

The steps for the research process are: research aim and objectives, literature review, exploratory case study, research focus identified for the main study, main study, framework development, and writing up thesis. This process is illustrated in Figure 1.1.

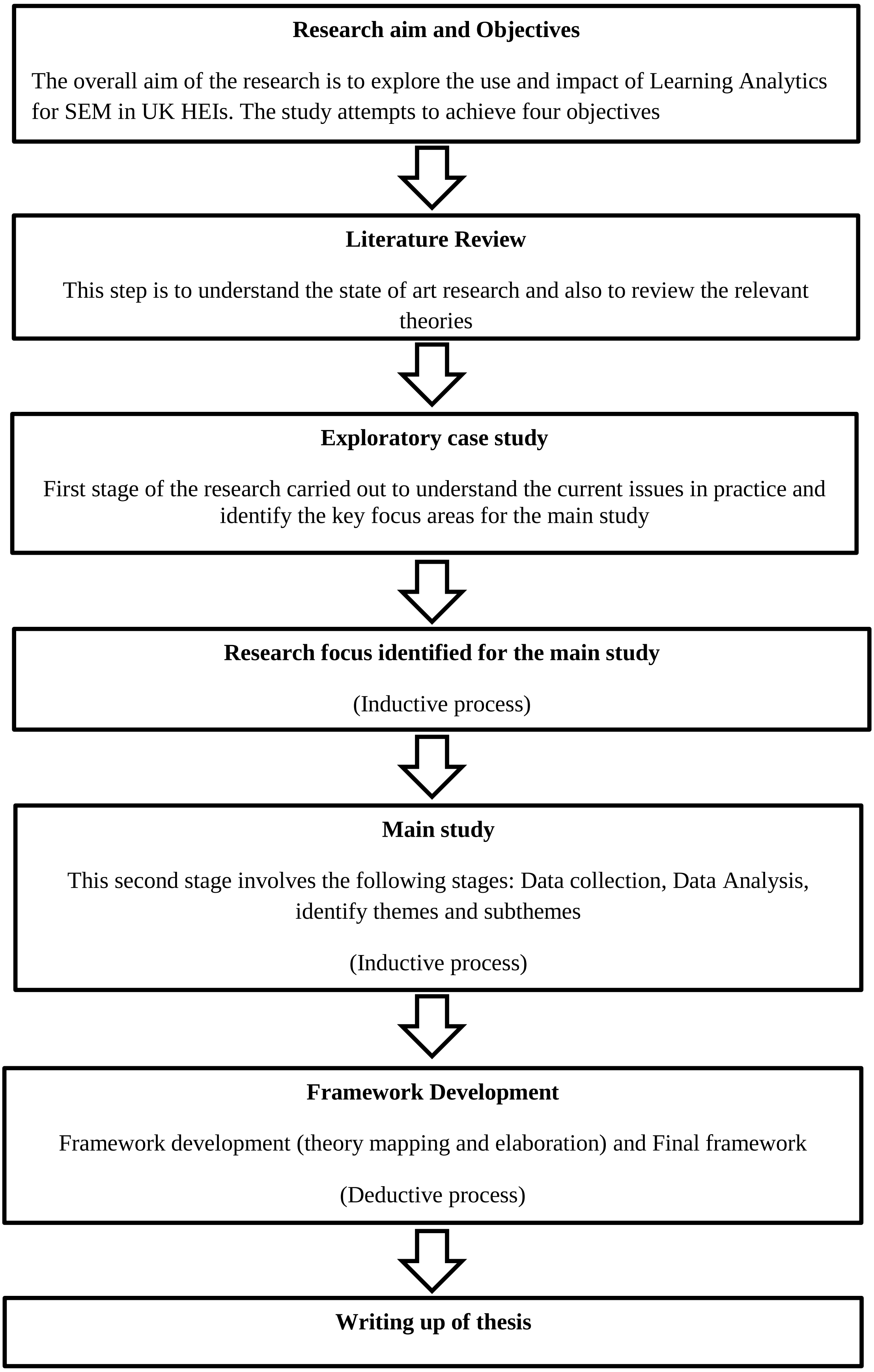

Figure 1.1 Research Process

1.7 Thesis Outline

This thesis comprises of seven chapters, Figure 1.2 shows the outline of the thesis and is followed by the details of each chapter.

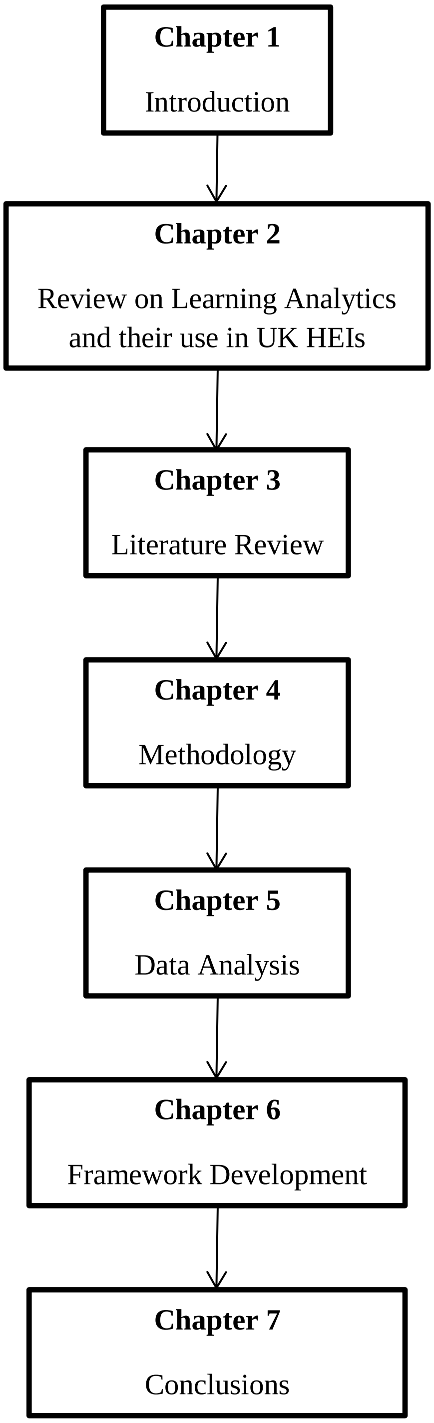

Figure 1.2 Thesis outline

Chapter 1 gives an overall view of this research. Firstly it offers an insight into the research background, and then goes into the research rationale (importance of this research and research gaps), research questions, aim and objectives of the research, an outline of the research methodology used and the research process, the structure of the thesis and key definitions that form the basis of this research.

Chapter 2 is the review on Learning Analytics in UK HEIs. It gives an introduction to the chapter, how Learning Analytics is used in organisations, the techniques used in HEIs; then the impact of Learning Analytics in HEIs is reviewed and the key issues with Learning Analytics.

Chapter 3 is the literature review chapter. It reviews SEM within HEIs and the chapter is completed with a review of relevant information systems theories used.

Chapter 4 is the research methodology chapter and summarises the research methods for information systems. This section clearly states the difference between research methods and research methodology. A background into the philosophical stance of the study is given and what research philosophy this research has decided to adopt is addressed. The research approach, sampling strategy, sample, unit of analysis, what data analysis method is chosen, data collection methods and ethical issues to be considered for the study are also covered. The methodological setting of the study is also described and the justification of the research method used is stated.

Chapter 5 depicts the data analysis process. In this chapter a step–by-step process is given on how the analysis was carried out using Thematic Qualitative Analysis (TQA) in NVivo and then how the codes, subthemes, main themes and the research findings were developed. The subthemes and themes linked with the exploratory case study and main study are also examined and examples are given for both.

Chapter 6 is the framework development chapter. This chapter states the theoretical lens used for this study and how the theoretical framework was developed. The constructs of the theoretical framework and how they relate to this research are also expanded upon in the conclusion chapter which gives the interpretation of findings according to the theory and extant literature and also the real life situations of Learning Analytics in HEIs, followed by key recommendations.

Chapter 7 is the last chapter of the thesis and it provides a conclusion to the overall thesis. In this chapter the contribution to research and practice, limitations and any future research are summarised.

1.8 Key Terms for the Study

Since this research follows the literature review approach, the first step is to define the key terms based on the literature and then identify the key terms that lead to the relevant literature. The following key terms are defined below: SEM and the main areas covered by SEM – student recruitment, student engagement, student retention and student success.

1.8.1 Student Experience Management

According to Morgan (2018) the HE market has gradually become competitive and as well as that students have additionally become demanding and have had more enhanced learning about what services and support they are supposed to obtain whilst studying at university. They also state that because of this HEIs need to offer exceptional quality student experience in order to protect their ongoing organisational existence. In addition to this, argues that being dedicated to enhancing the student experience can cause a rise in the 'retention' of students by decreasing withdrawal rates and helping student progression; on top of that it is also essential to a HEI's ability to draw in students. Morgan (2018) states that it is not acceptable any more to treat students coming into this level of study as an identical group; also things such as the rising level of student diversity, the rising expenses of providing HE, the decrease in government/state funding and resource restraints mean providing an exceptional quality student experience has become an ever more growing challenge.

SEM can cover all aspects of student-facing management activities from marketing, recruitment, engagement, retention and performance, to graduation and alumni relationship management. To improve student experience and ensure student success, SEM forms a critical part of HE management. SEM is important in HEIs because institutions strive to distinguish themselves from their competitors through a number of processes, such as improving teaching and learning success and the quality of services given to their students, and managing the costs of their procedures by enhancing efficiency and effectiveness. This definition and the term SEM will be used throughout the thesis. For this research, the key areas of SEM are defined as student recruitment, student engagement, student retention and student success. These areas are described in the following sections and are shown in the SEM model in Figure 3.2 in section 3.3.3.

1.8.2 Student Recruitment

This involves finding potential students to enrol to a university; recruitment can take place through graduate fairs/exhibitions. Usually, institutions have a specific department for marketing, admissions, recruitment and enrolment.

1.8.3 Student Engagement

The working definition used for this research is adopted from the Student Engagement Literature review by (Trowler, 2010, p5), which defines student engagement as:

> Student engagement is concerned with the interaction between the time, effort and other relevant resources invested by both students and their institutions intended to

optimise the student experience and enhance the learning outcomes and development of students and the performance, and reputation of the institution.

Student engagement is part of the SEM cycle.

The terms student success and student retention following are often used in partnership with one another, however student success is much broader and a preferred term in some HEIs.

1.8.4 Student Retention

Sarker et al. (2010) state that in order for HEIs to maintain their high standards and to gather support from the public, student retention has to be one of the main focuses. In the UK HE sector student retention refers to the how long learners stay in an institution and finish their course within a fixed period of time (Jones, 2008).

1.8.5 Student Success

According to Jones (2008), with student success it is not essential for a student to finish their HE programme in order to meet their targets within the institution; for example, a student might view success as finishing 120 credits of an Honours course and be satisfied with that. Student success does not just cover who stayed within their institution but specifies how the overall experience brought benefits.

1.8.6 Descriptive analytics

This uses data collection and data mining to provide an understanding of the past and answer: ‘What has happened?’ Descriptive analytics in HEIs can examine data in LMS by observing factors such as course completion.

1.8.7 Predictive analytics

This is ‘*an area of statistical analysis that deals with extracting information using various technologies to uncover relationships and patterns within large volumes of data that can be* *used to predict behaviour and events*' (Eckerson, 2007, p5). It is used to answer the question 'What could happen?'

1.8.8 Prescriptive analytics

Prescriptive analytics uses models to identify optimal behaviours and actions (Davenport, 2013) and is used to analyse the current problems faced by HEIs such as '*student retention, enrolment management, prospect analysis, improving learning outcomes and curricular planning*' (Schaffhauser, 2014, p1). It is used to answer the question 'What should we do?'

1.9 Summary

Overall, this introduction chapter has shed light on the background and rationale of this research. It has also provided the gaps for this research in preparation for Chapter 3, the literature review.

Chapter 2: Review on Learning Analytics and Their Use in UK HEIs

2.0 Overview

Analytics has been defined in different ways and the most commonly used term is Business Analytics (BA). This section starts first and foremost by reviewing BA and then focuses on the application of analytics in education that is Learning Analytics.

2.1 Introduction

Big Data and technological approaches in the field of Business Intelligence and Analytics (BI & A) are increasingly important in both business and academic communities (Chen et al., 2012). BI & A are often stated as techniques and applications used for the analysis of business data to enhance business decisions (Chen et al., 2012, p1166, Davenport and Harris, 2007) whereas Big Data is an idea that has been developed to define the 3V's – variety, velocity and volume of the data produced within information and communication technologies (ICTs) (Duan et al., 2013, p1). Big Data is a term invented to focus on the challenges that new data streams have brought to business firms and HEIs.

2.2 Big Data

2.2.1 Introduction

Currently, Big Data is making large headlines, particularly in the commercial sectors; however Big Data is not an occurrence affecting large commercial companies only (Duan et al., 2013). According to Duan et al. (2013), with the growing volume of data being gathered and shared from both internal and external sources, business firms of all varieties are now able to gain access to supposed Big Data. Big Data is a term invented to focus on the challenges that new data streams have brought to business firms and HEIs.

2.2.2 Definition of Big Data

Even though the term "Big Data" has become increasingly popular, its meaning is not always clear. There have been many who have offered their own definitions of Big Data; for example, Gartner IT Glossary (2018) defines Big Data as:

> High volume, high velocity and high variety information assets that demand cost-effective, innovative forms of information processing for enhancing insight and decision making.

Also, Mills et al. (2012, p10) give:

> Big Data is a term that describes large volumes of high velocity, complex and variable data that require advanced techniques and technologies to enable the capture, storage, distribution, management, and analysis of the information.

Zikopoulos and Eaton (2011, p3) define Big Data as:

> Big Data applies to information that can't be processed or analysed using traditional processes or tools. Increasingly, organisations today are facing more and more Big Data challenges. They have access to a wealth of information, but they don't know how to get value out of it because it is sitting in its most raw form or in a semi structured or unstructured format; and as a result, they don't even know whether it's worth keeping.

And finally, Manyika et al. (2011, p1) refer to Big Data as *"datasets whose size is beyond the ability of typical database software to capture, store, manage and analyse"*.

2.2.3 Characteristics of Big Data

Big Data is often regarded by three factors: volume, velocity and variety. Many authors and researchers have given their definitions of each factor:

Volume

Data volume concerns the quantity of data obtainable to a firm, which does not essentially have to own all of it as long as it can access it (Kaisler et al., 2013).

Velocity

This relates to a growing rate at which data moves within a firm, or example firms allocated with financial information have the ability to cope with this (Daniel, 2015).

Variety

Data being created is not just of a single type as it not only involves traditional data but also semi-structured data from a variety of sources like web pages, web log files, social media sites, emails, documents, and sensor devices from both dynamic and inert devices (Katal et al., 2013).

There are also two significant additions to the above 3 V's, which make 5 V's in total:

Verification

- This is in reference to security and data verification (Daniel, 2015, Duan et al., 2013).

Value

- Oracle came up with the concept of Value as an important characteristic of Big Data. Based on Oracle's explanation, Big Data is often regarded as of relatively "low value density" (Gandomi and Haider, 2015).

As a result of the current explosion of Big Data, ways to collect and store this data, software tools for data and data-driven insight are more available to business professionals than before. BI & A has now evolved to that of BA.

2.3 Business Analytics

Business analytics is quite a new term that is becoming popular in the business world like nothing before in recent history. Olson and Delen (2008) state that nowadays analytics can basically be described as finding out important patterns in data. They also state that in this time of abundant data, analytics is likely to be used on large amounts and varieties of data. The current use of analytics may require extensive computation because of Big Data, so the techniques and tools used for analytics projects influence the most up-to-date methods developed in a wide range of fields such as data science, computer science and management science. The term Business Analytics has been widely used in various contexts, but there is no commonly accepted definition of what BA is. This research follows the Davenport and Harris (2007, p7) definition, which defines BA as *"the extensive use of data, statistical and quantitative analysis, explanatory and predictive models, and fact-based management to drive decisions and actions"*.

Companies have used analytics in a variety of ways, which include:

- Improving their relationship with their customers (so incorporating all spheres of customer relationship management (CRM) as well as stakeholders),
- Developing product and service characteristics and their pricing, which helps to improve customer satisfaction, and
- Providing employees with insight as well as the information that they require to make quicker and better decisions,

Progressively, more companies are now preparing their employees with knowledge of BA to drive efficiency and effectiveness in their decision making activities from day to day.

2.4 The Use of Analytics in HEIs

Different ways to classify Business Analytics have been demonstrated in literature based on its evolution process, key functionality and application domain. Davenport (2013) stated that the development of analytics started from Analytics 1.0, which was the **era of “business intelligence”**:

- Analytics 1.0 was a time of real progress in achieving an objective.
- Deep understanding of providing managers fact-based knowledge to go beyond institutions when making decisions and essential business phenomena.
- This was referred to as the era of the enterprise data warehouse used to capture information and of Business Intelligence software, used to question and report it.
- In wider terms, people did view analytics as a source of competitive advantage but no one talked about it in today’s terms of “competing analytics”.
- The advantage came in the former of greater operational efficiency, therefore making improved decisions or certain significant points to enhance performance.

Cooper (2012) in his discussion about the history of analytics pinpoints a variety of groups from which Learning Analytics draws practices, which includes BI. He stated that “*Business Intelligence is essentially the same as “Analytics” but BI has its own character if we consider the typical applications and capabilities of the product category that is generally labelled Business Intelligence*” (Cooper, 2012, p5).

Then came Analytics 2.0, which is the **era of “Big Data”**:

- Even though the term “Big data” was not created immediately, the new reality it represented changed the role of data and analytics in those firms that used it very quickly.

- The difference between big data and small data came about as the former was not generated solely by a firm's internal transaction system.
- Big data came from the internet, sensors of various types, public data initiatives such as the human genome project and captures of audio and video recording, which means it was externally sourced as well.
- From a single server, Big Data could not fit as well as being analysed fast enough, so an open source software framework Hadoop was used for fast batch data processing across parallel servers.
- No SQL, a new class of databases was used by companies to cope with relatively unstructured data.
- During this period, other technologies brought forward include: "in-memory" and "in database" analytics for fast number crunching.

Finally came the arrival of Analytics 3.0, the **era of data-enriched offerings:** *"As emphasis turns to build analytical power into customer products and services"* (Davenport, 2013, p67):

- The innovative big data firms in Silicon Valley started investing in analytics to provide customer-facing products, services and features.
- These firms drew viewers into their websites through better search algorithms, recommendations from friends and colleagues, suggestions for products to purchase and highly targeted ads, all steered by analytics planted in large amounts of data.
- When other large organisations started to emulate these actions, the Analytics 3.0 point was marked.
- Every device, shipment and consumer leaves a trail, giving the opportunity for the analytics and optimisation to be embedded into every decision made at the front lines of an operation.

Davenport (2013) also described ways in which Analytics 3.0 can be capitalised. For example:

a) **Faster technologies and methods of analysis**

   With the 2.0 period, Big Data technologies are noticeably quicker than prior generations of technology for data management and analysis were. To accompany them, new "agile" analytical methods and machine learning technologies were introduced to give insights at a much faster rate. The difficulty in the 3.0 era however is to adapt operational product development and decision processes to take advantage of what the new technologies and methods bring forth.

b) **Embedded analytics**

   These are constant with the greater speed of data processing and analysis, models in Analytics 3.0 are often embedded into operational and decision processes, intensely increasing their speed and impact.

This study focuses on the use and impact of Analytics 2.0 and 3.0 in HEIs, supposing Davenport's perspective on the evolution of analytics is valid.

2.5 Introduction to Learning Analytics

Siemens and Long (2011, p1) state that *"analytics is seen as one of the most dramatic factors in shaping the future of higher education".* According to Van Barneveld et al. (2012), their review on analytics in HE argues that more than two-thirds believe that analytics is a major priority. The current use of analytics may require extensive computation because of Big Data so the techniques and tools used for analytics projects influence the most up-to-date methods developed in a wide range of fields such as data science, computer science and management science.

Campbell and Oblinger (2007) brought academic analytics to fruition as a powerful tool for the US HE sector; they state that academic analytics is described as the way to evaluate and analyse organisational data obtained from university systems for decision making and reporting purposes. According to Campbell and Oblinger (2007), academic analytics is used to assist HEIs in addressing things such as student success and accountability while achieving their academic missions. Learning Analytics was then brought forward around 2010 (Ferguson, 2012a), whereas academic analytics became associated more with the business. Goldstein and Katz (2005) state that academic analytics refers to all areas dealing with the business of an academic institution, from financing and budgeting, enrolment management to student progress.

Even though data capabilities have been emerging over the last 10 to 20 years, there has been a wide disengagement between BI and data use for supporting learning-based hypotheses (Freitas et al., 2015). For instance, even though data have been collected in educational databases, the competence and proficiency for using it to improve learning and the student experience has not really started and hardly ever been explored (Ferguson, 2012a, Ferguson, 2012b). Therefore Learning Analytics is becoming popular in HEIs like nothing before in recent history. Learning Analytics is the application of analytics in education. As a result of the current explosion of Big Data, which refers to the variety, velocity and volume of the data produced using ICTs, Learning Analytics is commonly used in the education sector to improve SEM. Van Harmelen and Workman (2012) state that Learning Analytics is the use of analytical techniques to investigate educational data which involves data about learner and teacher activities to find behavioural patterns and give actionable information to enhance learning. Bach (2010) also defined Learning Analytics as techniques used to aid target instructional, curricular and support resources to maintain the success of particular learning goals. Learning Analytics is significantly important to HEIs as it serves as a way to guide operational and strategic activity through improving the student experience.

Learning Analytics has been defined in Chapter 1, but there is also another definition which is *"the process of developing actionable insights through problem definition and the application of statistical models and analysis against existing and/or simulated future data"*(Cooper, 2012, p7). Learning Analytics has also been defined by Del Blanco et al. (2013, p1) as *"a discipline that gathered and analysed educational data with different purposes such as seeking a pattern in the learning process and trends or problems in student performance"*, and by Greller and Drachsler (2012) as an academic area that concentrated on learners, their learning procedures and behaviours. SLA *"focuses on how learners build knowledge together in their cultural and social settings"* (Ferguson and Shum, 2012, p2). Learning Analytics has arisen as a new idea to capture educational big data (Czerkawski, 2014). It is enabled by the development of increasingly refined analytics tools for instance visualisation software, better data formats and improvements in computing technology (HEA, 2017). According to HEA (2017), scientific practices such as Climate Sciences, Biology and Physics have been utilising analytics ever since the 1970s and learning is a late arrival to this particular area of investigation. According to Becker (2013, p63) *"Learning analytics places a greater emphasis on the qualitative data that originate from learning behaviour".* Czerkawski (2014) states that in the past few years, the Horizon report incorporated Learning Analytics as one of the developing areas of research from 2011. Horizon (2014, p40) offered the following definition for Learning Analytics: *"Learning analytics research uses data analysis to inform decisions made on every tier of the education system, leveraging student data to deliver personalised learning, enable adaptive pedagogies and practices, and identify learning issues in time for them to be solved."* Learning Analytics utilises intellectual online data and has the potential to *"to transform educational research into a data-*driven science, *and educational institutions into organizations that make evidence-based decisions*" (Buckingham Shum, 2012, p12). According to Shacklock (2016a), Learning Analytics has the prospect to be hugely powerful for enhancing the student experience of the university. Shacklock (2016a) also states that to guarantee the students get the optimum benefit from analytics, HEIs should utilise analytics systems that are: planned in discussion with the students, sustained by an ethical framework or policy, driven by the enhancement of learning and teaching procedures and student engagement, tailored to the particular requirements of each HEI and integrated in an HEI's strategic plan.

Siemens (2013) on the other hand argues that Learning Analytics is about sense making and understanding; He also states that establishments such as the Society for Learning Analytics Research (SOLAR) and the International Educational Data Mining Society are trying to create a research community for Learning Analytics. According to Clow (2013), there are a variety of methods that Learning Analytics utilises, for instance, Social Network Analysis (SNA), web analytics, natural language processing and predictive modelling. Siemens (2013) adds to this by mentioning techniques such as cognitive modelling, which has origins in artificial intelligence (AI), machine learning, BI and statistical analysis. Adejo and Connolly (2017) state that there are three main stakeholders that have great accountabilities in the improvement and utilisation of Learning Analytics technology:

1. **The Administrators:** Classify the technology, put forward its use, offer a supportive environment, put forward the implementation strategy and observe the utilisation of the tools. Other accountabilities rotate around administrative decision making.
2. **The Teachers:** select the acceptance, importance and personalisation of the tool to meet the awareness and preference of the learner. The teachers examine the appropriateness of the tools and offer feedback on how to enhance the functionality and performance.

3. **The students:** decide on the impact of the utilisation of the tools on their learning as well as their learning environment. The students provide the required feedback on the benefits of the tools for their performance.

Action analytics is a term suggested by Norris et al. (2008) associated with academic analytics and it highlights the requirement for benchmarking both in and through institutions, with specific importance placed on the improvement of practices that make them effective. Analytics in education can be regarded as occurring at many levels, for example, from separate classrooms, department, university, region, state and international (Siemens, 2013). Buckingham Shum (2012) categorises these organisational levels as micro-, meso- and macro-analytics layers, as follows.

Macro (region, state, national and international)

According to Norris et al. (2008), macro-level analytics strive to allow the crossing of institutional analytics, for example, through 'maturity' surveys of present institutional practices or enhancing state wide data contact to unvarying assessment data over students' lifetimes.

Meso-level analytics (institutional level)

According to Buckingham Shum (2012), at this level HEIs share mutual business procedures to sectors already advancing from BI; they can be viewed as a new BI market sector. They also state that practically the sector can appropriate tools to incorporate data silos in enterprise warehouses, improve workflows, produce dashboards, mine unstructured data, enhance the prediction of 'customer churn' and future markets, etc.

Micro-level analytics (Individual user actions)

This level maintains the tracking and understanding of process-level data for distinct learners (and by extension, groups), the data is of key interest to learners themselves as well as those accountable for their success, since it can offer the finest level of detail, preferably as quickly as possible (Buckingham Shum, 2012). This data is consistently the most private, since (depending on platforms) it can reveal online activity click by click, physical activity, for example, geolocation, personal data, for example, social networks, library loans and purchases (Buckingham Shum, 2012). Buckingham Shum (2012) also states that researchers are adjusting methods from fields comprising of educational data mining (EDM), automated marking, serious gaming, computer supported collective learning, intelligent tutoring systems / adaptive hypermedia, recommender systems, knowledge on visualisation, SNA and computational linguistics and argumentation.

2.6 Where Learning Analytics is Currently Used and How

A key network inside the EU is the Learning Analytics Community Exchange (LACE); have published a platform for Learning Analytics in the workplace; this particular community is cross-sector but incorporates UK HE (HEA, 2017). The reasons behind educational institutions utilising Learning Analytics vary considerably, although there is some common ground. Most HEIs discuss wanting to improve the student learning experience in many ways, for example, improving achievement, decreasing the number of resits, offering better feedback and allowing students to become more reflective learners (Sclater, 2014a).

Learning Analytics along with Big Data can be used to change the current processes of administration, teaching, learning and academic work (Baer and Campbell, 2012). Big Data can also help with process outcomes in HEIs, such as the improved use of data analytics and predictive modelling, as well as enhanced understanding of the need for efficient data preparation for analytics. Learning Analytics can also be used to monitor the performance of students over time and give feedback to their designated tutors or support services in order to make useful interventions if necessary (Freitas et al., 2015). However, the area of Learning

Analytics is very broad and complex; for instance, there are various Learning Analytics applications for the different areas within SEM. According to Kiron et al. (2012), Business Analytics can be classified into descriptive, predictive or prescriptive, based on its key functionality.

According to a top IBM Analytics partner, Presidion (2015), universities feel by engaging in the use of predictive analytics from various data sources, problems can be predicted early and intervention plans formed. This gives a full view of each student and provides a learning experience catered to the student. Eduventures (2013) also states that by investigating historical data, predictive analytics can let an institution know which applicants are expected to enrol and far ahead in the student life cycle which students are likely to go on and graduate.

Prescriptive analytics uses models to identify optimal behaviours and actions (Davenport, 2013) and is used to analyse the current problems faced by HEIs such as *"student retention, enrolment management, prospect analysis, improving learning outcomes and curricular planning"*(Schaffhauser, 2014, p1). The opportunities Learning Analytics provide for HEIs include improving student performance, increasing graduation numbers and reducing dropout rates. This is dependent on the application of three analytic categories: descriptive, prescriptive and predictive (Daniel, 2015), as described above. Freitas et al. (2015) also argue that Learning Analytics can also be used to monitor the performance of students over time and give feedback to their designated tutors or support services in order to make useful interventions if necessary.

In UK HEIs, analytical tools and systems such as Virtual Learning Environments (VLEs), Learning Management Systems (LMSs) and Student Information Systems (SISs) have made it much easier for managers to access student data and are the main data sources used by institutions. Newland et al. (2015) state that lecture capture, attendance monitoring along with swipe card access to buildings are new features looking to be implemented into UK universities.

Table 2.1 shows the different Learning Analytics tools used in UK HEIs (Sclater, 2014a).

Table 2.1 Different Learning Analytics tools used in UK HEIs

Institution	Learning Analytics tool / What they are doing	Data being collected
A	An Oracle data warehouse and interactive business intelligence software are used along with a student engagement dashboard developed by a third-party software house.	Data sources are VLE use (Blackboard), e-Vision use (student's private information), monitoring attendance and university presence (through RFID device in student ID cards).
B	Testing out Blackboard Analytics and uses IBM Cognos as its main BI system.	Attendance data.
C	Qlikview to evaluate data kept in MS SQL Server and Oracle data warehouses.	Activity data from VLE (Moodle), Library activity (Athens), coursework receipt activity.
D	Google Analytics, Google Charts, SAP Business Objects, Tableau, Qlikview.	A variety of data sources which can be utilised for analytics at this particular HEI. The main VLEs are Blackboard Learn and Moodle. Tribal SITS: Vision is the SIS.
E	Tableau.	The VLE (Moodle) is a data source but it is not feeding into analytics at present.
F	Co-Tutor (the university's own system).	Data is brought into Co-Tutor from a variety of systems such as the VLE (Moodle), the SIS, the timetabling system, Symmetry, Attendant and Caspa.
G	Microsoft BI Stack.	Data sources comprise of the Moodle log files, SIS, coursework receipting and the internal student satisfaction survey.
H	Hewlett Packard Autonomy, custom-made by DTP Solution Path.	Data is gathered in a data warehouse with feeds from smart cards, the library system, assessment systems, the VLE, smart cards and the SIS.

I	Uses SAS BI software as well as an in-house tool named OUAnalyse. At this time, this HEI is acquiring a new corporate data visualisation tool.	The data is collected from many systems as well as the in-house SIS and the VLE.
J	Qlikview is used to visualise this HEI's data as well as an in-house technologically advanced data warehouse but is moving to SAP Business Objects.	-
K	Presently trialling IBM Cognos.	At the moment, exploring the possibilities of Learning Analytics.
L	Has identified the advantages of employing Learning Analytics.	-
M	Has recorded in their written proposal that analytics can also assist students in better understanding their own progress.	-
N	Has come up with an analytics-supported intervention project that has considerably improved retention.	-
O	Lately, has implemented a project assessing the use of lecture capture software.	-
P	They are currently coming up with a client relationship management system as part of its university-wide student education service. Even though the key aim of the Client Relationship Management system is to improve the service to students through the student lifecycle for example across the enquiry, application, admission and on-course stages, it is also being developed to improve the quality and trustworthiness of business data for business analytical reasons.	-

2.7 Factors Driving the Growth of Learning Analytics

There is limited research on the factors affecting BA and there are limited papers on factors affecting Learning Analytics, However, Ferguson (2012a) examined the factors driving the growth of Learning Analytics: online learning and political concerns, discussed in the following paragraphs.

Online learning

Ferguson (2012a) argues that the growth of big data in education reflects the rise in uptake of online learning, she states that online learning has numerous advantages but it is also linked with issues as well. Mazza and Dimitrova (2004) indicate that students may feel lonely due to decreased contact with friends or teachers and they may become confused in the online space, encounter technical issues or their motivation diminishes entirely. In addition, Ferguson (2012a) states that teachers do not have the visual signs that can indicate when students are not adequately challenged, when students are uninterested, puzzled, overcome or simply inattentive. Dringus and Ellis (2005) suggest that students may also find it hard to understand and assess the learning and quality of involvement of individuals when this is suppressed within a large number of student offerings to discussions that have persisted for several weeks.

Political concerns

There is a huge demand for HEIs to measure, establish and develop performance (Ferguson, 2012a). According to Campbell and Oblinger (2007), the demand is apparent in several countries. In reference to analytics, it has been most noticeably expressed within the USA, where the government's goal is to intensify the general educational attainment of the population and has been ready to put in billions of dollars in order to accomplish this.

2.8 Big Data and Learning Analytics

Learning Analytics and Business Analytics are all based on Big Data. Big Data provides data sources for using analytics to generate insights. Big Data can have big value and impact, but to make sense of Big Data, organisations need to use analytics (Chen et al., 2012). Some people use the term “Big Data Analytics” interchangeably for Business Analytics. Analytics in Business is referred to as Business Analytics and analytics in HE is referred to as Learning Analytics.

Siemens and Long (2011) state that Big Data includes the developing area of Learning Analytics, which is at present an emergent area in education. Wagner and Ice (2012) also brought to the forefront the application of Big Data in HE and stated that technological advances have definitely served as facilitators for the move to the increased use of analytics in HE.

Also from a HE perspective, Big Data suggests the understanding of a vast range of administrative and operational data collected procedures focused on examining institutional performance and improvement so that future performance can be predicted and possible challenges linked to research, academic programming and teaching and learning can be identified (Picciano, 2012, Hrabowski III et al., 2011). In the same vein, Daniel (2015) argues that currently most of the work on analytics within HE comes from interdisciplinary research, covering the areas of educational technology, statistics, maths, computer and information science and a key component of the present work on analytics in education is focused on data mining.

Siemens and Long (2011) also indicate that Big Data is now well placed to begin addressing some of the key issues presently facing HE. Bichsel (2012) adds that technologies of today allow institutions to obtain better perspectives from data with previously unachievable levels of sophistication, speed and accuracy. According to Hrabowski III and Suess (2010), as technologies carry on probing all aspects of HE, valuable data is being produced by students, systems and computer applications. Siemens (2011a) specified that [Learning] Analytics is basically an introductory tool for learned change in education and offers evidence on which to form a better perspective and make learned rather than inherent decisions. As a result of BI and data mining, the procedure of collecting, examining and reporting educational Big Data is referred to as Learning Analytics (Reyes, 2015). As mentioned in Chapter 1, Learning Analytics is a developing area of research that can offer students, teachers and other stakeholders understanding of the learning process (Shum and Ferguson, 2012, Clarke and Nelson, 2013). According to Merceron et al. (2016), the key advantages linked with relating Big Data ideas to Learning Analytics could be student course performance prediction, identifying risk of abrasion, interactive visualisation and reporting of data, smart feedback, course commendations, approximation of development of skills, identification of group-based collaborative feedback and schedule management. In addition, Hammad and Ludlow (2016) also state that the concept is extended to smart learning environments and interactive educational systems to maintain active learning and therefore a general development for the practice of learning and interaction.

With the existing change in educational environments to blended and online learning and the presentation of LMSs such as Moodle and Blackboard, it does not come as a surprise that Big Data has found its place within education and is forecasted to be broadly executed in HEIs (Johnson et al., 2013).

From the literature it is evident that Big Data and Learning Analytics can be used to change the current processes of administration, teaching, learning and academic work. Big Data can also help with process outcomes in HEIs, such as the improved use of data analytics and predictive modelling, as well as enhanced understanding of the need for efficient data preparation for analytics. The opportunities Big Data and Learning Analytics provide for HEIs include improving both learning experience and student performance and increasing graduation numbers and reducing dropout rates.

2.9 Examples of Learning Analytics

Types of analytics

Sclater (2014b) categorised the range of Learning Analytics tools/systems into four categories. Table 2.2 shows the different Learning Analytics tools/systems, their actions and examples.

Table 2.2 Types of Learning Analytics tools/systems

Type of tools/systems	Actions	Examples
VLE-based engagement reporting tools	They sit within the VLE, usually look at the VLE data only and offer non-complex suggestions of a student's progress.	Blackboard Retention Centre, Moodle Engagement Analytics plug in
VLE-centric analytics systems	Established by VLE sellers, joining data from the VLE together with data from the SIS to allow more thorough analysis.	Blackboard Analytics for Learn, Desire2Learn Insights
SIS-centric analytics systems	These are placed beside the SIS but may also collect data from the VLE, delivering Learning Analytics beside wider BI.	Ellucian Student Retention Performance, Compass promonitor
Generic business intelligence systems	Established to offer improved analysis in any business, not exactly for education, placed outside both the VLE and SIS but gathering data from those and other systems, frequently in combination with a data warehouse.	Qlikview, Tableau, IBM Cognos, HP Autonomy

This leads on to Table 2.3 which shows the Types of Analytics and who benefits.

Table 2.3 Types of analytics and who benefits (adapted from (Siemens, 2011b)

Type of analytics	Who benefits?
Course level: social networks, conceptual development, language analysis	Learners, faculty
Aggregate: predictive modelling, forms of achievement/failure	Learners, faculty
Institutional: learner profiles, academic performance, knowledge flow	Administrators, funders, marketing
Regional (state/provincial): contrast between systems	Funders, administrators
National and International	National governments

LMS/VLE Analytics Dashboards

Buckingham Shum (2012) state that Blackboard and Moodle are popular examples of VLEs; they can also be labelled as content management systems (CMSs). According to Buckingham Shum (2012), both Blackboard and Moodle routinely accumulate huge amounts of log data linking to student activities; also they do not only take note of student activities and look through time but personal information (academic results, user profiles and interaction data).

Moodle

Moodle is a Virtual Learning Environment (VLE) which provides online support for individual courses.

Blackboard

Blackboard is extraordinarily effective as an online learning tool as well as being easy to use for uploading course content for specific units and courses. It is the responsibility of the university as well as the student to engage with the system to achieve the optimum learning experience.

Tableau

Tableau is a data visualisation software that assists HEI managers in seeing and understanding their data better. Tableau has helped some HEI managers with providing certain ways of counting students that executives and deans were comfortable with, for example; so they have a particular view of student numbers. With the Tableau tool, comparisons can be made across departments in HEIs to show them how well they have performed.

Tribal SITS

Tribal SITS is the most common SRS in UK HEIs and data from SITS can be interacted through Tableau. With SITS you can implement data in a variety of ways, but it is quite a controlled implementation for all intents and purposes. Most HEIs use SITS for the applicant journey by feeding the certain number of applications the HEI receive during registration period via SITS.

Banner

Banner is the world leading and most common student records system (SRS) for HEIs. Banner gives the opportunity for HEI managers to implement the system as and when they feel like.

EvaSys

EvaSys is an online module and evaluation system which gives feedback on individual learned modules in teaching and learning. Some HEI managers are adopting EvaSys so that better decisions can be made in areas such as learning environments and course content.

Predictive analytics

One popular HE project in Learning Analytics is the work at Purdue University (Arnold and Pistilli, 2012) on the Signals software known as the Signals project. This project is the field's leading case of the effective application of academic analytics, recording considerably higher retention rates and grades than were detected in control groups (Arnold, 2010, Arnold and Pistilli, 2012). According to Shum and Ferguson (2012) and Buckingham Shum (2012), the Course Signals project mines data from a VLE and joins this with predictive modelling to offer a real-time red/amber/green lights to students on their progression, as well to as educators, assisting staff in interceding in a suitable manner where it will be most valuable. Buckingham Shum (2012, p5) also states that *"Results from the evaluation reports thus far show that students who have engaged with Course Signals have higher average grades and seek out help resources at a higher rate than other students."* In addition to that, Czerkawski (2014) argues that Course Signals is used to identify students at risk utilising Blackboard Vista data mining methods; forecasting modelling for initial discovery and feedback.

Adaptive Learning Analytics

Adaptive learning platforms create a model of a learner's knowledge of a particular topic (for example, dental surgical techniques, algebra or photosynthesis), often in the perspective of consistent tests which command the curriculum and styles of testing (Buckingham Shum, 2012). Some examples of these analytics include the free Open Learning Initiative courses built on the Carnegie Mellon institution's research and marketable services such as Knewton and Grockit (Buckingham Shum, 2012).

Social Network analytics

The Social Networks Adapting Pedagogical Practice (SNAPP) is developed by the University of Wollongong. The SNAPP tool produces visualisations (social network diagrams) of activity, user relations and behavioural patterns on discussion forum posts and replies (Atif et al., 2013). The visual drawing depicts the users' level of engagement and activity with the purpose of recognising students at risk of underachieving due to decreased levels of partaking in contrast to other students. According to Bakharia and Dawson (2011), the SNAPP tool extracts data from and makes reports established on students' relations from commercial (Blackboard) and open-sourced (Moodle) LMSs, as well as the amount of times a login has happened, the amount of downloads and dwell time. SNAPP is also an easily available network visualisation tool that examines forum contributions and offers them as a network diagrams; its architects recognise uses for such diagrams from the view point of teachers (Ferguson and Shum, 2012), for example, recognising disconnected students, recognising key information brokers within a class and specifying the degree to which a learning community is emerging within a class (Bakharia and Dawson, 2011).

Discourse analytics

It is not hard for a learning platform to work out the number of times a learner has carried out simple actions, for example, logging in, posting a message and viewing a forum: This is the level at which many present analytics products function (Buckingham Shum, 2012). According to Taylor and McAleese (2012) and Wagner and Ice (2012), discourse analytics is particularly altered for learning, or according to De Liddo et al. (2012), sense making in queried domains is at the level of research prototypes. There are a number of open source research platforms as well as enterprise grade products that have the ability to examine written and spoken natural language to help with computational reasoning, however they are not designed with learning precisely in mind (Buckingham Shum, 2012). They also state *per se* that they signify raw technologies with fascinating potential for Learning Analytics researchers to appraise to education.

2.10 Learning Analytics Techniques

While Learning Analytics is more centred around sense making and action, Educational Data Mining (EDM) is *“an emerging discipline, concerned with developing methods for exploring the unique types of data that come from educational settings, and using those methods to better understand students, and the settings which they learn in”* (Baker and Yacef, 2009, p2). According to Siemens and Baker (2012) even though the techniques utilised are alike in both areas, EDM has a particular emphasis on reductionist analysis. Bienkowski et al. (2012) state that as Learning Analytics pulls from and encompasses EDM methodologies it is expected that the prospect of analytics techniques and tools from both populations will connect. According to Siemens (2013), Learning Analytics has two connecting constituents: techniques and applications. Techniques entail the particular algorithms and models for carrying out analytics while applications involve the methods in which techniques are utilised to impact and enhance teaching and learning. Table 2.4 shows the Learning Analytics techniques and applications:

Table 2.4 Learning Analytics techniques and applications (adapted from (Siemens, 2013)

LA approach	**Examples**
Techniques	
Modelling	Attention metadata Learner modelling Behaviour modelling User profile development
Relationship mining	Discourse analysis Sentiment analysis A/B testing Neural networks
Knowledge domain modelling	Natural language processing Ontology development Assessment (matching user knowledge with knowledge domain)
Applications	
Trend analysis and prediction	Early warning, risk identification Measuring impact of interventions Changes in learner behaviour, course discussions, identification of error propagation
Personalisation/adaptive learning	Recommendations: Content and social connections Adaptive content provision to learners Attention metadata
Structural analysis	Social network analysis Latent semantic analysis Information flow analysis

Ahern (2017) also wrote about some applications of Learning Analytics:

- Initial Alert and student success
- Course commendation
- Adaptive learning
- Curriculum design.

Initial Alert and student success

Ahern (2017) offered some statistics on this area from the University of Exeter:

- Currently there are 20 million university students in the EU; out of those 7 million will certainly not finish their degree.
- Particular sub-groups are over-represented; for example, mature students and Black and Ethnic Minority students.
- Universities differ in their retention rate, for example, some record dropout rates as high as 43%.

As mentioned earlier in this chapter, Course Signals are an example of an intervention method for student success.

Course commendation

An example of a university that carries out this practice is Austin Peay State University in the USA.

Adaptive Learning

This refers to the practice of personalising learning.

Curriculum design

This is incorporated into teaching and learning.

2.11 Advantages and Disadvantages of Learning Analytics

Advantages

According to IBM (2012), Learning and teaching analytics can be used for a number of things:

- Classify drivers of student behaviour through predictive modelling and survey analysis.
- Forecast student success through each step of the student academic lifecycle.
- Bring about teacher success by improving learning/teaching gaps.
- Highlight first-hand knowledge of programmes and curriculum into real-time decision processes.
- Utilise advanced analytics to assist in discovering unpredicted patterns and links to lead front-line interactions and develop results.

IBM (2012) also states that analytics can used for recruitment and retention:

- Classify Key Performance Parameters (KPPs) as well as student retention and recruitment.
- Improved predictions of the outcome of student actions, such as performance relations and drop out.
- Gain better knowledge of unstructured data across countless sources – from notes, blogs, open-ended survey questions to email communications.

Disadvantages

Shacklock (2016a) reports challenges which were brought to the forefront with the introduction of Learning Analytics:

1. **The ethical fears around student's knowledge and consent to the use of their personal data in Learning Analytics**

   There were fears that students may not be totally aware of how their data was being utilised in analytics or even that they were producing data, which was then being gathered and used by their institutions.

2. **Privacy**

   There is a fear that analytics systems could in the long run include less suitable data about a student's relations with their institution and their behaviours while registered. For example, if a university can observe that a student is not present at early classes and no activity is shown on the VLE, however their ID card is demonstrating their activity in the campus bar every night – is that an adequate reason for an intervention?

3. **The worry that analytics systems will be gamed and manipulated by students, thus decreasing the eventual impact of the system**

   For instance, a student who has an understanding that VLE usage is utilised in their analytics may focus more time on working with the website, downloading files and following links, however without essentially engaging in the behaviour being measured.

4. **The security of student data**

   There are also fears surrounding the security of student data kept by universities and utilised in Learning Analytics, as the dataset holds important value for many people and might therefore be a focus for cybercrime. If universities want to implement analytics systems with the lack of a strong data management system in place then the risk of a security break of their systems may be intensified.

5. **Not having suitable data management systems in place**

   Improving and employing an analytics system needs the underlying data reporting the analytics is reliable, precise and easily available. This is the first challenge for many universities as a majority do not have suitable data management systems in place.

6. **Financial pressures**

   Another challenge for universities hoping to develop the way they bring about data and carry out analytics is cost. At present, universities are dealing with growing financial pressures, the cost of implementing and employing an analytics system can seem unaffordable for many.

Also in other literature, Dringus (2012) states that LMSs do not display student data in an evocative way to the instructor, instructors do not have adequate tools in the system to bring about the data and develop conclusions. So all in all with Dringus's (2012) point of view, although promising, Learning Analytics does cause inadequate decision making about student learning.

Kay et al. (2012) argue that universities have to be transparent and clear about the data they are gathering and the aim behind the data collection, give learners an opportunity to withdraw if they want to and offer a mechanism of grievance and take-down if unexpected concerns come about from managing data. In addition to that, Slade and Prinsloo (2013) state data gathered through Learning Analytics should have a life expectancy and an expiry date agreed, also procedures for students to demand data be deleted under agreed principles. Since Learning Analytics deals with student data it is vital to make sure there is security and transparency, and also attention paid to all ethical issues around gathering and preserving separate data.

2.12 Type of Data Collected and Examined by Some Other Well-known Learning Analytics Tools

1. Ali et al. (2012) state that **LOCO-Analyst** gives teacher's feedback for web-based courses. It categorises the most significant parts of courses and offers course content statistics (content resulting in tag clouds). It can also link course subjects stated in forums with course parts. The tool is dependent on user access to the variety of course resources and the time allocated on each of them; it also reads the contents of the forum and course materials.
2. Del Blanco et al. (2013) gave an example of the **Desire2Learn Learning Management System** which incorporates a Learning Analytics tool called student success system. They state that this tool is also concentrated on high-risk student detection in order to allow early interference; the system is also dependent on raw data for its investigation, for example, student grades, the number of times a login occurs, discussion posts and marks, and the amount of attempts in quizzes.
3. According to Koedinger et al. (2010), the Pittsburgh Science of Learning Centre (PSLC) Data Shop is a source of data extracted from a variety of learning courses, particularly MOOCs provided by the **Open Learning Initiative** (Siemens et al., 2011). The PSLC Data Shop's aim is to assist in the improvement of standards for private student data interoperability and exchange. According to them, MOOCs separate student progress into knowledge constituents in which students can either pass or fail. Each lesson consists of many knowledge constituents and the MOOC takes note of the results for each of them.
4. The **Khan Academy**, as mentioned by Ruipérez-Valiente et al. (2015), is a non-profit educational organisation that offers web-based micro lectures that are free through online video tutorials. Khan Academy takes note of the achievement in the entire course exercises tried out by the students. Students can view their results overall and teachers

can also have an insight of the students' improvement and of the exercises with weaker achievement. Table 2.5 shows other analytics tools and their data for analysis:

Table 2.5 Other analytics tools and their data for analysis (adapted from (Del Blanco et al., 2013)

Analytic tool	Platform	Data for analysis
LOCO-Analyst	External tool	Resource views, resource contents, forum contents
Desire2LearnStudents Success System	LMS	Student marks, amount of times a login occurs, discussion posts, results and amount of quiz attempts
Open Learning Initiative	MOOC	Knowledge constituents passed and failed
Khan Academy	MOOC	Performance in exercises

2.13 Conclusion

Overall, this chapter has given an outline to Learning Analytics in HEIs, where Learning Analytics is currently used and how, Learning Analytics techniques, Learning Analytics tools, advantages and disadvantages and some statistics. There are a variety of Learning Analytics tools available for HEIs but they are not being used to their full potential even though there are a number of opportunities with Learning Analytics. There also has not been an in-depth discussion of how Learning Analytics impacts what areas of SEM.

