Data Changes Everything - An Investigation Into The Acceptance Of Learning Analytics To Support Student Success

Thesis

Data Changes Everything:

An investigation into the acceptance of learning analytics to support student success

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Abstract

The development and implementation of learning analytics as a mechanism to support student success has been an emerging trend within Higher Education. Previous research identifies that learning analytics is an innovative educational development but recognises that little attention has been paid to evaluating its effectiveness or pedagogic usefulness. Researchers recognise that learning analytics is a new field in need of further research to aid its credibility within the educational arena. This research study provides a better understanding of learning analytics to support student success through the examination of opportunities and challenges of learning analytics from a multi-stakeholder perspective. This study also demonstrates how learning analytics can be successfully implemented within Higher Education.

Through an interpretivist paradigm, this cross-sectional research study captures the unique experiences of students, academic staff and learning analytics experts. Data collected through twelve semi-structured interviews and three student focus groups enabled the researcher to gather a broad understanding of learning analytics from those involved and provides an holistic portrayal from this cultural group.

The main findings of this study suggest that learning analytics need to have a clear context and purpose within Higher Education to ensure successful development, effectiveness and pedagogic usefulness. Effective organisational change, culture, academic and student engagement, ownership and motivation are paramount. Findings also indicate disparities in the implementation of learning analytics within Higher Education, which require resolution to ensure success, and there is some discussion about how challenges can be overcome to ensure effective institutional adoption and student success.

These findings contribute to the increasing evidence base into learning analytics and will influence future practice by enhancing pedagogic knowledge, increasing understanding and supporting organisations to implement learning analytics as a mechanism to ensure student success.

Acknowledgements

I always vowed that if I was ever going to do a PhD, that would be it and I would be done academically. I have a feeling that I was wrong, and that completing my Ed D may lead me down a new and different academic path….

As always, I would like to express my eternal gratitude to the special people that helped me to get this far. Without a doubt, I am forever in debt to my Ed D supervisors, Dr Liz Marr and Prof. Alan Floyd, who have helped, supported, laughed and guided me throughout this (at times) painful process. My sincere thanks also go to Sally Anderson who had the mammoth task of proofreading my thesis when I could read it no more, and to Suzanne Nelson for her fabulous graphics which quite frankly put my versions to shame. My endless love and eternal thanks go to my partner, Paul, and my children, Luca and Lara, who have put up with my moaning and choosing the Doctorate over them to enable me to succeed. I guess I owe you massively.

I always said that if I ever finished this, I would dedicate my thesis to East Midlands trains as thanks for allowing me to work in relative comfort on their train services. I would also like to extend my gratitude to the various soft-play outlets in Leicestershire that successfully managed to keep my child entertained while I sat at my laptop and worked. Quite frankly, I couldn't have done it without your help.

In all honesty, this thesis deserves to be dedicated to my Mum and my late father who have always believed, supported and (financially) contributed so that I can achieve my goals. This is for you both - I love you with all my heart. Finally, I would like to extend my dedication to all those mad people that choose to do this.

In the words of Nelson Mandela….

'It always seems impossible until it's done.'

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Acronyms

DMS	Data management system
FE	Further Education
HE	Higher Education
HEFCE	Higher Education Funding Council for England
HEI	Higher Education Institution
LMS	Learning management system
MOOC	Massive open on-line course
OfS	Office for Students
TEF	Teaching Excellence Framework
UK	United Kingdom
VLE	Virtual Learning Environment

Chapter 1 Introduction

1.1 Introduction to the chapter

The introductory chapter will provide a broad outline of the research topic under investigation. The research aim, research question and the research design will be briefly presented; these are further explored in subsequent chapters of this thesis. Finally, an overview of the thesis structure will be provided, followed by a concluding element and link to the next chapter.

1.2 Rationale and origins of the research

My own institution is a post 1992 public university situated in the East Midlands in the UK, with student numbers of approx. 20,000. As an institution that is surrounded by competitor public and research universities there was a perceived need to demonstrate excellence in teaching and learning as an attempt to retain students. Due to rising interest in the field of learning analytics at the time, the then PVC in Learning and Teaching commissioned a one-year pilot project to develop and implement learning analytics. This was conducted in 2015/6. This was the fundamental catalyst that influenced this research study as I was directly involved in the development, implementation and evaluation of the institutional pilot through my job role as Head of Studies, where I was directly responsible for learning and teaching developments in my department (Health and Life Sciences). Through conversations with the software developers during the project development phase, and subsequently with staff and students during the implementation and formal evaluation phase of the project, my personal interest into learning analytics grew, and I saw that there were very mixed views regarding using learning analytics as a mechanism in relation to student success, and that the approach was seen as somewhat controversial by my academic peers. I found that my own thoughts and opinions changed as the project continued, and I began to question the value of using learning analytics as an effective approach to support student success. As my understanding was that the domain of learning analytics was relatively new within higher education (HE), I felt that my own professional experiences in my own institution could be used to develop and increase the knowledge base into learning analytics more widely, and that this topic would be an interesting and innovative are to focus on more deeply.

As part of the project evaluation, I conducted a limited literature review into learning analytics, as I was unaware of the historical context of this educational innovation. I began to see that there was a significant research gap within current empirical research, as the majority of early studies reported in literature were from a quantitative perspective and appeared to be related to data-mining and from a technological perspective. Literature conceptually describes the purpose of learning analytics and the key uses of it, but despite extensive searching through published literature dating as far back as 2001, I discovered that more formally learning analytics originated in 2010/11, but previously to this, other terms such as academic analytics and educational data mining had been used. I could