Chapter 3: Literature Review

3.1 Overview

This chapter aims to develop a comprehensive understanding of the relevant literature and theories for the adoption and impact of Learning Analytics. It also aims to establish the research gaps within the literature that provide the basis and direction for this study.

This chapter begins with the literature review strategy implemented for this research, followed by the literature review covering management within HEI, general literature on Learning Analytics. The chapter then reviews literature on theories for understanding the information systems adoption, such as Diffusion of Innovation Theory (DOI), the Technology-Organisation-Environment (TOE) Framework, the Information Systems Success (ISS) model, and the Absorptive Capacity (ACAP) theory. A justification of the theories to be adopted for this study is given along with an overall summary of the literature.

3.2 Literature Review

The literature review starts by identifying the key words in the areas of student management, information systems (IS) and management and the relevant theories in IS/IT adoption and implementation.

Table 3.1 Literature review strategy summary

LITERATURE REVIEW STRATEGY SUMMARY	
Keywords	student experience, the management of students, learning analytics, information systems
Timeframe	1970 – 2017
Databases	Google Scholar, EBSCOhost, DISCOVER (University of Bedfordshire), the Wiley journal collection, ScienceDirect and the Springer journal collection
Types of literature	Academic journals, book chapters and articles
Fields	Title, keywords and abstract
Limiters	Full text, Boolean/keyword and English language

3.3 Student Experience Management

An example of a system used within Student Experience Management is discussed in the following paragraph

Student management systems (SMS)

Student Management Systems also known as Student Record Systems (SRS) and Student Information Management Systems (SIMS) are types of software used to organise day-to-day operations for HEIs.

3.3.1 Student Experience Management within HEI

UK HEIs collect and gather large volumes of information each day which is why the HE sector is referred to as being data-rich. According to Shacklock (2016a), HEIs have different varieties of data that they deal with such as: student record data – a student record may contain A-level results, exam results and degree classification; staff data – typically, universities have information about their staff, for example, which members of staff are employed full-time or part-time and staff data on equal opportunity; admissions and applications data – the number of students who applied to the institution is included in these records, ethnicity and the acceptance rate; financial data – institutions have data on their expenditures and income streams; alumni data – this includes data on whether a student has gone on to further study or employment after graduation and their contact details; course data – students who have enrolled in each course; and finally, estates and facilities data.

The UK HE sector has four main data collectors, namely: Higher Education Statistics Agency (HESA), Universities College and Admissions Service (UCAS), Student Loans Company (SLC) and UK Visas and Immigration department UKVI (Shacklock, 2016a). HESA provides the information on the how the student body is structured, degree results and where students go after graduation. UCAS has data on past qualifications of successful and unsuccessful university applicants. SLC provides data on how students apply for support and the duration over which it takes for a student to pay back their loan after graduation. UKVI keeps attendance data on international students.

3.3.2 Student Lifecycle Relationship Management (SLRM)

According to Chambers and Paull (2008), SLRM is important as it involves investigating how interactions, activities and events are managed which are used to generate and deepen the social and academic bonds between the student, a variety of staff members and other students to encourage improved understanding and engagement by the learner. Chambers and Paull (2008) examined in the JISC report the drivers behind why colleagues in HEIs chose to implement certain systems and the advantages that they were proposed to bring. Some of them are listed as follows:

1. **Competition**

Competition is progressively becoming targeted on ‘student experience’ as well as the services provided to students. The success of many HEIs is highly dependent on the relationships built with potential students and their parents and advisors at an early stage.

2. **An overall belief that using an information system can help improve the student experience**

By allowing HEIs to maintain enhanced relationships with their students and allow useful interactions to take place (providing information through portals, also valuable instructions and information depending on the which stage of the lifecycle a student is at), and offer an improved learning experience (by tracking of progress to support formative assessment and feedback, this is needed basically to catch those students who are in need of additional support on time).

3. **Understanding of market and buyer behaviour**

SIS are large data sources used to support a HEI’s understanding of their market, the attributes of both applicant and student associates, the reputation of certain programmes and tracking the success of campaigns. In the future, this data can be used to improve targeted marketing campaigns.

3.4.3 Student Lifecycle

The lifecycle stages were determined by wide-ranging functions carried out within HEIs which may have been managed by different organisational units and reinforced by individual processes. Figure 2.1 shows the main stages of the student life cycle from the JISC report by Chambers and Paull (2008).

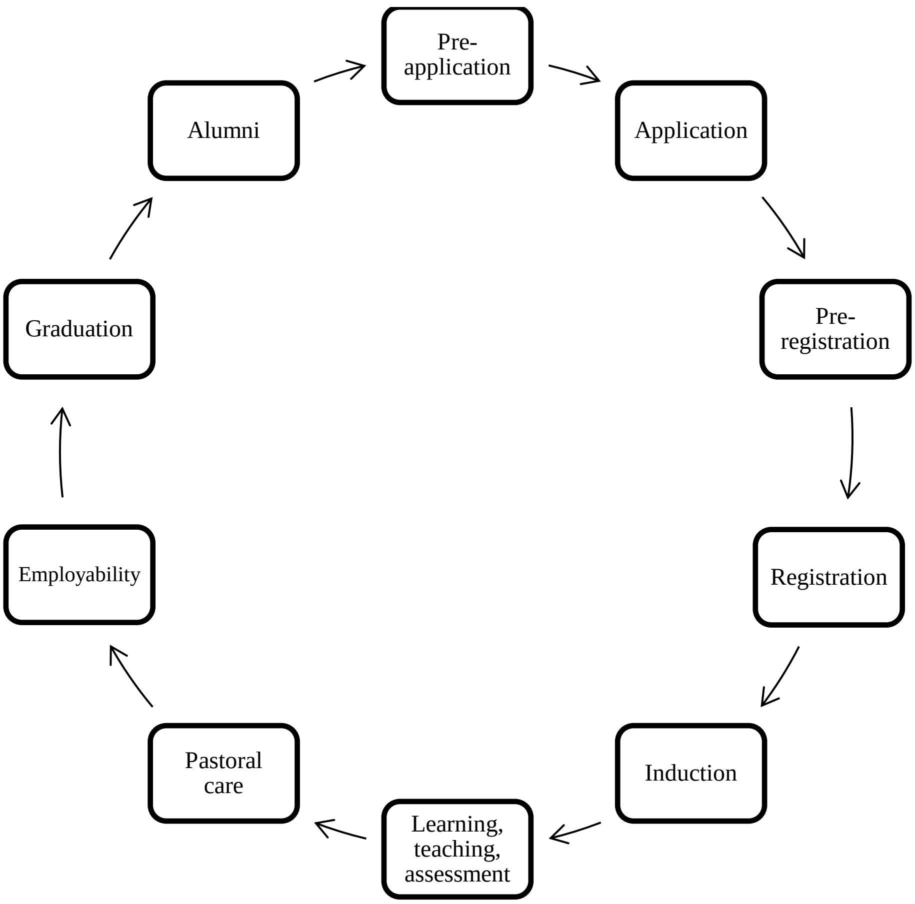

Figure 3.1 The main stages of the student life cycle (from the JISC report by Chambers and Paull (2008)

SEM Lifecycle

HEIs are starting to become aware of the large amount of data and intelligence that are available in their own systems. This can then be utilised to understand the needs of the students, the market and to make sure that the business advantages that arise from the successful management of direct relationships with students are secure. However a unified approach among managers and students is required for the benefits to be realised through the use of Learning Analytics.

The main student life cycle proposed does not include areas such as student engagement or student retention in the process (which are important steps in the student lifecycle), which is why another version is required to be adopted for this study. The cycle starts from when students are recruited through to student success, so students are recruited and then partake in university lectures or seminars in the course of their study, so the students are engaging in the particular HEI, if facilities, lecturers and academic staff are of a good standard in the university more students remain in their HEI (student retention), hopefully resulting in success in exams and coursework etc.

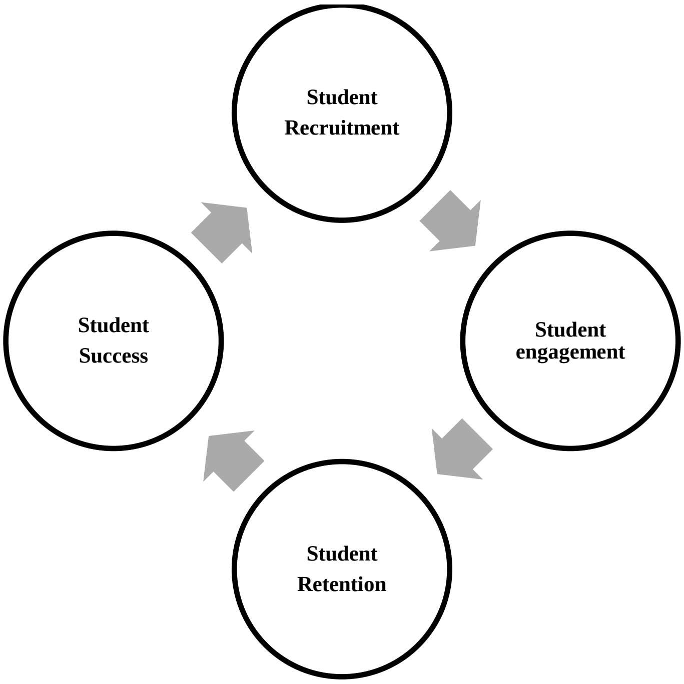

Figure 3.2 The SEM cycle

3.3.4 Summary of SEM literature

There is limited research on SEM, therefore it is hoped this study will be able to provide further insight to this area.

3.4 Research Gaps

Based on the comprehensive review of the current research and application of analytics in HEIs, a number of research gaps are identified. These gaps are also summarised in the Chapter 1.

1. HE is data intensive sector and various types and amounts of data are generated. However, there appears to be a lack of research on understanding the challenges in utilising data effectively for SEM in the era of Big Data and Analytics.
2. Due to the growing importance of Learning Analytics, UK HEIs are very keen to use Learning Analytics, but there appears to be a serious lack of academic research that explores the applications and impact of Learning Analytics in HEIs, especially in the context of SEM.

In reference to point 1, HEI managers also do not seem to have a thorough understanding of the evolution of Learning Analytics which could prove useful to know the different terminologies concerning Learning Analytics and also the current status of Learning Analytics. Many HEI managers view Learning Analytics as complex, technology that will culturally change the future of HEIs and also as an expense. So all in all the questioned could be posed them, is the use of Learning Analytics related to the management of students really what they need. HEI managers may feel more at ease when a framework is put in place.

Expanding on Point 2, there also seems to be a lack of understanding on the process of the student lifecycle and at what stage of the lifecycle managers feel that Learning Analytics should be implemented to enhance the student experience that is why there is a need for a separate lifecycle model in relation to SEM to be adopted.

All in all there is need to have a systemic and rigorous research to understand the use and impact of Learning Analytics from the relevant theoretical perspectives. The following sections review relevant literature on IS/IT adoption and implementation.

3.5 IS/IT Adoption and Implementation

To close the research gaps identified, this study aims to improve the adoption of Learning Analytics by developing a better understanding on the current practice in Learning Analytics applications, factors affecting its use and impact in the studied UK HEIs. Therefore, it is necessary to review the relevant literature on the adoption, use and impact of information systems (IS). IS adoption and diffusion have received extensive attention over the 1990-2000. As a result, a number of theories have been developed to help researchers better understand the critical issues to examine. According to Yeh et al. (2015), IS/IT is used mainly to provide support to a firm’s operation, which thus improves the competitive growth of a company. Orlikowski (2000) in the same vein states that organisational structure, technology skills and conventional strategies have an effect on the adoption of IS/IT. Peppard and Ward (2004) argue that IT capabilities have an effect on business strategies, IT operation and services and IS/IT strategies thus leading to a better organisational performance.

3.5.1 Review of Important Theories Employed in Information Systems (IS) Research

There are various noteworthy theories employed in this field such as the Technology-Organisation-Environment (TOE) framework, Absorptive Capacity Theory (ACAP)**,** Information System Success (ISS) model and Diffusion of Innovation Theory (DOI), to mention but a few. This research has undertaken extensive review of the relevant theories that have been developed and adopted by researchers to investigate and understand the current phenomenon. The next section briefly provides a review of the relevant theories that potentially can be used to help unveil the theoretical underpinnings of the Learning Analytics use and impact.

3.5.1.1 Technology-Organisation-Environment (TOE)

TOE framework looks at the factors that influence technology adoption along with its characteristics (Meroño-Cerdán, 2008). This framework is one of the most well-used and widely recognised in technology adoption and diffusion research. The TOE framework was proposed by Tornatzky et al. (1990). They suggest that there are three areas where an enterprise can decide to adopt technological innovation: technological context, organisational context and environmental context. The technological context is in reference to both the internal and external technologies that are important to an organisation; according to Thompson (1967), this includes the set of technologies that are accessible to an organisation externally and may include equipment as well as processes. There has been a variety of researchers that have investigated the significance of a number of first- and second-order concepts that have an impact on the technological context. For example, Kwon and Zmud (1987) stated the significance of technology resources in the interior of an organisation, such as infrastructure, technical skills, developer and user time for effective IT adoption. Their statements were agreed by a number of authors (Crook and Kumar, 1998, Cragg and King, 1993, Kuan and Chau, 2001, Grover, 1993). In the same vein, Zhu et al. (2003) theorised and investigated the technological context by finding technology competence through three second-order constructs: Internet skills, e-business awareness and IT infrastructure. Also, in Zhu et al.'s (2003) study, in the model that they suggested, the technological context is described in three first-order variables: reliability, deployability and security concerns. The foundation for every one of these technological variables is established in present research.

Nambisan and Wang (1999) also found that security was a problem, both real and perceived as an influence affecting the aim to implement adoption behaviour. They describe security as the perception or judgement along with being afraid of safeguarding mechanisms for the storage of information through electronic databases. Lippert and Govindarajulu (2015) argue that firms are reliant on their information systems for day-to-day activities. Information system databases are said to contain important data about business transactions and processes. The element of security has garnered much attention in recent literature. For example, Coetzee and Eloff (2005) argue the significance of security in building trust between the provider and consumer of web services. In addition, Joshi et al. (2004) stated that security was a great hindrance to the adoption of web service technologies. Shah and Murtaza (2005) also state that solving security and reliability problems are important in the extensive adoption of web services. In the same vein, Zhao and Cheng (2005) argue that security and reliability problems in relation to web services are still not solved. The studies described demonstrate the significant of web service security and reliability.

The organisational context refers to the resources of the organisation including the organisation's size, human resources and managerial structure (Oliveira and Martins, 2011b). Tushman and Nadler (1986) argue that there are three ways in which top executives can make key changes to an organisation which include conveying messages both internally and externally outside an organisation regarding the importance of the innovation, producing a team that is in charge of mapping out a strategy in reference to innovation, and ensuring that an organisation's strategy, core values and role of technology is clear. Many researchers have investigated organisational constraints as independent variables to the implementation of technology. Thong (1999) saw the significance of bearing in mind organisational features in IS implementation and acceptance. In terms of the organisational factors for technology adoption, Rogers Everett (1995) and Tornatzky et al. (1990) state that firm scope and size are particularly important; this notion was also confirmed in IS literature, for example, Hitt (1999) and Dewan et al. (1998) found out that the larger the scope of the organisation, the larger the request for IT investment. In the same vein, Brynjolfsson et al. (1994) argued that firm size is greatly linked with IT investments. Damanpour (1992) also suggested that organisation size has been constantly demonstrated to be a decent predictor of implementation of IT in organisations. With larger organisations, they have better economies of scale; they can take larger risks linked with innovation implementations and have more resources (Thong, 1999, Kuan and Chau, 2001, Zhu et al., 2003, Gibbs and Kraemer, 2004). On the other hand due to their resource constrictions, smaller organisations do not freely implement newer technologies; despite this, small organisations are more active and flexible in comparison to large organisations. Zhu and Kraemer (2005) state that when organised for financial as well as technological resources, larger organisations utilise technology to a lesser extent. Although this may be correct for a mature technology, small organisations cannot risk resources to implement unknown innovations (Lippert and Govindarajulu, 2015).

Tornatzky et al. (1990) state that the environmental context refers to a specific area around an organisation where business practices are carried out and include several stakeholders such the government, the community and the organisation's competitors. These stakeholders are used to determine how an organisation makes a decision on the need for innovation and whether it is capable of actually putting innovation into place (Angeles, 2013). The environment context also includes the structure of the industry, regulatory environment and macroeconomic context. In innovation adoption literature there have been many researchers that state that competitive pressure is an influence on adoption (such as Grover (1993), Iacovou et al. (1995), Crook and Kumar (1998) and Premkumar et al. (1997)). In the same vein, Porter and Millar (1985) studied the strategic reason behind underlying competitive pressure as a driver of IT adoption. They brought forward the suggestion that by implementing information systems, organisations may be able to change the procedures of competition, leverage innovative methods to outdo their competitors, affect the organisation of the industry thus altering the competitive environment. Lippert and Govindarajulu (2015) state that the study of the link between competitive pressure and technology adoption can also be related to web services. Zhu et al. (2003) acknowledged that trading partner readiness was a factor in technology adoption.

According to Tornatzky et al. (1990), the three contexts of TOE provide limitations as well as opportunities for technological innovation. Therefore the way in which an organisation examines and implements new technology is dependent on the three contexts. Yeh et al. (2015) study therefore utilises the IT capability and organisational performance associated model provided by Peppard and Ward (2004) along with the TOE framework as a hypothetical basis for the research framework and also acknowledged the factors that affect e-business IT capability using the TOE framework. The participants of the study were heads of an IT department in 1,000 large organisations in Taiwan. In terms of the technological context, the two factors were IT maturity and IT infrastructure. From Yeh et al. (2015) study it is evident that IT maturity and IT infrastructure are positively linked with e-business IT capabilities.

Yeh et al. (2015) argue that sources of competitive advantage for companies include organisational capital resources and human capital resources. They also state that when presenting information systems as well as effective integration with a company's processes, enterprises must study the human factors. In terms of the organisational context the two factors were IT human resource and top management support.

Zhu et al. (2003) explored data from 3,100 organisations to recognise the impact of technology capability, organisational aspects of an organisation's scope and size and how environmental context has an impact on consumer readiness and competitive pressure for e-business adoption. Additionally, Zhu and Kraemer (2005) utilised the TOE framework to examine original influences on business value and e-business use in a worldwide investigation of 624 firms. Also, Zhu et al. (2004) created a research model established on the TOE framework in order to find out and test the impact of technological, organisational and environmental aspects on e-business value. Matsebula and Mnkandla (2016) study pinpointed factors for Big Data and analytics implementation in HE. The study employed the TOE framework and provided the technological, organisational and environmental factors that have an impact on the implementation of Big Data particularly in a South African context. As aforementioned in the Chapter 2, BI is similar to Learning Analytics, in that respect, Malladi (2013) employed the TOE framework in order to suggest a theoretical model of factors linked with the amount of organisational adoption of BI&A technologies and investigate it with a large cross-sectional sample. In their study they discovered that an organisation's technology sophistication, perceived benefits in relation to data infrastructure and organisation size are definitely linked with the amount of BI&A adoption.

As already discussed, there have been many researchers who have used the TOE framework to map out the factors affecting use; they are given in Table 3.2.

Table 3.2 Summary of studies using the TOE framework

Author (s)	**Title**	**Main research methods**	**Relevant key TOE factors identified**
Wang et al. (2010)	Understanding the determinants of RFID adoption in the manufacturing industry	Questionnaire survey	**T=** Relative advantage, Complexity, Compatibility **O=** Top management support, firm size, technology competence **E=** Competitive pressure, trading partner pressure, Information intensity
Scott (2007)	An e-transformation study using the technology-organization-environment framework	No empirical data used	**T=** IT infrastructure competence, e-business know how **O**= Organisational culture, organisational change **E=** Competitive pressure, customer readiness, regulatory environment
Oliveira and Martins (2010)	Understanding e-business adoption across industries in European countries	Data were collected from 2,459 firms belonging to EU27 countries across two industries.	**T**= Technology readiness, Technology integration, firm size **E=** Competitive pressure, trading partner collaboration
Zhu and Kraemer (2005)	Post-adoption variations in usage and value of e-business by organizations: cross-country evidence from the retail industry	Questionnaire and multicountry survey	**T**= Technology competence **O**= Size, international scope, Financial commitment **E**= Competitive pressure, regulatory support
Lippert and Govindarajulu (2015)	Technological, organizational, and environmental antecedents to web services adoption	No empirical data used	**T**= security concerns, reliability, deployability **O**= firm size; firm scope; technological knowledge; perceived benefits **E**= competitive pressure; regulatory influence; dependent partner readiness; trust in the web service provider

Jia et al. (2017)	Enterprise 2.0 post-adoption: Extending the information system continuance model based on the technology-Organization-environment framework	Online survey	**T=** Perceived Usefulness **O=** Firm scope, firm size, subjective norms **E=**Competitive Pressure
Nkhoma et al. (2013)	Contributing factors of cloud computing adoption: a technology-organisation-environment framework approach	Questionnaire	**T=** Cloud security, compatibility, reliability and availability, Extendibility of existing apps to cloud, compliance policy **E=** Lack of IT standards, compliance policy
Srivastava and Teo (2006)	Facilitators for e-government development: An application of the technology-organization-environment framework	Secondary data	**T=** ICT infrastructure, technology development **O=** Human Capital **E=** Public institutions, Macro-Economy
Yeh et al. (2015)	Using a technology-organization environment framework to investigate the factors influencing e-business information technology capabilities	Questionnaires	**T=** IT maturity, IT infrastructure **O=** IT human resource, top management support **E=** Partnership quality, competitive pressure
Zhu et al. (2006)	Innovation diffusion in global contexts: determinants of post-adoption digital transformation of European companies	Survey data	Technology competence, organisation size, competitive pressure, Partner readiness
Li (2008)	An empirical investigation on the determinants of e-procurement adoption in Chinese manufacturing enterprises	Logistic regression	Relative advantage, top management support, external pressure and external support
Matsebula and Mnkandla (2016)	Information Systems Innovation Adoption in Higher Education: Big Data and Analytics	No empirical data used	Management, change, technology and ethical issues

The human factor has always been considered as a critical factor affecting the adoption and success of IT/IS adoption. Rising et al. (2014) argued that "Technology does not create value, People do". Technology can only work if people use it. Christensen (2013) stressed that technology is only a resource and that when people change resources into services or products, value is produced for organisations. Rising et al. (2014) also stated that producing value from Big Data is no exception and data-savvy employees are important.

In using the TOE model, Buabeng-Andoh (2012) discussed the factors influencing teachers' adoption and integration of ICT into teaching. On a technological level, Buabeng-Andoh (2012) states for effective adoption of ICT into teaching, teachers must observe the technology as more enhanced than prior practice; consistent with their present values, prior experiences and needs; easy to use, can be investigated on a limited basis before making a decision to adopt and lastly, the results of the innovation can be seen by others. In their study Zhu et al. (2003) established a conceptual model for studying the adoption of electronic business, also known as e-business, at the firm-level involving six adoption inhibitors and facilitators based on the TOE theoretical framework, in which users' technological competence is one of important factors. Also using the TOE framework, Kuan and Chau (2001) found that the technology factor is where most people perceived benefits.

Gagnon et al. (2012) conducted a systematic review of factors influencing the adoption of ICTs by healthcare professionals, which included 101 studies. They found that perceived usefulness was the principal adoption factor whereas lack of familiarity with ICT and time constraints were the key barriers. This reveals that if people do not understand the benefits of the technology, they will not be motivated to use it. They also used the term "individual factors" and "human environment" to describe the factors covering people-related issues, such as knowledge, awareness, familiarity with ICTs, attitudes towards using ICTs and interactions among different users in the ICT-facilitated working environment.

In summary, most of IT adoption research uses the TOE framework to identify the influential factors at the organisational level, but it seems that people-specific factors are not explicitly mentioned.

3.5.1.2 Absorptive Capacity Theory (ACAP)

Figure 3.3 shows the model of Absorptive Capacity.

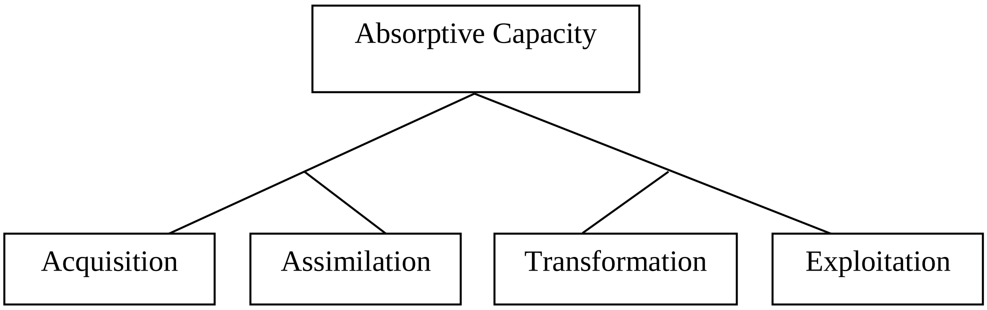

Figure 3.3 Model of Absorptive Capacity (adapted from (Zahra and George, 2002)

There is a large amount of IS research that relates to the concept of ACAP (Lichtenthaler, 2009, Joshi et al., 2010, Zahra and George, 2002, Roberts et al., 2012). Over the years ACAP has also been defined in several ways; for example, Mowery and Oxley (1995) define it as a group of skills required to deal with the tacit part of transferred knowledge as well as the requirement to convert this knowledge. Kim (1997), on the other hand, refers to ACAP as the capacity to learn and resolve problems and suggests that knowledge capability is driven by problem solving and knowledge transfer capabilities.

In the same vein, Lane and Lubatkin (1998) identify ACAP as the ability of institutions to learn from one another and indicate that learning is dependent on the likeness between teacher and student. Taking a different perspective, Van Den Bosch et al. (1999) argue that ACAP involves a firm’s acquisition, assessment; incorporation and commercial exploitation of new exterior knowledge. This aligns with the position of Sun and Anderson (2010) who refer to ACAP as a firm’s capability to study and act upon systematic findings and technical activities outside of its limits. Lichtenthaler (2009) in terms of ACAP examined the ability to transform and integrate important information systems knowledge.

The universally accepted definition and the one that is used in this study is by Cohen and Levinthal who first coined the term "absorptive capacity" (ACAP) in 1989 and subsequently defined it in a wider view as *"…an ability to recognize the value of new information, assimilate it, and apply it to commercial ends"* (Cohen and Levinthal, 1990, p128) The term ACAP was conceptualised by Cohen and Levinthal (1990) to describe how organisations acquire their knowledge and gain competitive advantage. Cohen and Levinthal (1990) and Zahra and George (2002) theories on ACAP are similar as they both view the ability of organisations to gain and apply knowledge as critical, due to fact that the information created from the use of IT cannot generate value.

In Cohen and Levinthal (1990) study they deliberated that recipient organisations have the largest possibility to learn from source organisations with alike basic information. They spoke primarily about the first dimension of ACAP – that is the valuing of external information. Zahra and George (2002, p185) define ACAP as *"…a dynamic capability pertaining to knowledge creation and utilisation that enhances a firm's ability to gain and sustain a competitive advantage"*. Cohen and Levinthal (1990) identified three dimensions of ACAP: identification, assimilation and exploitation; this was further extended by Zahra and George (2002) to acquisition, assimilation, transformation and exploitation of knowledge. These are four capacities which demonstrate an organisation's ability to integrate new knowledge which is vital to the performance of an organisation. Abecassis-Moedas and Mahmoud-Jouini (2008) research focused on the transformation and exploitation of the assimilated external information and its grouping with the prior information through exploitative and transformative learning, permitting the latter to be utilised in innovative ways.

Zahra and George (2002) differentiated between two areas of ACAP; one of the areas is called Potential Absorptive Capacity (PACAP) and the other area Realised Absorptive Capacity (RACAP). Lane et al.'s (2006) research highlights the significance of reducing the gap between both PACAP and RACAP.

PACAP refers to the way in which an organisation acquires and assimilates its external knowledge, whereas RACAP refers to the way in which an organisation exploits and transforms its knowledge. PACAP contains the acquisition and assimilation dimensions: acquisition refers to the process of identifying important information from external resources such as news. Assimilation is finding out the meaning behind knowledge. RACAP contains the transformation and exploitation dimensions: transformation involves combining the already existing knowledge in the organisation with the newly acquired knowledge. Finally, exploitation refers to incorporating knowledge to improve the current performance of an organisation and gain value.

The Absorptive Capacity concept has been widely used in extant literature to broadly indicate firms' receptivity to technology change and innovation (Joshi et al., 2010). According to Cohen and Levinthal (1990), ACAP is used as a predictor of innovative activity as well the extent of managerial information technology use. The following dimensions are included in Cohen and Levinthal (1990) study: ability to assess knowledge through prior experience and investment, ability to assimilate based on knowledge characteristics, a firm's organisational characteristics and technological overlap and ability to apply knowledge based on technological opportunity and appropriability.

Zahra and George (2002) reviewed the literature to determine the key dimensions of absorptive capacity and offer a new concept of this construct. Based on their research, they highlight activation triggers as requirements for lessening the impact of knowledge sources and experience on ACAP development. They describe triggers as actions that either encourage or force a firm to respond to certain internal or external stimuli. In their research, Abecassis-Moedas and Mahmoud-Jouini (2008) analyse the different types of external knowledge available to the firm, the process through which such information is used by the receiving organisation, and the outcome of new product development (NPD). They also examine the absorption process concentrating on the transformation and exploitation of the learned knowledge by studying the source and the recipient knowledge in a dyadic perspective rather than just acquisition and assimilation.

Leal-Rodríguez et al. (2014) address PACAP and RACAP individually and investigate their effect on innovation outcomes in firms; this study also investigates the role of RACAP in the connection between PACAP and Innovation Outcomes. In their study the results demonstrate that RACAP fully facilitates the influence of PACAP on Innovation Outcomes. Ritala and Hurmelinna-Laukkanen (2013) study observes why some organisations are more capable than others to obtain benefits from working with their competitors in innovation. This study offers evidence of factors related to this, proposing that the organisation's ability to get knowledge from exterior sources (PACAP) and to protect its innovations and main knowledge against imitation (appropriability) are significant in raising the Innovation Outcomes of working with its competitors. Ritala and Hurmelinna-Laukkanen (2013) study also states the difference between incremental and radical innovations as a result of competition and offers different consequences for both of the innovation types.

Rather than just concentrating on acquisition and assimilation, Abecassis-Moedas and Mahmoud-Jouini (2008) focuses on knowledge transformation and exploitation. Their research also investigates what effect source team knowledge characteristics have on knowledge absorption as well as resultant NPD performance. Easterby-Smith et al. (2005)

use ACAP mainly centred on the model of Zahra and George (2002). The case studies conducted for the research were obtained from three organisations each in a different industry which were: IT, chemicals and Healthcare. The results from the qualitative data were tested against the model.

The results from Ritala and Hurmelinna-Laukkanen (2013) study propose that PACAP and appropriability system have a positive result on the search of incremental innovations in competition. In terms of radical innovations, the appropriability system has a positive result when the effect of ACAP is not statistically significant. The results also demonstrate that PACAP is positively linked with the formation of radical innovations within raised levels of the appropriability system. For example, Joshi et al. (2010) invoke ACAP to conceptualise firms' types of IT-enabled knowledge capabilities and link these capabilities to firm innovation. They examine the relationship between IT and firm innovation both theoretically and empirically. Joshi et al.'s (2010) findings demonstrate that the three types of IT-enabled knowledge capabilities have a distinct effect on firm innovation.

Liao et al.'s (2007) research examines the connection between ACAP, innovation capability in Taiwan's knowledge intensive industries and knowledge sharing. Their findings demonstrate that knowledge sharing has a positive effect on ACAP and that ACAP is a dominant factor between knowledge and innovation capability. Tsai (2001) argued that a firm's units can make more innovations and have an improved performance if they inhabit central network positions that offer entry to new knowledge created by other units.

Similar to Cohen and Levinthal (1990), in Ferreras-Méndez et al. (2016) study of company internal records as well as a questionnaire survey were used to collect data on innovation, performance and business unit R&D intensity. In their research Ferreras-Méndez et al. (2016) investigate how the extent and depth of search strategies have an effect on the dimensions of a firm's absorptive capacity, which are exploration, transformation and exploitation. Results from their study demonstrate that directness of external knowledge search add to a firms' exploratory, transformative and exploitative learning processes in a multitude of ways. They also state that for an organisation to advance their explorative learning, deep relationships are not essential; also for an organisation to improve transformative learning it is not necessary to create extensive relationships.

There have been many studies that have given evidence on the requirement for an interceding link between the use of BA and organisational performance (Cao et al., 2015, Popovič et al., 2012, Trkman et al., 2010). According to Sharma et al. (2005), due to the nature of high competitive intensity, healthcare firms always need to seek and spread new knowledge to answer to industry regulations and market requirements. Cohen and Levinthal (1990) and Zahra and George (2002) state that organisations' ability to gain and apply knowledge becomes important since knowledge produced from IT use per se cannot create value.

Addorisio et al. (2014) review the use of ACAP theory in information systems (IS) research. The four key areas are explored: an overview of ACAP in IS papers, areas where ACAP are used, study of hypotheses to demonstrate how ACAP is utilised to clarify several organisational phenomena in IS research and finally, a study of measures to obtain insights into the operationalization of ACAP in IS research. Addorisio et al. (2014) contribute to ACAP as well as IS studies by examining and explicitly identifying how ACAP is used in IS research.

Tzokas et al. (2015) study pinpoints how the interaction between an organisation's ACAP and its technological and customer relationship capability add to its whole performance. Since Tzokas et al. (2015) stress the nature of absorptive capacity's backgrounds and how these relate to an organisation's performance, their study adds to the understanding of the role of ACAP as a mechanism for converting exterior knowledge into noticeable benefits in high tech SMEs, therefore leading to both significant practical and theoretical implications.

Fabrizio (2009) observe the connection between organisations' absorptive capacity-building activities and the search process for innovation. They argue that improved contact with university research is enjoyed by organisations that are involved in basic research and co-operate with university scientists, which leads to more searching for new inventions as well as providing a benefit in terms of both the quality and timing of search outcomes.

Similar to Tzokas et al. (2015), Kostopoulos et al. (2011) examine the role of ACAP as both a mechanism to classify and convert external knowledge into noticeable benefits, and also as a way to achieve both time-lagged financial performance and greater innovation. Taking a different perspective, Lin et al. (2016) measure the effect of four dynamic capabilities on four phases of the innovation process. This is done by rating the four dimensions on a five-point scale. The absorptive capacity was based on the research of Zahra and George (2002) as AC-1 to AC-4 (i.e. knowledge acquisition, assimilation, transformation and exploitation). Chiang and Hung (2010) state that there are a variety of ways to acquire new knowledge which might lead to many styles of organisational learning; this then can be divided into diverse processes, specifically transformative, exploitative and explorative learning procedures (Lane et al., 2006). In the same vein, Zahra and George (2002) and Enkel and Heil (2014) have described exploratory learning as gaining external information as well as referring to the idea of potential absorptive capacity. On the other hand, Garud and Nayyar (1994) argue that transformative learning links to the upkeep of information over a period of time and associates exploratory learning with exploitative learning. Zahra and George (2002) and Patel et al. (2015) also state that exploitative learning relates to applying information obtained and linking it to the idea of realised absorptive capacity. According to Eisenhardt and Martin

(2000), these learning procedures are the tools that make the improvement of a dynamic capability inside the organisation possible.

All in all, Roberts et al. (2012) state that utilising ACAP as a concept in IS research is becoming very common due to its significance to IS value, transfer of information and assimilation. In the same vein, Seo et al. (2011) argue that ACAP raises employees' capability to acknowledge innovation, enhances decision quality and boosts the development of information inside an organisation. Many authors have discussed the part ACAP plays in predicting the purpose of using technology. This is examined in Zhang et al.'s (2006) study where ACAP was discussed as the antecedent of the two key variables of TAM, PU and PEOU in the setting of a university website. Another example of where ACAP is used is in Park et al.'s (2007) study where the positive effect of all three areas of ACAP on performance of Enterprise Resource Planning (ERP) was investigated. They state that when individuals have previous information on ERP, they are more aware of it and it has an impact on their viewpoint that it is easy to use. In addition, if they adapt and apply ERP information it is foreseen that they observe it to be easy as they are carrying out their everyday activities with it.

Wang et al. (2015) try to create a research model to look at the mechanisms which BA capabilities in healthcare units demonstrate to indirectly have an effect on decision making effectiveness through a facilitating role of ACAP. Wang et al.'s (2015) study investigates the role of BA in attaining business value; in more detail, the study investigates whether the effective use of BA tools support healthcare organisations in improving organisational benefit, for example, decision making effectiveness. Using Bharadwaj (2000), Santhanam and Hartono (2003) and Wang et al. (2013) IT capability literature as a foundation and the resource-based view of IT, Wang et al. (2015) present the multi-dimensional role of BA capabilities, which are formed by a group of technological BA resources. The suggested BA capability is described as the ability to efficiently use functionalities of BA systems to assist the daily medical operations and activities (Wang et al., 2015). They also state that healthcare firms rely on precise evidence-based decisions to aid medical practices and have the likelihood to be assisted by BA capabilities. Wang et al.'s (2015) study suggests ACAP as the missing link in the connection between BA-related concepts and decision making effectiveness and dispute that it plays an intermediate role in converting knowledge gained from the use of BA systems into the valuable decision making resource. In this study, ACAP is seen as a capability based on Roberts et al.'s (2012) view; building on this view Wang et al. (2015) investigate how business value of IT, particularly for decision making effectiveness results from a link between BA capability and ACAP. Wang et al.'s (2015) study follows the extended conceptualisation by Zahra and George (2002), which is acquisition, assimilation, transformation and exploitation of knowledge; they study these four capacities together for the absorptive capacity of the firm. Wang et al. (2015) argue that these four capacities reflect organisations' ability to focus and relate new knowledge, which is vital to organisations' performance. In summary, Wang et al.'s (2015) study aims to answer the following research question: Do BA capabilities enhance decision making effectiveness through an intermediating role of ACAP?

Table 3.3 Summary of some studies using the ACAP theory

Author(s)	Title	Main research methods	Purpose
Cohen and Levinthal (1990)	A new perspective on Learning and Innovation	Surveys.	They argue that the ability of a firm to recognise the value of new, external information, assimilate it, and apply it to commercial ends is critical to its innovative capabilities.
Zahra and George (2002)	Absorptive capacity: A review, reconceptualization and extension	-	To review the literature to identify key dimensions of absorptive capacity and offer a reconceptualisation of this construct.

Abecassis-Moedas and Mahmoud-Jouini (2008)	Absorptive Capacity and Source-Recipient Complementarity in Designing New Products: An Empirically Derived Framework	Exploratory study based on multiple case studies.	Examines the type of the external knowledge obtained external to the organisation and the process through which it is utilised by the receiver firm and the effect on NPD (New Product Development) performance. The purpose of the study is to observe the absorption process, concentrating on the transformation and exploitation of the acquired knowledge by considering the source and the recipient knowledge in a dyadic view.
Easterby-Smith et al. (2005)	Absorptive Capacity in Practice: An Empirical Examination of Zahra and George's Model	Semi-structured interviews (between 16 and 23 in each organisation), complemented by reflection of meetings, organisational systems, and production processes.	They apply the notion of ACAP established primarily on the model of Zahra and George, to case studies drawn from companies in three different industries: IT, Chemicals and Health Care. The purpose of this paper is to test the model of Zahra and George against qualitative data obtained from case study material of three companies, each in a dissimilar industry.
Joshi et al. (2010)	Changing the Competitive Landscape: Continuous Innovation Through IT-Enabled Knowledge Capabilities	Secondary data about firms' IT-enabled knowledge capabilities.	They theoretically and empirically examine the link between IT and organisation innovation. Raising the theory, they introduce and improve the ideas of three types of IT-enabled knowledge capabilities.
Tsai (2001)	Knowledge transfer in intra-organisational networks: effects of network position and ACAP on business unit innovation and performance	As well as a questionnaire survey, business internal records were utilised to gather data on business unit R&D intensity, innovation, and performance.	He argued that company units can make more innovations and look forward to improved performance if they inhabit central network positions that offer access to new knowledge advanced by other units.

Ferreras-Méndez et al. (2016)	The relationship between knowledge search strategies and absorptive capacity: A deeper look	In order to get a typical sample they made preliminary contact by mail and telephone and then agreed on appointments with respondents so that the questionnaire could be responded to during a personal interview. They employed trained interviewers to carry out on-site interviews so that valid information and high quality data could be produced.	To examine how the breadth and depth of search strategies have an effect on the dimensions of an Organisation’s ACAP: exploration, transformation and exploitation.
Wang et al. (2015)	The Use of Business Analytics Systems: An Empirical Investigation in Taiwan’s Hospitals	This study used a survey method to collect primary data from Taiwan's healthcare industry.	Aims to improve a research model to analyse the mechanisms by which BA capabilities in healthcare units are demonstrated to ultimately affect decision making effectiveness through an interceding role of ACAP.
Addorisio et al. (2014)	Critical analysis of the use of absorptive capacity theory in IS research		Critically examines the use of ACAP theory in IS research. The analysis involves four main parts: 1) summary analysis of ACAP in IS papers; 2) areas of ACAP usage; 3) investigation of hypotheses to demonstrate how ACAP is being utilised to clarify many organisational occurrences in IS research; and 4) investigation of measures to increase understandings into the operationalization of ACAP in IS research. They contribute to IS and ACAP studies by examining and explicitly stating the utilisation of ACAP in IS research.

Fabrizio (2009)	Absorptive capacity and the search for innovation	-	Investigates the relationship between an organisation's ACAP building activities and the search process for innovation. They suggest that the improved entry to university research enjoyed by organisations that are involved in simplistic research and work with university scientists leads to superior search for new inventions and offers advantage in relation to both the timing and quality of search outcomes.
Lin et al. (2016)	How dynamic capabilities affect adoption of management innovations	-	Measures the effect of four dynamic capabilities on four stages of the innovation process.

3.5.1.3 Information System Success (ISS) model

DeLone and McLean's IS success model (DeLone and McLean, 1992, DeLone and McLean, 2003), also known as the D&M model, is widely used to examine the factors affecting IS success and impact. The original D&M model (DeLone and McLean, 1992) elaborates six major aspects of IS success measures including System Quality, Information Quality, Information Use, User Satisfaction, Individual Impact, and Organisational Impact. Whereas the DeLone and McLean (2003) model consists of: System Quality which refers to the features required for a good information system such as ease of use, flexibility and ease of learning. Information quality forms the features needed for system outputs (web pages and management reports) such as timeliness, accuracy, completeness and usability.

Service quality measures the quality of support from the IS department and IT support to the system users, for example, reliability and accuracy. System use refers to the extent that both customers and staff use the features of an information system, such as extent of use, frequency of use and nature of use. User satisfaction refers to the level of satisfaction of the reports according to the users. Finally, net benefits are how far information systems will go to influence the success of organisations and individuals. Examples include improvement in decision making, economic development and consumer welfare.

Learning Analytics studies using ISS

Siemens (2013) in his study proposes that it was e-learning that contributed to the growth of Learning Analytics. The definition of e-learning is given by Sangrà et al. (2012, p9) who states

> E-learning is an approach to teaching and learning, representing all or part of the educational model applied, that is based on the use of electronic media and devices as tools for improving access to training, communication and interaction and that facilitates the adoption of new ways of understanding and developing learning.

Therefore, this section discusses studies that used the ISS model in relation to e-learning. Lee-Post's (2009) study puts forward the utilisation of an e-learning success model to guide the design, growth and supplying of e-learning advantages. Their e-learning success model is modified from DeLone and Mclean's ISS model (DeLone and McLean, 2003). Brought together from past literature on ISS, six aspects of success factors – specifically information quality, use, user satisfaction, system quality, service quality and net benefit – are recognised and integrated into a complete success model (Lee-Post, 2009). From Lee-Post's (2009) study some of the following observations were made: the first step to guarantee effective growth and delivery of e-learning advantages is to have knowledge of students' learning needs and outlooks towards e-learning through experimental studies. By doing this, challenges in planning and evolving e-learning initiatives can be recognised sufficiently before their actual delivery.

Also a key factor of e-learning success is the online readiness of the students; online readiness should be evaluated along four readiness processes: academic preparedness, lifestyle ability, technical skill and learning fondness towards e-learning (Lee-Post, 2009). The entire achievement of an e-learning advantage is reliant on the attainment of success at each of the three steps of e-learning system development, specifically system delivery, system design and system outcome. Another study by Halonen et al. (2006) describes how the ISS model (DeLone and McLean, 1992, DeLone and McLean, 2003) has been utilised and advanced over time and in diverse settings; they pinpoint the model's use in e-learning environments. Halonen et al. (2006) study shows that DeLone and McLean (2003) can be utilised as a descriptive tool when assessing a VLE. The six areas suggest potentials to discover and define the environment from a variety of methods. The D&M 2003 model was used by Halonen et al. (2006) by implementing prior changes and then bringing forward some measures of their own. In their descriptive case study, they examined the relations between the actions by understanding the research material. Also using the D&M 2003 model as an aid, Halonen et al. (2006) argue that the VLE had thrived to help in achieving degrees. Five constructs (service quality, use, system quality, net benefit and user satisfaction) were construed as positive. Information quality was also seen as decent but extra material was preferred in the environment.

Holsapple and Lee-Post (2006) study improves the knowledge of how to describe, assess and support e-learning success from an IS perspective. This study also presents the e-learning success model which suggests that the entire success of an e-learning advantage is determined by the attainment of success at each of the three steps of e-learning systems growth: system design, system delivery and system outcome. In order to investigate this model, Holsapple and Lee-Post (2006) brought forward an online account of an undergraduate quantitative methods core course for business students created using an original plan. Four phases of growth are outlined each consisting of analysis, improvement, testing, design and enactment. From their study results demonstrate the rationality of utilising the suggested success model for e-learning success assessment. In the survey, these are the construct and measures of Holsapple and Lee-Post (2006) in relation to the ISS model, system quality – the required features of the Blackboard environment, information quality – the required features of the course content, service quality – the required features of student-instructor interactions, use – the degree to which course features are accessed, user satisfaction – the thoughts of the students on e-learning and net benefits – the entire benefits of e-learning.

Using prior ISS literature, Wang et al. (2007b) established and confirmed a multi-dimensional model for measuring e-learning systems success (ELSS) from the viewpoint of the employee (e-learner). The techniques used in theorising an ELSS concept, producing items, gather data and authenticating a multiple-item scale for determining ELSS are outlined in the study, also.

3.5.1.4 Diffusion of Innovation Theory (DOI)

This theory was originally proposed by Rogers (1983). It is a theory of how, why and at what rate technology as well as new ideas are spread through cultures functioning at the organisation and individual level (Oliveira and Martins, 2011b). Rogers Everett (1995) states that the DOI theory examines innovations as being transferred through particular channels over time and within a specific social system. He also argues that individuals are viewed as having different degrees of readiness to adopt innovations and therefore it is commonly perceived that the portion of the population adopting an innovation is roughly normally spread over time.

According to Rogers Everett (1995), dividing this normal distribution into sections leads to the separation of individuals into the resulting five categories of individual innovativeness:

innovators, early adopters, early majority, late majority and laggards. However, Oliveira and Martins (2011b) state that the innovation process in organisations is more difficult; it usually involves many individuals, possibly including both supporters and opponents of the new idea, and each individual has a role in the innovation decision.

Rogers Everett (1995) also argues that centred on the DOI at firm level, innovativeness is connected to independent variables such as individual (leader) characteristics, internal organisational structural characteristics and external characteristics of the organisations (see Figure 3.4).

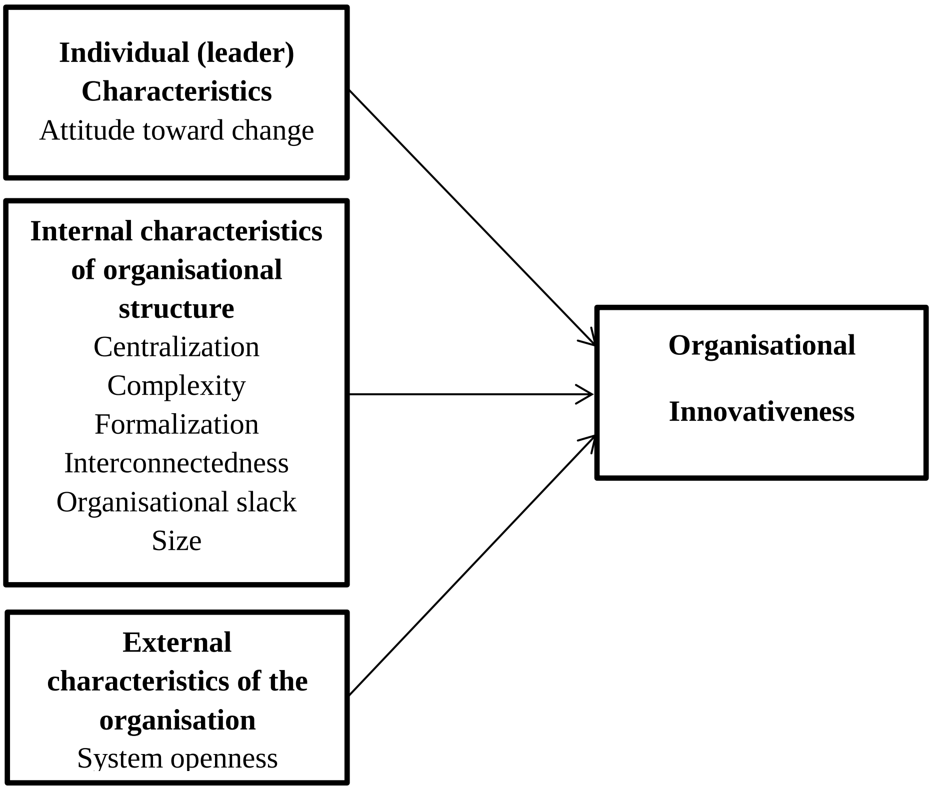

Figure 3.4 Diffusion of innovations (Rogers Everett, 1995) (Adapted from (Oliveira and Martins, 2011b)

Individual characteristics

These define the leader's attitude to change.

Internal characteristics of organisational structure

According to (Rogers Everett, 1995), this comprises of observations whereby: **Centralisation** is the extent to which power and control in a system are focused in the hands of a quite a few individuals. **Complexity** refers to the extent to which an organisation's members have quite a great level of knowledge and expertise. **Formalisation** is the extent to which an organisation emphasises that its members following rules and procedures. **Interconnectedness** refers to the extent to which the components in a social system are connected by interpersonal networks. **Organisational slack** is the extent to which different resources are available to an organisation. **Size** is the number of employees in the organisation.

External characteristics of the organisation

This refers to system openness. There are several studies that are based on the DOI theory. Eder and Igbaria (2001) study concentrates on the application process of intranets by investigating factors linked with diffusion and infusion in businesses. Findings propose that earliness of adoption; top management support and organisational size have a positive effect on intranet diffusion. With intranet infusion is positively linked with earliness of adoption, top management support and IT infrastructure and these factors are mediated by intranet diffusion.

Rogers argues that the adoption and diffusion of new technologies and innovations are related to five distinctive attributes of the technology/innovation to be adopted: Relative advantage, Compatibility Complexity, Trialability and Observability.

Beatty et al. (2001) study examined the factors influencing corporate website adoption; findings from the study showed major differences in the explanations as to why the organisations decided to implement web technology depending on when the organisation made the adoption decision. The study showed that early adopters placed more importance on perceived benefits and compatibility of the web with present technology and organisational norms than later adopters. Bradford and Florin (2003) use the DOI and Information System Success (ISS) theory to create and test a model of ERP implementation success. Findings from study show that top management support and training have a positive effect on user satisfaction, while competitive pressure as well as perceived complexity of ERP has a negative effect.

Zhu et al. (2006) used the DOI theory to create an integrative model to examine the factors of post-adoption stages of innovation diffusion, utilising enterprise digital transformation as an illustration of technology-enabled innovations. Four innovation characteristics are identified: relative advantage, compatibility, costs and security concern. Along with those, there a four contextual factors: technology competence, organisation size, competitive pressure and partner readiness as causes of post-adoption usage; and they propose usage as an intermediary link to impact on firm performance.

Zhu et al. (2006) assessed the suggested model by using a dataset of 1415 organisations from six European countries. They discovered that innovation is required to be used broadly in value chain activities before its impact can be understood. Amid the innovation characteristics, they discovered that compatibility is the biggest driver and security concerns overshadow cost as a usage inhibitor. With the contextual variables, partner readiness, technology competence and competitive pressure are important when driving e-business usage.

Jointly, these findings suggest that innovation diffusion can be understood better by involving both innovation characteristics and contextual factors. Hsu et al. (2006) examined the factors leading to differences in e-business use among US organisations. E-business refers to the use of Internet-based computing and communications to implement both front-end and back-end business procedures, e-business is being executed in firms more and more (Hsu et al., 2006, Lee and Whang, 2001). Using the DOI theory, Hsu et al. (2006) created an integrated model that clarifies the relative effect of eight known factors. Variety and volume of e-business use are empirically examined using a selection of 294 firms. In the study the analysis shows that bearing in the mind the variety of e-business use, the most significant driver is pressure from trading partners; when e-business volume is examined, government pressure arises as the strongest factor, and government promotion may not influence the variety of e-business use by private companies, but does have an effect on the volume of e-business use by organisations doing business with the government.

Learning Analytics study using DOI

Buc and Divjak (2016) study discusses the diffusion of an e-learning model as an advancement in an HEI (university, faculty). This research revealed five main factors of the social environment, six factors of the business environment and sixteen factors of the inner environment which influence the organisation in the preliminary stage of the process of diffusion. In terms of the DOI model in HE, as the e-learning application in many parts is technology-driven it is vital to observe the application method very meticulously and implement the action plan constantly. Also by using Learning Analytics further valued information can be acquired so that learning and teachings goals of an e-learning application can be assessed (Buc and Divjak, 2016). The procedure of adoption of innovations at the organisational level, according to Rogers (1983) theory of DOI, has been supplemented by the final phase of the DOI model in HE “Evaluation and improvements”, the phase in which the effectiveness of the implemented innovation is evaluated and also its developments, for example, the commencing of the new innovation cycle is made likely (Buc and Divjak, 2016). The social system has an impact on the development of DOI through three simple stages: the business environment, the internal environment and the social environment of the institute and this takes place during the entire cycle of DOI, which can be timely (Buc and Divjak, 2016). Buc and Divjak (2016) study also identifies environmental factors and social systems that have an impact on the possible ACAP of the institute to implement innovation based on the case of the implementation of e-learning by HEIs in Croatia.

3.5.2 Summary of the IS theories relevant to this study

Relevant theories have been selected and thoroughly reviewed. This review has in turn helped to decide the theoretical lens to examine the use and impact of Learning Analytics for HEIs.

According to Silva (2007) and Awa et al. (2015), TAM is one of the main adoption theories used in the field of IT for understanding the end user's intention of the technology adoption. Awa et al. (2015) also argue that TAM suggests PU and PEOU as important factors of IT adoption by users. PU is defined as a potential user's subjective likelihood that utilising a specific application enhances operations (Lu et al., 2003). PEOU refers to a potential user's assessment of the conceptual efforts needed of the use of target applications. A person's intention to use an application is dependent on their perception of the technology's usefulness and its uncomplicatedness. Davis (1993) argue that the advocates of TAM suggest that PU has an effect on PEOU and both determine attitudes. Although Gounaris and Koritos (2008) propose that TAM has received observed justification, application and replication, in the context of this study the model does not provide information on the factors that affect Learning Analytics use in HEIs as its constructs are only limited to PU and PEOU at the individual, not organisational level.

The Technology-Organisation-Environment (TOE) framework is one of the widely recognised and well-used frameworks in technology adoption and diffusion research at the organisational level. Tornatzky et al. (1990) proposed the TOE framework to study the adoption of technological innovation. According to Kauffman and Walden (2001), this theory proposes that adoption is influenced by technology development and organisational reconfiguration. They suggested that the decision to adopt a technological innovation is based on factors in the organisational and environmental contexts, and also on the characteristics of the technology itself. Technology, organisation, and environment are three common contexts that have been considered when IS researchers in organisational studies seek factors (Oliveira and Martins, 2011a).

Awa et al. (2015) argue that the technological context means that adoption is dependent on the group of technologies both internal and external to the organisation as well as gains, compatibility (both technical and organisational), complexity, trialability (experimentation) and observability. Organisational context encompasses an organisation’s business scope, top management support, organisational culture, complexity of managerial structure, the quality of human resource and size related issues (specialization and internal slack resources) (Jeyaraj et al., 2006, Awa et al., 2015, Tornatzky et al., 1990). Environmental context refers to the assisting and impeding factors in areas of operations. Important factors among them include competitive pressure, government encouragement, socio-cultural issues and technology support infrastructures, for example, gaining entry to quality ICT consulting services (Tornatzky et al., 1990) TOE has been widely used in investigating factors affecting technology adoption and used at the organisational level whereas TAM is used at individual level.

In terms of ISS it is used at both individual and organisational level. The ISS model can be understood as follows. A system can be assessed in relation to information, system quality and service quality; these features have an effect on the intention to use and user satisfaction. When the system is used certain advantages will be accomplished. Either negative or positive, the net benefits have an effect on user satisfaction and the additional use of the information system. DOI on the other hand is used at group, firm, industry and society level. DOI theory has been widely applied to assess the adoption and diffusion of ICTs.

Among a number of theories linking the use of IS to organisational performance, the Absorptive Capacity concept has been widely used in extant literature to understand firms' receptivity to technology change and innovation. ACAP can be used as a useful theoretical lens to examine the nature of absorptive capacity in terms of data acquisition, assimilation, transformation and exploitation and how these relate to an organisation's performance, in this case, SEM.

3.6 Conclusion of Literature Review

In summary, this literature review has provided an understanding of the main areas being examined in this study, which are management within HEIs, SEM, BA and Learning Analytics. It has also pinpointed the research gaps in the present literature on the research topic and provided an outline of important theories normally used in IS research. As aforementioned, coherent with the abductive approach utilised for this research, the exact theoretical lens adopted for this research is stated after the data analysis (Chapter 5) has been completed, i.e. in Chapter 6, the framework development chapter.

Chapter 4: Methodology

4.0 Overview

This chapter discusses the philosophical perspective chosen for this study, provides the research strategy for this study, discusses the research approach, provides the unit of analysis and an overview of the sampling strategy. It also discusses the research method for this study, summarises the data collection techniques for this study and provides an overview of the interview process steps along with the interview process for this research. The data analysis technique – Thematic Qualitative Analysis (TQA) is discussed, the time horizons for the study are summarised, the research ethics for this study are provided as well as the risk assessment for the study and finally a summary of the research process is provided.

4.1 Background

This chapter discusses the methodological approach used for this research along with the research process used. According to Saunders and Lewis (2009), the methodology summarises the theory of how the study should be carried out as well as the philosophical and theoretical norms that the research is established from and the implications of these for the methods implemented. Based on this, before stating the research design employed for the study, the philosophical position implemented by the researcher requires identification as this forms the whole methodological style of the research. Figure 4.1 shows the methodological approach used for this study.

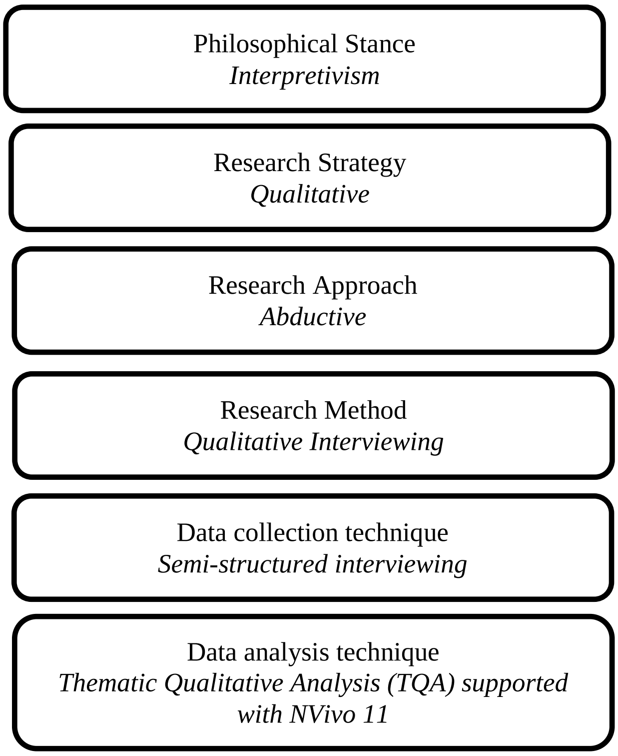

Figure 4.1 Research methodology process

The chapter begins with a review of the philosophical stances that are acquired in research before stating the philosophical perspective used for this research, namely interpretivism. The next stage is providing information on the research strategy used for this research, the research approach, followed by the research methods chosen, then the data collection and analysis techniques, the sampling strategy and finally, any ethical issues which have been considered.

4.2 Philosophical Perspective for this Study – Interpretivism

According to Bryman (2012), research philosophy refers to a group of beliefs relating to the nature of the reality being investigated. Flick (2011) also states that the assumptions made by a research philosophy provide the reasoning as to how the research will be undertaken. There are different views of what research is across disciplines and how it links with the kind of knowledge being developed. A paradigm guides how decisions are made in terms of carrying out the research; it is basically a theory or belief system that establishes a set of practices. Guba and Lincoln (1994) state that paradigms can be characterised through their ontology, epistemology and methodology:

- Ontology: Different researchers have provided their own interpretations on what ontology is. Schwandt (2007, p190) states that it is '*The worldviews and assumptions in which researchers operate in their search for new knowledge*'. Ontology therefore refers to how things really are and how things really work.
- Epistemology: Each paradigm has an epistemology. Different researchers have specified what their idea of epistemology is. In regards to epistemology, Creswell (2007) states: what is the link amid the researcher and that being investigated?
- Methodology: Each paradigm contains an assumption about methods, a grouping of techniques used to investigate into a particular situation. Schwandt (2007, p190) states that the methodology is '*The process of how we seek out new knowledge. The principles of our inquiry and how the inquiry should proceed*'. Creswell (2007) asks in regards to methodology: *What is the method of research?* In summary, what tools do we use to know that reality?

Orlikowski and Baroudi (1991) offer two paradigms, **positivism** and **interpretivism.** Their work is more applicable to this study as they explore the methodological problems in information systems (IS) research. This helps set the scene explaining why this research's philosophical perspective is **interpretivism**.

The two different paradigms are described in Table 4.1.

Table 4.1 Attributes of the research perspectives of positivism and interpretivism (adapted from (Weber, 2004, Bryman, 2012, Easterby-Smith et al., 2012)

Attributes	**Research Philosophy**	
	Positivism	**Interpretivism**
Ontology	*"Belief in a single identifiable reality. There is a single truth that can be measured and studied. The purpose of research is to predict and control the nature"* (Denzin and Lincoln, 2011, p103).	*"Realities occur in the form of many mental constructions, both socially and experimentally based, local and detailed, reliant for their form and content for the person who hold them"* (Guba, 1990, p27).
Epistemology	Belief in total objectivity. Interaction with who or what researchers study is not needed. Scientific rigour is the only thing researchers' value and not its influence on society or research subjects (Guba and Lincoln, 2005).	Assumes that reality is constructed intersubjectively through the values and understandings developed socially and experientially (Guba and Lincoln, 1994).
Research Object	Research object has characteristic qualities that exist without the help of the researcher.	Research object is understood in light of meaning structure of person's (researcher's) lived experience.
Methodology/Methods	Belief in the scientific method, so this paradigm is grounded in the conventional hard sciences (Merriam, 1991). Methods: statistics, content analysis, experimental, deduction.	*"Individual constructions are produced and developed hermeneutically and also associated with dialectically generating one or a few constructions on which there is considerable consensus"* (Guba and Lincoln, 2005, p195). Methods: Hermeneutics, Phenomenology, Thematic Qualitative Analysis (TQA).
Data collection	Structured interviews and self-administered questionnaires with large sample sizes.	Semi-structured interviews and unstructured interviews, field notes, focus groups and diaries with small sample sizes.
Data analysis	This usually involves methods which are quantitative for example content analysis. Statistical tools are used. For example: SPSS, which implements techniques like Structural Equation Modelling- a multivariate analysis.	Uses Thematic Qualitative Analysis (TQA), grounded analysis and narrative analysis. Computer Assisted Qualitative Data Analysis Software (CAQDAS) such as NVivo and Atlas.ti to make analysis easier.
Theory of Truth	Correspondence theory of truth: mapping between research and reality on a one-to-one basis.	Truth is purposely fulfilled, interpretations of research object equal to the lived experience of the object.
Validity	Certainty, data truly measures reality. The results measure and reliably answer research questions correctly.	Defendable knowledge claims.

Reliability	Replicability, whether the results of the study can be repeated. Same results, different times, different researchers.	Interpretive mindfulness, researchers identify and speak about implications of their subjectivity.
Strengths	Offers an extensive coverage of a variety of circumstances, generalizable, cost-efficient and fast.	Implements a naturalistic approach to data gathering, concentrates on understanding people in their usual settings and can assisting in helping with new theory generation.
Weaknesses	Not appropriate for theory generation, methods tend not to be flexible and are false. Not suitable for understanding future changes.	The analysis and understanding of data can be quite complex and is very much reliant on the researcher's familiarity and knowledge. Data collection can also take up quite a lot of time and is concentrated around resources.

4.2.1 Why Interpretivism?

Even though some researchers may favour one research philosophy over another, it does not mean essentially that one philosophy is better than other (Podsakoff et al., 2012). This argument is basically used to provide the reasoning behind the chosen research methodology. This research follows the interpretivist paradigm as it is used as a way to gain understanding of how managers feel they will be able to utilise Learning Analytics in the area of SEM. Research questions have also been formulated for the scope of the study which is associated with the interpretivist paradigm instead of hypotheses which are linked with the positivist paradigm.

The interpretivist paradigm is concerned with discovering the underlying meaning of events and activities, in relation to this research: why do managers act or deal with the processing of information in the way they do in the area of SEM? This paradigm also involves the use of thematic qualitative analysis (TQA) as a method which is used for the data analysis of this study.

4.3 Research Strategy – Qualitative Inquiry

The overall aim of this research is to explore the use and impact of Learning Analytics for SEM in UK HEIs. In conjunction with the philosophical position of the study and in order to accomplish the aim stated, a qualitative approach is used. According to Creswell and Poth (2017), this allows for further interpretation of human or social issues established on creating an intricate, whole picture using words to feedback the many observations of informants in their normal setting. In the same vein, Denzin and Lincoln (2000) argue that qualitative research is seen as suitable for understanding the views and practices of participants in certain surroundings. The qualitative approach is distinctive in the sense that is utilised to assist researchers in viewing the area of analysis through the eyes of those who are taking part in the research. Bryman (2012) also states that the qualitative approach focuses on rich description and is categorised by an additional malleable structure which enables the researcher to get used to any changes that may arise as the study goes on. Qualitative research is also flexible in comparison to quantitative research which is not very flexible in nature. Based on this, qualitative research has the ability to acquire the different views of social actors about the subject being investigated, which makes it perfect for discovering HEIs' perceptions of the factors that affect the use and impact of Learning Analytics.

4.4 Research Approach – Abductive

There are three main research approaches: namely, the deductive, the inductive and the abductive approaches (Saunders, 2012). The inductive approach is more commonly used in qualitative research, where having no theory to inform the research process, it might be of benefit by decreasing the possibility of researcher bias in the data collection stage (Bryman and Bell, 2011). According to Silverman (2013), the deductive approach develops the hypothesis/hypotheses based on pre-existing theory and then generates the research approach to test it. The deductive approach may be predominantly suited to the positivist paradigm as it involves the formulation of hypotheses and statistics to an accepted level of probability (Snieder and Larner, 2009).

On the other hand, the inductive approach is linked with interpretivist research designs in contrast to the deductive approach. Flick (2011) states that with the inductive approach, the research focus can be generated after the data has been collected, as there is no framework at the start that informs the data collection.

The abductive approach is a mixture of characteristics from both the deductive and inductive approaches. Similar to the inductive approach, the researcher does not need to choose any theory before data collection. Centred on the research findings, a theory is chosen in order to map out the study findings (Bryman, 2012). The abductive approach is the product of theory refinement.

This PhD study follows the abductive approach because it was considered the most suitable approach due to the fact that the abductive approach allows the research process to be inductive at the start and adapt/extend the relevant theory to theorise the findings towards the later stage of the research when the initial analysis results are clearer. Early researchers view the abductive research approach as the structured creativity or perception in research to cultivate “new” knowledge (Andreewsky and Bourcier, 2000, Taylor et al., 2002). For this research Dubois and Gadde (2002) method will be followed. According to Dubois and Gadde (2002), abductive research is different to inductive and deductive approach because it can describe, improve or alter the theoretical framework before, during or after the research process. Abductive research also moves back and forth between inductive and open-ended research settings to more theoretical and deductive attempts to validate hypotheses. Kovács and Spens (2005) along with Dubois and Gadde (2002) state that with the abductive approach the understanding of theories allows the researcher to effectively match an appropriate theory to the data created from the research: this is known as ‘theory matching’.

Regarding the differences between Grounded Theory and the abductive approach, the key difference is that Grounded Theory starts with a broad aim without specific focus and generates the research focus and theory from data. Therefore it is completely data-driven, while abductive approach allows the researcher to effectively match an appropriate theory to the data collected from the research during the data analysis process.

In the introduction chapter of the thesis it was stated that the study was carried out in two parts: the exploratory case study and the main study. The exploratory case study was a way of discovering ‘*what is happening; to seek new insights; to ask questions and to assess phenomena in a new light*’ (Robson, 2002, p59) and to get an extensive idea of UK HEIs’ view on Learning Analytics in the area of SEM. Due to the fact that no theoretical underpinning was chosen, data from that area of the research was investigated using only a data-driven approach. Using the results and data analysis of the exploratory case study along with an in-depth literature review, the most appropriate theoretical lens was chosen for supporting the remainder of the research. Since the theory was chosen subsequent to the data analysis in conjunction with the abductive approach used for the research, in Chapter 6 the framework development chapter information about the theoretical lens for the research is offered.

Using the theoretical lens for this research made the overall approach more malleable and allowed the improvement of the theoretical framework for examining the factors affecting the use and impact of Learning Analytics in UK HEIs. Table 4.2 shows the main differences between the deductive, inductive and abductive approaches in terms of logic, generalizability, use of data and theory (Saunders, 2012).

Table 4.2 The main differences between the deductive, inductive and abductive approaches

	Deductive	Inductive	Abductive
Logic	With deductive reasoning, when the premises are true, the conclusion must also be true.	With inductive reasoning, known premises are used to produce untested conclusions.	With abductive reasoning, known premises are used to produce testable conclusions.
Generalizability	Taking a broad view from the general to specific.	Taking a broad view the specific to the general.	Taking a broad view from the interactions between the specific and the general.
Use of data	Data collection is utilised to assess hypotheses in relation to an existing theory.	Data collection is utilised to discover a phenomenon, find themes and patterns and produce a conceptual framework.	Data collection is utilised to discover a phenomenon, find themes and patterns, locate these in a conceptual framework and test this through consequent data collection and so on.
Theory	Theory falsification or verification.	Theory generation and building.	Theory generation or modification; including existent theory where appropriate, to form new theory or change existent theory.

4.5 Unit of Analysis

The Unit of Analysis (UA) is the main level at which data is collected and forms the basis of any analysis. Several samples can be established as units of analysis but the most common are countries, families, groups, individuals and organisations (Easterby-Smith et al., 2012). There is usually a single unit of analysis in most research, but Easterby-Smith et al. (2012) argue that a study can have more than one unit of analysis if there is justification of theoretical aims.

There is one unit of analysis for this study, this being the HEIs. Data was gathered from senior and middle managers in UK HEIs. Senior and middle managers were used as a key part of the study to identify through the semi-structured interviews, what Learning Analytics systems the HEI uses, and the impact Learning Analytics has in the HEI that they work in.

4.6 Sampling Strategy

In qualitative research, Kvale (1996) argues that the focus should be on conducting thorough analysis of data, instead of large sample size. Therefore, the purpose of an exploratory study is for discoverability as opposed to statistical generalisability. According to Bryman (2012), sampling techniques are used to select an appropriate sample size for a wider study. There are several accepted techniques that can be used, such as random sampling, stratified sampling, snowball sampling, convenience sampling and probability sampling.

4.6.1 Purposive sampling

This study adopts the purposive sampling approach. With purposive sampling, the researcher has an exact idea of what sample units are required and then approaches possible sample members to examine whether they meet eligibility criteria. Those that do meet the criteria are used, while those that do not are rejected (Easterby-Smith et al., 2012).

4.6.2 Exploratory case study

Ten invitation emails were sent out to the participants for an interview along with an information sheet describing the research and seven responded to state their interest to be interviewed. The sample size therefore included 7 HEI managers. They came from different university departments including student services, IT, HR and planning.

Table 4.3 Classification of participants for the exploratory case study

No.	Pseudonym	Gender	Department
P1	Ellie	Female	HR
P2	Rachel	Female	HR
P3	Gareth	Male	IT
P4	Michael	Male	Library/student services
P5	Craig	Male	International Office
P6	Rory	Male	Planning
P7	Anthony	Male	Finance

4.6.3 Main study

In this second stage of the empirical investigation, a large round of interviews was undertaken with 30 interviewees working in 30 different UK HEIs. These interviewees were approached using purposive sampling. The eligibility criteria of the main study were: participants currently work at senior management level in a UK HEI, have knowledge of Learning Analytics and Big Data and the participant's role is related to student experience. They were selected from areas such as data analysis, information systems, IT, student management information, student services, planning, academic and research support, student experience, marketing, student recruitment and e-learning.

Table 4.4 Classification of participants for main study

No.	Pseudonym	Gender	Job title	Department
P1	Terry	Male	Pro-Vice-Chancellor of teaching and learning	Teaching and Learning
P2	Earl	Male	Student Engagement Manager	Student Engagement
P3	Hilda	Female	Director of student recruitment	Marketing, Communications and Student Recruitment
P4	Henry	Male	Director of Marketing, Admissions, Recruitment and Communications	Marketing, Admissions, Recruitment and Communications
P5	Phillip	Male	E-learning co-ordinator	Enhanced Learning
P6	Fred	Male	Head of Academic Support, Technology Innovation	Academic Support
P7	Bradley	Male	Director of Learning resources and service excellence	Learning Resources and service excellence
P8	Jim	Male	Director of Planning	Planning
P9	Mark	Male	Professor of Innovation and knowledge exchange	Continuing Education
P10	Gary	Male	Director of Student Experience	Student Experience
P11	James	Male	Interim Director of IT	IT
P12	Pauline	Female	Director of Strategic Planning	Strategic Planning
P13	Todd	Male	HE Data analyst	Data Analysis
P14	William	Male	Head of Student Management Information	Student Management
P15	Ian	Male	Emeritus Professor of Operations Management and Information Systems	Operations Management and Information Systems
P16	David	Male	Careers and Data Planning officer	Careers
P17	Susan	Female	Head of the student centre	Student services
P18	Amy	Female	Academic registrar	Academic Registry
P19	Carl	Male	Reader in Learning Analytics	Learning Analytics
P20	Sandy	Female	Planning Officer	Planning
P21	Julian	Male	Director of strategic Planning and analytics	Strategic Planning and analytics
P22	Kenneth	Male	Head of Planning strategy, planning and performance	Planning
P23	Lionel	Male	ICT manager	ICT
P24	Liam	Male	Programme leader for student experience	Student experience
P25	Patsy	Female	Head of Marketing	Marketing
P26	Greg	Male	Pro-Vice-Chancellor of student experience and international	Student Experience
P27	Nancy	Female	Pro-Vice-Chancellor of student experience	Student experience
P28	Otis	Male	Student engagement manager	Student engagement
P29	Jessica	Female	Head of service excellence, change leader	Service excellence
P30	Wendy	Female	Academic Head of Student engagement	Student engagement

4.6.4 Epistemological justification of sample

The reasoning behind only interviewing managers instead of students is that one of the challenges managers face, especially those in student services, is the increasing amount of data when it comes to managing students, processing information in relation to student data and making sense of the different applications of Learning Analytics available. Even though Learning Analytics should be seen as a solution to facilitate problems managers face, they currently lack understanding of where in the student lifecycle these analytics can be implemented or where generally to start from when using analytics.

4.7 Research Method – Qualitative Interviewing

Since this research uses the interpretivist approach, there are a variety of research methods that can be used by researchers: for example, case study, grounded theory, ethnography, action research and qualitative interviewing. Robson (2002, p178) describes a case study as '*a strategy for doing research which involves an empirical investigation of a particular contemporary phenomenon within its real life context using multiple sources of evidence*'. Silverman (2013) states that it can provide insight into the particular nature of any example and form the significance of culture and context in differences between cases. In terms of Grounded Theory (Glaser and Strauss, 1967), it is sometimes looked upon as the best example for the inductive approach whereby patterns are derived from the data as a requirement for the study (May, 2011). In grounded theory, data collection begins without any theoretical framework being formed. Theory is developed from data produced by a range of observations. This data may therefore lead to the generation of predictions that are then tested in further observation which may or may not confirm the predictions (Saunders, 2003).

Bryman (2012) states that it is often used in the area of social sciences. For ethnography, Bryman (2012) states that it involves the close observation of people, investigating their cultural interaction and their meaning. Ethnography is also predominantly an inductive approach. This research strategy however is very time-consuming and occurs over an extended period of time. In regards to this research process, the observer carries out the research from the point of view of the people being observed and tries to understand the differences of meaning and behaviours from their view. Action research on the other hand is seen as an everyday approach to a particular research problem within a community of practice (Bryman, 2012). According to Wiles et al. (2011), action research is commonly associated with professions such as teaching, where the specialist in that field can find ways in which they can enhance their professionalism and understanding.

After reviewing all these methods, the most appropriate is qualitative interviewing which is used for this study. Easterby-Smith et al. (2012) pinpoints circumstances in which qualitative interviewing is suitable to use:

- In situations where the researcher is required to recognise the constructs that participants use as a foundation for their views about a certain belief
- In situations where the researcher goes to improve their interpretation of the respondent's world so that they can have an effect on it in unison
- Where the reasoning behind a situation is vague, the focus of the study is very personal and the privacy of a one-to-one situation is needed for the interviewee to answer honestly.

Since the overall aim of this research is to explore the use and impact of Learning Analytics for SEM in UK HEIs, the most suitable method for this study as stated before is qualitative interviewing. The key aspects of qualitative interviewing that make it appropriate for this research are:

- The researcher is able to delve in to the participants' world which allows the interpretation of the topic from the views of the participants. This means, that it allows a comprehensive understanding of Learning Analytics from the view of UK HEIs in the area of SEM.
- The researcher is able to look into the reason behind participants adopting a certain view – so in this case, an in-depth understanding of the purpose of utilising Learning Analytics in UK HEIs.
- With qualitative interviewing, the researcher is given an insight in order to have an effect on the participants' world in unison – this allows the chance to acquire insights that are key to understanding the factors affecting the use and impact of Learning Analytics in UK HEIs in the area of SEM.

4.8 Data Collection Techniques

Data for both the main study and exploratory case study were gathered through interviews, with most of them being face-to-face interviews and some via Skype and telephone. In qualitative research, the main aim of interviewing is to gather information that is based on the meaning and understanding of a phenomenon in reference to the interviewee's point of view (Kvale, 1996). According to Kahn and Cannell (1957), an interview is a discussion of purpose between two or more people. Fontana and Frey (1994) also state that interviewing involves examining the interaction between people in order to understand our fellow human beings. Interviews are used to help collect reliable and valid data that are related to the research question(s) and objectives. They can also be used as a follow-up to further investigate responses from respondents in questionnaires (McNamara, 1999).

Interviews may be very formal and structured, where standardised questions are used for each respondent, or they can be unstructured and informal conversations (Saunders, 2003).

Interviewing can therefore be categorised as structured, unstructured and semi-structured; they are all described below:

4.8.1 Structured interviews

Structured interviews are when the interviewer follows a pre-set list of questions, each of which may have predetermined response categories (Easterby-Smith et al., 2012). The interview is conducted in a standardised manner and involves reading out each question and then recording the response, typically with pre-coded answers. However, this means that there is hardly any flexibility. In order not to show any bias, the questions are usually read out to the interviewee in the same tone of voice. Structured interviews are predominantly used for deductive purposes in order to examine a larger sample size. Market research is linked with structured interviews, so the type of interview would be a market research interview.

4.8.2 Unstructured interviews

Unstructured interviews give the opportunity for the interviewer to investigate deeply and reveal new insights (Easterby-Smith et al., 2012). These interviews are referred to as in-depth interviews as they are used to discover a general area of interest in depth. Unstructured interviews are also informal so compared to structured interviews they give flexibility to the interviewer and respondent due to their non-standardised nature.

Since the interviewee is given the chance to open up freely about beliefs, events and behaviours in connection with the topic area, this type of interaction can often be termed non-directive. According to Burgess (1982, p107), an in-depth interview '*is an opportunity for the researcher to uncover new clues, open up new dimensions of a problem and to secure vivid, accurate inclusive accounts that are based on personal experience*'. Unstructured interviews have also been labelled as informant interviews; ethnography is a type of unstructured interview.

4.8.3 Semi-structured interviews

A semi-structured interview is where the researcher has a list of questions and themes to go over but this may vary from one interview to another. (Kvale, 1996, pp5-6) defines a semi-structured interview as: '*An interview whose purpose is to obtain descriptions of the life world of the interviewee with respect to interpreting the meaning of the described phenomena.*' In semi-structured interviews the order of questions may vary based on the flow of conversation.

Due to the nature of events within certain organisations, in order to discover further insight into the research question and objectives additional questions may be needed. The nature of the questions in semi-structured interviews is usually open-ended, and because of this the data is recorded by note taking or using a tape recorder. According to Kadushin (1997), there is less restriction and more flexibility with semi-structured interviews because of the open-ended questions. Due to time constraints and the possibility of interruptions in the duration of the interview, managers are unlikely to commit to an unstructured (in-depth) interview. According to Saunders (2003), managers would rather be interviewed than complete a questionnaire, especially if the topic is relevant to their line of work or there is just a genuine interest.

Semi-structured interviews also give the opportunity for feedback and certain issues can be explored. Kadushin (1997) states that due to the highly structured and flexible nature of semi-structured interviews there is more freedom when developing the open-ended questions. The interviewee also has a sense of individuality as he or she has more control and there is freedom to communicate their ideas or perspectives. Semi-structured interviews may also produce new concepts that the interviewer may not originally have thought of.

According to Kvale (1996), semi-structured interviews are utilised to gain explanations of the world of the interviewee, and by doing this obtaining insight to importance of the defined phenomena. For the exploratory case study and main study semi-structured interviews were used as the method of data collection and also to go in depth into UK HEIs' views, practices and interpretations in the area of SEM and the factors that affect the use and impact of Learning Analytics in UK HEIs. These semi-structured interviews were carried out with a total of 30 participants and there were dialogues on these key areas: challenges that they face, the Learning Analytics tools they use, how they define SEM and the future of Learning Analytics.

4.9 Interview Process

Semi-structured interviews for this research took seven stages: thematising, designing, interviewing, transcribing, analysing, verifying and reporting (Kvale, 1996), as shown in Figure 4.2.

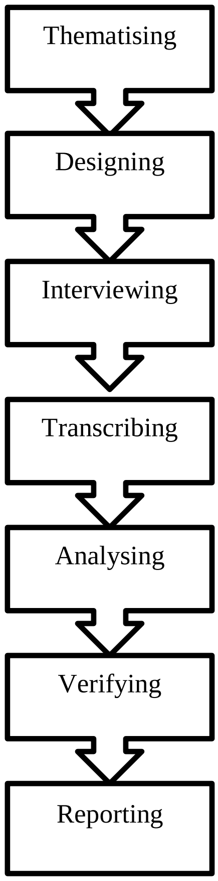

Figure 4.2 The 7-step interview process (adapted from Kvale (1996)

4.9.1 First stage: Thematising

Thematising involves framing the purpose of the research and defining the concept of the topic to be investigated before the interviews begin (Kvale, 1996). When planning the investigation at this stage, the *what* (**gaining prior knowledge of the subject matter to be explored**) and *why* (**explaining the purpose of the study**) should be formulated before the question of how (**determining the procedures of interviewing and investigating in order to gain the intended knowledge**) is posed.

4.9.2 Second stage: Designing

Preparing the design of the study involves taking all of the seven stages of the investigation into consideration before the interview begins; the reasoning behind designing the study is to gain the intended knowledge while taking into account the ethical implications of the study.

4.9.3 Third stage: interviewing

This stage involves carrying out the interviews centred on an interview guide and with an insightful approach to the knowledge required and the interpersonal relation of the interview situation (Kvale, 1996). It also involves deciding the duration of the interview as well as the recording equipment to use. According to Maloney and Paolisso (2001), digital recording is an effective replacement for cataloguing, storing and managing. All interviews were conducted at the workplace of the interviewee.

Planning of the interview procedure is important in order for the participants involved in the research to understand that they are valued for their taking part and contribution, the intention behind the research, that they should answer all questions presented to them and also be content with the confidentiality agreement.

4.9.4 Fourth stage: Transcribing:

Transcribing involves preparing the interview material for analysis, which usually comprises of a transcription from oral speech to written text (Kvale, 1996). Drisko (1997) argues that the level of transcription should match the level of analysis.

4.9.5 Fifth stage: Analysing

According to Kvale (1996), there are five steps of interview analysis: Meaning condensation, Meaning categorisation, Narrative structuring, Meaning interpretation and Generating meaning through ad hoc methods. The following steps by Kvale (1996) are described below:

1. Meaning condensation: involves a synopsis of the meanings stated by the participants into shorter formulations. Long statements are converted into shorter statements in which the main logic of what is stated is resaid in a few words. Therefore meaning condensation refers to the lessening of large interview texts into smaller, more concise formulations.

2. Meaning categorisation: This suggests that the interview is coded into categories. Lengthy statements are decreased to simple categories such as positive or negative, this shows occurrence and non-occurrence of a phenomenon or a sole number on a scale of 1 to 5, i.e. to specify the strength of a phenomenon. Therefore categorisation can decrease and structure huge amounts of text into a few tables and figures. The categories can be established ahead of time or they can arise ad hoc during the analysis; they may be obtained from theory or from an interviewee's dialect as well as their own idioms.

3. Narrative structuring: This involves the sequential and social organisation of text in order to bring out its meaning. It concentrates on the stories voiced during an interview and works out their structures and their plots. If there are no stories told unexpectedly, a narrative analysis may try to create a clear story out of the numerous happenings described in an interview.

4. Meaning interpretation: This goes further in terms of structuring of the apparent meanings of a text to profound and more or less speculative interpretations of the text.

Examples of meaning interpretation originate from humanities, i.e. a critic's understandings of a film or a play.

5. Generating meaning through ad hoc methods: This is an extensive method. A number of common sense methods to the interview text, also refined textual or quantitative approaches, can be utilised to bring out the implications of different parts of the material. The outcome of this meaning generation can be used to bring out meanings of different sections of the material. The result of this meaning generation can be in words, figures, flow charts and in their combinations.

4.9.6 Sixth stage: Verifying

This stage establishes the reliability and validity of the interview findings. In terms of reliability this means how consistent the results are, whereas validity refers to whether an interview study examines what is proposed to be investigated (Kvale, 1996).

4.9.7 Seventh stage: Reporting

This stage involves presenting the findings of the study and practices applied in a form that lives up to scientific standards (Kvale, 1996).

4.10 Interview Process for this Research

4.10.1 First stage: Thematising

The semi-structured interviews from the exploratory case study provide knowledge for the main study. The semi-structured interviews for the main study are used to gain deeper insight into HEI managers' challenges and their information needs in the era of Big Data and Learning Analytics and explore the use and impact of Learning Analytics.

Table 4.5 shows the use of thematic research areas to form the interview questions for the main study. These areas were used to help enhance the conversational flow of the interviews.

To make sure that managers understood the questions properly, the open-ended questions used for the interview were worded carefully. The rest of the interview questions can be found in (Appendix 7).

Table 4.5 Thematic research areas and Interview questions

Thematic research areas	Interview questions
Challenges	"What are the challenges in managing student experience?"
Use of Learning Analytics tools	"How is your institute using Learning Analytics?"
Factors	"What are the factors affecting the Learning Analytics use and impact on SEM?"

Also, part of thematising involves examining the literature on Learning Analytics and SEM which brought about the research gaps which are emphasised in the literature review chapter. Chapter 3 also enabled the creation of objectives for this research.

4.10.2 Second stage: Designing

The second stage involved 30 semi-structured interviews with middle and senior managers across different UK HEIs. To address the moral implications of the study, informed consent was gained from all participants with signed consent forms and the participants were made aware of the nature and scope of the research.

The semi-structured interviews in the main study aimed to address the following general topics with the managers:

1. Challenges managers faced in the HE sector with Learning Analytics

2. The use and impact of Learning Analytics on SEM.

The first discussion topic above served as thematic research area to meet the following objective of the main study:

- To understand the challenges in utilising data effectively for SEM in the era of Big Data and Learning Analytics

The second discussion topic served to meet the expected outcome of the following objective of the main study:

- To identify the key factors affecting the use and impact of Learning Analytics

4.10.3 Third stage: Interviewing

For the main study, some interviews were 30 minutes, others ranged from 1 to 2 hours. The limitation of using an iPhone is that without a microphone attached to the iPhone, the audio recording can be of low quality. This is why for the main study a digital recorder was used because it reduces the risk of loss of data, for noise reduction and more accurate transcription.

Planning of the interview procedure is important in order for the participants involved in the research to understand that they are valued for their taking part and contribution, the intention behind the research, that they should answer all questions presented to them and also be content with the confidentiality agreement.

The interview procedures for this research are summarised below:

1. Thanked the participant for taking time out for the interview
2. Read the information sheet about the research background if they had not read the one attached to the email
3. Gave the participant a consent form to sign
4. Explained what the research was for and what would happen to the data collected

5. Even though it is stated in the consent form, it was asked again whether they were comfortable with the recording taking place on the iPhone / digital recorder
6. Start out with reading definitions of complex terms in the area of Learning Analytics and SEM
7. Read out interview questions to participants
8. Asked if there is anything they wanted to add in addition to what they have specified in the interview
9. Thank the participant for their time.

4.10.4 Fourth stage: Transcribing

The semi-structured interviews were fully transcribed in a verbatim account in MS Word. The interview transcripts for both studies (Appendix 10 sample interview transcript for the main study) were typed in MS Word and then saved in Rich Text Format (.rtf). They were then transferred to the Computer Assisted Qualitative Data Analysis (CAQDAS) NVivo for analysis. Patterns and meanings at this stage that were important were written down which served as a foundation for developing themes and subthemes through the data analysis.

4.10.5 Fifth stage: Analysing

Kvale (1996) states that how the analytic approaches are chosen depends on the thematic question specified at the thematising stage and then followed through to designing, interviewing and then transcribing. In this research, the analysis involved being familiar with the data first, then reading the interview transcripts in depth several times, quotations that were significant and appropriate for the research were highlighted and the TQA steps used by Braun and Clarke (2006) were conducted.

4.10.6 Sixth stage: Verifying

To ensure the research is valid, respondent validation was carried out. Respondent validation refers to when a researcher offers respondents of the study with an interpretation of his/her findings in order to verify or contest the researcher's account of the contact he/she has arrived at (Bryman and Bell, 2015). In order to do this, copies of the transcripts were sent to all interview participants to ensure that everything stated in the transcript was accurate and to their satisfaction.

For reliability, an inter-rater reliability test was undertaken (Appendix 8); this is usually carried out in quantitative research and is described as the degree to which raters either agree or disagree on the interpretation offered to the evidence they are given (Voss et al., 2002). Raters came back with an average of 76.6 percent agreement on the understandings of the data and how well suited they were to the assigned themes.

4.10.5 Seventh stage: Reporting

This stage takes the moral characteristics of the investigation into consideration and the outcome is a readable product.

4.11 Data Analysis – Thematic Qualitative Analysis

4.11.1 The process and techniques of TQA

This section explains the process of the data analysis techniques used for data analysis. TQA proposes an available and theoretically flexible method to analysing qualitative data. According to Holloway and Todres (2003), qualitative approaches are varied and complicated; therefore thematic analysis is offered as the basis for qualitative analysis. TQA delivers key skills that are beneficial for carrying out various forms of qualitative analysis. Boyatzis (1998) describes it not as a specific approach but as a tool to utilise across varied methods.

Braun and Clarke (2006, p6) state that thematic analysis can be defined as '*a method for identifying, analysing, and reporting patterns (themes) within data. It minimally organises and describes your data set in (rich) detail*'. In the same vein, Boyatzis (1998) argues that the definition of thematic analysis is more advanced than this and it deduces several areas of the research topic. Braun and Clarke (2006) go on to state that thematic analysis should be seen as a method in its own right. There are many advantages of thematic analysis, one of them being flexibility. The reason why thematic analysis is flexible is that it lets the researcher define themes in various ways; a vital factor is being consistent in how the researcher carries this out within any specific analysis. Qualitative analytic approaches can be approximately split into two areas. One area is those that stem from a certain theoretical or epistemological position (Braun and Clarke, 2006). The second area are the approaches that are fundamentally independent of theory and epistemology and can be put across a variety of theoretical and epistemological approaches (Braun and Clarke, 2006).

Often thematic analysis is indirectly outlined as a realist/experiential method (for example, Aronson (1994) and Roulston (2001). Thematic analysis is firmly situated in the second area and is attuned with the essentialist and interpretivist paradigms. Along with being flexible, thematic analysis serves as a useful research tool, which can offer a rich and comprehensive, yet intricate account of data. Thematic analysis is different from other analytical methods that try to find patterns across qualitative data, for example, thematic discourse analysis, thematic decomposition analysis and interpretative phenomenological analysis (IPA). According to Wilkinson (2000), content analysis is seen as another approach that can be utilised to classify patterns in qualitative data and is often treated the same as other thematic approaches.

Content analysis, however, is concentrated more at a micro-level, often delivers counts (Wilkinson, 2000) and allows the quantitative analysis of data that was originally qualitative. Thematic analysis is different from content analysis in the sense that the themes are not likely to be quantified (however sometimes they may be). Boyatzis (1998) proposes that thematic analysis can be used to convert qualitative data into a quantitative method. With thematic analysis, the unit of analysis is often more than a word or a phrase, which it normally is in content analysis. In reference to IPA, this approach seeks patterns in the data but is restricted in terms of theory. On the other hand, thematic discourse analysis is used to refer to a wide scope of pattern-type analysis of data, going from thematic analysis within a social constructionist epistemology (Braun and Clarke, 2006).

According to Stenner (1993), thematic decomposition analysis is a type of thematic discourse analysis which classifies themes within data and puts forward language as constitutive of meaning. These various methods correspond with thematic analysis; however, thematic analysis does not need the comprehensive and technical knowledge of methods such as Discourse Analysis (DA). Also, compared to methods such as IPA, narrative, discourse or content analysis, thematic analysis is not joined to any previous theoretical framework, therefore it can be utilised within different theoretical frameworks (but not all) (Braun and Clarke, 2006). In terms of research philosophy, thematic analysis can be an essentialist or realist approach or it can be a constructionist (interpretivist) approach which looks at the way events, meanings, experiences etc. are the effects of a variety of discourses working in society.

In reference to the constructionist viewpoint, Vivien (1995) states that importance and knowledge are socially produced instead of inhering inside individuals. So this means that thematic analysis that is carried out within a constructionist framework cannot strive to concentrate on motivation or individual psychologies but rather strives to put forward socio-cultural contexts and structural conditions (Braun and Clarke, 2006). Latent thematic analysis according to Braun and Clarke (2006, p13) refers to the '*examination of underlying ideas, assumptions and conceptualisations and ideologies- that are theorised as shaping or* *informing the semantic content of the data*'. If latent themes are focused on in the thematic analysis then it is likely to be more constructionist and overlaps with thematic discourse analysis. The constructionist approach is not always associated with latent thematic analysis.

4.11.2 Key terms of TQA

4.11.2.1 Data corpus

This refers to '*all data collected for a particular research project*' (Braun and Clarke, 2006, p5). The data corpus for this study is the semi-structured interviews conducted with a sample of key stakeholders (senior and middle managers) in HEIs.

4.11.2.2 Data set

The data set is *'all the data from the corpus that is being used for a particular analysis*' (Braun and Clarke, 2006, pp5-6) For this study the data set is the data collected from the semi-structured interviews.

4.11.2.3 Data item

The data item is '*used to refer to each individual piece of data collected, which together make up the data corpus or data set*' (Braun and Clarke, 2006, p6), so each individual interview in the context of this study: 30 semi-structured interviews and seven semi-structured interviews from the exploratory case study.

4.11.2.4 Data extract

This refers to "*an individual coded chunk of data which has been identified within and extracted from a data item.*"(Braun and Clarke, 2006, p6) In terms of this study, this refers to quotes from the interview transcripts that are present in the data analysis.

4.12 Time Horizons for this Study

Time horizon refers to the time frame which it would take to complete the research project. According to Bryman (2012), there are two types of time horizons: cross-sectional and longitudinal studies. With the cross-sectional time horizon, the time frame in which the data need to be collected is specified, whereas the longitudinal time horizon refers to the data collected over a long period of time and is an important factor when, for example, the particular research field observes changes over time (Goddard and Melville, 2004).

Since data are collected at a certain point and this research is associated with the study of a particular phenomenon (Learning Analytics and Big Data in the area of SEM) at a certain time, the time horizon is cross-sectional. This research was also carried out as a cross-sectional study as it demonstrates a ‘snapshot’ of how HEIs enhance student experience and the factors that affect the use and impact of Learning Analytics at a certain point in time. Another reason why making this study cross-sectional is appropriate is due to the length of the PhD study as well as finance constraints. The exploratory case study was carried out over a four-month period from April 2014 to July 2014 and the main study lasted ten months from June 2015 to March 2016.

4.13 Research Ethics

Since Big Data is considered as a research priority, the importance of ethical guidelines is vital. This research follows the ethical guidelines of Bell and Bryman (2007). Before the data collection for the exploratory study, approval was received from the University of Bedfordshire Research Ethics Committee by submission of the Research Ethics Scrutiny form along with the RS1 (the original examination before PP1). Data collection for the main study was not carried out until the Progression Point 2 (PP2) was passed.

4.13.1 Informed consent

According to Kvale (1996), informed consent involves notifying the participants about the overall purpose of the study and the key characteristics of the design as well as any likely risks and advantages from participating in the study. Informed consent also entails gaining the voluntary participation of the interviewee; the interviewee also has the right to pull out from the study at any time, thereby countering possible unnecessary influence and pressure. Problems about consent may come up in interviews with organisations '*where a superior's consent to a study may imply a more or less subtle pressure on employees to participate*' (Kvale, 1996, pp112-113). Informed consent also includes the question: how much information should be provided and when.

Other ethical questions at the start of an interview in relation to informed consent are (Kvale, 1996):

1. Should informed consent be decided upon orally or should there be a contract which is written?
2. Out of the participants or their superiors – who should give the consent?
3. How much information about the research is required to be given ahead of time, and what information can wait till questioning after the interview has taken place?
4. How can informed consent be handled in exploratory studies where the researchers themselves will have only a bit of prior knowledge of how the interviews will progress?

So for this study to obtain consent from the individuals participating in the study a consent form was provided as seen in Appendix 9

4.13.2 Anonymity

Anonymity was observed by ensuring that personal details were not used that can identify the individual, for example, name and gender in the interview transcripts.

4.13.3 Privacy and confidentiality

In terms of confidentiality, Kvale (1996) states that it suggests private data classifying the participants will not be reported. He also argues that if research includes publishing information possibly identifiable to others, the participants are required to decide the release of identifiable information. If this was to happen, it should be specified clearly in a written agreement. With the reporting of interviews, the protection of participants' privacy by changing their names and classifying features is a significant issue.

Ethical questions at the start of an interview in relation to confidentiality are (Kvale, 1996):

1. How can the confidentiality of the interview participants be protected?
2. How important is it that the participants remain anonymous?
3. Who will the interviews be available to?
4. How can the identity of the participants be hidden?
5. Will there be any legal problems around the protection of the participants' anonymity?
6. Will any potential harm to the participants balance out with the potential advantages?
7. Will the interviews cover therapeutic problems, if so what precautions can be taken?
8. When publishing the research, what consequences can be expected for the participants and for the groups they signify?

The privacy of the research subjects were protected by not delving into areas that were deemed sensitive and sticking solely to the purpose of the research. Confidentiality was observed by ensuring that the information used in the exploratory study was not passed on to any other parties and will be used solely for research purposes. Personal data stored on a PC or laptop was password protected. Any confidential paperwork was stored in secure drawers. The use of USBs was limited to non-confidential information.

4.13.4 Deception

Deception of the nature and aim of the research was avoided by ensuring that the participants were fully aware of the study they were partaking in, which is why an information sheet was provided. When communicating to the participants about the research, this was done with full honesty and transparency and also any false reporting of research findings was avoided.

4.13.5 Ethical issues of the seven research stages

4.13.5.1 Thematising

'*The purpose of an interview study should be beyond the scientific value of the knowledge sought, also be considered with regard to improvement of the human situation being investigated*' (Kvale, 1996, p111).

4.13.5.2 Designing

With designing, the ethical issues are about obtaining informed consent from the participants taking place in the study also acquiring confidentiality, and also bearing in mind the likely consequences of the study for the participants.

4.13.5.3 Interview situation

With interviewing, the confidentiality of the participants' reports needs to be explained and also the concerns of the interview interaction for the participants is required to be taken into consideration, for example, stress during the interview.

4.13.5.4 Transcription

The issue of confidentiality crops up again in transcription, also '*the question of what is a loyal written transcription of a participant's oral statements*' (Kvale, 1996, p111).

4.13.5.5 Analysis

With analysis, the ethical issues question how critically the interviews can be examined and whether the participants should have a say in how their transcripts are written out deduced.

4.13.5.6 Verification

This is important for the researcher as their ethical responsibility to convey knowledge that is as safe and verified as possible.

4.13.5.7 Reporting

The problem associated with confidentiality crops up again when it comes to reporting interviews, also '*the question of consequences of the published report for the interviewees as well as for the group or institution they present*' (Kvale, 1996).

4.14 Risk Assessment

Since the majority of the semi-structured interviews were face to face, many possible risks were considered and are stated below:

- The participant could get upset at any time during the interview and become aggressive towards the researcher.
- The interviewee being upset at an interview could lead to them suffering psychological effects.
- There is a possibility the researcher may be exposed to data or information which may cause distress.

These are the precautions that would be taken to minimise risk if one occurs:

- Addressing the first point, contact will be made with participants via the researcher's university email address; location of the interviews will be in a safe environment – in regards to this research that will be the university buildings. Supervisors will be aware of where the interview is to take place and telephoned only in case of emergency.
- For the second point, the interview will be stopped and a later date is rescheduled with the participant if feasible.
- Finally, for the third point, ask the university what support will be available before conducting the interviews.

4.15 Summary of the Research Process

Figure 4.3 presents the research process of this study. It began with finding the research aim and objectives, then the literature review in order to discover the research gaps and to find out about the current debate, an exploratory case study in order to determine the study's practicability, then the research focus is identified for the main study, the main study is then carried out, development of the theoretical framework of the factors affecting the use and impact of Learning Analytics for UK HEIs, then finally, the writing up of the thesis.

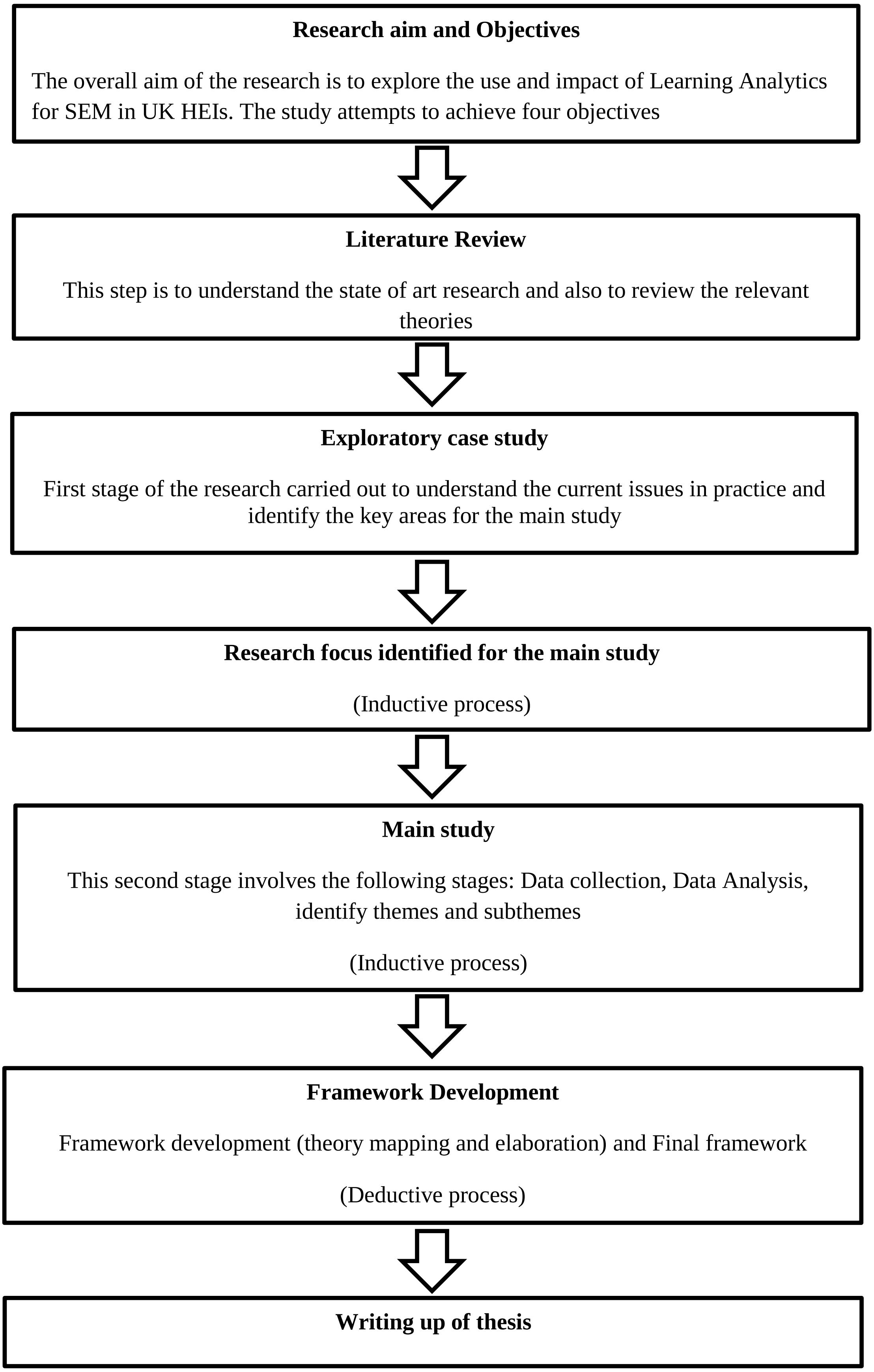

Figure 4.3 Research Process

4.15.1 Research aim and objectives

These are the general intentions of the research and give an overall depiction of the research project. The aim (overall purpose of the study) is also clearly and concisely defined.

4.15.2 Literature review

This stage entailed reviewing existing literature on the area of information systems (IS) research and sheds light on the current discussion of Learning Analytics in UK HEIs in the area of SEM. It also involved the reviewing of several theories including TOE and ACAP and potential theories to be considered.

4.15.3 Exploratory case study

This research was carried out in two parts – an exploratory case study and a main study. The exploratory case study involved seven semi-structured interviews with managers in a UK HEI. The purpose of this first phase was to gain a rich understanding of the current situation regarding how and why Learning Analytics is used and its impact on SEM from the managers' views in the context of Big Data within this UK HEI. The exploratory study is used to inform the research further. TOE and ACAP are confirmed as most the suitable theories.

4.15.4 Research focus identified for the main study

This is an inductive process, therefore using the aim and objectives to narrow down the research topic.

4.15.5 Main study (inductive process)

This second part of the research, the main study, involves the semi-structured interviews. The interview guide (Appendix 7) was reviewed according to the outcomes of the exploratory case study. Thirty semi-structured interviews were conducted with participants from different UK HEIs. With the data analysis, using the Braun and Clarke (2006) inductive, bottom-up

Thematic Qualitative Analysis (TQA) process, the findings of the study were analysed with the help of NVivo 11. With TQA the themes are obtained solely from the data without the restrictions of a predetermined theory. The theoretical framework was developed using this process of the factors affecting the use and impact of Learning Analytics in UK HEIs constructed using data-driven themes obtained from the analysis.

4.15.6 Framework development (deductive process)

In terms of the framework development of the study, a theoretical framework was developed on the factors affecting the use Learning Analytics and its impact on student experience management in UK HEIs. How the theoretical framework was developed and information about the final framework is given in Chapter 6. This is a deductive process. In this stage the themes derived from the data analysis are mapped out and a theoretical framework is created using the relevant theories.

4.15.7 Writing up of the thesis

This is the final part of the research. How the research findings are linked to the theoretical framework and how the research aim and objectives were achieved are written up as well as the research’s contributions to knowledge, theory and practice as well as limitations and future research.

Chapter 5: Data Analysis

5.0 Overview

This chapter first explains the data analysis processes and the thematic content analysis techniques used for this study. It then analyses and presents the findings of the exploratory case study and the main study.

5.1 Data Analysis Process

This research follows the thematic analysis process (see Chapter 4, section 4.11) suggested by Braun and Clarke (2006). Braun and Clarke (2006) when describing thematic analysis pinpointed two methods to categorising themes and patterns within the data; they are the inductive approach and the theoretical approach. In terms of the inductive approach, it is a bottom-up approach in which the themes identified are associated with the data. The reason why data is gathered is for the purpose of research and resultant themes are not driven by previous theoretical assumptions. The inductive approach is basically data-driven; therefore data is coded without trying to place it within a pre-existing coding frame. On the other hand the theoretical approach in terms of the analysis is driven by the person who is conducting the research and their analytical and theoretical interest in the topic area. In comparison to the inductive approach, this method typically creates a description of the data which is not as rich but a more in-depth explanation of particular parts of the data (Braun and Clarke, 2006). As discussed in Chapter 4, the data analysis process of this study firstly follows an inductive data analysis approach. As shown in Figure 5.1, the data analysis is an eight-step process that supports the inductive data-driven approach used for this study.

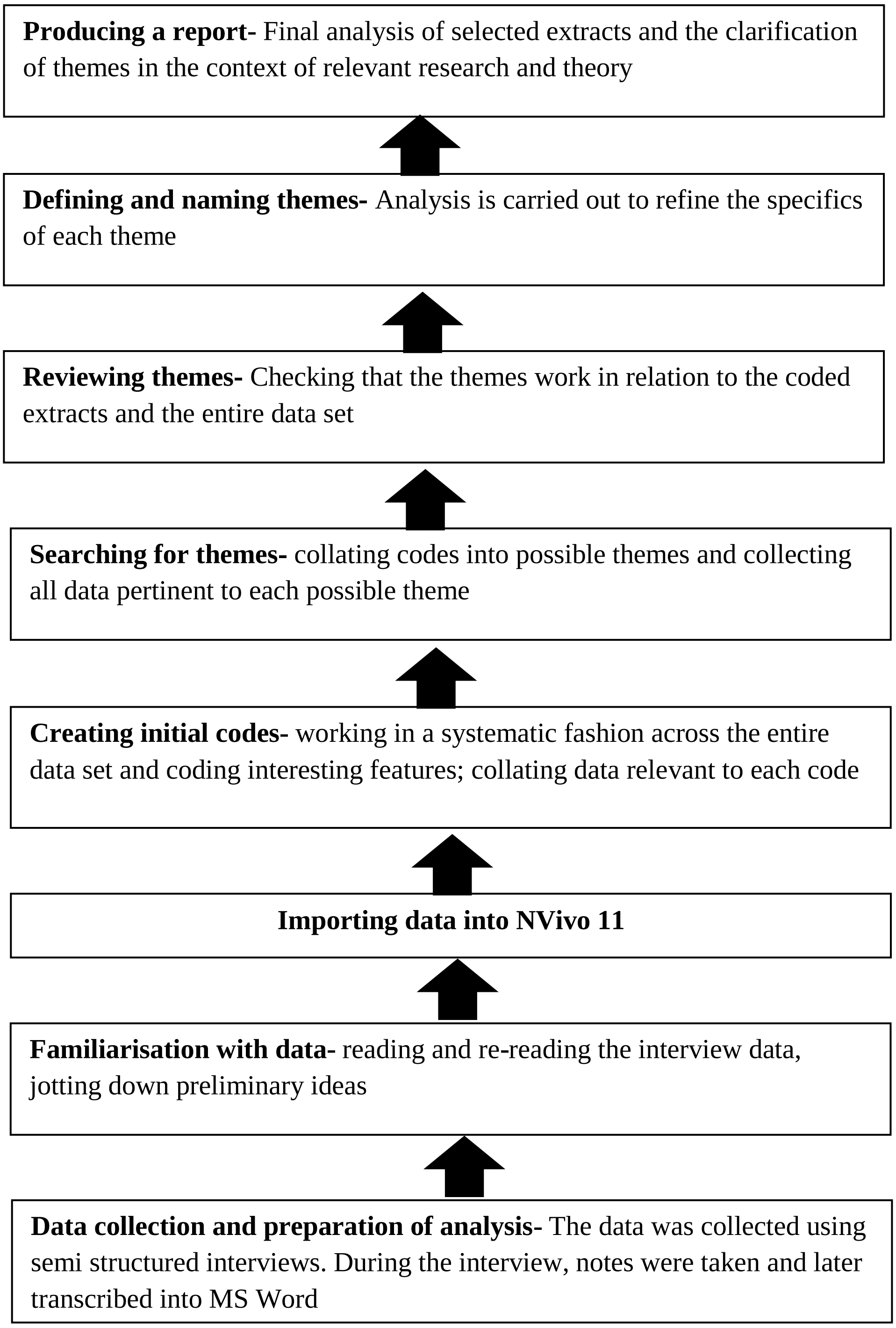

Figure 5.1 Eight-step process using the inductive data-driven approach (adapted from (Braun and Clarke, 2006)

5.1.1 Data collection

In the research methodology chapter (Chapter 4) the details of how the data collection was carried out are included. As mentioned in that chapter, data for this research was collected via semi-structured individual interviews. Seven semi-structured interviews were carried out in the exploratory case study and the main study involved data collection using semi-structured interviews with 30 participants in different UK HEIs. All interviewees were based in the UK.

5.1.2 Data analysis preparation

All of the interview data were transcribed verbatim in order to gain a better perspective on how participants viewed the use and impact of Learning Analytics. Interview keynotes were made during the transcription process to engage with the data and gain further understanding about the data. Also, during the course of the analysis, important points that developed were noted down for exploration purposes.

5.1.3 Familiarisation with the data

This step entailed going through and occasionally reading and re-reading the data and making additional notes on the concepts and patterns that materialised from the data. In order for the researcher to become sufficiently familiar with the data, the familiarisation process was carried out recurrently. The keynotes jotted down during this stage were used to generate the initial codes further ahead in the process.

5.1.4 Import into NVivo 11

The use of Computer Aided Qualitative Data Analysis Software (CAQDAS) can help perform useful functions during qualitative analysis, for example data, management and coding and retrieval (Saunders, 2003). Weitzman (2000) also argues that the quality of qualitative research can be improved by CAQDAS due to its reliability, and the facilitation of rigour and transparency involved in the analytic process.

However, CAQDAS does raise the fear of mechanistic analysis, making it more similar to quantitative or ‘positivist’ approaches (Dey, 2003, Bazeley and Jackson, 2013). Kelle (2000) also raised the assumption that CAQDAS programs were written to support grounded theory methodology; otherwise even worse, generate their own approach to analysis. Weitzman

(2000) gave these packages as examples of code-based theory builders: AFTER, AnSWR, AQUAD, ATLAS.ti, Code-A-Text, HyperRESEARCH, NUD●IST, NVivo, QCA, the Ethnograph, and winMAX. Barry (1998) states that NVivo and ATLAS.ti are seen as the most commonly used Qualitative Data Analysis (QDA) software packages.

Richards (1998) argues that qualitative software was created on the notion that researchers required both closeness and distance, so in summary, closeness for knowledge of the data but distance for synthesising data. Weitzman and Miles (1995) referred to QSR (a qualitative research software developer) software as one of the high standard qualitative software packages used worldwide. Richards and Richards (1994) were the developers of this software. The two key QSR software packages are NUD*IST and NVivo. NVivo was employed for the qualitative interview data analysis.

NVivo is used during the analysis of qualitative data through the management of ideas; theoretical and conceptual knowledge generated in this research can also be organised and easily accessed. More importantly, transcripts can be imported in .rtf format and presented in many fonts, colours and styles (Richards, 2002). NVivo 11 was used to facilitate the analysis for this research.

At this stage, the Thematic Qualitative Analysis TQA was carried out by the CAQDAS program NVivo. According to Banner and Albarrran (2008), CAQDAS, also known as Qualitative Data Analysis (QDA) software, is useful in helping with organising, managing and analysing information. The interview transcripts were imported into NVivo 10 for the exploratory case study and NVivo 11 for the main study. Figures 5.2, 5.3 and 5.4 demonstrate data being imported into NVivo 10 for the exploratory case study and NVivo 11 for the main study, respectively.

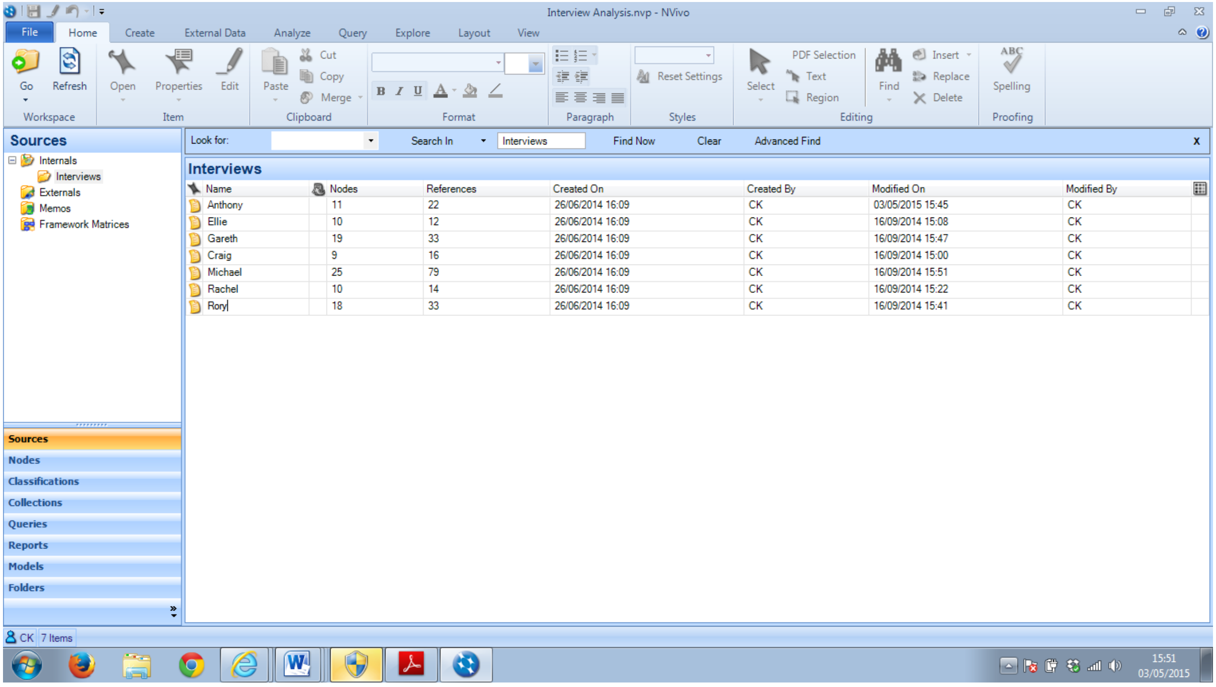

Figure 5.2 Screenshot showing transcripts from exploratory case study imported into NVivo 10

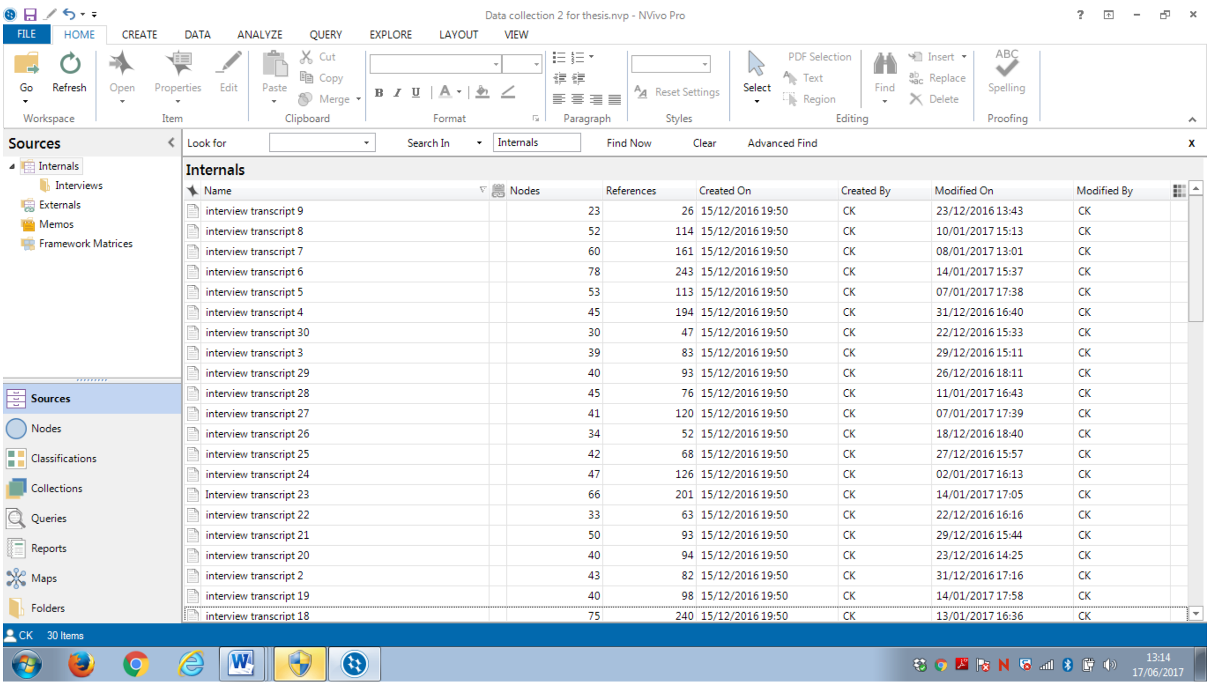

Figure 5.3 Screenshot showing transcripts from main study imported into NVivo 11

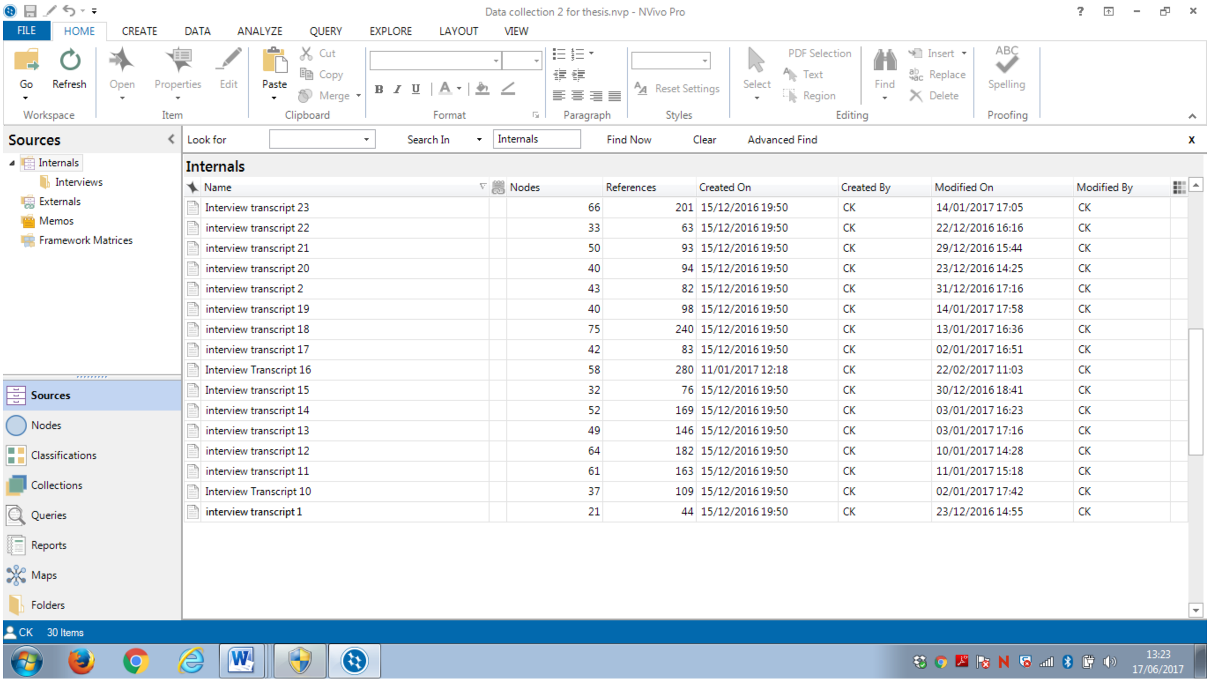

Figure 5.4 Screenshot showing transcripts from main study imported into NVivo 11 (continued)

5.1.5 Creating initial codes

The next stage after familiarising the data, making interview keynotes and identifying the patterns in the data, is to create an initial set of codes from this data. Codes are a useful way of linking the interview data to the researcher's idea of the data. According to Boyatzis (1998), codes are the most basic element of the raw data that is accessible in a significant way in regards to the phenomenon. Braun and Clarke (2006) also state that coding entails recognising parts of the data that seem important and categorising them into groups which are significant. There are two types of approaches that can be adopted in terms of the codes; they can be either theory-driven (theoretical approach) or data-driven (inductive approach). With the inductive approach, themes generated from the data are established on the data, but Braun and Clarke (2006) suggest with the theoretical approach, the themes might be created based on particular questions which the researcher is interested in answering. Braun and Clarke (2006) stress the significance of ensuring full attention is being paid to each data item; this then identifies fascinating features inside the data items, which in turn might form repetitive patterns or themes across the set. They suggest that it is important to work methodically through the whole data set.

Braun and Clarke (2006) also indicate that parts of the data that appear to stray away from the main story being expressed should not be disregarded. In this research the inductive approach is utilised to recognise themes and patterns; therefore the codes created were primarily data-driven. Figure 5.5 shows examples of the initial codes from the main study, created using NVivo.

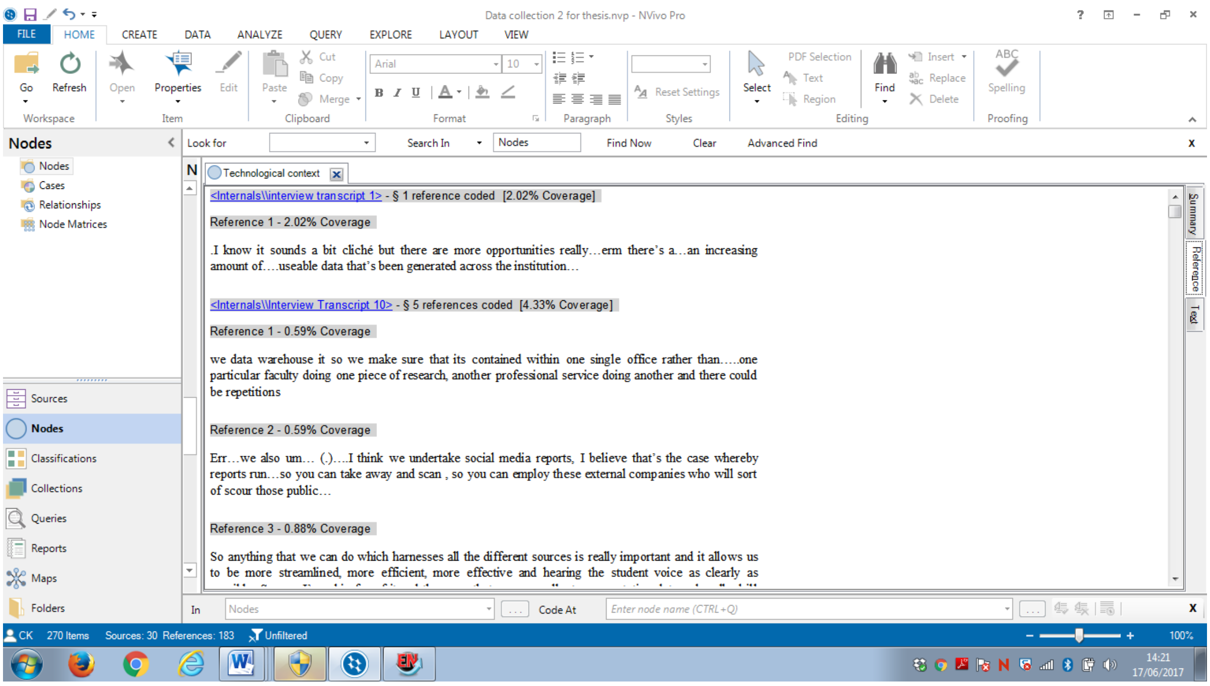

Figure 5.5 Data extracts from the main study coded for participants' contributions to technological factors that affect the use and impact of Learning Analytics

5.1.6 Searching for themes

Braun and Clarke (2006) define themes as patterns recognised inside the data set that capture significant areas linked to the research questions. Themes are established based on the codes found in the transcripts or interview keynotes and offer a foundation for a theoretical understanding of the data. According to Bryman (2012), this helps the researcher make a theoretical contribution to knowledge in terms of the literature and is linked to the research focus. This stage involves organising the different codes into possible themes and assembling all the important coded extracts into the recognised themes. Braun and Clarke (2006) also suggest that nothing should be rejected at this stage (as mentioned in the previous stage), not even the codes that do not seem to be categorised into any particular theme, and these can be labelled momentarily as mixed codes.

In this research, initial broad themes are identified and are portrayed in the NVivo 11 screenshot in Figure 5.6.

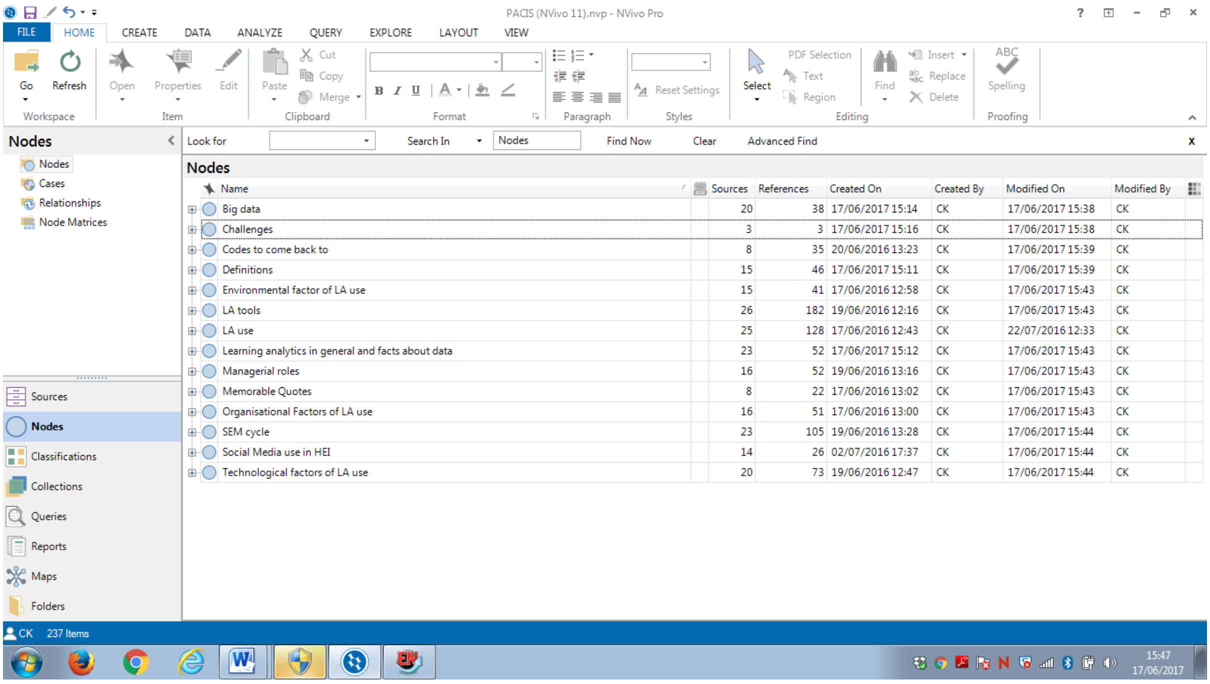

Figure 5.6 NVivo screenshot of initial broad themes identified from the data

5.1.7 Reviewing themes

In this step, themes generated in the prior stage are developed further. This process could entail joining similar themes together, sorting out themes into multiple themes or leaving the theme altogether if there is inadequate data to support a theme. According to Braun and Clarke (2006), it is important that the data within the themes join together and there should be strong and recognisable differences between themes. There are two stages of reviewing that take place here: reviewing of the whole data set as well as reviewing at the level of extracts which are coded. With the extracts that are coded, each data extract is joined together for each theme is looked over to make sure that a clear pattern emerges, after this stage has occurred then the review of the whole data set can take place. This review entails viewing the validity of each individual theme in regards to the entire data set and if they successfully replicated, the meanings apparent in the whole data set. In order to ensure that the themes created work for the entire data set, the whole data set should be re-read at this step.

In this research the codes were developed further as well as re-read in terms of how they worked with the overall themes and where required, data extracts for the diverse themes were joined together, defined again, separated or removed to make sure the themes made a clear pattern.

5.1.8 Defining and naming themes

At this stage, the themes are developed further and defined again along with further analysis carried out with the data. This encompasses understanding in depth what the theme is about and checking what areas of the data it captures. Also at this stage, the researcher is required to go through each group of collected extracts for each individual theme to confirm whether they form a clear account. Additionally, it is important is to find out is what is exciting and new about each data extract offered and why it is interesting to offer an analysis of each individual theme. The reason for partaking in that activity is in order for the researcher to recognise how each individual theme works within the entire story told by the data in regards to the research questions and to make sure that the themes do not overlap very much. There is also a requirement for the names of the themes to be altered to something succinct in order for the themes to indicate what they are about.

5.1.9 Producing a report

This stage involves writing up the report along with the final analysis. The purpose of this is to create a story with the analysed data in order to prove to the reader that the data are valid and that the analysis is of a good quality. According to Braun and Clarke (2006), data extracts from the data set should be shown that validate the themes found within the data and should be written in a succinct, logical, concise, non-repetitive and exciting manner.

The preliminary findings from this study are described in the next section, titled ‘An Exploratory Case Study’.

The themes created from the data were explained further and defined in order to recognise their areas of significance and the reason for their significance. The next step involved grouping them into broad themes and subthemes where possible.

The next two sections of this chapter provide an insight into the data analysis and provide the results of the exploratory case study and the main study.

5.2 An Exploratory Case Study

In order to gain insights into the current situation regarding the use and impact of Learning Analytics in one UK HEI, an exploratory case study was carried out.

The exploratory case study aims:

1. To understand the current situation of Big Data and Learning Analytics and their use in student management.
2. To investigate factors that may affect the effective use of Learning Analytics for SEM.

3. To guide the main study data collection by identifying the areas to be focused on in the main study.

A UK HEI was selected for the exploratory case study. The reason for this UK university being examined for an exploratory case study is twofold: one is their involvement in enhancing the student experience using Big Data and Analytics, and another is for the researcher's ease of access to the case.

5.2.1 The case study background

The case study HEI, named 'Post 1992', is one of the newer universities in the UK with a culture of high quality education. The institution provides students with support in areas such as study skills and career and job-seeking guidance and also has outstanding facilities across all of their subject areas. Five years ago, Post 1992 established an ICT project for monitoring student engagement. This involved examining the identification of student engagement patterns, giving them to academic tutors as well as to student engagement monitors with a traffic light system. This university is currently utilising Learning Analytics as a way to improve student experience; this is mainly being driven by the HEI's senior management team. The Deputy Vice-Chancellor Academic is particularly interested to find out if analytics can be used to further understand the student experience.

Also, there is a proposal to develop an approach to deliver BI across the university and that will include different types of analytics. On top of that a student engagement management project is being financed, with the Academic Registry and IT taking an important role in its implementation. The data being collected at the moment include: library visits as well as library use (items borrowed), class attendance and using Radio Frequency Identification (RFID) devices in student ID cards to monitor campus presence, the VLE through Blackboard, the use of the Student Information Desk (SiD), e-Vision used to register a student's personal information and exam results, and also assignment submissions and meeting attendance.

In terms of the analytics systems being used, this university uses interactive business intelligence as well as an Oracle data warehouse. The student engagement dashboard used by the university currently was developed by a third-party warehouse and also through working with the university registry and IT department. Post 1992 is still looking to improve the current student engagement systems by integrating various reporting tools using Excel, SharePoint, Oracle and Report Builder.

5.2.2 Why an exploratory case study?

An exploratory case study is used to obtain insights from a selection of key stakeholders in a UK HEI. The purpose of the exploratory case study is to gain a rich insight into the current status of how and why Learning Analytics is used along with its impact on SEM from the manager's perspective in the context of Big Data within this UK HEI. The sample for the exploratory case study encompassed seven managers from all over the UK and data was collected through semi-structured interviews. The interviews ranged from half an hour to an hour, with all seven being conducted face to face. The seven participants in this study are a mixture of directors, senior managers and middle managers. Content analysis software, NVivo, is used for qualitative data analysis. TQA is conducted with the interview data to identify the key themes. The following section presents the key findings of the data analysis of the exploratory case study and the outlined focus areas for the main study. Table 5.1 shows the profile of the seven HEI managers who took part in the exploratory study. Each manager was given a number to differentiate them for the data analysis and a pseudonym for NVivo analysis purposes. Their gender, the particular department that they work in their HEI along with the sector is also stated in the participant profile.

Table 5.1 Participant profile

No.	Pseudo name	Gender	Department
P1	Ellie	Female	HR
P2	Rachel	Female	HR
P3	Gareth	Male	IT
P4	Michael	Male	Library/Student Services
P5	Craig	Male	International Office
P6	Rory	Male	Planning
P7	Anthony	Male	Finance

5.2.3 Analysis of data from the exploratory case study

Objective one: To understand the current situation of Big Data and Learning Analytics and their use in Student Experience Management

Participants were asked if they were aware of the term Big Data, and if they used it, they were also asked if they used any Learning Analytics tools. Participants were also asked what the role of Big Data and information was in their decision making and whether they used any BI or BA tools.

There is clear evidence that Learning Analytics is used and having a positive impact on SEM in the case study. There is a variety of tools for different purposes; participants spoke of basic tools such as Microsoft Excel, Word and Access as tools to inform their decision making. Referring to decision making again for the HR department in this particular HEI, Business Objects is seen as the main BI tool. Managers deal with a large amount of student data; RFID technology is one of the ways used to track student attendance and the data is collected in Excel. In relation to student-focused data this is also managed with student systems such as the Student Records System (SRS) (i.e. SITS, in this case) as well as financial information systems. In student services, text mining tools are also useful, for example, text analysis tools are used on a survey in the HEI called the National Student Survey (NSS). The main data sources used in their managerial roles are emails, library systems, spoken word, and data sources from professional bodies. Participants also spoke of more advanced tools such as

Oracle SQL and MS SQL Server for decision making, and for large planning projects MS Project. There was also use of the statistical software SPSS for statistically orientated analysis for one of the managers. All in all there is not a clear picture of the tools used because they vary from a basic level to an advanced level. In terms of challenges relating to use, participants spoke of accuracy of data, existence of data, completing objectives, not having enough evidence available, scarce resource, reactive management, time, challenges of taking information from different sources, data quality, data warehousing, processing student data and too much/too little data. With the HR department of the particular HEI in the exploratory case study, coding by staff is viewed as one of the largest challenges, along with making sure that the information that is provided is meaningful. Another issue that came to the light was privacy concerning social media and having sensitive information in some areas of HE that should not be available on social media sites. Some of the managers also felt that the problem with Big Data is that people are fearful and concerned about what is being done with their data and also that it has the potential to magnify mistakes.

Managers' understanding and use of Big Data and Analytics

The university in this study is currently reaping the benefits of BA by the use of RFID technology to track student engagement activities in their academic study (e.g. online and offline activities). The managers interviewed stated their awareness of Big Data, how it informed their decision making and how it will be used in the future of HEIs. This then reiterates the fact of Big Data being the source of information.

Findings suggest that managers have a limited understanding of what Big Data is and only view the term as a reference to volume rather than the inclusion of velocity (speed of data) and variety (different types of data). This suggests that HEIs may not yet be able to unlock the full potential of Big Data, so managers require guidelines on the benefits of analytics in student management. Participants in the study are also seen to be fearful of Big Data projects because managers are not asking the right questions about the benefits it offers.

Managers are heavily involved in the decision making process where students are concerned. They make various types of decisions ranging from strategic to operational based on information or evidence they have. For example, one participant said: *"decisions that I would make would be about interpreting report requirements, so people might ask for a list of, um, current staff but then I might have to make decisions about well actually they don't need bursary students for example on that list so I'll take those out, um, operational decisions"* **(P2)**.

Participants in the study found using analytical tools useful for making decisions within student management but have not realised the full potential and their impact of the majority of BA tools.

Manager's role in the student management area and the information processing challenges

Regarding the managers' roles in managing student experience, The roles suggests that managers are involved in a wide range of tasks and responsibilities from student retention management to dealing with their emotional, financial and personal issues. The findings indicate that most managers perform all three types of roles, i.e. interpersonal, informational and decisional (Mintzberg, 1973). HEIs deal with a large volume of data; managers stated with new information coming and the current information available at the university is that it is "*a challenge to keep on top of everything*" **(P4)**.

Mintzberg (1973) argues that making decisions is a vital part to any managerial activity. Participants in the study found using analytical tools useful for making decisions within student management but have not realised the full impact of a majority of tools. Managers in this study specified the overload of information is a challenge when it came to information processing. Information overload as a whole is defined as *"a transitory sensation that is experienced by individuals developing schemes that will them to upgrade their performance in job related task* (Kock, 2000, p261). When information overload increases, this means the decision maker has less control over the processing system, both stress and arousal become raised, and subsequent coping adjustments such as narrowing attention are introduced. For example, one participant indicated that *"...potentially too much data can be as bad if not worse than too little data."* **(P6)**.

Another said that: *"New pieces of information come in, they demand your attention and if you are overburdened it can be difficult not to make a decision at that immediate time, without proper reflection or not necessarily having all the information there"* **(P4)**. One manager stated: *"HEI's have to provide something like 550 different items of data on an annual basis to a whole plethora of different external organisations and those information requirements even within sort of, UK sort of bodies are far from consolidated in alliance"* **(P6)**.

Too much information available, new information being processed and conflict of data are seen as causes of information overload, Big Data is seen as a solution to counteract information overload. Therefore the participants believe that *"Business Analytics can help HEIs with the increasing amount of data."* Changes to HESA returns as well as large information requests are also seen as the main causes of information overload and another way to overcome information overload is through the standardising of reports **(P4)**. Participants also specified that *"data quality", "accuracy of data", "the existence of the data"*, and time spent in *"interpreting meaningful data"* are also challenges in performing their roles: *"It's about obtaining that information from somewhere else to make sure that the information then that is provided is meaningful"* **(P2)**.

Another participant linked Big Data and information: *"The role of Big Data is to inform and it informs... I'm sorry, it informs, it gives me the information I need in order to make the decisions because you can get information and it informs me in such a way that I can make that decision"* **(P7)**. Although social media data have been regarded as a rich source of information to understand customer behaviour and feedback (Aral et al., 2013), their use in improving the student experience in HEIs is still not fully explored. One participant explained that *"I'm dealing with so much data all the time; I don't have the capacity to be engaged in all social media"* **(P4)**.

Challenges managers faced

With decision making in HEIs challenges do occur; one participant specified time as an issue: *"So time criticality is a real factor and challenge in decision making"* **(P4),** and another put it down to evidence: *"I supposed the immediate one that comes to mind is making sure you've made the right decision based upon the evidence you have available"* **(P3)**.

Managers also face challenges in information processing which create differences in information processing behaviour. The sheer volume of data has been identified as a challenge: *"There is... is the data you need at that single point being collected in the first place. So we collect lots of data, quite often you really think I need to find out x, that data is not being collected because nobody has thought to collect it, uh there's the currency of that data."* **(P4)** as well as different data formats: *"the fact that we want to take data from lots of different sources which may be in very different formats, um, whether that's sort of flat file structure, .csv, different field formats, um, you know, XML provisions"* **(P6)**. Another challenge was also specified by a participant: *"There are challenges around the knowledge and training barriers which will enable people to self-service in terms of sort of data, erm, so* *trying to make our data structures and our reporting tools easy to use and intuitive as possible"* **(P6)**.

Learning Analytics/BI tools used

BI is currently used as stated by one of the participants for the improvement of academic performance and student engagement: *"So we are a looking very much at the student record system and associated systems as well but primarily that one because that tracks, allows us to track the student, if I use the word performance in the wider sense I don't just mean academic performance and for example student engagement"* **(P3)** and *"So we have a lot of data there on student engagement which we need to analyse bringing in from different sources, such as the library systems, such as the student record systems to try to make sure we are able to respond to students who may not be engaging"* **(P3)**.

The current development of a BI strategy was also discussed by two participants: "*We have our BI strategy, which we are working on at the moment, trying to develop a more enhanced BI system that can pull the information from the, uh, the raw data and the databases"* **(P3)** and *"what we're doing at the moment, um I suppose on the macro level is the university is... has just relatively recently established a BI strategy, which is the university approach to BI., it's all around sort of data warehousing"* **(P6)**.

Future of Big Data and analytics

The managers also discussed the potential use of BI and BA in the future which derived positive outcomes. One of the participants wanted to see applications that would improve decision making: *"I think the applications I would like to see is some additional value for money analytics, Uh… and impact analysis on decisions that are made"* **(P4)**. This participant also highlighted their ideal BI system for students and on the general future use of BI:

> "*So I would want a system to intelligently analyse per student input and ok we are buying that, is it really expensive? But the students who actually got off and used that database, they all got firsts or they all progressed to the second year."* **(P4)**

Future of Big Data, social media and analytics

According to some managers, in terms of analytics, the future will be keeping track of people who are searching for jobs in the HR department. In terms of the future of Big Data, some managers stated it should be used to predict what will happen in the future, linking data in a more efficient manner and BI and BA can also be used to improve student success. Another thing that is seen as important for the future of Big Data and decision making is web recruitment. In terms of the future of social media that will involve the use of social media platforms such as Twitter, Facebook and LinkedIn.

The future development theme is identified when talking about if a particular faculty in the HEI has any projects in the pipeline using BA and BI in the future. Siemens and Long (2011, p1) state that *"Big Data and analytics are seen as the most dramatic factors in shaping the future of higher education."* The managers discussed the potential use of BI and BA in the future which derived positive outcomes:

> *"I would want a system to intelligently analyse per student input and ok we are buying that, is it really expensive? But the students who actually got off and used that database, they all got firsts or they all progressed to the second year."* **(P4)**

Objective two: To investigate factors that may affect the effective use of Learning Analytics for SEM

To achieve this objective, the case study explores the influential factors affecting the use of Big Data and Learning Analytics. This section highlights the findings identified as factors affecting Learning Analytics use in the case study.

Overcoming information overload

This theme is defined as steps/tasks taken by managers to reduce the challenges they face with having too much information. Information overload has been identified as a challenge in making decisions in the literature: *"Current research suggests that the surging volume of available information—and its interruption of people's work—can adversely affect not only personal well-being but also decision making"* (Hemp, 2009,p83). The development of the intelligent software agent as a concept as well as a technology has been brought forward as one of the solutions for decreasing information overload problems faced by contemporary business organisations and assisting decision making in the more integrated and distributed environment of the internet (Belfourd and Furner, 1997, Edmunds and Morris, 2000). This challenge has been confirmed in the data analysis. For example, participants pointed out that:

> "*…standardizing those terms has made that easier and it has then, um, streamlined the data that we are using rather than having multiple categories."* **(P1)**

> *"...make sure I consider the important information and the essential information."* **(P3)**

> *"Big Data systems, I think they should solve some of the overload problems."* **(P4)**

Issues with information overload

The subtheme is identified by examining the challenges managers face with processing data and focusing on the areas which managers state are common with information overload. Managers explained what issues they have when dealing with information overload. For example, some of them stated that

> *"...potentially too much data can be as bad if not worse than too little data"* **(P6)**

> *"Data quality is probably another issue."* **(P7)**

> *"New pieces of information come in, they demand your attention and if you are overburdened it can be difficult not to make a decision at that immediate time, without proper reflection or not necessarily having all the information there."* **(P4)**

Dealing with challenges with decision making

This theme is defined as difficulties that managers have to deal with when making decisions. With decision making in HEIs challenges do occur; for example, Divjak (2016) states that major changes in economic, social and technological domains bring about challenges for the HE sector, in particular for decision making in HEIs. This challenge has been confirmed in the data analysis, For example, participants pointed out that:

> *"...basically comes down to the information able to provide, so if the information within the system for example isn't up to date, I know it's not up to date, it's about obtaining that information from somewhere else to make sure that the information then that is provided is meaningful."* **(P2)**

> *"Making sure you've made the right decision based upon the evidence you have available."* **(P3)**

"…accuracy of data, the existence of the data." **(P4)**

Use of social media

This theme is identified by the use of social media platforms in different managerial departments in HEIs. Social media symbolises one of the most transformative impacts of information technology on business, both within and outside firm boundaries (Aral et al., 2013). Social media is used in HEIs to improve areas such as student engagement; however, there are growing concerns. Managers explained how they used social media and the issues they had with it, For example, one participant stated that:

"I'm dealing with so much data all the time; I don't have the capacity to be engaged in all social media." **(P4)**

Managing student data

This theme is defined as how managers organise the data relating to students. Managers in this study use BI in a variety of ways to help the university. As stated in Chapter 2, student record systems (SRSs) is a type of software used to organise day-to-day operations for HEIs. How participants manage student data has been confirmed in the data analysis, for example:

"Installing RFID and it's both near and long sensing RFID equipment in classrooms so we can track cards as they go through the building." **(P4)**

"Student records system, but we also have the Agresso financial information system which obviously has a lot of the transactional level data that the university does." **(P3)**

Objective three: To guide the main study data collection by identifying the areas to be focused in the main study.

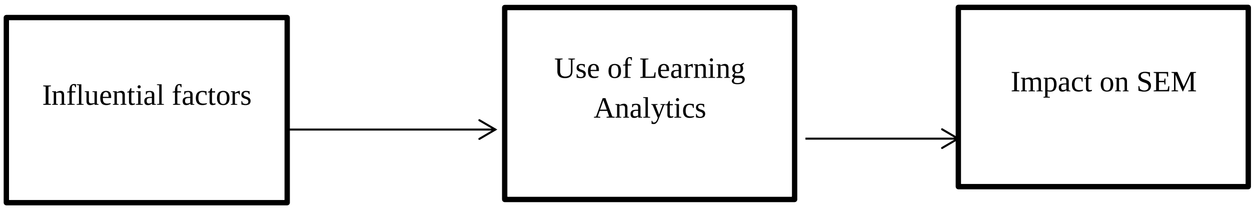

Figure 5.7 Main themes identified from the exploratory study

Findings from the exploratory case study provide some evidence for developing a framework in the main study based on the three themes derived. The relationships of the three main themes are also depicted. The findings for identifying the main focus areas are described in the following section.

Impact on SEM

In terms of the SEM cycle, one of the participants touched on student engagement: for monitoring student engagement there is a student engagement system called Jenzabar.

5.2.4 Conclusion of exploratory case study

The exploratory case study reveals that HEI managers are having difficulties in performing their roles and making informed decisions mainly due to either the lack of meaningful and actionable information, or information overload. As a result, they spend much time searching or processing data in order to make sense of them. Although Big Data and Learning Analytics are being used in HEIs, many managers are still not clear about the technologies, their relevance to managers' roles and the associated benefits. However, they wish to have better decision support tools, such as Learning Analytics, and welcome the increasing investments by the sector. The exploratory case study has provided useful preliminary insights into the current challenges faced by HEI managers in managing student experience and how Learning

Analytics are and can be used to help to deal with the challenges. The findings reveal that Learning Analytics has been used to support HEI managers for SEM, but many factors will affect the success of their use. The exploratory case study also suggests that Learning Analytics use varies depending on the organisational capacity in utilising the tools. Therefore, it is important to identify the significant factors in the main study and to understand and explain how Learning Analytics is used and impacts on SEM. All in all, the exploratory case study was used to provide good insights to guide the focus of data collection for the main study.

5.3 The Main Study

This section follows the data analysis process explained in section 5.1. Semi-structured interviews were carried out with 30 participants from HEIs in the UK.

5.3.1 Objectives of the main study

The main study aims:

1. To understand the challenges in utilising data effectively for SEM in the era of Big Data and Learning Analytics
2. To identify the key factors affecting the use and impact of Learning Analytics
3. To understand how Learning Analytics is being used for SEM
4. To develop a conceptual framework to provide a systematic overview on the use and impact of Learning Analytics on SEM in HEIs.

The results from the exploratory case study were used to improve the interview questions by making them more in depth and suitable to examining a wide range of factors that affect the use and impact of Learning Analytics in UK HEIs.

The main questions used for the semi-structured interviews are:

Factors

- What challenges do you face when making effective decisions in relation to SEM, and why?
- What are the challenges and issues in making effective use of Learning Analytics in your HEI, and Why?
- What are your views on the limitations of Learning Analytics?

Use

- Do you use any analytic tools or dashboards?
- What BA / Learning Analytics / BI systems do your university use to enhance student experience?

Impact

- If you had a choice, what would be an ideal analytics system/tool to support SEM for yourself and your university?
- What are your views on the future development and applications of Learning Analytics for SEM in your university?

5.3.2 Sample for the main study

Differing from the exploratory case study, the sample was obtained from a cross-section of HEIs across the UK. The target population was senior and middle managers, so this includes heads of departments, directors and managerial officers. They were selected from areas such as data analysis (HE data), information systems, IT, student management information, student services, planning, academic and research support, student experience, marketing, student recruitment and e-learning.

Semi-structured interviews were carried out with 30 participants from the HE sector. The durations of the interviews varied: some were half an hour to 45 minutes, with the longest being one-and-a-half hours and most were face-to-face interviews, with some being Skype and telephone interviews.

5.3.3 Access strategy

The contacts were selected via looking at the websites of a wide range of HEIs across the UK and getting in touch with the managers that work in areas specified. The selected manager's job titles were checked against their LinkedIn pages (those who have one). Another way is through attending networking events, asking for business cards from HEI managers who work directly with students or manage student data. An introductory email was sent to each manager to be interviewed with the aim, objectives and expected contributions of the study. If the manager agreed to be interviewed, an invitation letter (either through fax, post or email) was sent to the individual manager. Also an information sheet about the research and consent form was sent via email.

5.3.4 Interview study participants

Table 5.2 shows the profile of participants who took part in the main study. To differentiate the participants for data analysis each of them was given a number and a pseudonym was given for ethical reasons. The participant's gender, job title and the department that they work in within the HEI is specified in the profile.

Table 5.2 Classification of participants for main study

No.	Pseudonym	Gender	Role	Department	Level	Type of university
P1	Terry	Male	Pro-Vice-Chancellor of teaching and learning	Teaching and Learning	Senior manager	Post 1992
P2	Earl	Male	Student Engagement Manager	Student Engagement	Middle manager	Post 1992
P3	Hilda	Female	Director of student recruitment	Marketing, Communications and Student Recruitment	Senior manager	Plate Glass
P4	Henry	Male	Director of Marketing, Admissions, Recruitment and Communications	Marketing, Admissions, Recruitment and Communications (MARC)	Senior manager	Post 1992
P5	Phillip	Male	E-learning co-ordinator	Enhanced Learning	Academic	Redbrick
P6	Fred	Male	Head of Academic Support, Technology Innovation	Academic Support	Senior manager	Post 1992
P7	Bradley	Male	Director of Learning resources and service excellence	Learning Resources and service excellence	Senior manager	Post 1992
P8	Jim	Male	Director of Planning	Planning	Senior manager	Post 1992
P9	Mark	Male	Professor of Innovation and knowledge exchange	Continuing Education	Academic	Russell Group
P10	Gary	Male	Director of Student Experience	Student Experience	Senior manager	Post 1992
P11	James	Male	Interim Director of IT	IT	Middle manager	Post 1992
P12	Pauline	Female	Director of Strategic Planning	Strategic Planning	Senior manager	Post 1992
P13	Todd	Male	HE Data analyst	Data Analysis	Data Specialist	Plate Glass
P14	William	Male	Head of Student Management Information	Student Management	Senior manager	Plate Glass
P15	Ian	Male	Emeritus Professor of Operations Management and Information Systems	Operations Management and Information Systems	Academic	Russell Group
P16	David	Male	Careers and Data Planning officer	Careers	Middle manager	Plate Glass
P17	Susan	Female	Head of the student centre	Student services	Senior manager	Post 1992
P18	Amy	Female	Academic registrar	Academic Registry	Senior manager	Post 1992
P19	Carl	Male	Reader in Learning Analytics		Academic	Plate Glass
P20	Sandy	Female	Planning Officer	Planning	Middle manager	Russell Group
P21	Julian	Male	Director of strategic Planning and analytics	Strategic Planning and analytics	Senior manager	Russell Group

P22	Kenneth	Male	Head of Planning strategy, planning and performance	Planning	Senior manager	Russell Group
P23	Lionel	Male	ICT manager	ICT	Middle manager	Independent
P24	Liam	Male	Programme leader for student experience	Student experience	Middle manager	Russell Group
P25	Patsy	Female	Head of Marketing	Marketing	Senior manager	Post 1992
P26	Greg	Male	Pro-Vice-Chancellor of student experience and international	Student Experience	Senior manager	Plate Glass
P27	Nancy	Female	Pro-Vice-Chancellor of student experience	Student experience	Senior manager	Post 1992
P28	Otis	Male	Student engagement manager	Student engagement	Middle manager	Post 1992
P29	Jessica	Female	Head of service excellence, change leader	Service excellence	Senior manager	Post 1992
P30	Wendy	Female	Academic Head of Student engagement	Student engagement	Senior manager	Russell Group

5.3.5 Analysis of data from main study

The main study followed the inductive data-driven approach, which according to Braun and Clarke (2006) is the data-driven TQA analysis process. Semi-structured interviews were used to collect the data. In order to combat ethical issues, the participants were recorded in the interview sessions with their permission and the interviews were transcribed in MS Word verbatim. The next step that was followed was getting familiar with the data; this was carried out through reading and re-reading the data and making keynotes about the data. The next step was identifying initial themes created from the data. These themes were then analysed further and developed into broad themes and subthemes, and this helped establish the foundation of the theoretical framework which came from this study supporting SEM with Learning Analytics in the UK HE sector.

5.3.6 Main study themes

The main themes which represent the factors that affect the use and impact of Learning Analytics in the UK HE sector were identified from the data. These were grouped into broad themes and subthemes. The broad themes relate to the key theme whereas the subthemes refer to the minor themes that feed into the key themes. Figure 5.8 demonstrates the broad themes created for this stage in the study. The broad themes along with the subthemes are depicted as well as described in the later sections.

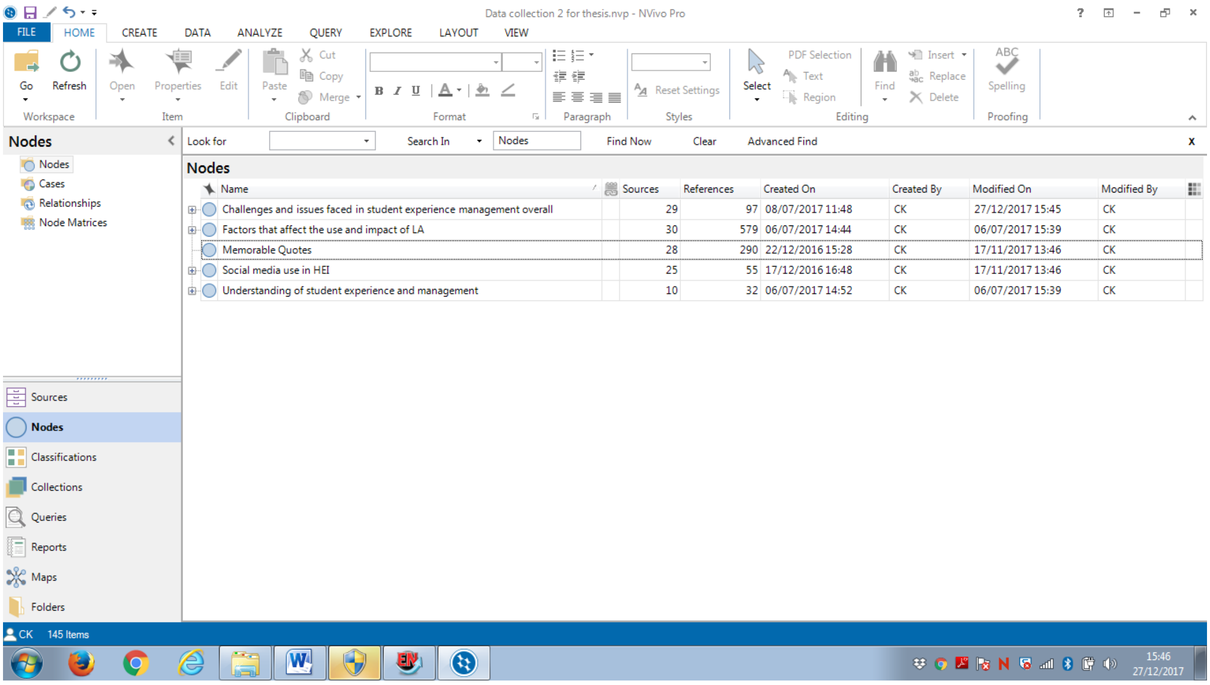

Figure 5.8 NVivo screenshot of broad themes

Table 5.4 shows the number of respondents (sources) who contributed to each theme along with the overall number of references (quotes) linked with each theme.

Table 5.3 Broad themes of study showing the number of sources and references

Theme Name	Sources	References
Challenges and issues in SEM overall	29	97
Factors that affect the use and impact of Learning Analytics	30	597
Social media use in HEI	25	55
Understanding of student experience and management	10	32

5.4 Data Analysis of the Main Study

The data analysis of the main study is presented by linking research objectives to the main themes identified.

The broad themes along with the subthemes where appropriate are stated in depth in the following sections. To examine how the themes link with the research objectives in this study, they are categorised coherently with each research objective.

5.4.1 Objective one: To understand the challenges in utilising data effectively for SEM in the era of Big Data and Learning Analytics

Participants were first asked if they were aware of the terms, *Big Data*, *Business Analytics* and *Learning Analytics*. This was important so that they understood the idea of Big Data and analytics and also to find out what was meant by Big Data and the analytics terms. Participants seemed to have a good understanding of what Big Data is as confirmed by the data analysis: *"I think my understanding of Big Data is loads of data"* **(P13)** and ***"****So Big Data to me would be looking from a variety of sources to be able to almost crosscheck I suppose"* **(P17)** and another participant *"one definition of Big Data is that it's too much to store"* **(P5)**. Also a relatively good understanding of what BI is: *"I think that BI is really about looking at… I think it's really about a quick analysis of the data rather than in-depth data"* **(P13)**. Participants also spoke about different variations of analytics and their understanding of them. Firstly on academic analytics, one participant stated that: *"To me well all the other functions around an academic institution such as admissions, marketing, finance even though finance is not related to learning directly. That's what I view academic analytics"* **(P23)**. Secondly, two participants gave their definition on Learning Analytics: *"Learning Analytics I would have thought of more as an online learning environment, the kind of tools that a student would use… not so much in terms of an analysis for a manager"*

(P18) and *"Learning Analytics should be about trying to understand the social and cultural erm ways of how people are learning, so lots of Learning Analytics erm analysis are focusing on just monitoring data and acquiring data but data as such without understanding the social and cultural contacts"* **(P19)**. Finally, another participant gave their take on what Learner Analytics is: *"Learner Analytics may be more about the learner"* (**P5)**.

In conclusion, most respondents were aware of all three terms (Big Data, Business Analytics and Learning Analytics) and have a relatively good understanding of them, for example: *"Yes I have heard of all three of them, Um we… we…certainly we use Business Analytics, um Learner Analytics um I think we are in our very early stages of doing that as many places are, Big Data in relation to managing err I guess student engagement… no, we are not using it"* **(P14)**.

Understanding of SEM

Participants were also initially asked if they were aware of the term *student management*; this was important so that they understood the idea of SEM and also to find out what they felt was their definition of student management.

Table 5.4 Participants' understanding of SEM with its subthemes and relevant data extracts

Broad theme	Subtheme	Data extracts
Understanding of SEM/student management	Limited understanding	"I just see it as being an instrument to the teaching process. I would describe all of those things as part of the teaching so managing students is part of the teaching." **(P15)** "Student experience management… I think is quite specific… but again it could be different in terms of… the areas that were using that term, and you know you could look at the difference between student expectation management and student experience management" **(P7)** "Depends on what your overall strategic goals are… but there is going to be a balance within it in terms of student attainment, career outcomes… (.) … satisfaction, retention… so you are looking to secure your objectives against those strategic goals through a variety of different interventions" **(P1)** "Erm there is management of students within… erm… a module… erm so even lecturers need to organise routes and different activities like that in a management sense" **(P5)**
	Comprehensive understanding	"If you are managing the student experience it much more clearly defines on to something that's… about the interaction the student has with the university and what they would get out of that" **(P12)** "Student management is everything from the point of students expressing their interest to the institution all the way to them becoming a member of our alumni community" **(P10)** "it's about empowering managers to make decisions, so from a student management perspective, that would translate to me as empowering our academics to be able to um… understand their students, identify where there are good things happening and not so good things happening" **(P14)** "We would use student management to describe just the operational level of management of our students through to looking at managing the student's profile of activities… their selections of study pathways through to performance analytics" **(P12)** "So student experience is a broader term but has become

		quite a specific term within many universities and I think we are probably on that trend where we are looking at it in terms of how the university is measured particularly externally" **(P7)**

It is evident from the data analysis that there is no agreed definition for SEM, as well as there not being a clear understanding of what SEM is, as the participants have demonstrated different levels of understanding – limited and comprehensive. Other points that came to light from the analysis were that student management can be defined depending on what your overall strategic goals are, but essentially, it is a balance in terms of Student attainment, Career outcomes, Student satisfaction and Student retention. From this participant's view the objective of student management is *"to try and ensure that students are supported towards those particular goals of the university/institution"* **(P1)**. Although one participant gave his interpretation as *"all sorts of administration around courses from before students join the university to when they become alumni"* **(P5)**, student management can also refer to management of students within a module. Even lecturers need to manage groups/activities like that in a management sense. In terms of the management of students and the student life cycle this particular HEI is very interested in the student life cycle.

Another participant states that they use student management to describe just the operational management of their students: to look at managing the students' profile activities, their selections of study pathways, through to performance analytics. This participant feels student management will need to be narrowly defined and that SEM is a better term: *"yes, if you are managing the student experience it much more clearly defines on to something that's… about the interaction the student has with the university and what they would get out of that"* **(P12)**. Management was also defined by another participant in the context of data, so empowering managers to make decisions. Therefore student management is empowering their academics to be able to understand their students, identify where good or bad activities are happening and to make some decisions and interventions, which could be a change to the curriculum or informally sitting down and having a chat (counselling), giving the academics the insight to intervene whether positive or negative, in the student life cycle.

One participant argues that in their HEI they have to be careful that they are not just treating the student as a number, which is always a concern, the relationship they have with their students in their HEI having changed dramatically over the last few years because of the introduction of full funding. They say that students are partners, co-designers, but not customers: that term is frowned upon. What they want to do is keep the relationship with the certain individual, that is key, and to give them the quality experience. There are also discussions about enabling students rather than managing students; clearly there is a requirement to track the student journey. From this participant's perspective it is not about managing the student at all, it is about understanding the student's journey throughout the university and tracking that journey and making that information available in a way that is appropriate, that academics can use to improve the student experience in a way students are comfortable with; but this participant is not looking to control or constrain that journey at all.

Student management depends on the size of the group that is being taught: if it is a group of 300–400 students, this participant does not really think there is management of the students at all but hopes they come to lectures and engage in the practical classes; there is not management of that process because it is too large. The idea is to keep an eye on attendance, try to ensure that the students engage with the materials and practical work and identify any problems they can early and try to deal with them. This is viewed as managing the students as part of the teaching; managing students in a meaningful way would be using analytics more effectively for appreciation of how well the students are doing, ensuring the students are engaging in a way that teacher/lecturer wants them to engage; there is always some uncertainty around how engaged the students are. One participant expressed student management could start with that *"initial expression of interest, an open day all the way through to when they graduate and they become part of our graduate community"* **(P10)**. They also go on to state that student management is about ensuring that the students' whole experience, whether inside and outside the classroom, so curricular, co-curricular or extracurricular, is maximised, so student management is making sure that the students have the best possible experience in all those different facets.

In terms of student management it not a term all participants had thought of, but one participant discusses the concept of student engagement and that their HEI is engaging quantitatively and qualitatively; so asking whether the students are reading their materials, are engaging with the concepts in a deep and critical way and so on and so forth.

Challenges in utilising data effectively

In line with **objective one** of this study, responses about what respondents felt were the issues with utilising data effectively were coded to this theme. We are living in the era of Big Data and data can be a significant issue. By splitting the challenges into data and people issues it is possible to find the context of Big Data. Table 5.5 shows the challenges of utilising data with its subthemes and relevant data extracts:

Table 5.5 Challenges of utilising data effectively with its subthemes and relevant data extracts

Theme	Subtheme	Data Extract
Data quality related issues	Data quality	"I think the other thing is… is you know processing data, um and ensuring data quality" **(P21)** "I think the problem is data quality" **(P16)** "second thing the quality of data in some of our systems and its robustness is not the best, so again that hinders the ability to do that" **(P14)** "we are looking at timetabling data and last year we felt that the quality of the data wasn't good enough to then be able to be used as part of the analytics tool" **(P2)** "we have imperfect data" **(P5)**
	Data consistency	"The main challenge that I experience with data management is data integrity and consistency" **(P16)**
	Data reliability	"So I think some of the challenges there from a data perspective are um… you know how reliable is that?" **(P14)** "sometimes errors can creep into the spread sheet and you need to be careful of what you are looking at"**(P17)**
Data usage	Data analysis	"so pulling them altogether is a real challenge" **(P16)** "So there is all issues around you know ensuring the data is used appropriately" **(P21)** "one is that we went to a new student record system (SRS) four years ago now so you had a point where we had no comparative data, we had… we were remodelling our curriculum into the new systems" **(P18)** "The other thing I think is always about the specification of data, so as an Academic registrar if someone says to me how many students have you got, I have got 20 questions back before I can answer that question" **(P18)** "It's knowing which data I need to be capturing and to have the data when captured presented to me in a way that is intelligible, to answer the questions we ask of it." **(P26)**

	Data integration	"connecting the different data systems within the institution is a very big challenge" **(P30)** "so the main problem that we have is that data is recorded in lots of different ways and it's often difficult to compare like for like" **(P3)** "I think that is one of the biggest challenges facing everybody at the moment it's very easy to say oh we should just put everything into a data warehouse…" **(P6)** "Essentially it is a repository of data its extracted largely from our SRS and a little bit from other places, and that corporate information system then is presented as a series of dashboards that go to senior management" **(P11)** "we data warehouse it so we make sure that its contained within one single office" **(P10)** "Yep… um we use the data that's generated by several of our systems..." (.) **(P1)** "That means that we could extract staff that are students and how much, kind of getting those interconnectivity between the systems." **(P18)** "we can't track people through and different people own systems, different people feel they own that data" **(P5)**
Volume of data	Data and information overload	"well, the biggest challenge by far is probably data overload and as a programme leader I've got information flying at me from all sorts of different directions" **(P24)** "There is a bit of that… erm, certainly email overload; email is the curse of a modern manager's erm… I don't think I'm too bad actually, yea trying to keep on top of all the information you are being sent is quite tricky" **(P17)** "Data management in general takes such a lot of data which comes through the University from the start of the student experience through to the end its really which piece of data do we need" **(P16)**
	Lack of data	"so I think the challenge is that we don't have enough data ready to be used for in depth analysis" **(P13)**

Making sense of data/information	Information availability	"don't know what kind of information is available and the information that is available would need to be presented in the way in which was useful" **(P15)** "…accessing information that is relevant to student experiences and being able to turn that hard data information into something tangible to share with particularly academic staff" **(P30)**
	Problems with systems	"whenever we calculate some statistics for example the proportion of students who obtain good honours or average type scores there is always some discrepancies, so that's sort of a challenge" **(P13)** "I mean we have got our student system which is our database where we hold all the student records which is quite difficult to get information out of…" **(P17)**

Wang and Strong (1996) define data quality as fitness for use and created the notion that data quality judgement is dependent on data consumers. They also described *"a 'data quality dimension' as a set of data quality attributes that represent a single aspect or construct of data quality"* (Wang and Strong, 1996, p6). Cai and Zhu (2015) argue that currently Big Data quality faces the following challenges: *"The diversity of data sources brings abundant data types and complex data structures and increases the difficulty of data integration"* (p9).

In this study, along with data quality itself, the data quality related issues are consistency and reliability. From the data analysis it is evident that the quality of data and their systems and their robustness is not the best in a particular HEI, so that hinders the ability for Big Data. A large challenge particularly at this HEI is the quality of data. This university has not really managed the data that has gone into the SRS very effectively; it is as if no one has been responsible for saying which way they have to structure a course such that underpins everything they do and have reliable facts and statistics. Another participant discussed ensuring data quality when processing data. In this HEI they have just recruited really well so there is strain upon areas of their estate and that is affecting processes like timetabling; this therefore meant the quality of the data was not good enough to be a part of an analytics tool. One participant also talked about imperfect data, so in terms of processes like room change for students in terms of their lectures, as it is best to communicate with students in ways that are successful. Cai and Zhu (2015) refer to data consistency as *"whether the logical relationship between correlated data is correct and complete"* (Cai and Zhu, 2015, p22). A participant spoke about data consistency and data integrity when it came to data management in reference to students: *"Quite often students don't supply the most up-to-date details. It is very difficult to get hold of up-to-date details if the students are not supplying the details"* **(P16)**. Data reliability is referred to as *"the accuracy and completeness of computer-processed data, given the intended purposes for use"*(Auditor, 2004, p3). One participant gave the example of student engagement as a link to reliable data: *"You know just because somebody isn't engaging, necessarily attending their course, doesn't mean they are not engaged"* **(P14)** and another talked about the reliability when it came to MS Excel.

With the data usage theme, the subthemes are data analysis and data integration. In reference to data analysis, challenges participants addressed were the specification of data, making sure that data is used appropriately, having no comparative data and pulling data together. According to Lenzerini (2002), data integration refers to the issue with joining data located in different sources, and offering the user with a unified interpretation of these data. Data integration seems to be a major problem for participants in this study with data either being held in different ways or in different systems. Within the volume of data theme the subthemes are data and information overload along with lack of data. Feather (1998) refers to information overload "as the point where there is so much information that it is no longer possible effectively to use it" (Feather, 1998, p118). In general, participants feel there is a challenge with the increasing amount of useable data that has been generated; one participant even spoke about dealing with email overload, that it is a problem with modern managers nowadays in the sense they are trying to keep on top of all the information that they have been sent, which can be difficult as there is so much of it.

In contrast, there also is the issue of there not being enough data. The theme for making sense of data/information has the two subthemes information availability and problems with systems. According to Cai and Zhu (2015, p20) *"Availability is defined as the degree of convenience for users to obtain data and related information, which is divided into the three elements of accessibility, authorisation, and timeliness"*. A challenge for one participant is that important management information is not made available in a way that is easily accessible. Other participants spoke about data being troublesome to find. In terms of problems with systems one particular HEI has a student system, a database, where they hold all the student records, from which it is quite difficult to extract information, which is a challenge**.** There are also issues with data governance as shown in Table 5.6:

Table 5.6 Issues with data governance

Theme	Data Extract
Data governance issues	"I think the issues again is the data policy which as I said at the beginning I would ensure that the quality is consistent" **(P16)** "On data, making sure everyone in my department and college comply with all legal and regulatory requirements" **(P9)** "I think the biggest issue from the point of view of Big Data for us is the governance issue" **(P11)** "I think the problem is information governance" **(P16)** "I would say the main difficulty I have in making decisions is more about the policy and regulations and landscape changes like government changes because you never know what's coming" **(P17)** "I think the bigger issues like the removal of the student maintenance grant erm is a potential student experience problem"**(P8)** "biggest challenge we have is localised practice and I suppose this is actually a governance issue" **(P6)** "Ownership of data, um… um it took me overall about 18 months to get hold of the VLE data to do some work with. Err it took 12 months to convince people to say yes and another 6 months before they actually did that" **(P5)**

Sclater (2016) states that ethical and legal oppositions to Learning Analytics are a hindrance to growth of the field, therefore possibly not offering students the advantages of adaptive learning and predictive analytics. Governance is a large issue in terms of Big Data. *"There is pressure from the government particularly in relation to international students but more generally to monitor attendance. Um we could provide technology solution quite easily for that… but um it's potentially intrusive"* **(P11)**. This HEI has recently set up an information committee; they have student representation and academic representation. Dealing with technical issues and being agile enough to deliver a service this HEI needs while still complying with the ethical and governance standards of the university is a large issue. Another participant stated the largest challenge they face is localised practice, which can be seen as a governance issue as well, it was also stated by this participant that coming through the Learning Analytics literature is that students actually want to know what is going on, they want to know the weightings, algorithms being used and they want to know the data sources; the needs and requirements of students have been completely been overlooked in the analytics field; this participant is working with senior leaders and governors because it is seen as a governance issue. Learning Analytics is on the radar but they are just making sure they have the right data sources. Many of the participants mentioned policy as a challenge. One participant mentioned in particular that the largest challenge is finding his way through the raft of polices that they have and therefore has to be careful about not writing policies that stop them from innovation. The participant also stated that he had to be careful about the alignment of policy with the practice: he spends the majority of his time writing policy documents to make sure what they do is applicable to the HEI. Another thing that presented itself in the data is the importance of complying with legal and ethical requirements, ownership of data and problems in student experience, for example, the removal of the student maintenance grant. With reference to that in this particular HEI they have a high proportion of students from more disadvantaged backgrounds, so they need to monitor the effect that that is having. Another participant stated that *"I think the challenges are probably… you know we've got that structure that I've described where by students are part of the overall… governance and dialogue… you are regularly hearing what the students think"***(P10)**.

5.4.2 Objective two: To identify the key factors affecting the use and impact of Learning Analytics

Factors that affect the use and impact of Learning Analytics

In line with **objective two** the data is analysed to produce factors that affect the use and impact of Learning Analytics. Table 5.7 shows the factors that were identified initially; more details are provided in Chapter 6.

Table 5.7 Factors that affect the use and impact of Learning Analytics and relevant data extracts

Factors	Data extract
Affordability	"We would like bigger software but again its budgets. It is very expensive to purchase the licences. I think the desktop intelligence of individual licences cost £1,000 pounds per year so for me to use that system for £1,000 a year to the University" **(P16)** "the really…really big challenge of doing any of this stuff is not technical we have the tools, we have the technology, we have the tools, we have the data, we might need a bit more storage and we may need a slightly bigger processor… but those things are quite cheap now there really isn't a big cost implication" **(P11)**
Complexity	"we use SAP… the dashboard is called Dashboards which is really complex" **(P12)** "there are different layers of complexity to the data that we receive and the data is not usually presented in the most data friendly format either" **(P24)** "the limitations of Business Analytics is no matter how good your predictor is, there will always be outliers" **(P19)** "it's only a prediction and its only as good as the prediction, so if you work in a very stable environment… and there is very little change in relation to the population, student population sizes… there is no desire to radically move you to a different kind of environment then predictive analytics is going to be great" **(P12)** "I think in terms of the limitations, again I understand when we talk about Business Analytics, mainly I use quantitative data, that's my background so again if we just use quantitative data you can understand the student's performance or the experience to only some extent" **(P13)** "…that model can only explain less than 10% of the variability of students who are more likely to obtain good honours, so that means there are… 90% of that fact can be explained by something else" **(P13)**
System integration	"we have got an awful lot of data, but the data is actually held in loads of individual systems" **(P6)** "two and a half years ago a point solution issue where we had… you would end up with ten different systems in ten different areas, not joined up so we wouldn't be passing information" **(P11)**
Usability	"I suppose Tableau is becoming the principal tool that we use, um and I think the big advantage of that… that's over other data visualisation tools… um is that it's easy to use" **(P22)** "Yea I think something that was really easy to use" **(P17)** "(EvaSys)… "Um in terms of evaluating the courses, its only effective as the way in which we analyse and interpret the data within the system and then use it to

	close that loop, so the data in itself isn't effective, the system is effective **(P24)** "I fundamentally believe in Learning Analytics if it focuses on giving power to teachers but more importantly students to see where they are in this tree and what they can do to help" **(P19)** "So that's making sure that if you are presenting stuff through… the student's stuff is going to be through a mobile app because they don't want a dashboard and things like that, they just want it there" **(P6)**
Data-driven culture	"I think all universities need to be data driven, some are a big fan of this…erm I think the only way you can make informed decisions is by collecting data efficiently and effectively" **(P10)** "Yea I see… yea I see, I see a process of moving towards data, but I feel we still rely on evidence as well, so I guess evidence in that sense is like a straightforward quick analysis of data rather than going into more detailed analysis" **(P13)** "I can't say I particularly noticed the culture but I do think it's totally down to an individual, so we changed VC five years ago and we have had some changes of Pro-Vice-Chancellors and Deputy Vice-Chancellors and the previous ones actually were very… very data driven so erm really wanting to make decisions based on the data" **(P18)** "that's certainly what we are doing here, I won't make a decision myself unless I've got a comprehensive set of data in front of me and any policy document or any document I receive, I expect to see evidence… erm detailed numeric evidence base. I also expect to see the evidence base used to measure performance" **(P26)**
Senior management support	"I mean if that comes to fruition it could bring some huge gains because what there are looking to do is to bring in some specification that will align universities data so that everybody could look at it so a bit like that HEIDI data um… that it will go into one place" **(P18)** "I am involved with working with the senior team on understanding student experience using analytics, so that's my contribution" **(P21)** "I think we are still in an era where um the whims and prejudices of senior management dictate that data has to be fitted to a certain extent to prove their point, I think we are still at that stage a little bit, perhaps not as enlightened as we should be, there is always going to be a bit of that" **(P14)** "Partly SPMG will drive it in terms of getting the data out" **(P18)**
Resource	"I think at the moment our university is facing a resource issue in the sense that um… because of its strategy, where it wants to have a better calibre of students coming in, it puts finances at risk" **(P14)** "Yea, so our issue is people… I have got… actually a team of 5 people it sounds like a lot of people… ah couple of people would say that's a lot… couple of those… one technical person who really understands the product and a couple of

	people whose job it is to go out and look at dashboards and reports and whatever…" **(P11)** "I would say the primary one is a staffing issue, err more… erm (*I don't want to use the term rich, it makes me sound envious*) but universities with more income or err… than ourselves often have learning resources posts that are dedicating to data analysis, we don't have that" **(P7)** "erm time, we have got loads and loads of ideas and not enough time which I supposed you could put it back to resource…" **(P12)** "I think at the moment we are facing a resource issue in the sense that um… because of its strategy, where it wants to have a better calibre of students coming in, it puts finances at risk" **(P14)** "um and also human resource… in order to make… in order to make sure… we've got the right people dealing with that data and getting the right output" **(P4)** "I suppose one challenge would be ensuring you have got the budget sorted to acquire the data you need" **(P4)**
Strategic IT alignment	"I mean I always think people tend to focus on the wrong place in which they tend to focus on the datasets or on the IT to support them, in fact the reality is it's usually the institutional alignment, getting the people in the right place and erm making sure that their organisation is ready structurally and culturally to deal with it and that I think is the biggest challenge" **(P1)** "So we did a little bit of work on that and that was pretty inconclusive but erm a few months ago I bid for funding for Higher Education Academy under their senior leaders, I can't even remember the exact erm… erm funding stream, but that's myself, our Pro Vice-Chancellor of Teaching and Learning and our interim Vice-Chancellor and that piece of work, that project is really aimed at not developing a Learning Analytics solution for the university but making recommendations and the recommendations are going to be based on the needs and requirements coming from our student body" **(P6)** "well I've already mentioned one which is that I think err… institutions tend to miss the point that you need the organisation to be aligned structurally and err… it needs culture" **(P1)**
Regulatory environment	"we are also working with senior leads across the institution and we are also working with our Board of Governors because this is a governance issue and should it all go horribly wrong, the people that get all of the flak for it and our legally responsible for the university are our Board of Governors" **(P6)** "the thing that is making this all the more important now is this thing called the Teaching Excellence Framework (TEF) which I don't know how well you are informed about Higher Education policy but the TEF is in the green paper which came out about a week or two ago." **(P21)**

	"I think we are very reliant on the NSS data." **(P20)** "A lot of the management information we provide is very much looking at the student experience, um you know coming to understand the NSS and DLHE results and things like that" **(P8)** "So that's a big… big challenge at the moment, it's actually putting those… and working out what policies that we have got and what is missing, uh and rather than just writing more policies, it's actually saying as an institution where are we going to go" **(P6)** "if you build it in to something like err the international student stuff so like you know are we being policeman for the UKVI now and that sort of thing we have to be really careful with the language, we are trying to do it for the right reasons" **(P18)** "We have external bodies who want different kinds of data" **(P16)**
Competitive pressure from other HEIs	"…So I think universities collect a lot of data but I think there could be more transparency about how we are compared to others but the problem with the introduction of fees is that it's created this competitiveness now, which was never really there before" **(P10)** "you've got the other challenge if you take a business course where it's highly competitive and every university is offering it, then… um we are all trying to compete err… to recruit as many students as we can" **(P4)**
External **Support**	"We have also been involved in the JISC Learning Analytics programme" **(P6)** "We are working with JISC on the performance analytics project…" **(P12)** "The student experience project which was very much looking at JISC, one of their diagrams on the SLC, erm so they were interested in how they support the student through all stages…" **(P5)**

There are also people issues affecting the effective use of Learning Analytics, of which more details are provided in Chapter 6. Table 5.8 shows the people issues related to Learning Analytics with its subthemes and relevant data extracts.

Table 5.8 People issues related to Learning Analytics with its subthemes and relevant data extracts

Subtheme	Data Extract
People's engagement with using data and Learning Analytics	"the challenge is much more about then now that we have this data what does one do with it…. how are we expected to engage with it, how are expected to use it to support students" **(P2)** "so getting people to just accept the data is always a major challenge" **(P18)** "Obviously our academics use it and lecturers use it. Well that very much depends on the lecturer, their willingness, their energy, their technical capability" **(P23)** "in fact we have gone from gut reaction decisions where you do it on the basis of an anecdote, I mean I've lived near universities where that's the way it's been for a very long time, and these are people that have been doing the job and watching and they're… you know if you have got a very good experienced person their gut reaction is normally spot on" **(P12)**
People's awareness of data protection and privacy	"Obviously there is data protection issues where we are accessing potential sensible data that we want to look at" **(P23)** "not be intruding on any issues around data protection to enable it to have a voice… for students to have a very loud voice about what was going on" **(P12)** "Data protection there are all sorts of rules about supressing data below a certain threshold are we ensuring that as an Institute that that is done" **(P16)** "otherwise you have got whole issue about data protection, how do you know who you are dealing with, erm yes unless it's a very general enquiry it because very difficult to answer it with any real accuracy" **(P17)** "Obviously there is data protection issues where we are accessing potential sensible data that we want to look at" **(P23)** "We also actually have a lot of problems, we got in trouble recently because of data protection issues and the fact that you could get down to units of 5 or less and therefore there is an argument that is identifiable which means that basically we cannot use it." **(P3)** "you might be the kind of person who says I am not doing no survey – this is an invasion of my privacy" **(P16)**
Digital literacy	"I suppose data literacy for us, that's at all levels and for students is still a challenge in getting them to understand um… when you visualise data it's what it says and what it doesn't say"**(P5)**

	"kind of thinking about colleague's literacy with the data and the understanding they have had to interpret and read what is being presented" **(P28)** "is that people don't understand data, so people read lots of things in trends and graphs but they don't really understand what's behind the graphs and behind the numbers" **(P19)** "I think one of the other… erm… issues is trying to get people to understand the nature of the data that we have" **(P5)** "most of my time is spent working with staff, making sure that the staff are confident and are sane and really know how to use this stuff and that will then cascade down, so if we have got staff with digital skills they can support the students, because when I talk to students and say who should be supporting you for this? They will instantly say my tutor, my lecturer, that's what we do" **(P6)**

Other areas in the data analysis

There was an area in the data analysis identified as a broad theme that was not linked to the research objectives; for example, participants were asked what social media platforms they used to enhance student experience. Table 5.9 shows the social media systems used.

Social media use in HEIs

Table 5.9 Social media platforms used in the UK HEIs

Social media platforms	Data extracts
DeviantArt	"it makes me laugh when I see universities will suddenly go through and create a Pinterest and DeviantArt and everything that is going and we have got all of this and it ends up being a very long tail as well" **(P6)**
Facebook	"So for example in my team here I have got a number of Facebook accounts" **(P17)**
Hootsuite	"Yea, yea, we have Hootsuite to monitor social media" **(P3)**
Instagram	"I have no idea what we do with Instagram… as you can see 1685 followers" **(P11)**

Internal Page use	"We know how many hits we are getting on the website, like counting things but while I… one of my colleagues reports on the outcomes of it, how… we do it because of the number as supposed to really… really heavily involved in the way that we are using social media at this point." **(P12)** "we also collect the data that sits behind that in terms of the number of hits, erm how often people are using it, where they are using it" **(P24)**
ITunesU	"erm, also included within the social media environment as well, things like erm ITunesU" **(P24)**
LinkedIn	"I think the alumni want to use LinkedIn a bit more than they are using it at the moment… we use it a little bit but not really" **(P11)**
Pinterest	"as it happens but they use Pinterest quite a bit" **(P11)**
Student Room	"We do erm keep an eye on things like Student Room , erm but again its more for kind of narrative information, I wouldn't say we, I certainly don't… but we do look at… me and a few of my team look at… track Student Room because we deal with erm the accommodation…" **(P18)**
Twitter	SID as an example have a Twitter feed, the library have a Twitter feed… there are… different services have social media engagement. **(P10)**
YouTube	"I think they use Twitter, YouTube" **(P13)**

There is a variety of social media platforms used in HEIs. One of the university's digital team uses Pinterest, and they do not really use LinkedIn; however the alumni in their HEI want to use LinkedIn more. In terms of YouTube usage in this HEI it varies by department: their computer science group have much material on YouTube and this HEI also uses Instagram, although they have no idea what they do with it. There are different ways HEIs adopt social media, for example, this HEI for clearing had six people following topics that were trending about their HEI, so whatever positive or negative comments students were making about their course, the staff went in and intervened. This participant stated *"it's the first time they have done it, it is very embryonic in its use here at our HEI"* **(P14)**. Another HEI used Student Room: so *"tracking the Student Room feedback, that's a kind of social media aspect, because I did say sometimes if one student says something very negative it's extremely powerful, if* *someone during the application period says don't go to our university because of the accommodation, that's a huge impact"* **(P18)**.

The majority of the HEIs mainly use Facebook and Twitter. One participant spoke about having their own personal Twitter account as anything important comes on that platform because people are talking about it. In terms of the social media presence at the HEI, it is reasonably strong but currently could be better. There are a number of Facebook and Twitter accounts being set up and in their main university account there are many customer service enquiries that go through. Another HEI also states they do have accounts on Twitter and all the popular social media sites and they have marketing tools to do all of this; however this area is left more to their marketing and student engagement liaison people. On top of that they have a CRM system which works around all these processes as well, so they know how many hits they are getting on a website etc. One of the colleagues in the HEI state they are very heavily involved in the way they are using social media at this point.

Returning to the use of Facebook and Twitter, one participant spends time talking to students about what they use: *"25% of the students use Twitter, when you go do you want to use it as part of your learning… no because what they are doing they are just using it as a way of just getting information"* **(P6)**. On the other hand this participant states that academics are veterans with Twitter, and just because academics like Twitter they think students should too. Students use Facebook, but this participant poses the question: *"should we be using Facebook for teaching and learning?"* **(P6)**. This participant states that a group might be set up on Facebook to provide lecture details. In another HEI, their SID has a Twitter feed, along with the library, so all in all there are a variety of services which have social media engagement, so this HEI as a whole is quite responsive. They also compile social media reports. So in this particular HEI they can get a sense of what is going on and whether they should respond. *"They also look at how many times they have been mentioned in the news, positively, negatively… and they've really become far more proactive in that regard"* **(P10)**.

However, some participants are not directly involved in the student experience so could not comment on their HEI's use of social media. One participant also stated that the reason why their VLE, Moodle, is not used to its full potential is because of social media. Another participant stated that they can do more at their HEI in terms of social media. In this particular HEI it is their marketing department who look after that material, but whether they do it in a very robust data-driven way is not certain. They have not really dealt with social media in this HEI so there is definitely room to improve that. There are also other social media platforms as well. Some universities have created Pinterest and DeviantArt accounts, and it ends up being a very long list of social media as well; there is also ITunesU (a section of Apple's iTunes Music Store that features educational audio and video files from universities); Hootsuite is a social media management platform; and internal page use monitoring measures the number of hits on a website.

Future of Learning Analytics

One participant states that the task is to predict individual outcomes in the future. Learning Analytics might be used to identify individuals who should be continuing in HE for a Master's degree, and Learning Analytics is currently used in their HEI to help students stay on their course in terms of revenue generation etc. In terms of future plans for another HEI, senior management are looking to apply good analytical skills to other areas in the student life cycle, such as the student experience using survey data. They are also interested in progression/retention statistics as well and are interested at looking at the Destination of Leavers from Higher Education (DLHE) data, their graduates' destinations and what kinds of students are successful. They need to define what student success is and from there can find out which students are more likely to be successful. So basically the future is applying Learning Analytics in any of the areas mentioned.

There is an increasing demand to be more proactive in recruiting students or obtaining research funding. From a student perspective in another HEI there is a need to spend time actually talking to their students to find out what they want; for this HEI that is the most important piece of work, as well as the institution engaging with thinking about data warehousing to reduce their many systems. A challenge is determining what data they want in third-party systems.

One participant states that Learning Analytics is absolutely critical as the HE market is becoming more competitive. Without Learning Analytics, they would not be able to be as effective and they would be wasting budget by not knowing where to target it, and Learning Analytics also improves the applicant experience. In the same vein another participant argues that Learning Analytics is here to stay. They are hoping to work with Higher Education Information Database for Institutions (HEIDI) as well as launching something where they can start benchmarking: there is a new benchmarking tool being developed. They have also been working with the Higher Education Data and Information Improvement Programme (HEDIIP) on the information landscape project where they are very keen to look at their data capabilities as an institution and not as individuals so that they are ready for some of the sectoral changes that are starting to make data available much faster and in a much more end-point focused way so they need to be better at handling the large quantities of data.

So all of the issues mentioned for this HEI are just the way of the world now; they are not doing it for their own benefit: there is the government pushing them to be able to do it plus the HEI is asking questions to enable them to defend their position in terms of the way they have set up HE. All in all this HEI is very keen on demonstrating to the student body that it offers value for the money the students have spent on their education, so it means they have to give the students an experience even if they are hesitant, so that if they ask the students three years down the line they would agree it was worth it.

Another participant states that many companies are trying to make money out of Learning Analytics; many of these companies have very little knowledge of HE, however they have extensive knowledge of retail, even other parts of education. Some of the companies that this participant has spoken with evidently know very little about HE, and the same argument resonates with people in the US, the participant claims. This participant states that however they still feel they need to engage with the Learning Analytics approach.

At this particular HEI, they would like to think they will improve at the utilisation of Learning Analytics; this participant found that another institution near their HEI is better at Learning Analytics. They feel at the HEI it is important to get the source information right in order for the data to make sense; their student system is sometimes quite restrictive and unless they get the source of information right they will never get the big picture.

In this HEI they are trying to take it to the next stage: at the moment, they report on the current state of the university but they could make it more analytical, thus getting the data to make predictions. According to this participant, with Big Data you can almost predict something is going to happen before it does based on all the trends and forecasts etc. They think becoming more sophisticated at that would be good. Student retention is a really good example of that: so looking at what they know from the data and then applying those behaviours that they see to the students they currently have and being able to pinpoint certain people based on their engagement that they need to interact with in order to help them not drop out, this is taking it to the next level of analytics. One participant also stated *"I'm really keen to enhance Learning Analytics, really keen to ensure that it's greater… sharing of* *information as well"* **(P10)**. Another participant stated that in terms of applications, Learning Analytics has to be done very carefully and consensually; the approach has to be a partnership between the students, the people who are doing the monitoring and the academic staff, and they have to be prepared to change staff behaviour, both the academics and the professional services, because it is about them all changing their behaviours.

5.4.3 Objective three: To understand how Learning Analytics is being used for SEM

To achieve **objective three** the data analysis has been split into three areas: how to acquire data, how to make sense of data using Learning Analytics, and how does the use of Learning Analytics impact on SEM. Data is very significant in our everyday lives; therefore it is important to acquire data in order for Learning Analytics to make sense of data for better SEM. The tables following show the themes that were identified initially; more details are provided in Chapter 6.

How do HEIs acquire data?

The themes have been categorised into three parts: data integration, data collection using emerging ICTs and multiple data sources. Table 5.10 shows the how HEIs acquire data with its themes and relevant data extracts.

Table 5.10 Themes related to data acquisition in HEIs

Theme	Data Extract
Data integration	"we data warehouse it so we make sure that its contained within one single office" **(P10)** "Yep… um we use the data that's generated by several of our systems..."(.) **(P1)** "That means that we could extract staff that are students and how much, kind of getting those interconnectivity between the systems." **(P18)** "we can't track people through and different people own systems, different people feel they own that data" **(P5)** "it's a repository really, you structure a repository that allows people to

	um… get hold of the data from the SRS and actually understand what that data field is and whereabouts in the system it comes from" **(P14)** "So Tableau takes… it's a data visualisation tool, so it takes… it can take data from a number of different sources, erm and kind of knead them together and present them… so you can have the data presented in a number of different ways erm through the visualisations". **(P20)**
Data collection using emerging ICTs	"that's when we first start to capture data… erm in fact with UCAS now we actually erm… hire scanners from them so every event we go to, we actually erm… a student comes up to our stand and we… we scan their ticket, that data then gets sent through to the university three days later saying what subjects they are interested in and a whole range of things, so we capture that data…" **(P4)** "one of which was installing RFID and it's both near and long sensing RFID equipment in classrooms so we can track cards as they go through the building" **(P31)** "we use the Jenzabar system, the student engagement system is still used which is gathering data from various systems" **(P31)** "we have just now introduced EvaSys which is the online module and evaluation system which I'm sure you are familiar with, which gives feedback on individual learned modules in teaching and learning" **(P3)** "we are just bringing more formal attendance monitoring so students swipe electronically we have always had that on a weekly basis, we have 300 odd readers so you can swipe anyway we are just bringing it in to classrooms"**(P18)**
Multiple data sources	"there is an increasing amount of useable data that's been generated across the institution" **(P1)** "we are… at this moment in time we are experimenting by adding in new data sources so at the moment we can't capture the use of um electronic books and e-journals very well, so that's one of our projects now" **(P2)** "um we have been working with HEDIIP on the information landscape project where we are very keen to look at our data capabilities as an institution not as individuals but as an institution" **(P12)**

How do they make sense of data?

The themes have been categorised into three parts: generating better understanding and new insights, interpreting data using KPI and learning from data. Table 5.11 shows the how HEIs make sense of data with its themes and relevant data extracts.

Table 5.11 Themes related to how HEIs make sense of data

Theme	Data extract
Generating better understanding and new insights	"we produce market intelligence" **(P12)** "forecasted some challenges in the area of process" **(P11)** "data cubes to explain and model financial performance at the course level but at a wider business level as well" **(P7)** "We have got loads and loads of ideas and not enough time which I supposed you could put it back to resource…" **(P12)** "…know how they (students) are performing on their studies, their attendance and various things like that and trying to translate that into some facts where we can understand" **(P14)** "so for the Cognos tool… erm it draws in high level data from our Banner, from our student records, from our timetable etc. and what it does is produces reports on cohorts so that the whole year group or the whole… whole course" **(P2)**
Interpreting data using KPIs	"so in the sense that we do use a variety of BI approaches and tools in order to gain and distribute an understanding of issues relating to students" **(P22)** "We have erm university institution departmental performance dashboards that cover all aspects of um KPIs that we are collecting data on and we are measuring on performance again, they can range from student experience through to financial…" **(P26)** "that is just working with departments, so you need to put contexts around err metrics and use of KPI's" **(P20)** "We have our own areas of reporting like we are responsible for like admissions numbers and KPIs and things like that so very sort of management focused stuff" **(P8)**

Learning from data	"well retention… is… something that we focus on quite a lot, so we measure student retention rates or non-completion rates and we cascade those out to departments through enterprise wide dashboards" **(P21)** "in terms of Business Analytics you try to find out why this happens and I think I try to achieve it by using a regression model to understand why this happens" **(P13)**

Table 5.12 shows the how HEIs assimilate data using Learning Analytics tools: Descriptive analytics, Predictive analytics and Prescriptive analytics with its themes and relevant data extracts.

Table 5.12 Assimilating data using Learning Analytics tools

Theme	Data Extract
Descriptive analytics	"in terms of the reporting that comes out of it we have just moved across to BI publisher" **(P18)** "erm we have Alteryx which does the kind of back end data merging and all that stuff" **(P8)** "I'm calling it Business Objects; it's now called the Business… SAP Business Intelligence suite with Business Objects being the main reporting tool" **(P12)** I use Business Objects to extract data, students data to be ready for the… so we need to identify who are the PGT [post-graduate taught] students, PGR [post-graduate research] students by using BOXI **(P13)** "Business Objects is our main analytical tool" **(P11)** "I get the data from HEIDI for example you know HESA's…" **(P13)** "We use… erm the SAP ETL development software, so everything comes from the SAP suite of products" **(P12)** "I mentioned OBIE that does some of the operational reporting, that is still around and has its sort of advocates out there err in other teams" **(P8)** "we use erm a software called FOCUS and what that does is that monitors our erm… the number of media mentions that we get across the… well across the UK" **(P4)** "developed a dashboard so when I login to my Tech one, it comes up with how my registry are doing" **(P18)** "in order directly to enhance the student experience probably not a lot,

	indirectly much... much more so in the sense that we do use a variety of BI approaches and tools in order to gain and distribute an understanding of issues relating to students" **(P22)**
Predictive analytics	"forecast student numbers which is obviously a very significant thing because its linked to a couple of 100 million pounds worth of income" **(P21)** "often you know predicting whether they are going to drop out or if they are at risk of dropping out" **(P14)** "we will use an algorithm from what happened last year to then project forward and say yea ok based on this many people who have made us their conditional firm we know that say 10% would have then translated to people who actually came here" **(P17)** "In terms of engagement currently here we are looking to use predictive analytics um on student engagement" **(P21)** "one of things that we are increasingly finding is that yes we have very good predictive analytics at the moment we have two different models that can predict very well who is at risk and who is not at risk" **(P19)** "one is run by the information office and the information has a model where we basically look at the 30 most predictive characteristics of students that determine how well they are performing over time and this initially" **(P19)** "So we were looking at a bunch of data about all of our students and saying can we predict which students are more likely to drop out" **(P11)** "model is now currently also used for our student support team so they would get, if I would call and would see if I'm a high risk student, they would say yep well according to our predictors……is a high risk person because he hasn't logged in for weeks and I haven't done anything" **(P19)** "Well student success links quite a lot to attainment as well… um and links to that whole predictive agenda to… so you know you can obviously use analytics to look at the root… different factors that affect um student success and the thing that is making this all the more important now" **(P21)** "we also use IBM TM1's specifically for student number income forecasting which is again a specialist planning tool" **(P22)** "we have two primary analytics modules, one is run by the information office and the information has a model where we basically look at the 30 most predictive characteristics of students" **(P19)** "we've developed our own predictor model for example in admissions

	that we present to the Vice-Chancellor every two weeks" **(P4)**
Prescriptive analytics	"we are starting to use all these pieces of data we have about students and you know how they are performing on their studies, their attendance and various things like that and trying to translate that into some facts where we can understand, often you know predicting whether they are going to drop out or if they are at risk of dropping out" **(P14)** "…we have managed to reduce our non-continuation from really quite high levels in the high teens just a few years ago to a position where the most recent published figure is within the benchmark" **(P1)** "we got to a place where we know all the gaps and we can spot students at risk, we absolutely know that that is a fact now, so really it's now that developing tools to then enable us to intervene better" **(P2)** "Student retention is the number one driver, so eventually in a year's time I would be judged on all those modules, whether we have been able to improve student retention based on the real-time analytics that we are currently providing and I am crossing my fingers that there will be a positive effect." **(P19)**

How does the use of Learning Analytics impact on SEM?

Table 5.13 shows how does the use of Learning Analytics impact on SEM with its subthemes and relevant data extracts.

Table 5.13 How does the use of Learning Analytics impact on SEM

Main theme	Subtheme	Data extract
Student recruitment	Identifying and addressing problems with student recruitment	"this institution has gone through a few problems over the last year, what impact has that had on recruitment from you know our local postcode areas, I don't know it would be nice to know, I'd imagine it has had some impact" **(P6)**
	Benchmarking with competitors	"we do use a lot of data here and we purchase a lot of data from UCAS and other bodies looking at what student trends are, what our competitors are doing and a whole range of things like that" **(P4)** "we make data purchases from UCAS and HESA and they look at our competitor positions in relation to other UK institutions, erm so we would do that on recruitment" **(P20)**

	KPI information	"We have our own areas of reporting like we are responsible for like admissions numbers and KPIs and things like that so very sort of management focused stuff but we work on the principle that like marketing are responsible for their own reporting and registry are responsible for theirs and the research office is responsible for theirs" **(P8)** "The other way we use our business of BA information is around reviewing our portfolio of programmes to make sure they are healthy and current and so we have a set of key KPIs, assess is one of them, applications, conversions to applicants" **(P27)**
Student engagement	Better engagement management	"So in terms of the engagement though, any of those referrals that come through the PAT system or via email erm we log and then we get back to the referee to let them know what is going on, so predominantly it would be the PAD team who are using the PAT system so I would get a referral from a Personal Academic Tutor" **(P7)** "it is an alert system for students you are at risk, so what is looking at is more based on the American model of some soft stuff so we can easily do if somebody is not attending or if they haven't submitted some coursework or if they have missed a one to one with a tutor" **(P18)** "so you get a kind of heat map of red, green and um… so we are in a way a weighty kind of analytics police right… which is not nice but what we are also moving towards is providing real time dashboards, so for example module teams or anyone who has access to the university as a member of staff can see of the 600 modules in week… we are now in week 3, say in module T100 you have 2000 students how many of those 2000 students have logged in" **(P19)** "We can invest as much time as possible to do the interesting things for us around learning analytics, around the student engagement monitoring because we know that that's the way that we can start leveraging far more out of the system and making a better experience for the student body." **(P12)**

	Keeping students engaged	"how we join up our data that we have on individual students and the student union's data to start to erm… look at kind of how the students are engaging and then put that alongside some of their activities around self-assessment and psychometric testing to try and map on quite a large scale on how the students are progressing through university" **(P28)** "we do engage with current students on this opportunity again using our CRM system" **(P4)**
	Attendance monitoring	"We often find… so attendance monitoring is a good example we don't have a process for attendance monitoring, so there's a… so every now and again it pops up that someone thinks we need attendance monitoring" **(P11)** "Ok well so the main challenge is maintaining attendance at lectures. Not because attendance in itself is meaningful, but to the extent it indicates that the students are engaging with the topic of the course we are trying to teach" **(P15)**
	Better management of students at risk	"just one example we have a… an approach which erm uses a range of data sources… erm to target students we believe are at higher risk of erm non-continuation" **(P1)** "More recently I was looking at a student's progression from year 1 to 2 or overall so among those students who started their study in certain years how many of them managed to complete their courses for example, so I was looking at that kind of data as well, erm again maybe that relates to more to student retention" **(P13)**
Student retention	Improving student retention	"…we have managed to reduce our non-continuation from really quite high levels in the high teens just a few years ago to a position where the most recent published figure is within the benchmark" **(P1)** "we got to a place where we know all the gaps and we can spot students at risk, we absolutely know that that is a fact now, so really it's now that developing tools to then enable us to intervene better" **(P2)**
	Student behaviour change	"you start to implement performance analytics and you can end up in the arena of changing student behaviour" **(P12)**

Student success	Learning satisfaction	"one of the key criteria is learning satisfaction, so we are trying to help with analytics to make module chairs more aware of learning satisfaction, so in that sense it's yes or no" **(P19)**
	Performance comparison with competitors	"No evidence, but the use does seem thoughtful and appropriate, so probably better than most" **(P9)** "I think what we have achieved with the Tableau server and the stuff that's on there is actually, from what I sort of anecdotally talked to other people in the sector they are not as far along as that" **(P8)** "I think other universities haven't taken the full benefit that they could and that I think what they have done is they have got the data and it probably goes to a senior management that isn't accessible to all staff so you don't get the transparency which means you don't get the engagement of staff to make changes" **(P27)**
	Improving performance and success	"…they were looking at that against student achievement… and they were able from that to identify that more contact engagement led to better achievement for first years but by the second and third year it had very little effect because by that time the students had already worked out a pattern of how they could succeed in their studies" **(P12)** "…we will start with student correlation but then working up to multi regression analysis so that we can actually identify from that the key things that would lead to good performance within a demographic structure" **(P12)** "…we can find out who are those students who are more likely to be successful, so I think we can apply Business Analytics in any area" **(P13)** "So putting lots of different initiatives lots of different erm… mechanisms, data and processes in place to ensure that students would get the best possible student experience" **(P10)**

In line with **objective three** of this research, participants were asked what BA / Learning Analytics systems their university used for SEM and if their university used Big Data at all. Responses for this objective were categorised into themes according to the types of Learning Analytics tools and functionality. The second part of achieving this objective was examining what the ideal tool was for participants.

Learning Analytics tools

In terms of e-learning systems there is a wide range, for example BREO: *"I think in terms of the overall student experience I think BREO…yea, so we have Blackboard BREO"* **(P10)**. Most participants use Blackboard and only one institution uses BREO, whereby you can access various resources and for teaching it is required to upload all the slides on to this environment as well as guidance; if that does not happen that can lead to a detrimental student experience. There are two other VLEs called SAKAI and CANVAS which are used by participants: *"We are also changing our Virtual Learning Environment (VLE) from um… an open source product called SAKAI to erm CANVAS"* **(P5)** and "*SAKAI and CANVAS are providing analytics, and we are interested in not keeping these all separate and putting them together*" **(P5)**; and another participant mentioned how they used their own VLE which is called StudyNet: *"So the university does have its own Virtual Learning Environment (VLE) so it's called StudyNet"* **(P17)**. Moodle is a very popular e-learning system: *"Moodle which is something you might use"* **(P23)**.

One HEI stated how they built their own VLE a few years ago with SharePoint, which was "hideous" and no one used it, so they then proposed a digital learning environment which uses Moodle called Campus M. Another HEI uses Moodle: it is their e-learning environment and is very useful in terms of academics' self-administration procedures, i.e. arranging tutorials, communicating with the student, if the time of the lecture is changed, and also effective for publishing learning materials. In terms of student data systems, participants institutions either have a SRS (i.e. Quirkus): *"So firstly we are a very centralised university, we have very centralised data systems so we have a SRS called Quirkus"* **(P18)** or an SIS, student dashboards may be used as well: *"we have a number of different systems that hold the data like our student records system (SRS)"* **(P28),** *"what we have currently erm would… would be within the academic information system (AIS)… our SIS"* **(P5)** and *"we use the* *student dashboard… it's used to stream technology*" **(P2).** Popular student data systems are SITS, Banner and Unit-E. One participant gave a comparison of SITS against Banner. SITS is a bit like Banner, this particular HEI has had Banner since 1999 when they started implementing it. Tribal SITS is the most common SRS in the UK: *"Well SITS is a huge student records system and principally it's there to keep a record of every student"* **(P23)**. Banner is the most common SRS in the world; it was designed in an American system: *"we've got Banner as our student database, so the data… we take the data on a nightly feed from Banner and we extract it, translate it, put it into a data warehouse every night and they monitor the applicants and what the students are doing at quite a granular level of detail"* **(P12)**. With Banner it is more definable by the institution, they can implement parts as and when they feel like it because most of the code Banner uses is more open source, so open to the people that have bought the system, to develop as they wish and they can code it very easily. With SITS *"the timetabling information goes in there, all of the rules in the University of that date has to go in there and with that we can then obviously enrol students, track students, record assessments, we can also record attendance at the lectures as well"* **(P23)**.

One HEI interacts most of the SITS information through Tableau and another HEI decided not to go with SITS because they would be a very small player with a very large provider, which means they would have very little influence on what they have, so they decided to go with Quirkus.

There is also a system called Unit-E provided by Capita. It works quite well but it is not really an HE product – it is used very widely in FE (further education); there are only two or three universities that use it: "*as far as student records is concerned so the core kind of static data for the student… we use a system called Unit-E"* **(P11)**. There is also My Campus within which much of this particular institution's data stays: *"we have a system called My Campus which is our… I don't know what the original platform was for My Campus but it is* *something that the university has created itself and a lot of our data sits within that"* **(P24)**. Qlikview and Tableau are popular Learning Analytics tools and are often compared to each other. Two HEIs decided not to go with Qlikview. One HEI saw Qlikview when it was first introduced and they made a positive decision not to go with it, it is improved however since the very first time that they saw it but what it was doing then was not what they really wanted it to do: *"I think somebody somewhere is experimenting or has experimented with something called Qlikview"* **(P14)**. Another HEI has a Qlikview licence and one of their staff members uses it and is an advocate for it but all in all they prefer Tableau. This HEI went through a tendering process and a kind of review of what users thought of the different products, but Tableau came to be the one that they thought that they would use.

In terms of Tableau (a data visualisation tool), there is one very useful way in which a particular HEI uses Tableau: *"we use Tableau"* **(P12)** –they take the data from the module evaluation survey system which is run in-house but it uses a software system called EvaSys which comes from Electric Paper UK and most of the institutions in the country have a very similar system and most of them tend to use the EvaSys system. All that data is gathered and they put it into Tableau and from Tableau they are able to do visual comparisons. With the Tableau tool, they can carry out activities within a department and show them how they have performed by each question compared to other departments, whether it is an autumn, spring or summer survey. They have got comparativeness, they have time comparison within it, and they can see how many people answered using visualisation; there is very little numeric data except the axes to graphs. Using visualisations they show departments how good their response rate is and how positive the response was for each of the programmes that participated in that particular department, so they can get quite a fine level of detail from a visualisation: so they have used Tableau quite successfully for that. This HEI also uses dashboards through Tableau, for example, they have dashboards in the income workbooks that they look at.

Another HEI uses Tableau to take data from a number of different sources and knits them together, and then the data can be presented in a number of different ways through visualisation. It involves taking various data sources and being able to put them into something coherent and hopefully intuitive to understand for the end user; therefore Tableau has been really good for them. They are moving more and more data over to Tableau because once they have got the data into Tableau and understand how it works, it is reasonably intuitive. They go into Tableau and they change the filters and they see what happens to the visualisation they have got; it does not matter where the data has come from, it is a familiar interface, it looks the same as other Tableau reports, so the managers have got an idea of how to go in and start working with it.

In contrast, another HEI uses campusM *"One of the things that we have run for a number of years is all our mobile apps....well campusM is the product…"* **(P6)**. In 2016, there was a huge spike of students downloading campusM, in early September before they started. So the students are receiving all the material before they come to university which is a good opportunity to give them information and access to materials before they come to the university. This HEI has a 5000 student intake, of which 2500 students downloaded the app before they turned up and once the students have got the app they carry on using it: it is very powerful.

There is also Electronic Service Desk (ESD): *"So we have ESD which is predominantly based within… I think it's the SID team so they use that to collect data. So we collect data so thereby we can manage it and profile the data and in different ways so that yea… this student came in with this enquiry, it's a way of,* you know, understanding your service offering *better"* **(P10)**. In terms of dashboards one participant spoke about using something called an opinion dashboard.

Ideal Learning Analytics tools

Participants were asked if they had a preference for what would be their ideal Big Data or Learning Analytics system/tool to support SEM for the university. From the data analysis it is evident that participants had different ideas on what their perfect tool would be, some of the participants preferred the tool that they are currently using in their institution: *"so from that point of view the ideal tool, Business Analytics tool um would be a corporate tool and we have a corporate tool"* **(P11)**. One participant stated that their ideal tool would be one enormous collection of data that is structured in a very logical way to answer the questions that they typically ask about the business: it would consist of data from different systems, transaction data, it could be some of their less transactional data branching out of Big Data and it is there in a warehouse that they have some "groovy" interactive tools that are nice visualisations and present all the dry information to people in a very compelling way so it grabs them.

On the other hand another participant gave an example of a system similar to Signals: *"At Purdue, we've developed Signals as a means of helping students better understand where they stand grade wise early enough so that they can seek help and raise their grade or drop the course without the penalty of a failing grade"*(Pistilli and Arnold, 2010, p2), one which has clear visual indicators would be ideal, similar to the traffic light system: *"we have some really groovy interactive tools that are nice and visual and present all these dry information to people in a very compelling way so it grabs them you know and if it's good stuff its green, if it's bad stuff, its red and its flashing and there is alarms ringing and all that kinds of stuff"* **(P14)**. The participant wants the system to be robust and the people using it to be able to make decisions with it whenever they want in a format they want. One participant spoke about it being ideal to have a super dashboard so that when they log on, it would tell them the number of students that have logged on that day, and the number of students that have never logged on and the number of downloads. In relation to dashboards one participant stated: *"A… student facing dashboard, that they can themselves um choose how they want to have the information"* **(P19)**. Another participant discussed a system that is easy to use, being able to access anything and to interrogate the data how you wanted it: *"I think it's just ease of use, that would be amazing and being able to access anything and to be able to sort of slice it and dice it how you wanted it"* **(P17)**.

An area that a particular HEI is struggling with is their CRM. They have a CRM system but are not using it to its full potential, it still needs much human intervention, and they are evaluating it and will perhaps return to it: *"we have a CRM system but we don't feel it's getting we are getting the best benefit from it at the moment, it needs a lot of um… human intervention which CRM always does but is um…you know um… it's something we are evaluating and maybe we will come back and have another look at"* **(P4)**.

Some participants already have the tool they want, for example, Business Objects. This participant states that Business Objects is a very good tool despite one or two weaknesses; it is a corporate grade tool which many large corporations use. There is also Banner: one participant is currently very happy with Banner: *"I'm very happy with using Banner"* **(P12)**. This participant thinks there are new developments in Banner that if the resources were available, they would have liked them to implement faster, but you can only have so many business analysts doing so many activities, what they have got to do is make sure that the systems they have got will talk to each other because they have, for example, a timetabling system that talks to Banner, they have a system for managing accommodation services that talks to Banner, as long as they can make sure that they build the interactions, manage them easily and effectively then in some ways you need to buy the software that is fit for purpose for what they want to do. Most software suppliers make sure that can integrate data flows. Another participant states they have designed the one that they wanted,: *"I think we've designed the one we wanted to be honest, erm so in a sense you know that... that was literally what we wanted so we created it ourselves…"* **(P1)**. Along the same lines another participant thinks they have their ideal tool, Tableau, and that is the preferred one: *"I don't know because I don't have enough experience, but I'm obviously going to say Tableau*." **(P20)**. In terms of modelling, two participants spoke about the different models that they would want: *"I think my ideal solution would be a kind of mixed model, um whereby you would have a proper data warehousing facility and then the ability to use reporting tools on top of that, which might be different for different purposes"* **(P22)** and *"it is an alert system for students you are at risk, so what is looking at is more based on the American model of some soft stuff so we can easily do if somebody is not attending or if they haven't submitted some coursework or if they have missed a one to one with a tutor"* **(P18)**. Another participant referred to their ideal tool as one single system which was accessible: *"so there is something to be said in terms of the ideal system is just one single system that allows everybody to access it and to input information but also to draw that information out and to query it*" **(P24)**. Finally, on using analytics to improve the quality of teaching: *"If we were able to demonstrate that we use analytics more systematically to improve the quality of teaching and improve the education experience the attainment of the students that would be useful"* **(P15)**.

5.4.4 Objective four: To develop a conceptual framework to provide a systematic overview on the use and impact of Learning Analytics on SEM in HEIs

The next chapter focuses on this objective as the theoretical lens for this study is identified and the codes identified mapped out using the adopted theoretical lens to develop the conceptual framework.

5.5 Additional Data Analysis Based on Participants' Profile

To explore if there are any significant differences among participants with regard to factors affecting the use and impact of Learning Analytics, the study conducted an additional data analysis with the interview outcomes based on the NVivo results. Table 5.14 provides a summary classification of the participant profiles.

From the summary table it is evident that there is a higher percentage of male participants (70%) than female participants (30%). The majority of the participants are senior managers (60%). Universities are classified into Post 1992, Redbrick, Russell Group, Plate Glass and Independent. Post-1992 universities, also known as new universities, are former polytechnics in the UK that were provided with university status through the Further and Higher Education Act 1992. Redbrick universities is a term initially used to discuss about nine civic universities that were founded in the main industrial cities of England in the 19th century. Russell Group universities are the top twenty-four universities in the UK. Plate glass universities are a group of UK universities promoted to university status in the 1960s and Independent universities are private universities offering independent Higher Education. The most common universities in this research are post-1992 universities followed by Russell Group and then plate glass. There is one each of a redbrick university and independent university.

Based on the participants profile summary, an analysis was conducted based on the gender. Table 5.15 shows the findings.

Table 5.14 Summary table of classification of participants

Categories	Number	Percentage
Gender (n=30)		
Male	21	70%
Female	9	30%
Management Level (n=30)		
Senior	18	60%
Middle	7	23.30%
Academic	4	13.30%
Data Specialist	1	3.33%
University type (n=23)		
Post 1992	11	47.83%
Redbrick	1	4.35%
Russell Group	6	26.09%
Plate Glass	4	17.40%
Independent	1	4.35%

Table 5.15 Analysis of factors based on the male and female participants according to the TOE framework

TOE Framework	Factors	Sub Factors	Supporting cases from Male (n=21)	Supporting cases of Female (n=9)
Technology	Usability	Ease of use	33%	88.9%
		Effectiveness	57%	44%
	Affordability		47.6%	100%
	Complexity		100%	55.6%
	System Integration		33%	44%
Organisation	Resource	Time	47.6%	22%
		Human	47.6%	11%
		Financial	38%	11%
	Data Driven Culture		90%	88.9%
	Senior Management Support		71%	44%
	Strategic IT alignment		71%	22%
Environment	Regulatory environment	Governance	47.6%	77.8%
		Policy problems	28.6%	55.6%
		UKVI regulations	9.5%	11%
	Competitive pressure		47.6%	77.8%
	External support		14.3%	33%
People	People’s engagement with using data and Learning Analytics		14.3%	22.2%
	People’s awareness of data protection and privacy		23.8%	44%
	Digital Literacy		9.5%	33%

In terms of the technology factors with regards to usability when broken down into ease of use and effectiveness, effectiveness is identified as an important factor by more male participants than by females. In terms of the organisational factors, resource is divided into time, human and financial with those characteristics being identified as more important factors by more male participants then female participants. Data driven culture, senior management support and strategic IT alignment are also identified as important factors to male participants with data driven culture being the most important. With regards to the environment factors regulatory environment is split into governance, policy problems and UKVI regulations, it is evident that more female participants than male participants identify all three factors as important along with competitive pressure and external support. In terms of the people factor, digital literacy is identified as a more important factor for female participants than male participants and People's engagement with using data and Learning Analytics and People's awareness of data protection and privacy is identified as more significant factors for female participants as well.

It is noted that it is difficult to distinguish the differences based on the participants' roles because the majority of them are senior managers (60%) and the number of the participants in other roles are too small to be compared with the senior management group. Also, as the qualitative research has limitations at identifying and establishing the patterns between demographic profile and factors, future research using surveys based on the identified factors could be developed to establish if, statistically, there is any significant differences among participants in different gender and management positions. These recommendations are outlined in the future research section in chapter 7.

5.6 Chapter Summary

In summary, the TQA process adopted for the data analysis of this research brought about a wide variety of factors that were important for the use and impact of Learning Analytics in UK HEIs. It also assisted in meeting the objectives agreed for this research overall and the creation of a theoretical framework for examining factors affecting the use and impact of Learning Analytics in UK HEIs in the area of SEM. Information on how the framework is developed is provided in Chapter 6, framework development chapter.

Chapter 6: Framework Development

6.1 Background

The overall aim of this research is to explore the use and impact of Learning Analytics for SEM in UK HEIs. In order to accomplish this aim one of the main objectives is to develop a conceptual framework to provide a systematic overview on the use and impact of Learning Analytics. This chapter aims to address this objective by discussing the development of the framework.

This research was carried out in two parts: firstly, the exploratory case study and then secondly, the main study. The first part of the research was carried out as an exploratory case study in order to understand how UK HEI managers see the idea of Learning Analytics being implemented in the HE sector. A theoretical lens was chosen for this study based on the findings and more in-depth review of the literature. This overall research follows the abductive approach as discussed in chapters 3 and 4; the data analysis follows the inductive data-driven approach. The process of theory matching was conducted as mentioned in the literature by Dubois and Gadde (2002); this involved presenting the theoretical lens of the research after the data collection and analysis. Also, the Dubois and Gadde (2002) method was grounded in an abductive logic. The Technology-Organisation-Environment (TOE) Framework along with Absorptive Capacity (ACAP) theory were most appropriate to structuring the findings of this research; from this a theoretical framework was mapped out which examined the factors that affect the use and impact of Learning Analytics in UK HEIs. The two theories are used for two different purposes: TOE for factor mapping and ACAP for the use of Learning Analytics. The following sections discuss the research findings in relation to the theoretical framework.

6.2 Theoretical Lens for this Study

In Chapter 3 various important theories to this research were reviewed that may be relevant for understanding the use and impact of Learning Analytics. Using the literature review as a foundation along with assessing the appropriateness for this research context, the TOE framework was selected as the theoretical lens for this study. TOE has been widely used in investigating factors affecting technology adoption and used at the organisational level. Therefore, for this research along with the ACAP theory, TOE was originally developed at the organisational level. Figure 6.1 shows understanding the use and impact of Learning Analytics on SEM from a TOE and ACAP perspective.

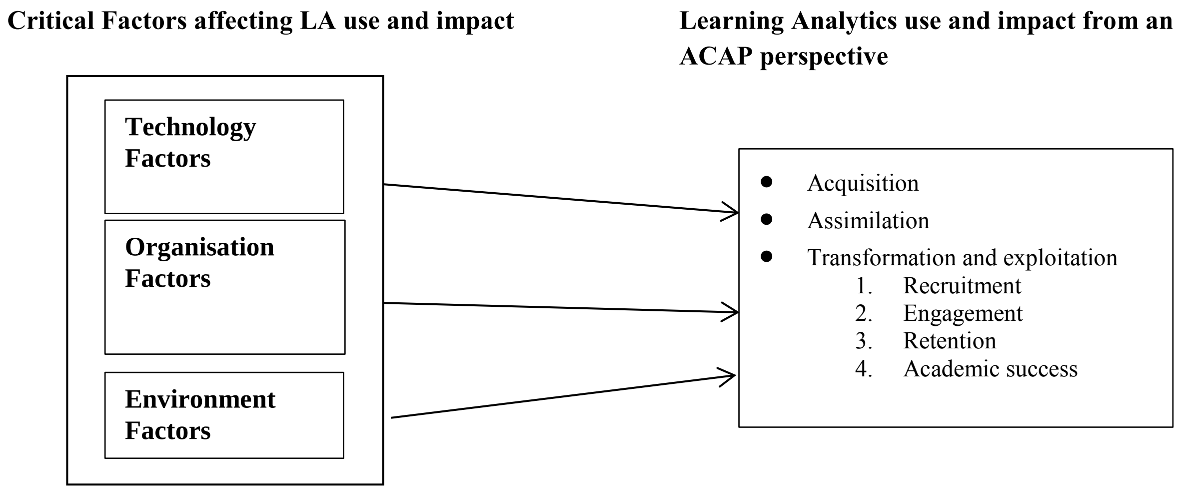

Figure 6.1 Understanding the use and impact of Learning Analytics on SEM from a TOE and ACAP perspective

6.2.1 Technology-Organisation-Environment (TOE) framework

Tornatzky et al. (1990) proposed the Technology-Organisation-Environment (TOE) framework to study the adoption of technology innovation. Tornatzky et al. (1990) created the TOE framework in order to define the organisational constituents that have an impact on an organisation's adoption decisions. The Tornatzky et al. (1990) TOE framework states that there are three key contexts: technology, organisational and environmental, which affect how an organisation implements and takes on a new technology. There have been many studies (Gibbs and Kraemer, 2004, Chau and Tam, 1997, Iacovou et al., 1995, Thong, 1999, Zhu and Kraemer, 2005, Zhu et al., 2004, Zhu et al., 2003) that have utilised the TOE framework as the theoretical basis for examining a firm's acceptance of new technologies; this is explored in more depth in Chapter 3.

In the context of SEM, the TOE framework can help understand the key factors that affect Learning Analytics use and impact on SEM. The Learning Analytics technologies are seen to be able to provide descriptive, predictive and prescriptive analytics to significantly improve SEM. The organisational factors could include organisational size, organisational support in terms of the slack resources an organisation has internally and quality of human resources (Wang et al., 2010, Tornatzky et al., 1990), SEM strategies, as well as processes and the culture of the HEI. For example, it has been recognised by researchers that a data-driven culture is essential for Learning Analytics to be used effectively.

Technology context

The technology context studies the existing technologies that are significant to the organisation, both internal and external, that may be valuable in refining a firm's productivity. It can also refer to the object of technology adoption that is new (Lippert and Govindarajulu, 2015).

Organisational context

The organisational context is defined as resources accessible to support the approval of the innovation. The conditions of the organisational context include centralisation, interconnectedness, formalisation, firm size and scope, the quality and accessibility of the organisation's human resources and complexity of the managerial structure (Lippert and

Govindarajulu, 2015). The organisational context can also be seen as the effect of organisational features on the choice to implement IT.

Environmental context

The environmental context signifies the location in which an organisation carries out business and is influenced by the competitors, the organisation's capability to access resources provided by others, connections with the government and by the industry itself.

6.2.2 Absorptive Capacity Theory

As stated in Chapter 3, Cohen and Levinthal defined ACAP as "…*an ability to recognize the value of new information, assimilate it, and apply it to commercial ends*' (Cohen and Levinthal, 1990, p128). Lane et al. (2006, p856) also defined absorptive capacity as *"Absorptive capacity is a firm's ability to utilize externally held knowledge through three sequential processes: recognizing and understanding potentially valuable new knowledge outside the firm through exploratory learning, assimilating valuable new knowledge through transformative learning, and using the assimilated knowledge to create new knowledge and commercial outputs through exploitative learning".* According to Szulanski (1996), in an organisation that lacks absorptive capacity there will be lower likelihood of it being able to identify the value of new information, less likely to assimilate that information and less likely to apply it effectively to commercial ends.

Acquisition

The acquisition capability refers to the acquisition and finding of externally produced information key to the organisation's operations (Abecassis-Moedas and Mahmoud-Jouini, 2008). According to Cohen and Levinthal (1990), the components of acquisition include prior investments, prior knowledge, intensity, speed and direction. They also state the role and importance of acquisition is for new connections, speed of learning and quality of learning.

Assimilation

Assimilation refers to the exploration, the understanding and the interpretation of the knowledge obtained (Abecassis-Moedas and Mahmoud-Jouini, 2008). According to Lane and Lubatkin (1998), the components of assimilation include understanding. They also state the role and importance of assimilation as interpretation, comprehension and learning.

Transformation

Transformation refers to a mixture of acquired information with the existent information leading to additional information, deleting information or deducing the same information differently (Abecassis-Moedas and Mahmoud-Jouini, 2008). Cohen and Levinthal (1990) state the components of transformation include internalisation and conversion. They also state the role and importance of transformation is synergy, recodification and bisociation.

Exploitation

Exploitation is the integration of the acquired or transformed information in the operations (Abecassis-Moedas and Mahmoud-Jouini, 2008). Cohen and Levinthal (1990) argue that the components of exploitation include use and implementation. In terms of the role and importance of exploitation, its core competencies are harvesting resources.

The second part of the theoretical framework in the Learning Analytics use section is ACAP. In the context of SEM and Learning Analytics, this study argues that ACAP is able to help understand how HEIs could use Learning Analytics to process high volume, velocity and variety of data to identify useful insights, thereby to develop organisational capabilities to improve SEM. It has been indicated that the absence of capacity in an organisation prevents better organisational learning and performance improvements (Lane and Lubatkin, 1998), therefore developing an organisational ACAP enabled by Learning Analytics is important for a HEI to improve SEM in the long term (Lane et al., 2006). In summary, it is hoped that in the context of this study, the use of Learning Analytics can be understood by examining how a HEI is able to acquire and assimilate internal and external relevant information and improve SEM by transforming and exploiting the newly obtained information and insights. Therefore, the theory of organisational absorptive capacity is used as a theoretical lens for the framework development.

6.3 Development of the Framework

6.3.1. Mapping the factors using TOE

The data is analysed to produce factors which are then grouped based on the following dimensions: Technology context, Organisational context and Environmental context. The TOE framework can be used to provide a theoretical understanding of the factors affecting Learning Analytics use by mapping the factors on the TOE framework.

6.3.1.1 Technology factors

The technology context is in reference to both the internal and external technologies that are important to an organisation; according to Thompson (1967), this includes the set of technologies that are accessible to an organisation externally and may include equipment as well as processes. Lippert and Govindarajulu (2015) state that the technology context is about the application of new technology adoption. It is evident that technology factors act as a critical enabler for the success of Learning Analytics. The first part of the theoretical framework in the Learning Analytics influential factors section is the technology context; it is made of the following sub-constructs: usability, affordability, complexity, and system integration, as seen in the Figure 6.2. This section presents the findings of this research that are linked with the technology context.

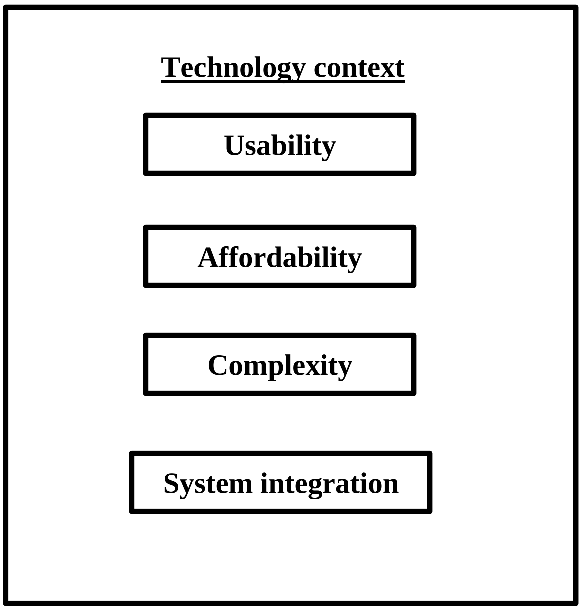

Figure 6.2 The Technology context

Usability

According to (Duan et al., 2012, p5539),*"Usability refers to the extent to which a system can be used by its users to achieve their goals with effectiveness, efficiency and satisfaction in a specified context of use."* Almost all participants mentioned the importance of usability of Learning Analytics tools and dashboards because staff members are normally very busy and do not want to waste any time when exploring the benefits of Learning Analytics tools. In relation to the theme ease of use, one participant described BREO as "*really easy to use, certainly from my teams that put information on there for units and courses…"* **(P7)**. Also, a significant factor is how effective the Learning Analytics tool is, as demonstrated by a participant: *"It is our own data repository, so I would say it's very effective because we can design it and tweak it as we wish"* **(P26)**.

Affordability

Affordability in this research is seen as an inhibitor for Learning Analytics use, for example: "*So once you been…… it takes huge investment to get them up and running and sorted to the point that people aren't constantly changing the SRS*." **(P12)**.

Complexity

This theme refers to the difficulty participants have with the data and tools. Various authors have spoken about complexity as a factor in relation to IS adoption (Scott, 2007, Paul Jones et al., 2013, Piaralal et al., 2015, Haddara and Elragal, 2013, Hwang et al., 2016, Wang et al., 2007a, Li, 2008). In this study one participant stated in regards to Learning Analytics tool complexity that *"there are different layers of complexity to the data that we receive and the data is not usually presented in the most data friendly format either"* **(P24)**. Many participants stated that Learning Analytics has limitations which affect Learning Analytics use, which is in line with complexity. One participant stated: *"I think in terms of the limitations, again I understand when we talk about Business Analytics; mainly I use quantitative data, that's my background so again if we just use quantitative data you can understand the student's performance"* **(P13)**. One participant spoke about people issues regarding the data as a limitation: *"People can pretend that the data is better than it is or people are disappointed……and there are reactions to the lack of quality in the data… which actually undermines the approach"* **(P1)**. Another participant put the limitation down to sample size: *"The limitations of data… I think it goes back to the sample size, I mean sample size and then getting also a representative understanding in terms of the makeup"* **(P10)**. One participant spoke about using BA effectively to do predictive analytics, and at the moment in the HEI they have started doing predicative analytics: *"So by default the limitation is… it's only a prediction and it's only as good as the prediction, so if you work in a very stable* *environment… and erm there is very little change… there is very little change in relation to the population, student population sizes…"* **(P12)**. In this HEI there is no radical desire to move the students to a different kind of environment, so predictive analytics is going to be great but the moment they add in any of those pressure points, that impacts on the modelling that they are doing. Another participant stated, *"I think there is a danger that we get too metric driven"* **(P20)** and "*it's useful to kind of sense check what we are asking departments to do or there is a sense check of how well they are performing, erm I think it can be dangerous to use that solely as way of making strategic decisions"* **(P20)**. One participant argued that there is always need for human expertise and context when it comes to BA. It is also argued that you cannot just have a statistician looking at just the figures and coming to a very sort of quantitative decision, e.g. this sort of students seems to drop out more so we should stop recruiting them, is what the statisticians might say. There is a requirement of people who are close to the actual activity, like actually in front of the students, you know dealing with them, who have the general context to add to the data side of stuff, so it does not come with the answer *per se* but it helps them find the answer, the participant states.

System integration

System integration refers to the process of connecting different computer systems together, which is key in most HEIs. One participant argued that systems in the university have evolved over time and they develop particular systems, such as their VLE and their SRS, so they keep on having different data in different systems. The participant also stated if you start putting data into systems things can get lost and you cannot see the relationships and that it is easy for them to say put everything into a data warehouse but that moves everything into a third-party solution. Another participant stated: *"so we saw two and a half years ago a point solution issue where we had….. you would end up with 10 different systems in 10 different areas, not joined up so we wouldn't be passing information ….. So, for example, because it's* *not joined up, the alumnus system would not be getting information automatically from the earlier systems; when students graduated they wouldn't automatically be going into the alumnus solution"* **(P11)**. One participant spoke about how the systems interact with each other: "*the systems don't necessarily talk to each other and they don't talk to each other very well"* **(P17)**. Also the reason why system integration is a very critical factor is because systems in silos create huge barriers to the successful application of Learning Analytics, and "*anything that we can do which harnesses all the different sources is really important and it allows us to be more streamlined, more efficient, more effective*" **(P10)** and *"so many isolated SILOS of analytics tools, so the VLE tells me about the VLE, the SIS tells me about the SIS, the library has got stuff about the library.... erm so we need to find a way to bring these things together"* **(P5)**. From the data analysis it is evident that there is a lot of data spewing around the place that is not joined up.

Table 6.1 Percentages of themes for the Technology context

Nodes	Sub-nodes	Number of responses	(%) of responses
Usability	Ease of use	15/30 = 0.50	51.5
	Effectiveness of LA tool	16/30 = 0.53	
Affordability		19/30	63
Complexity		27/30	90
System integration		11/30	37

6.3.1.2 Organisational factors

The organisational context refers to the resources of the organisation, including the organisation's size, human resources and managerial structure (Oliveira and Martins, 2011b). Tushman and Nadler (1986) argue that there are three ways in which top executives can make key changes to an organisation: conveying messages both internally and externally outside an organisation regarding the importance of the innovation; producing a team that is in charge of mapping out a strategy in reference to innovation; and ensuring that an organisation's strategy, core values and role of technology is clear. The organisational factors act as a critical facilitator for Learning Analytics success. The second part of the theoretical framework in the Learning Analytics influential factors section is the organisational context, it is made of the following sub-constructs: resource, data-driven culture, senior management support and strategic IT alignment as seen in Figure 6.3. This section presents the findings of this research that are linked with the Organisational context.

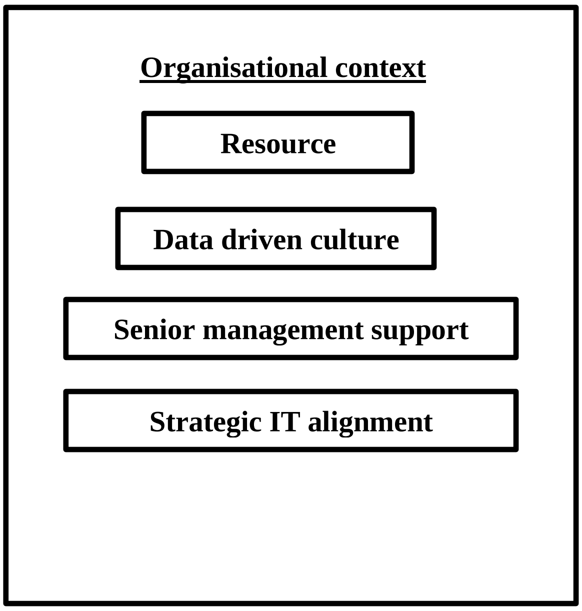

Figure 6.3 The Organisational context

Resource

According to IBM (2012), the two key areas of analytics are to improve the effectiveness of teaching and student outcomes, as well as making the most out of operational efficiency and effectiveness through improved resource analysis and finance tools. Most participants argue that resource is an important factor for Learning Analytics use whether it is time, human or financial resource.

For example, in reference to time participants stated *"I think probably linked to the resource issue is that there a lots of things and this is a specific resource issue here, there are lots of* *things that the new vice chancellor wants to change and improve, lots and lots of things and the university can't do all of them, certainly not in a short period of time"* **(P14)** and *"We have got loads and loads of ideas and not enough time which I supposed you could put it back to resource……..we spend a lot of our time being as efficient as we possibly can be to do the statutory work so we can invest as much time as possible to do the interesting things for us around learning analytics and student engagement monitoring"* **(P12)**.

With human resource one participant indicated *"in order to make….in order to make sure….we've got the right people dealing with that data and getting the right output"* **(P4)** and also *"I think it is on the knowledge of the users, I think particularly at university you are trying to cover data for so many people at so many different not only levels, because the levels are not going to be important but in terms of how IT literate that person is and trying to build something that kind of works to the lowest common denominator"* **(P18)**.

In terms of financial resource, participants stated: *"when you are in an organisation like ours particularly which you know has…has to be very prudent with how it spends its budgets, we probably would like more resource around that."* **(P4)** and *"we don't have the kind of budgets that those big corporates have"* **(P11)**.

Another participant argued *"our issue is resources and people…… if you haven't got the resources to exploit that tool, it doesn't do you a lot of good"* **(P11)**.

Data-Driven Culture

With Culture, participants stated whether their institution was data-driven or non-data-driven. Scott (2007) stated that organisational culture has an effect on e-transformation. She also suggested that organisational culture is linked with the organisation's identity and its core values. Most participants in the study speak about data-driven culture being vital to student experience management. For example, one participant stated: *"I think all universities need to be data driven, some are a big fan of this… erm I think the only way you can make informed decisions is by collecting data efficiently and effectively"* **(P10);** another stated *"That's certainly what we are doing here, I won't make a decision myself unless I've got a comprehensive set of data in front of me"* **(P26)**. One participant also argued there is a culture change; the participant states it came to be the fear of data, you can go into Tableau and you can play with the data, you are not going to hurt anything, you can ask your own questions and it is kind of a virtuous circle, so people start doing that and they start asking questions and then they want to know what more data they can look at. Therefore it can be a victim of its own successes as it were; there are more requests for that kind of data to be available. Some participants on the other hand spoke about non-data-driven culture in their organisation: *"Not really, not at my university, I don't… we're data driven….. Well, I'll give you a simple example, we used to get module feedback paper at the end of lectures so you couldn't leave the room until they had filled out the form but on the electronic data they can do it anytime and we have gone down from a response rate of about 50% to about 11%"* **(P15)**. Many participants spoke about making evidence-based decisions: *"I think what we try to do is to make err evidence-based interventions which are based on extensive data so that's a bit of both… isn't it really?"* **(P1)**, *"It's very, very successful because what they have done is they have reanalysed that you can't do everything just by talking to people, you can't do everything just by looking at the computer screen or a data input, it's got to be a combination of both so when you talk about whether your decision is data based or evidence-based, they are data based in my view"* **(P16)**, and *"I don't do anything without seeing the evidence, although I spend a lot of my time providing the evidence for decisions to be made, so you know I spend a lot of time talking to students and I suppose that is data, one of the things we are looking at is trends over time, erm and you know students attitudes sort of shift over time* *erm but for my academic colleagues to take it seriously"* **(P6)**. One participant spoke about data-driven culture and the decision making process: *"I think I work at a very traditional institution and I think some people in senior roles aren't familiar with using data in terms of making management decisions. So I think it's yet to be embedded that multiple levels of the institution may have access to the same data and then kind of make collected decisions, so I think sometimes it might be outcomes of data at the top that are reacted to rather than data being part of the decision making process."* **(P30)**. Two participants spoke about data-driven culture and impact: *"so the cultural impact of making data and information available across a wider audience was a bigger problem than the technology…"* **(P29)**, and *"It goes out to the Deans and it also goes to the programme leaders but it would also be used in appraisal for the individual lecturer, so it has a… it has an impact yeah on the performance management view of an academic"* **(P18)**.

Senior management support

A HEI could not facilitate Learning Analytics projects without senior management support, for example, the LACE Project: *"the LACE event tries to bring together evidence of research and Learning analytics across the world to see erm is there any evidence that learning analytics works and are there also some potentially dark stories about erm analytics"* **(P19)**. There is also the HEDIIP Project: *"….Yep, I mean if that comes to fruition it could bring some huge gains because what they are looking to do is to bring in some specification that will align universities data so that everybody could look at it so a bit like that HEIDI data"* **(P18).** The same HEI has implemented Athena SWAN, which is an agreement with the purpose of progressing the presence of women in science, technology, engineering, medicine and mathematics (STEMM): *"Athena Swan was originally about women in STEM subjects, so there was lots of data that was required to make a submission to get the Athena Swan accreditation"* **(P18)**. One HEI has executed a CRM Project: *"I mean our university like* *many institutions is looking at, we are implementing a big CRM project"* **(P6)**, along with a Learning Analytics project: *"I've got a Learning Analytics project and one of our starting points is actually looking at our data policy"* **(P6)**, a SharePoint project: *"We have now got a huge collaboration project starting and as part of we get a new shiny clean version of SharePoint 2013 which means I can actually put all this in place"* **(P6)**, and Skills Plus: *"we had an institutional process a few years ago called Skills Plus, embedding graduate attributes into the curriculum, it's really…..really good"* **(P6)**. Another HEI implemented Tell us: **"***so you know um….. quite often we will pick up individual information through Tell us, that's really good, if students would just say at the time whether they are satisfied we can then tell them what is really there"* **(P7)**. One of the things that have been interesting for one participant's departments is that they have become aware that the senior management team in this particular HEI is looking at the data and forming opinions that then encourage these departments to be involved. The heads of department (HODs) and senior management team might need to ask questions of programme leaders and admissions tutors to fully understand the data. So kind of from the top down, so each level of the university knows that somebody is looking at this data and wanting to make decisions based on it, it is encouraging engagement with the data; this participant thinks all the way through academic departments because each level is asking questions of the level below**.** They are conversations with HODs and they have power and think senior management are looking at this and they think that they need to go in and find out what that means so that they can respond to it, or defend that position. One participant spoke about the influence of the executive team in their HEI: *"So you have structures and terms will differ, but typically you'll have a very small group which is called the executive team who are the ultimate decision making body at the university"* **(P10)**. Another participant spoke about Learning Analytics in terms of senior management support: *"The big guys at the top are now into analytics and that is the way any initiative works. If senior management are interested things will move"* **(P23)**.

Strategic IT alignment

Findings also suggest that there are issues around institutional alignment: *"in fact, the reality is it's usually the erm institutional alignment, getting the people in the right place and erm making sure that they err…. organisation is ready structurally and culturally to deal with it and that I think is the biggest challenge"* **(P1)**.

Table 6.2 Percentages of themes for the Organisational context

Nodes	Sub-nodes	Number of responses	(%) of responses
Resource	Time	12/30 = 0.40	35.7
	Human	11/30 = 0.37	
	Financial	9/30 = 0.30	
Data-driven culture		27/30	90
Senior management support		19/30	63
Strategic IT alignment		17/30	56.7

6.3.1.3 Environmental factors

Tornatzky et al. (1990) state that the environmental context refers to a specific area around an organisation where business practices are carried out and include several stakeholders such the government, the community and the organisation's competitors. These stakeholders are used to determine how an organisation makes a decision on the need for innovation and whether it is capable of actually putting innovation into place (Angeles, 2013). The environmental context also includes the structure of the organisation, regulatory environment and macroeconomic context. Environmental factors can act as a driving force for the UK HEIs to adopt Learning Analytics. The third part of the theoretical framework in the Learning Analytics influential factors section is the environmental context; it is comprised of the following sub-constructs: competitive pressure, regulatory environment and external support as seen in Figure 6.4. This section presents the findings of this research that are linked with the Environmental context.

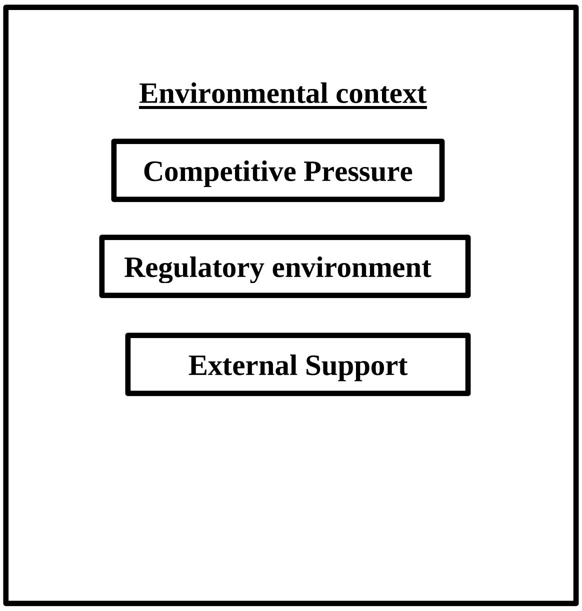

Figure 6.4 The Environmental context

Competitive pressure from other HEIs

Nowadays, HEIs are in competition in regards to giving the optimum student experience. This is demonstrated by one participant: *"I think we probably all use similar strategies, you know, there is lots of marketing going on around this time of year, I mean other universities offer all sorts of financial incentives, don't they, there will be iPads and this that and the other, so we don't tend to get involved in that"* **(P17)**; another participant states: *"I know the time going back a few years when we were looking at our BI strategy, there were some universities that were already embedded with things like data warehouses, Qlikview; there were some universities that hadn't even thought about that whole approach"* **(P29)**.

Wang et al. (2010) stated that competitive pressure has been recognised as a vital determining factor of IT adoption. In their study, Wang et al. (2010) came to the conclusion that competitive pressure would have a positive effect on Radio Frequency Identification (RFID) adoption. Scott (2007) study uses an e-business TOE framework to examine the benefits of e-transformation as well as the challenges. In her study, competitive pressure is seen as an important environmental influence on e- transformation.

Zhu and Kraemer (2005) state that competitive pressure is the amount of pressure an organisation feels from competitors within the industry. They also argue that organisations that face increased competitive pressure have a better likelihood of achieving a greater extent of e-business use. Lippert and Govindarajulu (2015) in their study of web services adoption stated that the greater the competitive pressure the better the likelihood of a firm adopting web services technology. In terms of this research, another participant states they are not saying their university is not struggling with things, but what they have achieved with the Tableau server and the stuff that is on there, from this participant's perspective, when they anecdotally talked to people in the sector they are not as far along as others. In some ways they are pushing forward but they are probably a lot of ways that they are lagging behind.

Regulatory environment

Findings suggest that participants face challenges in the area of governance, for example, one participant indicated: *"So there is all that kind of data spewing around all over the place that is not joined up, um so trying to… trying to kind of deal with that, be fast enough on our feet to deliver a service that the university needs whilst still complying with the ethical governance standard of the university I think is a big issue."* **(P11)**.

Most participants face problems with policy, whether it be drafting through old policies or creating new policies. One participant argues: *"I would say the main difficulty I have in making decisions is more about the policy and regulations and landscape changes like government changes because you never know what's coming"* **(P17)**, and another states: "*I've got a Learning Analytics project and one of our starting points is actually looking at* *our data policy so we are finding out what can we actually do, um this is one of the tricky things that we have because things like policies evolve over time*" **(P6)**.

Monitoring the attendance of international students is a very significant factor across most UK HEIs. Universities are now under pressure to abide by UKVI regulations, for example: *"we also have in-class registers which are done electronically and then that data is then loaded into the electronic database for future reporting but….. and that's all tracked, all goes back to the UKVI, we have had successful UKVI visits, so you can only conclude that that's actually very successful"* **(P7)**. UK Visa and Immigration (UKVI) has been a key factor for the UK HEIs using various tracking systems and related analytics to meet the UKVI's requirement for student engagement monitoring purposes.

External support

JISC works very closely with most institutions where Learning Analytics is concerned: *"we have also been involved in the JISC Learning Analytics programme and more so before….. when it started um mainly as a watching brief and put it into that and some of the work we are beginning to do with gaining opinion and advice from our student body to be feeding into that programme, um but I've said that we are very happy to join that programme in the discovery phase"* **(P6)**. This participant also stated that it is always good to get a third party to say "are you ready to do Learning Analytics?" They are currently working on the discovery phase and this will then move to the early adopter phase. Other HEIs are also working with JISC, one HEI looked at buying a Learning Analytics software package but instead they are going to be working with JISC on the JISC product. Another HEI is working with JISC on the performance analytics project, and they are going to be involved in HEIDI too (a new JISC/HESA project) that is coming.

Table 6.3 Percentages of themes for the Environmental context

Nodes	Sub-nodes	Number of responses	(%) of responses
Regulatory environment	Governance	17/30 = 0.57	34.7
	Policy Problems	11/30 = 0.37	
	UKVI regulations	3/30 = 0.10	
Competitive pressure from other HEIs		17/30	57
External support	JISC	6/30	13.3

6.3.1.4 People factors

While the TOE framework focuses on three key factors: Technology, Organisation and Environment, it has not specified people as a key factor, although prior literature on TOE identifies senior management support as an element of the organisational factor (Lautenbach et al., 2017, Aoun et al., 2011, Alsanea and Wainwright, 2014, Duan et al., 2017, Awa et al., 2016). Based on Chapter 5's findings as shown in Figure 6.5 and to be detailed in the following section, people has arisen as an extra factor in addition to the TOE factors. Therefore, this study has added an additional people-related dimension to the TOE framework due to the most important role human beings play in the process of adopting Learning Analytics, which is seen as largely consistent with evidence in the literature.

As mentioned in Chapter 3 section 3.5, Rising et al. (2014) argue that technology does not create value and it can only work if people use it. They stress that producing value from Big Data is no exception and data-savvy employees are important. Similarly, Christensen (2013) also states that technology is only a resource and that when people change resources into services or products, value is produced for organisations. Furthermore, adding People as an additional key factor to the TOE framework is also consistent with information systems success theory and the Technology Acceptance Model. While information systems success theory (DeLone and McLean, 1992, DeLone and McLean, 2003) emphasises user intentions to use and satisfaction and the Technology Acceptance Model (Davis, 1989) stresses the importance of how users come to accept and use a technology at the individual level, both theories could be seen to indirectly support the idea of people being an important factor to be added to the TOE framework at the organisational level. Additionally, the notion of People being a key factor is also seen to be supported by substantial evidence from Moghaddam and Khatoon-Abadi (2013), Hong and Zhu (2006), Iacovou et al. (1995), Thong (1999), IT-related literature that suggests that IT human capital has assumed considerable significance in the success of IT adoption or been one of the greatest impediments to IT success. By adding People as a specific dimension to TOE, this represents a major contribution of this research to literature and theory development.

The following section presents the findings of this research that are linked with the People context as shown in Figure 6.5.

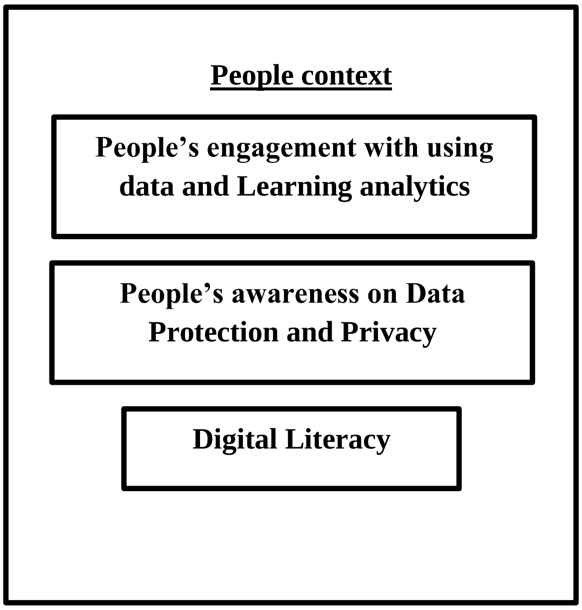

Figure 6.5 The People context

Based on Chapter 5 (Section 5.4.2) here are the themes for the people context:

People's engagement with using data and Learning analytics

A big challenge found from the data analysis is how the managers engage with the data, for example, one of the HEIs' biggest challenges is how they engage with student data before there were no processes for the engagement of students. One participant mentioned: *"So I think the challenge is we have got all that data and we have put it in a format that is accessible, that doesn't necessarily mean that the departments are engaging with it, so that's the challenge its actually getting them to engage with it"* **(P20)**. In the last 18 months, this particular HEI has tried to engage with the Student Union (SU), so they have SU representation on all their project boards. They meet with the SU president on a monthly-ish basis to share information with them and the SU's marketing director. Other challenges people are facing are getting people to accept the data and people's interpretations.

People's awareness on Data Protection and Privacy

A key area is privacy. Sclater (2016) states that there are fears stated especially concerning the possible invasions of student privacy growing from the mismanagement of their data. Participants mentioned about data protection issues and the invasion of privacy when monitoring social media: *"It turns in to Big Brother, Claudette, where do you start and for God's sake where do you stop if I'm monitoring social media… I can see thousands doing it"* **(P26)**.

Digital literacy

Data literacy is defined as "*the ability to understand and use data effectively to inform decisions*" (Mandinach and Gummer, 2013, p1). Mandinach et al. (2008) also mentioned that data literacy is made of a particular skill set and knowledge base that allows educators to change data into information and eventually into actionable knowledge. According to Mandinach and Gummer (2013), these skills consist of having the knowledge to classify, gather, organise, examine, summarise and arrange data. In this research the term digital literacy is used. People understanding the data was another main challenge in terms of not understanding what is behind graphs and numbers and also not understanding the nature of the data. One participant mentioned: *"I think it is on the knowledge of the users, I think particularly at university you are trying to cover data for so many people at so many different not only levels, because the levels are not going to be important but in terms of how IT literate that person is and trying to build something that kind of works to the lowest common denominator, can be very frustrating for people that are at different levels of IT understanding likewise if you build if for the top IT… you lose everybody at the lower end so I think trying to find that level"* **(P18)**.

Table 6.4 Percentages of themes for the People context

Nodes	Number of responses	(%) of responses
People's engagement with using data and Learning Analytics	5/30	16.7
People's awareness of data protection and privacy	9/30	30
Digital literacy	5/30	16.7

6.3.2 Mapping the Use of LA using ACAP

6.3.2.1 Understanding the use of LA from an Absorptive Capacity perspective

The following section analyses the relevant themes related to four important ACAP capabilities.

Acquisition

Acquisition refers to the process of identifying important information from external resources such as news (Zahra and George, 2002).

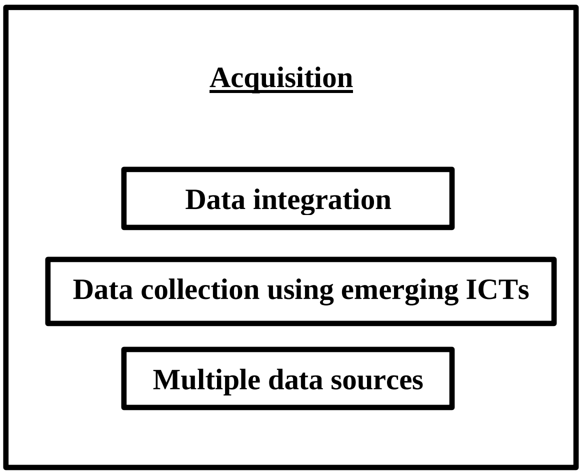

Figure 6.6 Themes derived from the data for Acquisition

Data integration

According to Lenzerini (2002, p233), *"Data integration is the problem of combining data residing at different sources, and providing the user with a unified view of these data"*. In this research data integration is ensuring that data is combined within one single location and is a significant issue in UK HEIs. Participants spoke about data warehousing in order for the data to remain in one place while other participants spoke about that data repositories used to extract data from the SRS: *"Essentially it is a repository of data its extracted largely from our SRS and a little bit from other places, and that corporate information system then is* *presented as a series of dashboards that go to senior management"* **(P11)**. Tableau is also mentioned by a participant as a tool for data integration for gathering data from different sources and moulding them together, so to speak. Other participants spoke about using data generated by the majority of the HEIs systems, interconnectivity between systems and the fact that different people own systems, so in a sense they feel that they own that data.

Data collection using emerging ICTs

This theme refers to how data is collected using upcoming technologies. In terms of UCAS, one participant mentioned the use of scanners to capture data from students on a whole range of things, including the subjects that they are interested in. Another participant talked about *"there being huge datasets of the kind of student engagement points like kind of the card use like the checking in, the printer use…….erm the library renewals and borrowing use and things like that"* **(P8)**. In the same vein, one participant spoke about having approximately 300 readers in order for students to swipe and they are currently bringing this technology into classrooms. There were also discussions in another HEI about the use of RFID technology to track students cards as they go through the HEI and the Jenzabar system (SES) used to collect data from many systems. In contrast, one HEI uses a system called EvaSys which provides feedback on separate modules within teaching and learning. Another participant spoke about the use of a system for induction-related things: *"we don't know who they are, then once they've signed up and they are going to come here we use another system which does kind of induction, lots of its health and safety, for its accommodation and things, but that doesn't use the same ID as the students use mostly here"* **(P5)**.

Multiple data sources

Participants acquire their information from different data sources: *"we are starting to use all these pieces of data we have about students and you know how they are performing on their* *studies"* **(P14)**. The majority of the participants processed their information through analytics and statistics. This theme refers to the different types of data sources used in a HEI, for example, a participant spoke about using a variety of data sources for students who are at risk: *"we have an approach which erm uses a range of data sources… erm to target students we believe are at higher risk of erm non-continuation"* **(P1)**. This same participant states that there is loads of data that is being produced across their HEI. In other HEIs there are discussions about the addition of new data sources, such as e-books and e-journals, and working with HEDIIP in order to examine data capabilities as an institution.

Table 6.5 Percentages of themes for Acquisition

Nodes	Number of responses	(%) of responses
Data integration	7/30	23.3
Data collection using emerging ICTs	6/30	20
Multiple data sources	8/30	26.7

Assimilation

Assimilation is finding out the meaning behind knowledge (Zahra and George, 2002).

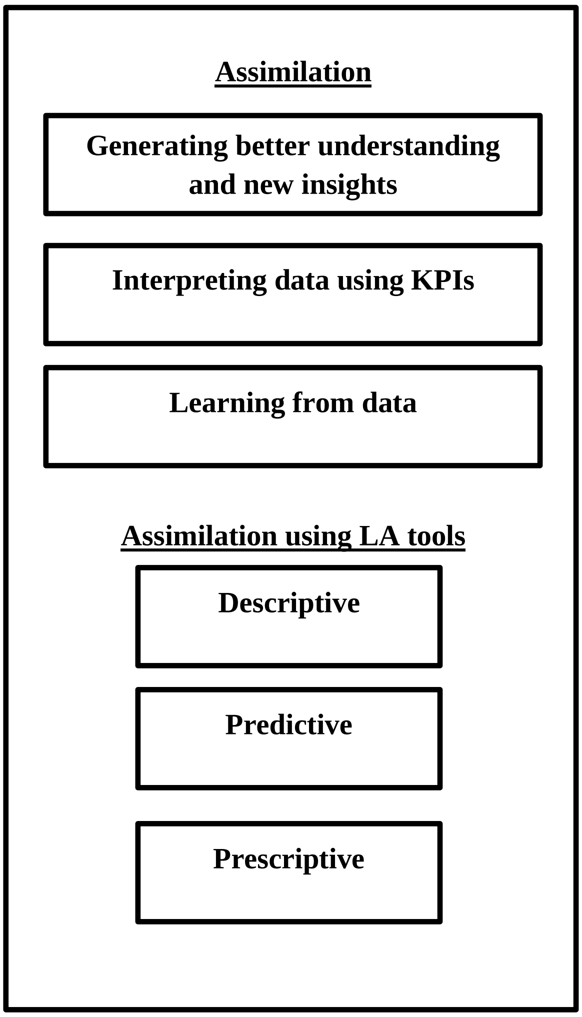

Figure 6.7 Themes derived from the data for Assimilation

Generating better understanding and new insights

This theme refers to creating an improved understanding and new perceptions about what is going on in HEIs. One participant discussed using all the pieces of data they currently have about their students to, for example, predict students at risk: *"we are starting to use all these pieces of data we have about students and you know how they are performing on their studies, their attendance and various things like that and trying to translate that into some facts where we can understand, often you know predicting whether they are going to drop out or if they are at risk of dropping out"* **(P14)**. Other participants spoke about producing market intelligence, predicting issues in the region of process and using data cubes to describe financial performance at course and business level. One participant discussed about using the

IBM Cognos tool to create reports on cohorts while another participant placed importance on knowing how students are achieving in their studies and turning that into evidence that the HEI can understand. Another participant stated that there are many ideas but insufficient time which can be put back to resource.

Interpreting data using Key Performance Indicators

This theme refers to how Key Performance Indicators (KPIs) can be utilised to interpret data. Two participants discussed using either analytical tools or dashboards to either monitor or cover all aspects of KPIs; firstly, Qlikview: *"We use a Qlikview software package but we have made it very institutional so it fits our institution and that then helps us all to monitor against key KPIs"* **(P27)** and secondly, institution departmental performance dashboards. In order to get an improved understanding of the challenges related to students one participant states that their HEI utilises many BI approaches and tools. Other participants speak about metrics and the use of KPIs and reporting in relation to KPIs.

Learning from data

This theme refers to how HEIs learn from the data. One participant talks about the usefulness of dashboards: *"so dashboards is really good, so that can really look at the difference visually that really helps them understand their performance so again that's quite straightforward data analysis but I think it still gives them understanding of their performance"* **(P13)**. Another participant spoke about retention being a key driver in their HEI, so they focus on retention data which they share out to different departments again using dashboards; in contrast, one participant discussed using a regression model to understand BA data.

Table 6.6 Percentages of themes for Assimilation

Nodes	Number of responses	(%) of responses
Generating better understanding and new insights	7/30	23.3
Interpreting data using KPIs	8/30	26.7
Learning from data	5/30	16.7

<u>Assimilation using LA Tools</u>

Descriptive

Descriptive analytics refers to what has happened in an institution. Findings show that some participants assimilate information through descriptive analytics: *I kind of quite like… descriptive analytics. So talk with students……um who might be coming in to education…. late returners maybe or um… you know they… they've not got the confidence of learning that actually that an 18 year old doesn't care about…* **(P5)**. One participant saw descriptive analytics coming out of their ears and they just pass it by. In this HEI their problem is not the volume of data, it is the volume of descriptive analytics and they can crunch the data very rapidly. Business Objects allows them to use descriptive statistics to build the frame and then the data updates itself nightly. Descriptive statistics are sometimes obvious about what is going on but people really need to work on trying to understand the statistics and trying to turn them on their head, so there is an element of predictability or predictiveness. With descriptive analytics, it involves the BI and data mining tools that participants use: most use Business Objects. The many ways that Business Objects is used in different HEIs is discussed in the paragraphs below.

Business Objects is used to schedule data, the managers can find out facts and statistics about how many applications they have had in (student recruitment), what decisions the university has made, have they made an offer or rejected the students and what is the applicant's response and has the applicant accepted the offer or rejected them etc. Business Objects can also be used as a staff dashboard which looks at finance and recruitment. In a particular HEI their main analytical tool is Business Objects. Business Objects from SAP is used for all the university's corporate intelligence work and the dashboards they provide to senior management. Another HEI have got the building blocks in place for it so data warehousing, SAP Business Objects as a reporting tool with SAP dashboards. Business Objects is one of the top three world-leading reporting tools across the whole of the business sector. Their use of it is very well embedded, they have been using Business Objects as their reporting tool for ten to fifteen years and they do all their finance reports using it. Business Objects is now called the SAP BIO suite with Business Objects being their main reporting tool, but they have a dash boarding tool, and a story boarding tool. They also think Business Objects is good but they know in some ways they can do some really wonderful things with Excel. In contrast, one HEI uses BI publisher for reporting: *"BI publisher itself, lends itself much more easily to things like pie charts and pie charts and we haven't been very good at that in the past"* **(P18)**. Another HEI uses Alteryx which allows the user to rapidly access and combine all the data for visualisation in Tableau: *"we have got an Alteryx license that basically helps us get to the stage of reporting it in Tableau"* **(P8)**. HEIDI is a UK database that consists of statistics on all UK HEIs: it comprises of HESA (Higher Education Statistics Agency) data on staff, students as well as finance. One HEI that gets their data from HEIDI said: *"HEIDI is basically HESA's reporting tool and you can extract data of students and staff and finance, which are available from HESA……basically that's a web-based reporting tool and you can extract data, you can choose fields and values, for example, you can look at both students, err broken down by ethnicity in the sector for example........, so once I extract data from HEIDI, using Excel I create tables and charts"* **(P13)**. There is FOCUS, which is not only a tool to monitor media but *"also what our competitors are getting…. so we monitor the amount of media output that we have against our competitors"* **(P4)**. One HEI has Tech one to view how one of their departments are doing, and: *"I login to my Tech one and it shows me whether I'm in the red or the green or kind of coasting along ok, we are starting to use more of those pictorial analytics, erm likewise the Student Performance Management Group that I was talking about"* **(P18)**. An example of how a HEI uses a variety of BI approaches and tools is through the NSS: *"we put all the data into an explorer tool, which is designed to enable our academic schools and supports services to interrogate the NSS results and derive from that useful insights which they can use to develop and enhance the student experience."* **(P22)**.

Predictive

In terms of predictive analytics this refers to what will happen in an institution: *"So we were looking at a bunch of data about all of our students and saying can we predict which students are more likely to drop out but we can intervene and an intervention is only probably going to be…. a system will notify the teacher and say. You…you should be concerned about the student"* **(P11)**. From the data analysis there are many different ways in which HEIs use predictive analytics whether it be finance or recruitment. IBM TM1 is planning software that has the ability to change your overall planning cycle from budgeting and setting targets to reporting; one HEI uses it for student number income forecasting. Another HEI uses information office to find the predictive characteristics of students, while in the admissions part of another HEI they have their own predictor model.

Prescriptive

With prescriptive analytics (how will it happen), they can be used in the area of student retention; one HEI is looking at developing tools to help intervene better when it comes to students, whereas another institution has used real-time analytics to improve student retention. Also mentioned in the data analysis was performance analytics. In terms of performance analytics a particular HEI does quite a lot of work on looking at performance by demographic to see the difference between male and female performance: "*we do quite a lot of works look at performance by demographic to see if our difference between male and female performance…we do age, we do age, gender, ethnicity, disability, in a way social class, even social economic coding (SOC)….codes*" **(P12)**. With performance analytics the participant states you can be in the area of changing student behaviour.

Table 6.7 Percentages of themes for Assimilation using LA tools

Nodes	Number of responses	(%) of responses
Descriptive	8/30	26.7
Predictive	7/30	23.3
Prescriptive	4/30	13.3

Transformation and Exploitation

Transformation involves combining the already existing knowledge in the organisation with the newly acquired knowledge (Zahra and George, 2002). Exploitation involves incorporating knowledge to improve the current performance of an organisation and gain value (Zahra and George, 2002).

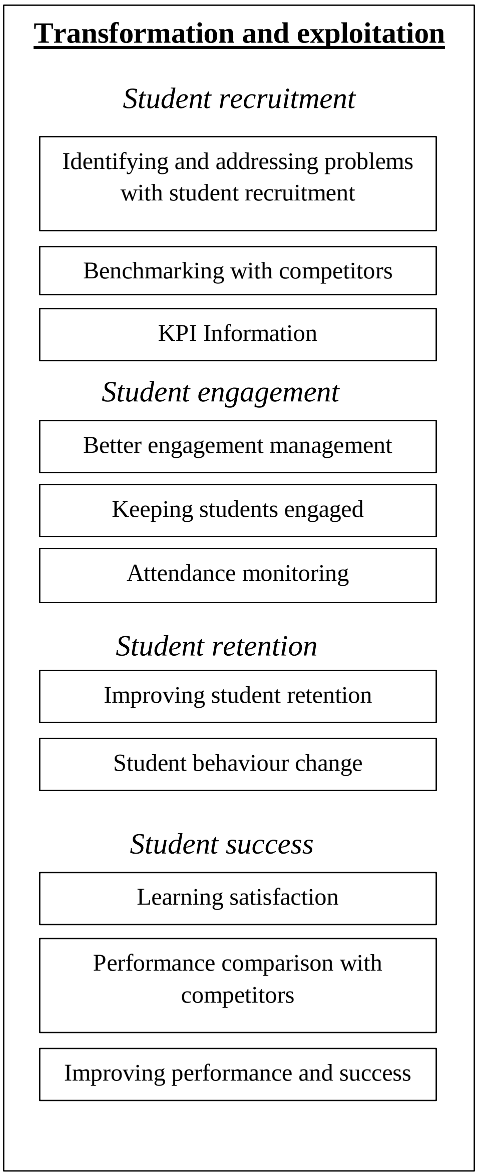

Figure 6.8 The themes and subthemes derived from the data for Transformation and Exploitation

Student Recruitment

The following themes are the ones for student recruitment. This involves finding potential students to enrol at an HEI and is an important part of the SEM cycle. Findings here suggest that analytics is used to monitor student recruitment, for example: *"so I use quite complicated analytics to look at programme performance… in terms of recruitment"* **(P3)**. Another finding was that Learning Analytics systems are also used to assist with student recruitment, for example, SITS: "*we…we receive 1,500 applications through UCAS, all of those are directly fed into our SITS system*" **(P4)**.

Identifying and addressing problems with student recruitment

Only one participant mentioned about whether the problems they had in their HEI had an impact on student recruitment in terms of their local postcode areas.

Benchmarking with competitors

Participants spoke about purchasing data from UCAS to look at what their competitors are doing, as well as HESA: *"we also look at in quite some detail what are our competitors doing, what types of courses are they developing, um what their engagement is with applicants and how we can get better…. so we do quite a bit of market analysis in terms of that, we also purchase quite a lot of data from UCAS"* **(P4)**.

KPI information

In terms of KPI information, some HEIs are responsible for admission numbers and KPIs while others use their business of BA information to ensure that there are a set of main KPIs. One participant spoke about HESA KPIs: *"if it's got a number in it we do the key performance indicators (KPIs) for court, we do…review the HESA KPIs"* **(P12)**.

Student Engagement

The following themes are for student engagement. According to one participant: *"Engagement is purely ensuring that they (students) are there attending and monitoring them…"* **(P7)**. Student engagement is stated in Chapter 1 as "*concerned with the interaction between the time, effort and other relevant resources invested by both students and their institutions intended to optimise the student experience and enhance the learning outcomes and development of students and the performance, and reputation of the institution"*

(Trowler, 2010, p5). Proxies for student engagement include: attendance, peer review, online activity, student facial expression, resource use (time, views), student group discussions, social media activity, web-based polling, feedback, triangulated: before, during and after teaching activities.

Better engagement management

This theme refers to improving engagement management. Participants have demonstrated many different ways to manage engagement, for example, through a Personal Academic Tutoring (PAT) system, through teaching analytics *"so monitoring blackboard engagement from a student's point of view but you can also say look here you have created this Blackboard or Moodle or whatever you want to call it"* **(P23)**, through alert systems and heat maps (red, green etc.).

Keeping students engaged

This theme refers to how students are kept engaged. One participant spoke about combining the separate data that they have on students and the SU data to see how students are engaging. In terms of analytics systems, another participant spoke about engaging with their students via their CRM system. One participant spoke of monitoring whether the students are using the resources as a way of managing student engagement: *"on managing that kind of student um engagement with the university, where the use of resources….. so you know are people using library resources, are they making use of and withdrawing the books that are on their reading lists for their course potentially"* **(P14)**.

Attendance monitoring

Attendance monitoring is another key theme when it comes to student success. One participant spoke about their HEI currently not having a process for attendance monitoring, but something comes to their attention which makes the staff think they require attendance monitoring. Another participant discussed maintaining attendance at lectures being a significant challenge. One participant stated that every student having an ID is a good way to track attendance, especially for the international students: *"so every student has an ID card and erm they are encouraged to swipe. So everywhere around the university we have got readers, so you just go click and then you are done, so most of the schools actually encourage people to do that and then international students that would be a way then for us to know whether they are attending or not"* **(P17)**.

Better management of students at risk

There are different ways in which HEI manage students at risk, for example, using an approach which utilises a range of data sources, looking at student progression data and also a student retention project: *"at the moment you mentioned retention we are working on a student retention project to understand our data to work out the reasons why um our retention rates are what they are, whether there is particular types of student based on their prior engagement in HE and their prior attainment and their UCAS scores and things like that erm whether there are certain students that are more at risk of dropping out than…than others"* **(P8)**.

Student Retention

The following themes are the ones for student retention. Student retention refers to students staying in one HEI and finishing their programme of study within a set timeframe; this is demonstrated by one participant*: "student retention if you look at it in very narrow form is largely the remit of schools erm to make sure that students um are retained and they are having experience in their academic school"* **(P18)**. Student retention is seen as very vital to the SEM cycle: *"student retention is the number one driver"* **(P19)**. More than one participant talked about the use of dashboards to monitor student retention: *"That will be here as a dashboard on the intranet as well so everyone will be able to see everybody's…. um teaching scores but put into context as well so not just sort of poor scores but things about progression, retention"* **(P3)**. Another HEI uses an approach which is a range of data sources to target students they believe are at a higher risk of non-continuation. In terms of the Learning Analytics tool, it is focused on non-continuation: it harvests data and it allows the managers to profile students against their risk of non-continuation so they can see what students scored by their risk of non-continuation. That score then drives a set of interventions which supports the student as well as showing their continuation. An example where student retention went wrong was where one HEI looked at data to predict which students were more likely to drop out and then they intervened. The intervention was a system that intended to notify the tutor and say that they should be concerned about the student as they have a chat with them (not particularly intrusive). The project was not successful and they were not able to predict the students who would drop out.

Improving student retention

One participant spoke about developing tools that enable them to intercede better, while another participant stated that their non-continuation levels have substantially decreased. One participant discussed student retention being the number one driver: "*so eventually in a year's time I would be judged on all those modules, whether we have been able to improve student retention based on the real-time analytics that we are currently providing and I am crossing my fingers that there will be a positive effect"* **(P19)**.

Student behaviour change

This theme was not a major factor at all; only some participants mentioned about applying performance analytics to drive change in the area of student behaviour.

Student Success

The following themes are the ones for student success. Student success is how well a student is performing in an HEI, for example, obtaining good honours (1st or 2:1) as stated by one participant: "*So student success, I think we….. there are loads of um…there are loads of forms….. There are loads of areas of student success; one of the areas I'm looking at again is going back to obtainment of 1sts and 2:1s"* **(P13).**

Learning satisfaction

This theme is not a major factor when it comes to student success. Some participants mentioned about utilising analytics to make module chairs more attentive to learning satisfaction.

Performance comparison with competitors

This is a major factor when it comes to student success. It refers to comparing performance with other HEIs. Some participants thought that they were performing better than most: *"Well the Higher Education Academy (HEA) tells us that we are, so yes"* **(P26)** and discuss whether universities are not taking the full benefit when it comes to data. One participant used the fact of how far they had got with Tableau as a benchmark against their competitors. In contrast, some felt they were not ahead of their competitors at all: *"I think we are slightly behind the pack rather than trailblazing in terms of using data in those ways"* **(P30)**.

Improving performance and success

This theme refers to ways in which performance and success can be improved. One participant stated that more contact engagement leads to better achievement for first years but when it came to the second and third years, the students were able to work more independently. The same participant spoke about using multi-regression analysis in order to recognise the main things that would cause better performance. Another participant discussed using BA to identify which students are likely to be more successful. In the same vein, another participant spoke using different initiatives to ensure that students get the optimum student experience. One participant discussed whether students who came to university on a full-time basis were more likely to succeed: *"so, for example, in last year's data we found out those students who came to the university with higher type scores or who studied on a full-time basis are more likely to obtain good honours and we did also find an attainment gap between white and black students and somehow black students are less likely to obtain good honours"* **(P13)**.

Table 6.8 Percentages of themes for Transformation and Exploitation

Nodes	Sub-nodes	Number of responses	(%) of responses
Student recruitment	Identifying and addressing problems with student recruitment	1/30	3.3
	Benchmarking with competitors	2/30	6.7
	KPI information	3/30	10
Student engagement	Better engagement management	4/30	13.3
	Keeping students engaged	8/30	26.7
	Attendance monitoring	10/30	33.3
	Better management of students at risk	8/30	26.7
Student retention	Improving student retention	3/30	10
	Student behaviour change	3/30	10
Student success	Learning satisfaction	2/30	6.7
	Performance comparison with competitors	12/30	40
	Improving performance and success	3/30	10

6.4 Theoretical Framework

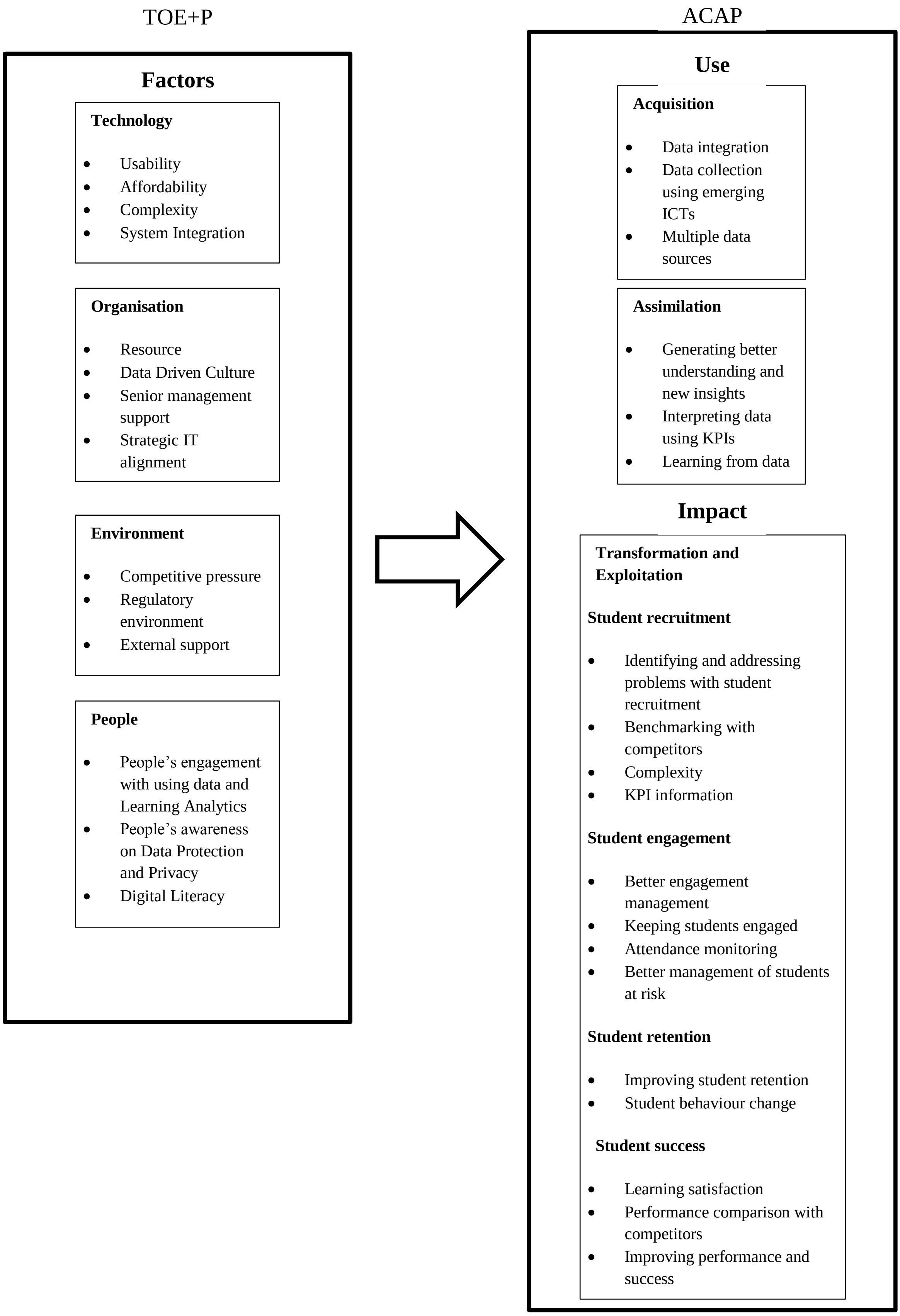

Figure 6.9 Theoretical Framework

6.5 Conclusion of the Framework Development Chapter

In summary, the factors that were significant for the use and impact of Learning Analytics in UK HEIs were mapped onto the theoretical TOE and ACAP lenses which brought about the production of a theoretical framework.

Chapter 7: Conclusions

7.0 Overview

This chapter forms the final part of the thesis and signifies the conclusion of this research process. Firstly, the study and its key findings are summarised; this research's contribution to research and practice are stated; the limitations of this research are addressed; and finally, the recommendations for future research are provided.

7.1 Summary of this Research and Key Findings

This section offers a summary of this research, highlighting the key findings and how they link to the study's objectives.

7.1.1 Summary of this research

The study sets out to explore the use and impact of Learning Analytics for SEM in UK HEIs. It was carried out as a qualitative study involving an exploratory case study and a main study using interviews with thirty participants from different HEIs based in the UK. The main objectives of this study can be found in Chapter 1 and were met as shown in the data analysis, Chapter 5 (section 5.3.1) and the framework development in Chapter 6. One of the main objectives of this research was to develop a conceptual framework to provide a systematic overview on the use and impact of Learning Analytics SEM in HEIs. The framework was constructed using the study's findings along with the theoretical underpinning. The theoretical lenses used were the Technology Organisation and Environment (TOE) framework (Tornatzky et al., 1990) as well as the Absorptive Capacity (ACAP) theory (Cohen and Levinthal, 1990). In order to follow the abductive approach, the theoretical lens was not presented until the data analysis had been completed.

7.1.2 Key findings

In Chapter 6, the framework development chapter, the findings from this research were discussed in depth. The main points and how they link to the objectives initially established for this research are briefly summarised below.

1. **Objective one: To understand the challenges in utilising data effectively for SEM in the era of Big Data and Learning Analytics**

There were a variety of issues affecting the utilisation of data for SEM and these were highlighted throughout the duration of this study. The data quality related issues were: data quality, data consistency and data reliability. In terms of data usage the issues were: data analysis and data integration. In relation to the volume of data the issues were: data and information overload and lack of data; and with making sense of data/information, the issues were information availability and problems with systems. There were also data governance issues. One of the most significant issues in terms of data quality related issues was data quality; and in terms of data usage, data integration was deemed rather important. With the volume of data, data and information overload was an important issue; and with making sense of data/information, information availability and problems with systems were both equally significant.

2. **Objective two: To identify the key factors affecting the use and impact of Learning Analytics**

The factors found were affordability, complexity, system integration, usability, data-driven culture, senior management support, strategic IT alignment, resource, regulatory environment, competitive pressure from other HEIs, external support, people's engagement with using data and Learning Analytics, people's awareness of data protection and privacy, and digital literacy. Findings from this research demonstrate that in terms of the technology factors, complexity was deemed the most important factor, with system integration being the least important factor. With the organisational factors, senior management support was the most significant, with resource being the least significant factor; and with the environmental factors, competitive pressure from other HEIs was the key factor, with external support being the least significant factor. In terms of people factors, people's awareness of data protection and privacy were the most important factors with digital literacy, and people's engagement with using data and Learning Analytics both being least significant.

3. Objective three: To understand how Learning Analytics is being used for SEM

In line with this objective the data from this research was split into three sections: How do HEIs acquire data? How do they make sense of data? And how does the use of Learning Analytics impact on SEM? In terms of acquisition the following themes were derived: data integration, data collection using emerging ICTs and multiple data sources. For assimilation, the following themes were derived: generating better understanding and new insights, interpreting data using KPIs and then learning from data; under this umbrella the Learning Analytics tools were divided into descriptive, predictive and prescriptive. For transformation and exploitation, the themes were divided using the SEM cycle. For student success the themes were: learning satisfaction, performance comparison with competitors, and improving performance and success. For student engagement, the themes were: better engagement management, keeping students engaged, attendance monitoring and better management of students at risk. For student recruitment the themes were: identifying and addressing problems with student recruitment, benchmarking with competitors and KPI information. Finally, for student retention the themes were: improving student retention and student behaviour change.

In terms of acquisition, data integration is of high importance. For assimilation, interpreting data using KPIs is the most important factor. In terms of type of Learning Analytics, descriptive analytics were the most widely used in UK HEIs. In relation to impact (transformation and exploitation) across the student lifecycle, performance comparison with competitors (student success) was deemed the most important followed by attendance monitoring (student engagement) as a close second.

4. **Objective four: To develop a conceptual framework to provide a systematic overview on the use and impact of Learning Analytics on SEM in HEIs**

A conceptual framework was developed showing the relationship between TOE and ACAP. The factors were listed under the TOE part of the framework. The use was demonstrated by acquisition and assimilation and the impact on SEM by transformation and exploitation.

7.2 Contributions of this Study

This section states this study's contributions to research and practice.

7.2.1 Contributions to research

This study makes a number of original contributions to research.

Firstly, it helps to close a knowledge gap in our understanding of the current challenges faced by managers in UK HEIs about how to utilise data effectively for SEM. These include issues related to data quality, data consistency, data reliability, data analysis, data integration, data and information overload, lack of data, information availability and problems with systems. These findings provide in-depth insights and systematic knowledge into the challenges that can offer a base for developing future research agenda.

Secondly, it provides a comprehensive and systematic analysis of the critical factors affecting the use of Learning Analytics. These factors are identified with extensive empirical evidence and mapped out using a theoretical lens from technology-organisation-environment-people perspectives. The technology-related factors include Usability, Affordability, Complexity, and System integration. The organisation-related factors cover Resource, Data driven culture, Senior management support and Strategic IT alignment. The environment-related factors include Competitive pressure. Regulatory environment and External support. Most importantly, the findings emphasise the importance of the people-related factors in addition to the TOE factors. The people-related factors include People's engagement with using data and Learning Analytics, People's awareness of Data protection and privacy and Digital literacy. The impacts of the learning analytics are also identified and analysed using organisational absorptive capacity theory.

Thirdly, the study extends the technology-organisation-environment (TOE) framework by adding another important and specific dimension – "people" – in the context of applying Learning Analytics. This extended view on factors affecting the success of Learning Analytics is important because the power of any analytics tools can only be realised by its users. If the users do not make use of the insights generated by the analytics, no impact is possible. Therefore, it is critical to highlight the element of people-related factors in addition to TOE factors.

Fourthly, the framework developed in this study enriches the ACAP theory with contextual factors applicable in a new context, compared with previous studies. No previous research has been found that applies this theory in the context of HEIs; thus the study represents a first research attempt to apply Absorptive Capacity in the context of Learning Analytics in HEIs.

Last, but not least, the integrated theoretical framework underpinned by TOEP and ACAP is new and makes an original contribution in terms of advancing research in the era of Big Data and Learning Analytics. It provides an analytical tool for a better understanding of the antecedents and outcomes of Learning Analytics, thus increasing our limited knowledge on the impact of Learning Analytics in HEIs.

7.2.2 Contributions to practice

The key findings and the framework provide very important implications for key stakeholders and practitioners in relation to developing and utilising Learning Analytics more effectively and efficiently.

Firstly, the findings can help HEIs managers to develop better strategies for effectively utilising Big Data using Learning Analytics. It enables them to better understand the current challenges and be more focused on addressing the most critical factors.

Secondly, the challenges and critical factors identified can help to raise awareness among HEI managers and enable them to allocate their resources and efforts to deal with the critical factors more effectively.

Thirdly, the findings also provide evidence-based insights for HEI managers and Learning Analytics practitioners to develop the most relevant capabilities to maximise the impact of Learning Analytics. The identified technology-related challenges and influential factors will help Learning Analytics and IT providers to further improve the usability and functionality of Learning Analytics, thus to speed up rate of successful adoption and diffusion of Learning Analytics among HEIs. For example, as the people-related factors are identified critical to successful Learning Analytics implementation, HEIs managers should provide appropriate training to improve users; digital literacy on using Big Data and Learning Analytics, to provide incentives to encourage more staff to use Learning Analytics tools, and to raise awareness of the data protection issues.

Fourthly, the findings are significant in terms of policy, especially regarding the implementation of the General Data Protection Regulation (GDPR), enacted from May 2018, The findings in this study reveal the concerns related to data protection when using Learning Analytics and provide supporting evidence on the importance of implementing GDPR in UK

HEIs. For example, it is essential that the university should inform the data subjects if their data is going to be used and what it is going to be used for.

7.3 Limitations of this Research

This part of the chapter discusses the limitations of this study and offers directions for future research. Despite this study following a strict research process and it satisfactorily meeting its aim and objectives, there are some limitations.

This research was carried out as a qualitative study with a restricted number of participants and concentrating on a particular context, namely UK HEIs. Consequently, the findings from this research are centred on the viewpoints of participants in the UK HEIs sector and therefore might only apply to that sector. Also bearing in mind the subjective and explanatory nature of qualitative research and its restricted capability to applying its findings to other settings, caution should be taken in applying this research's findings to other organisational settings.

7.4 Recommendations for Future Research

- In terms of future research, the findings of this study could be used as a foundation by relating the theoretical framework constructed for exploring the factors affecting the use and impact of Learning Analytics in UK HEIs in the area of SEM to other organisational settings, and in doing so examine how applicable it is to those settings.
- Many factors affecting the use and impact of Learning Analytics in UK HEIs in the area of SEM have been found in the duration of this study: therefore in terms of future research, an in-depth examination of each of the key factors could be focused on in other organisational settings and their application in diverse organisational settings.

- As the qualitative research has limitations in terms of testing research hypothesis and establishing and testing patterns of answers among different types of respondents and their associated organisations, future research can be conducted using the questionnaire survey to statistically validate the research framework and to establish if there are any significant differences among participants based on their demographic characteristics, such as: genders and roles.
- This research is also based only on the UK HE sector, so it could be expanded to other countries, and also looks to using the government sector in the future.

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Appendices

Appendix 1: Conferences and seminar presentations

Kika, C., Duan, Y., Cao, G. (2015), 'Supporting Student Management with Business Analytics in the UK Higher Education sector' (Abstract and presentation): UK Academy for Information Systems (UKAIS) consortium, 17th March 2015, University of Oxford, Oxford

Kika, C., Duan, Y., Cao, G.(2015), Supporting Student Management with Business Analytics in the UK Higher Education sector- an exploratory case study (Full paper and presentation): International Conference on Intellectual Capital, Knowledge management and Organisational Learning (ICICKM) 5 -6th November 2015, University of Bangkok, Bangkok- *Awarded joint 2nd prize for best PhD paper*

Kika, C., Duan, Y., Cao, G. (2016), 'The use and impact of learning analytics on student experience management in UK HEIs' (Abstract, poster and presentation)- 28th January 2016, University of Bedfordshire, Luton

Kika, C., Duan, Y., Cao, G. (2016), 'Understanding the use and impact of Learning Analytics on Student Experience Management' (poster) - Pacific Asia Conference on Information Systems (PACIS), June 27th-July 1st 2016, Taiwan

Kika, C., Duan, Y., Cao, G. (2017) 'Understanding the factors affecting the use of Learning Analytics in the UK Higher Education Sector' (presentation) - 1st February 2017, University of Bedfordshire, Luton

Kika, C., Duan, Y., Cao, G. (2017) 'The Use and Critical Success Factors of Learning Analytics: An Organisational Absorptive Capacity Analysis' – Americas Conference on Information Systems (AMCIS), August 10-12th 2017, Boston

Kika, C., Duan, Y., Cao, G. (2017) 'Understanding the factors affecting the use of Learning Analytics in the UK Higher Education Sector'- European Association for Research on Learning and Instruction (EARLI), August 28-2nd September 2017, Tampere, Finland

Appendix 2: Cover letter for Exploratory Case Study

Title of research: Supporting Managerial Decision making with Big Data in Higher Education

Dear Participant,

You are invited to take part in a research study to examine managerial decision making with Big Data in Higher education. I would like to interview you to ask you about your experiences with data in relation to decision making within your department. This research is part of a PhD Thesis at this institution, The University of Bedfordshire. Before you decide whether to take part in the study it is important that you understand what the research is for and what you will be asked to do. Please take time to read the following information; it is therefore up to you to decide whether or not to take part. You will also be asked to sign a consent form. You can change your mind at any time and withdraw from the study without giving a reason.

The purpose of the research study is to examine how big data, especially social media data, can be effectively utilised to support managerial decision making for in Higher Education. I am also trying to understand the current debate and research gaps on the use of Big Data and Business Intelligence in UK HEIs and investigating the current challenges faced by HE managers in dealing with big data, especially in utilising various forms of big data and BI tools/techniques to support decision making. I therefore would like to ask questions about decision making, social media in general and business intelligence/analytics. You have been chosen because as you currently work in a Higher Education institution, work with a lot of data and make decisions on a day to day basis. The interview will take approximately 30 min.

The information gained from this research will be used to make recommendations for best practice and will offer insights into the experiences of managerial decision making with Big Data in Higher Education. The results of the study may also lead onto further studies into Big Data. The interview will be recorded using my IPhone and then transcribed onto a computer. The audio tracks will be stored on the computer and will be protected from intrusion also. Your response will be treated with full confidentiality and anyone who takes part in the research will be identified only by pseudonyms. You can request a copy of the interview transcript if you wish. The interviews will be analysed by using N-Vivo.

Please do not hesitate to contact me if you need further information

Yours sincerely,

Claudette Kika

Appendix 3: Interview Guide for Exploratory Case study

Role of the Manager

Define your role as a manager/director in the Higher education sector?

(How does the participant role fit into Mintzberg's three theories and how does the participant see their role)

Decision making

What type of decision making activities are you involved in?

How do you make decisions as a director/manager?

Do you use any tools such as Microsoft Excel or intuition to make decisions?

Challenges faced in the HE sector

What challenges do you face in decision making?

(If not mentioned above) Is information overload a problem?

What challenges to you face with information processing/behaviour?

Are you aware of what the term 'big data' is?

What is the role of big data and information in your decision making?

The use of social media and business Intelligence/analytics

Do you use social media, if not why?

In terms of your social media, what do you use it for?

Do you have any text mining tools available in your department; if not do you feel they will be useful for you?

Are you aware of the terms Business Intelligence and Business Analytics?

Do you use either Business Intelligence or Business Analytics tools?

Appendix 4: Consent form for exploratory case study

Full title of project: Supporting managerial decision making with big data in higher education.

Name, position and contact address of Researcher: Claudette Kika, 1st year PhD student

	Please tick Initial Box
1. I confirm that I have read and understand the information sheet for the above study and have had the opportunity to ask questions.	☐
2. I understand that my participation is voluntary and that I am free to withdraw at any time, without giving reason.	☐
3. I agree to take part in the above study.	☐
4. I agree to the interview consultation being audio recorded	☐
5. I agree to the use of anonymised quotes in publications	☐

Name of Participant	Date	Signature
Name of Researcher	Date	Signature

Appendix 5: Cover letter for main study

Date: 13.11.2015

Dear Manager/Academic,

Interview on Student Management with Business Analytics in the UK Higher Education Sector

You are invited to take part in a research study to examine Student management with Business Analytics (BA) in the UK Higher Education sector. I would like to interview you to ask you about your experiences with managing student data and what tools are currently used to do so. Business Analytics is a term used to group learning analytics, social media, analytical systems and RFID technology. This research is part of a PhD Thesis at this institution, the University of Bedfordshire. Before you decide whether to take part in the study it is important that you understand what the research is for and what you will be asked to do. Please take time to read the following information; it is therefore up to you to decide whether or not to take part. You will also be asked to sign a consent form. You can change your mind at any time and withdraw from the study without giving a reason.

The purpose of the research is to explore the use and impact of BA for student management in UK Higher Education Institutions (HEIs) because improving student experience has been one of the top priorities in many UK HEIs. Providing students the best learning experience and ensuring their academic success through their university lifecycle has been a serious challenge for HEIs managers. It is argued by this research that BA should play a critical role in effective student management, and thus, leading to better student experience and academic performance. More specifically this research aims:

To investigate the current challenges faced by HEIs managers and how they deal with increasing amount of data to make informed decisions in relation to student management.

To explore the potential use of BA in supporting HEI managers for Student Management

To develop a conceptual framework for guiding the design and use of BA in enhancing student experience, underpinned by an information processing perspective.

You have been chosen because as you currently work in a Higher Education institution, work with a lot of student data and make informed decisions in regards to students on a day to day basis. The interview will take approximately a 1hr. The information gained from this research will be used to make recommendations for best practice and will offer insights into the experiences of student management with BA in the UK Higher Education. The results of the study may also lead onto further studies into BA in the context of Big Data. The interview will be recorded using an audio recorder and then transcribed onto a computer. The audio tracks will be stored on the computer and will be protected from intrusion also. Your response will be treated with full confidentiality and anyone who takes part in the research will be identified only by pseudonyms. You can request a copy of the interview transcript if you wish. The interviews will be analysed by using N-Vivo.

Thank you for your time and co-operation, please do not hesitate to contact me if you need further information.

Yours sincerely,

Claudette Kika

Researcher

Business Management Research Institute

University of Bedfordshire

Email: Claudette.kika1@study.beds.ac.uk; Claudettekika@hotmail.com

Number: 0794 838 5367

Appendix 6: Definition sheet for main study

University of Bedfordshire
Bedford and Luton

<u>Definition Sheet for Participants</u>

Big Data

The concept of "Big Data" is emerged to describe the volume, variety, and velocity of the data generated with Information and Communication Technologies (ICTs).

It has also been referred to as 'Huge volumes of data in both structured and unstructured forms generated by the Internet, social media and computerized transactions, are straining our technical capacity to manage it' (Chiang et al, 2012)

There are many definitions of Big Data, but key concepts of Big Data are three "V"s:

Volume: data has increased from terabytes to petabytes and has an influence on exabytes.

Velocity: refers to not only how fast we accumulate data, but also how fast some of the data that we already have is changing.

Variety: data is continually evolving; it is both structured and unstructured

Examples of Big Data include: sensors, internet of things (IOT), GPS data and Radio Frequency Identification (RFID) technology

Learning Analytics

Harmelen &Workman (2012) state that learning analytics is the use of analytical techniques to investigate educational data which involves data about learner and teacher activities to find behavioural patterns and give actionable information to enhance learning.

Business Analytics

This research follows the Davenport and Harris (2007) definition, which defines BA as “the extensive use of data, statistical and quantitative analysis, explanatory and predictive models, and fact-based management to drive decisions and actions” (p. 7).

Appendix 7: Interview Guide for the main study

The interviews for the main study focused on the areas of challenges, factors, use and impact of Learning Analytics. A list of example questions are prepared to guide the interview although the questions used for each can be flexible and varied depending on the responses of the particular participant.

Examples of Interview Questions

Personal details

Can you introduce yourself?

What is your role and responsibilities in your university?

Are you responsible for any student experience in your institution?

Use and impact of analytics

What Business Analytics/Learning Analytics/Business Intelligence systems does your university use to enhance student experience? Can you briefly explain what they do and how effective they are?

Do you use any analytical tools or dashboards? If yes, can you briefly explain what they do and how effective they are, if possible, please relate to student experience management when giving your examples

Does your institute collect and analyse any data from social media to enhance student experience, how and why?

Challenges and factors

What are the challenges that you face in performing your role in dealing with data and information in the context of big data? More specifically, what challenges do you face when making effective decisions in relation to student experience management?

Do you think your university/institution is doing better than other university's in the utilisation of Learning Analytics (so benchmarking your university's Learning Analytics applications against others and explaining why?)

What are your views on the limitations of Learning Analytics, if you have choice, what would be an ideal analytics system/tool to support student experience management for you and your university, why?

What are your views on the future development and applications of Learning Analytics for student experience management in your university and why?

Do you see analytics as satisfactory or successful for the student journey, why?

Appendix 8: Inter-rater reliability test

Sample table illustrating raters' agreement with research themes

Themes Comments	Understanding of student experience management	Challenges in utilising data	Factors that affect the use and impact of LA	Social media use in HEIs	Future of Learning Analytics
"future development I would say is that we just need to try and do things until we get basically what we want"					x
"SID as an example have a Twitter feed, the library have a Twitter feed…there are…different services have social media engagement"				x	
"erm time, we have got loads and loads of ideas and not enough time which I supposed you could put it back to resource……"		x			
"Student management is everything from the point of students expressing their interest to the institution all the way to them becoming a member of our alumni community"	x				
"The main challenge that I experience with data management is data integrity and consistency"		x			

"I suppose the future has got to be more of a blend of structured and unstructured data and getting a really enhanced big data strategy so we can start using what's already out there to inform our decisions"					x
"Yea I think something that was really easy to use"			x		
"Yea, yea we have Hootsuite to monitor social media"				x	
"I think the problem is data quality"			x		
"If you are managing the student experience it much more clearly defines on to something that's…..about the interaction the student has with the university and what they would get out of that"	x				

Table showing inter-raters' percentage of agreement

Inter-raters	**Percentage of Agreement (%)**
1	80
2	80
3	70

Appendix 9: Consent form for main study

Full title of project: Supporting Student Management with Business Analytics in the UK Higher Education Sector

Name, position and contact address of Researcher: Claudette Kika, Final year PhD student

Please tick box

1. I confirm that I have read and understand the procedures for the above study and have had the opportunity to ask questions. ☐

2. I understand that my participation is voluntary and that I am free to withdraw at any time, without giving reason. ☐

3. I agree to take part in the above study. ☐

4. I agree to the interview consultation being audio recorded ☐

5. I am aware that the interview transcript will be kept strictly confidential and anonymous and not be used for publishing purposes ☐

6. I understand that interview data analysis will completely anonymous (i.e. names of interviewees and their associated universities will not be identified) ☐

Name of Participant	Date	Signature
Name of Researcher	Date	Signature

Appendix 10: Sample interview transcript

(P18: Participant 18; female; I1: Interviewer 1, I2: Interviewer 2), ((.): pause; 'hhh': in breath)

I1: What is your role and responsibilities in your university?

P18: My role is academic registrar, um so my responsibility is to manage registry, at this institution. The academic registry has about 200 staff um and covers a central registry unit which deals with academic quality, um we also deal with all the data returns so we have a…..an information systems function, we deal also with student finance, accommodation, student registration, um international student support, research um so a very wide ranging remit

I1: So are you responsible for any student experience in your institution?

P18: Um….yea everybody is, I mean indirectly everybody is responsible for the student experience, my team are directly responsible for the NSS, analysing of the NSS results, for example we also uh….run a committee directly called the student performance and monitoring group and that is all based on data, uh but it's really to look at areas where students might be underperforming or over performing and trying to analyse why um and feeding that out to the schools so that there can be some impact locally in the schools, to use that data to help improve the student experience

I1: Ok, thank you very much

I1: In terms of the stages in the life cycle, for example, student engagement, student retention, student success where would you say your role particularly fits in?

P18: So I think I will go through them one by one so student erm….if you can say the first one again?

I1: Student engagement

P18: Yea so student engagement in the first instance for example, I should have mentioned my remit is with admissions so, very directly not in terms of the marketing element of getting students to apply but from the point of application to the point of somebody becoming registered that's totally within the units that I deal with, so we deal with applicant engagement as well so the engagement of people that are looking to apply right through to student engagement, um we also deal with the examination process, um so the student experience via that is obviously key and also the degree ceremony which also comes under my remit so the student experience during that and the engagement with those processes, erm but I would say that generally the student engagement agenda is dealt with within the schools which are not within my remit, and the next one was?

I1: Student retention

P18: Yea, student retention erm again we all have a bit of a remit in terms of student retention, in terms of how we deal with students erm our interactions with students and how they feel about being in the institution but also in terms of their entry qualifications and so were they quick to be able to be successful with us, we also deal with uh four local colleges, so the retention of those students coming from foundation degrees and erm HMCs and BTECs and A-Levels through to joining us and retaining those students as they come through is key and likewise moving students from undergraduate study to postgraduate study to research level study so retaining students through the different levels of study with us certainly comes into the remit of my area, erm but again student retention if you look at it in very narrow form is largely the remit of schools erm to make sure that students um are retained and they are having experience in their academic school.

I1: Ok and student success

P18: Yea student success, one of the other things that my area deals with is student finance for example, so we have been dealing with, I don't know if you have heard of the National Scholarship Programme so we look at ways of helping students to be successful whilst they are with us in a non-academic sense, so what are the barriers to students being retaining and being able to succeed um, one of those being finance, students come 97% from state schools, erm we have 25% students of 25,000 odd pounds or below household income so making sure those students can be a success here in terms of are they equipped financially, can we support them erm to work their way through is important to us but also making sure again that the entry qualifications and that we have the right hurdles at the right point to ensure that students can be successful when they work their way through the university

I1: Ok, thanks very much

I: So what are the challenges that your institution is facing with Student Experience Management?

P18: We are a large institution, so that's a challenge in terms of the individuality of a student that's within a marketised HEIs, so an institution that is large and diverse, erm we have 10 schools going from those that are quite small- physics, astronomy and mathematics school has 200 or so students erm but a large research base compared to somewhere like the business school which will have 4000 students erm and a smaller research base so trying to manage those things and making sure that the experience across is um equitable and right within the individual discipline so keeping hold of what is different about the schools as well, um the challenge centrally is to make sure that people are aware of things like the NSS that people are aware of the outcome scores, that we analyse the data well and that information does seep down and into the academic scores to make sure that they are understanding what their students are saying and what they are experiencing.

The other thing that we manage centrally is erm called a module feedback questionnaire (MFQ) which takes place in every module erm and it's up to us to make sure that we turn that information around quickly enough to have an influence on the module the next time it runs and again the schools receive this information in a format which means that they can digest it and they can make changes and that the students are aware of the changes they have made because of the comments of previous students, erm so that's been really important to us in the change at looking at student experience.

I1: Ok, thank you very much

I2: It seems like ok the information plays quite an important role….

P18: Very, I've found we used to do the MFQ until two years ago it was online, it was previously paper and when online came we went online but we found out that the response rate was just too low so 4 or 5% in some modules and so you just weren't getting the valid view of students so we reverted to paper which was a huge undertaking to do but we thought it was the right thing to do

I2: So it's an online form now?

P18: Not anymore, we have gone back to paper because on online we had 4 or 5% response rate

I2: oh response rate yea….

P18: We have gone back to paper and we are now to about 70% response rates and that's really driven behaviour in terms of people now people seeing the data as being validated in terms of this is what a student is saying and it's very immediate so there's two elements to it, there is the um kind of quantitative element to it which goes off and is analysed against different modules and against different cohorts, then there is immediate written responses which goes to the schools literally immediately so the schools get the comments in whilst the modules are still taking place and its handed to them at that stage so that they can make some quick changes to the cohorts there but more importantly building changes for the next time it runs and because those now have such a high response rate erm it's taken on a completely different view by the schools because you can't argue against those sorts of numbers whereas 4 or 5%, I think it's fair to say students who are very happy or students who are very unhappy, the neutral students were not really heard in that and we get much more of that…

I2: I think you need someone to type the data into the systems….

P18: No we err, It's done by QMP….it goes off to a scanning company so it is done on a sheet the students have, so there is two elements to it, to kind of choose between 1 and 5, that goes off….

I2: So it's like an exam paper?

P18: I'm sure it's that kind of thing

I2: So it's automatic data entry?

P18: Exactly

I2: So it's a scanning machine?

P18: It goes off to a scanning machine company, we have a contract with somebody, they also send back the analysis so they will provide the pie charts and bar charts and stuff….

I2: Oh, so they also do the analysis part as well?

P18: Yea, Yes for the data but for the written submission, we keep it and it goes immediately to the school so its separated and goes immediate to the school and the school then have a role in redacting personal information so somebody unfortunately with students you will get someone say well I don't like them because they are fat or someone's so smelly so that kind of thing is redacting but critical comments are not if they say somebody doesn't teach well because…..obviously that remains but anything that's personal will be redacted by the school just black penned and it means that they get immediate response to that where….

I2: But you do have the space for comments yeah….

P18: Yes

I2: ….and then for that part you can't scan do you have to get someone?

P18: That bit exactly….it can be scanned but it has little value of being scanned, really the value… what we have found we have developed over the last three years, we have found that the value of that is the immediacy of them, you get a comment this is not working well can we change it, where the qualitative data is much better if it is seen alongside other things and so it is on a scale of one to five, so we are looking for low results, ones and twos and then fours and fives

I2: I think it's a very good example of using, you know some kind of analytics actually to understand student feedback and provide timely change using all those systems, automatic entrance scan and things. That is really interesting actually but I don't think our university use automatic data entrance it's so time consuming

P18: absolutely and it was a challenge when we were going back to paper because previously obviously students were doing it online so it was being analysed immediately.

I2: What kinds of people can access the results automatically?

P18: It goes out to the Deans and it also goes to the programme leaders but it would also be used in appraisal for the individual lecturer, so it has a…it has an impact yea on the performance management view of an academic

I2: Thank you

I1: Ok, thanks as well.

I1: So are you aware of the terms Big Data, Business Analytics and Learning Analytics?

P18: Yea, not so much the Learning Analytics, other than having read your definition that you showed me earlier, Learning Analytics I would have thought of more as an online learning environment, the kind of tools that a student would use…..not so much in terms of an analysis for a manager but erm yea the Business Analytics and Big data yes.

I1: Ok, that's fine

I1: Does your university use Big Data and could you give examples please?

P18: Um….yes, in my definition of Big data and what I think of being Big data we do, if you take something like our student performance management group um we would be take the whole university's data set and analysing it for what we want to find so we might be wanted to we have got particular projects at the moment on BME attainment, so um….

I2: BME's??

I1 & P18: Black Minorities and Ethnic…..

I2: Oh ok…

P18: again we have found that that has had a real impact…we are quite a way above the sector average now in terms of our BME students are still not doing as well as our white students but the attainment gap has been massively reduced by using that kind of Big Data so what we have done for example is taken that data and we have now move to anonymised marking so we are trying to find a reason for why students who are coming in with so many qualifications so the data told us that they had the same entry qualifications, so they had done just as well at school, when they came in why were some students coming out with 2:1s and 1st's and others were coming out with 2:2s and 3rd's, we couldn't find any other reason so we decided that there is some unconscious bias in marking you know and that is what the sector finds, so there has been a lot of training on unconscious bias, err everybody has been trained actually and alongside that we have got anonymised marking process now which means that you can't identify the students and that has had an impact in terms of the marks of BME students but rolling it out across and institution is a huge undertaking so we are on a three year….we are into the end of the second year, so it is pretty well embedded now.

I1: Ok

P18:….but it was as a project, it was a huge thing in some areas obviously if you have got something like labs…you could anonymise because marking doesn't really work, but where you can…..people have had to justify where they are not doing it and that's actually improved in terms of ok for this type of assessment, no for this type assessment we expect it to be in the project, but some areas, some large areas, business school, Law school places like that, virtually everything now is anonymously marked so there is no way of attributing the student to the…… I think actually the feedback from the students has been interesting because some of the students want to be identified

I1, I2 & P18: (*Laughs*)

P18: …….they feel like they have a relationship with the lecturers and you feel like you are building up those relationships you know…..

I2: That’s not useful

P18: yes…..and so they will put their name on it…

I1: No way…..

I2: It can give lots of bias to people, if they have a good relationship with staff…

P18: …and so yea we have had to deal with that, we have had to give a penalty for that

I1&I2: oh wow…..ok

P18: ……some students want to be identified and that isn’t the purpose of it, um so we have taken, kind of going back to the question the SPMG would be using all of the data within the institution to first of all identify who are the BME students, what programmes are they on, the attainment gap, what was it we were trying to target for getting the attainment gap down what would be a success, you know we had to plot all of that to understand what it is going to look like and whether projects of that’s size was going to have any impact

I2: It’s a very good example, so you do collect a large amount of data and different kinds of data historically, then you analyse and identify the issue of unconscious bias and those sorts of things and then you try to take action…

P18: yes, so I will give you another example, at the moment we are doing a big project into whether BTEC students are as successful as A-level students because there is a myth that A-level students are better…..so is it true? So should we be looking for more UCAS points from a BTEC student than an A-level student, so rather than make an assumption that it is true, let’s look at the data, so have BTEC students historically come out with as good results as A-level students, so we are working our way through that project and actually at the moment it’s looking like the BTEC students do perform slightly worse…..slightly worse but not to the extent where we say you know don't be a student……so we are trying to unpick some myths about that, we have had previous projects where we have looked at we have lots of international students who are very diverse group.

We take international students into our final year only and there was a myth about those students not doing as well and so we via the SPMG group we could dispel that myth it wasn't true, they were doing as well as international students that came earlier they weren't doing as well as home students but English is their second language so there is an expectation of that but there was a feeling that they weren't doing as well even as the international students that had come first or second year but that wasn't true so we tried to use this data to give us a factual view of our students and of the student experience rather than what people think is happening

I2: I think it's good actually, I think moving towards data driven….evidence based decisions and management because you can say it but that's data…

P18: ….yea so is it true, so when someone says something now we say well let's test it if we can, you know there are only so many projects you can take on erm but let's test it….

I2: That's good actually yea

I1: What are the challenges that you face in performing your role in dealing with data and information in the context of Big Data?

P18: Couple of things one…..one is that we went to a new student record system (SRS) four years ago now so you had a point where we had no comparative data, we had…we were remodelling our curriculum into the new systems, so to get the university and the very senior managers to understand that if we change our SRS there will be a point where we will say we can't tell you that, we have not been used to that answer, so to build up new big data so now we can go back four years we are kind of getting there from the first couple of years not to be able to have comparison with what happened last year was quite a challenge in the way that we work, um so that has been a challenge. Also getting people to understand the data so one of the challenges is we might be asked for information so this year there has been big projects on the race equality charter mark and also I think the Athena SWAN, I think you may have come across these initiatives across the Higher education sector.

Athena SWAN was originally about women in STEM subjects, so there was lots of data that was required to make a submission to get the Athena SWAN accreditation, um the race equality charter mark similarly was about the diversity of your student body and staff body and how they….so lots of data was required, often we could be asked just to supply data but somebody else interprets and we wouldn't have interpreted in the same way so that's always a challenge just supplying data an as the owners of the data, not being asked what does this data mean just….I just want the data and I'll look at it, so that's a constant challenge in terms of erm highlighting to colleagues that the expertise is based within erm these registry teams that look at this stuff all the time that might interpret things in a different way to them so using that expertise and making sure that people know where that data has come from. The other thing I think is always about the specification of data, so as an Academic registrar if someone says to me how many students have you got, I have got 20 questions back before I can answer that question

I: Yes I understand

P18: So again getting people to specify the data that is required in a way that is meaningful to them because they just don't know at the time, I am a bit like this when dealing with my teams, so I end up with an iterative conversation, so I say I didn't really mean that or this when they want the specification right the first time because otherwise they are doing the work, that’s always a challenge a well it’s getting people to understand what we might call a mode of study what do we understand as that, what is a course instance in this institution, what is a module….because if they have come from another institution or that haven’t had to deal with the data in that way, the language behind data I think uh….is a challenge for people so trying to supply first time and properly what people are looking to……I think the other challenge around data is the returns so the huge burden of government returns, DLHE, NSS, HESA all of those returns are all done from within my team and its……it’s an industry and now it’s an industry that doesn’t bring much financial reward back…

I2: So it’s a burden yeah…..

P18: Yea…..it’s an additional burden, not that I don’t understand why we do it now, but really we are private businesses now and money comes directly from our students via the student loan company and the government give us very little but still the data burden is huge, but I think there are good things that are going on in the central government, I’m sure you have come across the HEDIIP project…

I1: Yes I am aware of HEDIIP…

P18: Yep, I mean if that comes to fruition it could bring some huge gains because what there are looking to do is to bring in some specification that will align universities data so that everybody could look at it so a bit like that HEIDI data um……that it will go into one place, I’m going to make these numbers up but they have said something like there is 935 people that call on data from universities and across millions of lines and if they could get those 935 to go to a big data warehouse and extract that data then obviously that burden from universities would be much reduced but what these universities have got to do is agree what the standard is for how you provide this information because somebody wants to know how many females, how many ‘x’ of this age group we have all got to cut it in the same way to allow this data to be extracted, so I think it's a very big job which could have very large benefits for institutions if we can coordinate it in a good way

I2: I can understand, It's not like say you know……people talk about say data returns and say if I do this I will see the benefit yea, I think maybe the starting point they are starting to collect all this data or I think in some way as you suggested the automatic way to collect data actually reduces the burden on the institution and at the end we have a big data warehouse and they could benefit from that, if people can see the benefit then maybe they will be more motivated to do something….

P18: I think also all institutions as well it's their worst enemy because we want to interpret what they want because everybody has a way that they want their university to be seen, and you are not even doing it deliberately, you have moulder your SRS in a way that reflects your institution and for HEFCE to then receive that information they don't care about that they just want it in a standard way but we want to make sure before we send that in it does reflect what we want to see from our institution and we want to answer questions about why not ourselves as well before so there is always a lot of internal interpretation to be done before it goes in so it seems like a simple kind of request and receive relationship but it is not at all it's a kind of request so we kind of look at it and say really I thought there were more study abroad students than that because that's part of what we do, we expect to have 'x' number of industrial placement students, is this what this is telling us, so we want to make sure that its reflecting everything that our institution represents um when it goes in

I2: I think that could bring up an interesting issue to see how people interpret data as well because I think HEFCE present data in the way they want to present to the public but the institution want to see it truly reflect what they are doing because sometimes it can be a twisted or different way, so it's not really truly the picture……so that's a very interesting point about data interpretation and the use of data as well

P18: …….because we want it to reflect our mission you know, not only down to the detail of this one student, we have written a new five year strategy last year and we want to make……we will be using data to track whether we are moving towards that vision of where we want to be and if not why not we would be expecting to see so our mission is largely around internationalisation and employability, so we will be using data to track whether we are close to our data at the end of the year so it is important to us that we make sure that we are not changing very much between year 1 and year 5 in terms of how we are pulling that data out because we want to be able to compare it a bit like what I saying about the ground zero day of changing systems we need to make sure that we can provide interpretation to our board of governors, erm so that they can measure whether we have gotten more industrial placements, have we increased our number of students studying abroad- more international students, more students going out and all of that has to come through the data so we have to make sure there is good information in, for us to get good information out. So the control of schools in terms of……for them understanding how to put the data in and what we need them to look like is important.

I1: So what challenges do you face when making effective decisions in relation to student experience management?

P18: (.)…..(.)…..First of all getting people to believe the data, so if you take something like the NSS, my view of surveys is that if it is good it is all about us and if it's bad people haven't understood the question, so if they are saying we are terrible……we are not terrible, I can't believe they've said that….they didn't understand the question and if they say we are good, we say oh yes we are, so getting people to just accept the data is always a major challenge in any survey actually because we are all naturally defensive we all want to do a good job, we work hard and so when students then turn around and say we aren't doing a good job, we defend that rather than…..as we say if they say we are doing a good job we just accept it even though from both sides the truth is in the middle somewhere, so getting people to accept the data and that has taken many years actually to say to people we are not discussing the data anymore, we are discussing the outcome of the data, so that's been a major challenge

Also within a multidisciplinary university getting people, getting us to accept that really we need to be comparing our art school with another art school rather than our art school with our business school, so doing that cross sector analysis as well as in university analysis because my understanding is that if you want really good NSS scores you have male geographers and if you want bad NSS scores you have lots of female artists they are just less happy and male geographers are happy so there are different types of students, so within the student experience you need to understand all of that in the data to make a real difference to students but I do think that the NSS has been really useful particularly in areas like feedback and erm I think the sector was not particularly good at listening to students about feedback and I think the NSS has had a real impact on that and the kind of continued improvement of…………erm still the question about the NSS is about prompt feedback for example, we have a four week turnaround and we have done an audit of it and its very well adhered to but is that what a student thinks is prompt?

Even if we think that is all we can do in terms of resource and the reality of turning around work, erm so using that data to understand erm what it is the students are telling us and again within those looking at the comments can be very telling, so you can look at the numbers and also look at the comments around it, so the other impact in terms of student experience is that we due to err poor NSS results actually, we have moved to centralised timetabling which is a huge thing to do in a university of this size and we are now in to our third year of that and it's had a huge massive impact on our student experience so now in July students have their full timetable including rooms and lecturer's names so before they arrive back they can sort out their part time work, they know where they are going they know what days they have got free and all of that kind of thing where it was very hand to mouth before and that came directly from looking at NSS feedback and results and we had a really bad year, the first year we did it, we did it as good as we could in one year, in the first it was bad but we knew we had to just keep going.

We were very tempted at that point to throw it out……this is not working but to be fair the management is so strong and said no, no we can see what the end game is for this and it's made a huge impact three years later it has been revolutionary really

I2: So you are on the central timetabling system?

P18: Yes and yea with these early deadlines everything in……basically we have the first timetable out in April for next year and so by august…….by July, last week of July a fully published timetable is with a student and that was all driven from the data

I1: What Business Analytics/Learning Analytics/Business Intelligence systems does your university use to enhance student experience? Can you briefly explain what they do and how effective they are?

P18: So firstly we are a very centralised university, we have very centralised data systems so we have a SRS called Quirkus,

I1: Oh Quirkus, that's the second time I'm hearing about that software…..

P18: Yes

I2: we all use different systems, we use SITS at our institution

P18: So Quirkus is part of Ellucian now, they used to be a company called CIT, there is only six universities using it actually when we bought it and they have now been bought out by Ellucian and who used to have the Banner system anyway in terms of that we really very….very rarely have side systems, we try to make the very best use of our SRS and we try to work with the company to enhance it, so we are very into partnership working in terms of enhancing systems so if we have an issue we will go to them first for a solution rather than saying ok we will create a separate data access database or spread sheet or whatever so we try very hard to that, in terms of the reporting that comes out of it we have just moved across to BI publisher

I2: What is it called?

P18: BI publisher, so erm….

I2: Business Intelligence?

P18: Yea…..which has brought more better enhancement in terms of it being able to be used much more locally on people's desktop's, rather than reports being provided you run the report…..

I1: Ok

P18: so it used to be much more of a system where you would say to one of the others, can you run this for me every Monday at whatever…….now you just draw the information down, again the challenge of that is making sure people understand again because there used to be a middle man, you could do some interpretation now you are drawing the data and you need to make sure that people can understand that data and it can be used but it does bring the power and the data into the people that are running it because you can do it whenever you like, for example we have just gone through clearing and confirmation during clearing previously 4 o'clock on any day I would have been provided with data, now I could say I want it a 10 o'clock and just run it….

I2: Ah so you can just run it yourself instead of…..

P18: At whatever point……and also BI publisher itself, lends itself much more easily to things like pie charts and pie charts and we haven't been very good at that in the past we haven't been very user friendly in terms of dashboards and that sort of thing and we are just starting to develop those, so the targets for recruitment are now showing on bar charts that the Deans can get to and run as regularly as they like. Our finance system is called Tech one and they likewise this year have developed a dashboard so when I login to my Tech one, it comes up with how my registry are doing on a kind of fuelled isle type and it shows me whether I'm in the red or the green or kind of coasting along ok, we are starting to use more of those pictorial analytics, erm likewise the SPMG that I was talking about, we are starting to look at that we haven't done it yet, we are looking at informatics this year in terms of what does an average student look like….

I1: Oh really?

P18: Yea….so almost like a story of what an average student looks like in a particular school so again because of the myths that build up, so we might have a myth from a school that says all of our students come in with 2 A's at A-level and they all went to Dame Alice Owen which is a very highly regarded grammar school locally and you say ok they don't have a single student that meets that criteria, they don't have a single student with 2 A levels from Dame Alice Owen but that is what they have built up in their minds, to build up a view of what is an average student and we are trying to show that it's probably a BME student with a BTEC that is still likely to come out with a 2:1 or a 1st but just to show people what is there, what does the student look like from the data, not from what we think and we are looking much more at informatics….

I2: So is that saying in the past looking at this student they perform like this, when you look at this student you can predict…..

P18: Partly prediction…..but partly that's who we should be marketing to if we are going in and doing lots of outreach work at Dame Alice Owen for the 2 A-level students so a student with 2 A's, the reality is they have not come into us, we should be going to our local college and talking to our BME students that are taking BTECs because that is the reality of the students that are coming here so our marketing material would need to reflect that, likewise our academic body need to know that to be able to interact with those students and open day those are the students they should be looking to invite to their open day things for not for these mythical students that they think…….so to use the right language, using the right examples, so showing the right role models…

I2: You are right actually, it's very important for the marketing…

P18: …..rather than who you think your market are...It's like Aldi selling to Waitrose…

I2: That's right

P18: It doesn't work does it? They need to understand…..

I2: That's really good, but who is doing this analytics?

P18: Partly SPMG will drive it in terms of getting the data out but we will use our marketing colleagues to err….

I2: SPMG is the provider?

P18: No it's the Student Performance Management Group

I2: Oh, the group, so they do have a data analyst somewhere?

P18: Yes we do, in fact our data people sit in that group with us so we have some academics, some professional staff and some of the data people so it is a mix of those things and what happens is we have a core group of questions which we answer every year, so what was our admissions like? What was our average tariff? All those kind of things, set ones and then you will have project stuff that's thrown in like the BME work, so something would have come out of the different group, we have a student experience committee from example it might have come out of that to say 'x' and they will say well let's ask SPMG to look at that so we will have those different projects going on throughout the year.

I2: Wow, that's very good actually; it seems to work well, with your BI publisher what kind of data feed do you have for that?

P18: What do you mean?

I2: Data feed? Do you know what kind of data you use to....?

P18: Straight from our SRS…..

I2: Oh so from Quirkus?

P18: Yea and its feeding it live….

I2: So it's like a build-up on the data feeds

P18: Yea…..so they are the major systems, we obviously have HR systems and that's all online now….all that kind of stuff, so that's called core…..um but generally as I say we are very centralised in terms of our data and it comes from Quirkus and we do try to be sort of bad data in, bad data out so the kind of cleansing and housekeeping and we have a central unit called our procedures unit, they are like a helpdesk for all the schools

I1: Sorry what was the name of the Unit.?

P18: Procedures….so the schools they use them as helpdesk if they are having issues with the data in terms of they if can't get someone to progress or if they have got a student issue they call the procedures who then come and work them through the policy so that they can get that student record to look right because poor data in, bad data out.

I1&I2: that's very good yea

I1: So you mentioned that you moved from Banner, is there any particular reason why?

P18: Actually we moved from…..it was Ellucian that owned Banner, we didn't move from Banner, but we used to have a system called Genesis and we were the only university using it, now there were some advantages to that when we first bought it, before my time many…..many years ago, we thought there would be more coming on board it was Banner based, but they didn't actually there were some advantages to that because it became a very bespoke system so whatever we wanted to do, it did all of our HR, all of our finance and all of our SRS so it was an enterprise system, erm the disadvantage in the end was that erm it was very old software……it was on very old platform, so we had to change and when we were looking to change the university then took the decision that they were going to with best of breed for all those things so now we don't have an enterprise system, we have bought systems we have to plug and talk to each other which bring their own challenges.

So our finance system is one company, our HR system is one company, our SRS is one company and all the people that were procuring them were going out for best of breed against our specification and it was the job of our internal people to get them to talk to each other and that has been a challenge so we've had the SRS now, this is our fifth year and we have been trying to get a data warehouse and that hasn't….we've only just started making progress with that so the data warehouse now does have HR and finance talking to each other but erm student have only just come in scope, so it's taken a lot longer than we expected to be able to get a data warehouse that means that we could extract staff that are students and how much, kind of getting those interconnectivity between the systems.

I2: I think it's the same everywhere you know having problems with data integration and data warehousing

P18: Again it's often about what's the interpretation? What's the cause? Who's the student?

I1: Do you feel any culture change in your institution in relation to Business Analytics for example moving towards data driven decisions or data driven culture?

P18: I think erm…..I can't say I particularly noticed the culture but I do think it's totally down to an individual, so we changed VC five years ago and we have had some changes of Pro-vice chancellors and deputy vice chancellors and the previous ones actually were very…..very data driven so erm really wanting to make decisions based on the data around so student staff ratio's really wanted that very tied down to make sure that they are making the right decision about where there was growth. The current erm people are less data driven, so it's become the centralised functions particularly people that run the data, we find now that our role has changed so we have to go out with the data and say this is what the data is……rather than asking for it here, we have to make sure that the data is at the forefront of the decision making erm so we will go and say don't give a specification, ask us what the problem is and we will try and solve it for you with data because if you try and just come to us and say how many students are like this the chances are you are not really asking the right question, tell us what the problem is in English, in a narrative and we will think about what data you need to solve that problem.

It's trying to change where the previous people were more data minded, so would be to ask the questions in a more data rich way I suppose and now we are more of in a narrative and that's fine we have had to change culturally in terms of saying we can provide that….the worst thing that can happen is that we have got all this data and it's not used, so it's trying to make sure that the people realise it's there and it can be used and the same time managing the resource of our over expectation because the same time have to do the annual returns which is a huge amount of work alongside the projects that come in so it's trying to pick off the ones that we think are going to have the most impact particularly on the student experience

I2: due to the variability of data the staff still use data, but they use data maybe in a more……they interpret in a way that they can better understand it…the higher managers yea…

P18: …..and I think that we would…..so if a decision was at a senior executive , which I do sit on if I wasn't sure about, then I'll come away and get the data and go back, and to be fair and then revaluate and say ok either a longer project or we need more resource for this or whatever it's not that they just say kind of plough on, plough on they just ask for it in a slightly different way and as I say it kind of empowers the two because as I say what we are just asking them to do it to ask the question, so what's the problem black males are not achieving the same as white males that's the question, so let us think about the data that's going to give you the information about that rather than you saying to us right I want a list of black males on this course who were born in this year because that's not their specialism, so it's trying to interpret the question for them.

I1: Does you institute collect and analyse any data from social media to enhance student experience?

P18: I don’t know if we do it very much we certainly do it around clearing time, it’s done by different areas it’s done by MARCOMS our marketing and communications area but they will provide after clearing erm, so we have had it now the number of hits on the website, the amount of interactions the growth from last year, what type of devices people were accessing on erm the types of questions that they were asking, how long they were on the page for, what pages they went to so they will provide all of that type of information but strictly about social media I don’t know whether they collect data on social media they certainly interact with it and they would be talking to people via Facebook and Twitter an all those other things but whether there is data around it, I don’t know.

I2: Not like large companies they do like say content analysis…..so different comments and then they can identify things, but I think maybe university is not that advanced

P18: I’ve not seen that…..

I1: I haven’t seen that as well

I2: Maybe not yet…

P18: We do erm keep an eye on things like student room , erm but again its more for kind of narrative information, I wouldn’t say we, I certainly don’t……but we do look at……me and a few of my team look at….track student room because we deal with erm the accommodation….

I1: Is student room like a student forum?

P18: Yea…..

I2: You can ask anything in student room

P18: Students ask students so it's not a moderated area so we will just check whether there is a particular issue, for me……I know it sounds horrible but it's one of the ways I can track my staff in a way, so if there is lots of complaints on there about…..or I haven't heard from the accommodation office….

I2: So you do it? I mean auditing….

P18: Yes but no numbers….

I2: I'm not talking numbers it's like…..err because Big data one important part is err text…

P18: Exactly….the narrative side

I2: So you don't do it…….tracking the student room feedback, that's a kind of social media aspect, because I did say sometimes if one student says something very negative it's extremely powerful, if someone during the application period says don't go to University of Institution because of the accommodation, that's a huge impact, if the university has a system they can pick up this immediately and take some action and give some feedback…..

P18: Sure…..I mean with student room we have kind of taken the approach that it is not moderated and actually what I find is students are very fair and the moderate each other, so some of them might go on to say that but because there is so many people using it others will go and say I haven't had that experience, they rang me today and as long as the service generally is ok it tends to kind of write itself and its almost worse if the university gets involved because you just can't help but look like you are too defensive whereas actually students doing it is a kind of real life experience for them, so certainly on student room I think on Facebook slightly differently because sometimes you can be putting up a very positive post and you get people saying well Institution is s**t and you then have to say well this isn't the place for that sort of thing but I find on student room which is self-moderated that generally people are pretty fair.

I1: How do you cope with Facebook groups and getting comments under posts, because you can't delete all of them can you?

P18: I'm not sure…..well again MARCOMS do it….I'm not too sure that they…..I think they have a policy where unless it's actually abusive of not deleting, but maybe a counter comment that kind of says that's your view but because they don't want to look like they are gagging anybody or something like that because Facebook is one of those places isn't it that it is for you to share your views in a way and I think it's a bit like when your friends are saying something you don't like, well that's your choice not to be their friend, it's not for you to say don't say it on here

I1: exactly

I2: Ah, that's interesting actually yea…

I1: Do you use any analytical tools or dashboards, if yes can you briefly explain what they do and how effective they are in helping you in your role? So if you could give examples relating to student experience

P18: Yea sure so the ones that we have really started to use are the target so applications to target registered students to target and they are used mainly by the schools, so it's more about us providing them to schools and they just give a visual quick representation of how a school is doing but generally people will then click down and go into the data because they want ok so the business school now know that there are 20 people off target but what they want to know is how are tourism done and how is accounting done and they will often drive down, so we don't use them very extensively not as extensively as I think we should and particularly at the highest level I think we should be providing more to the vice chancellor and deputy vice chancellor in terms of dashboards because I think they are particularly useful in that very high level of data.

I think when you are getting down to school level and I think the schools do want more information which dashboards we have done so far do provide, you keep clicking on the bar chart and keeps taking you in and in and in so you can get right down to the….. So it would say Business School and you click and you can go down to the department and the programme within the department and the course within that and then err the year of the course within that. So you can keep working your way through, but I think generally they want that information upfront, the dashboard isn't particularly so helpful…..

I1: Is there a particular name for this dashboard?

P18: It is just part of the BI publisher analytics…..

I2: I think this question is more related to your personal role……is that the one you use? BI publisher or?

P18: No …..Well it's provided to me, but I prefer the data, I'm not a particularly visual person….

I2: So you actually access data directly without……you prefer to see the data instead of like getting reports from BI publisher….

P18: Yes….well the data still comes from BI publisher but if you provide me with a dashboard I'm immediately going to want to see the numbers, that's just how I work and because I've been involved in admissions for so long, I know what particular sale I want on that day where I have colleague who started with us two years ago, she is very visual so she provides lovely charts of how many phone calls we took on clearing day

I2: Summarising the information and everything….

P18: Yep and I want to say number……it just doesn't do it for me, it's a very individual thing

I2: We always argue when you have a huge amount of data, if everything is fine is fine but the system should have a function to give you an alert when something is wrong and then you open the dashboard and it will call you to drill in to see what's wrong with it….

P18: Yea I understand

I2: So is that something you are thinking of doing?

P18: Possibly I mean……I'm not sure about in my role particularly but I think there is a…..there would be a place for that ad particularly when you are getting down to programme level I think, programme leader data for example might not change very often, so I often alert to them there has been a change, would be useful where the data…..the level data I'm looking at will change every day, so I will look at it every day yea.

I1: What are you views on the limitations of business analytics and if you had a choice what would be an ideal BA system/tool to support student experience management for you and your university?

P18: sorry what was the first bit again?

I1: Your views on the limitations of business analytics?

P18: I think it is on the knowledge of the users, I think particularly at university you are trying to cover data for so many people at so many different not only levels, because the levels are not going to be important but in terms of how IT literate that person is and trying to build something that kind of works to the lowest common denominator, can be very frustrating for people that are at different levels of IT understanding likewise if you build if for the top IT…………..you lose everybody at the lower end so I think trying to find that level, I think get an agreement as to what you want the analytics to say because if it's not saying very much, if it's not saying the right things to people, it will look pretty but you will just move on yea….so it's just making sure that you do understand what the question is to be able to answer it via the analytics.

I think…..I think though it such a personal thing, I think you always need to be providing both in some way I think that some people will want to drill the data, some people want to give a summary and I think you have to…..you can't do it exclusively, you have got to develop both at the same time

P18: What's the second part?

I1: The second question is if you had a choice what would be an ideal BA system/tool to support student experience management for you and your university?

P18: I think the thing that we are missing probably and I did an MBA in Higher Education Management and I did a bit of work on this for University of Birmingham because part of my project on that had to be for a consultancy for another institution you couldn't do it on your own and it is an alert system for students you are at risk, so what is looking at is more based on the American model of some soft stuff so we can easily do if somebody is not attending or if they haven't submitted some coursework or if they have missed a one to one with a tutor, but this brought in much more soft stuff so the bus driver worried about them because we own our own bus company, did the cleaners find someone hanging around at a strange time that they were concerned about, the people in halls is somebody not getting out of bed, erm so those kind of soft stuff that can also come into analytics, so you start to just raise the…………you start to get the picture of the whole person.

So if those things were going on and the academic progress was fine but if you start to get a picture of someone not attending lectures, so people in the halls have got some concerns about them, people in reception the kind of soft service people, we will bring those things together so we are not at the stage even with the hard services which I think is more easily doable, So what is poor attendance? What are attendance in universities as well as attendance on modules? Which we can more easily do our people getting in to trouble during times, during the Forum which is our entertainments place, you can bring all of that together and I think you get a much more rounded view of a student, have they had an appointment recently with a finance advisor? Have they had an appointment recently with counselling? You have to be careful about the amount of stuff that's shared but all of that gives you a much better idea of whether students are at risk of dropping out and to do that in a supportive way so if you can get a trigger early you can start pastorally help that student and see whether you can get them back on track rather than losing them.

Particularly with some of the nature of students that we have, first in the family to come to university and that kind of thing you want to keep them going, we have a big system for care leavers for example so students that might not have the normal support mechanisms, so we have to be their support, so at what point can we intervene so I think data can do that for us!

I2: That's an excellent idea!

I1: It is!

P18: (*laughs*) yea…..

I2: It's kind of Big data and also you know to broaden the people's thinking, it's never occurred to us

P18: Americans have done it…..

I1: They mentioned it at a Learning Analytics event…

I2: Oh I see, yea

I1: Yea I think a staff member in Blackboard

I2: You have to think more widely, think of all the possibly ways and come out with a more meaningful way to identify the…..

P18: well it is though…….my experience is there often are those people; the soft services people that start to see the first changes in students in terms of oh that person always used to come and say hello now they are just walking by, you know you always used to see them at 8 o'clock getting a coffee and suddenly they are not here so often those people that notice more than a 100 in a lecture room, it's a bit…you are a bit anonymous and you tend to kind of just move to the side-line so it's trying to find those people

I2: It's an ideal one but it's not very easy to do is it?

P18: No

I2: …….to get all the data, sometimes it's quite difficult…

P18: …..it is and also getting people to release it because people will often see it as policing and trying to convince people that we are doing it for good reason, that we are really doing it in a pastoral sense erm that convincing can be quite difficult particularly if you build it in to something like err the international student stuff so like you know are we being policeman for the UKVI now and that sort of thing we have to be really careful with the language, we are trying to do it for the right reasons, we are just bringing more formal attendance monitoring so students swipe electronically we have always had that on a weekly basis, we have 300 odd readers so you can swipe anyway we are just bringing it in to classrooms, so you can track attendance on modules and we can email students very quickly, by cohort so as they miss……we can email them quickly so we can get them back on track quickly, but we are have to work closely with the student union because they didn't want to be seen…………that we were tracking students, you can kind of look at it in both ways, we have had to prove to them in the project that it is for pastoral reasons and that if someone misses two we can get them in on the third and back on track whereas if they have missed 8 or 9, they have missed a semester and for that student it is very difficult to come back but to do that quickly and in a large institution is difficult.

I2: Mobile phones can do all this tracking now, yeah so they don't use their ID but you can block your mobile so nobody can see….

P18: I think we will be chipping children eventually as their born I think so parents can track them, see their every move…

(*All laugh*)

I1: Ok, Final question

I1: What are your views on the future development and application of Business analytics for student experience management in your university?

P18: I think it's partly going back to what we were saying about HEDIIP, I really think there can be some big gains for localised decisions based on HEDIIP big….big data, so how are we doing against others so and I think that's where again the NSS has been powerful in terms of whether you like it or not it's been able to give you a comparison of even if you think you are doing ok, students don't think you are doing as well as some other institutions, what is it that they are doing and trying to then…..and the sector is very good at talking to each other so if you do have a problem and you find that Coventry do this better or Bedfordshire do it better they will talk to you about it, it's a really unusual market so imagine Tesco's telling Aldi……

I1: Or Sainsbury's…..

P18: Yea…..it just doesn't happen, it does happen however in HE and I think it's the real strength of the sector that generally we have all got student experience at heart and so erm I think being able to use that Big data to analyse ourselves erm to say ok and this is what we are doing particularly well at let's keep going and pushing on we are going in the right direction but this is what we are not doing so well at, how comes we haven't got those types of students, so I think that's the big development to come but HEDIIP is slow and painful and that is certainly the feeling at the academic registrar's council because we get regular updates and we are just kind of saying and when and they are having to chop it slowly……slowly and I totally understand that but you just feel there can be such a huge win around data if we could get that off the ground

I2: I also found if that's available then that's a benefit for students, sometimes disadvantages for some universities because students know everything

P18: Yes……but I do think if you take something like the NSS, now that the differentials are percentage points, I think if you look at the league tables you can say this doesn't help some institutions but actually if you look at them the difference between people that erm…..the top 15 people in the kind of middle quartiles one or two percentage points and students recognise that if you look at the KIST data and it said the students here are 95% satisfied and the ones here are 97% satisfied I don't think it makes me go to the 97% and say……95 is enough it comes a point where you kind of go yea alright it would be different if it was 45% instead of 95% but you know where we get very hung up on the percentage point…………you know we have gone up 1% this year…the students don't care do they, I mean it's different if it was tens and twenty per cent they are not silly, they will match that against where their location is, what the course is, what they know about their institution, I think we get too hung up on that

I2: Yea I always say there are three parts top, middle; bottom within them there is not a huge difference

P18: Exactly, no and you get some rise that year and some fall……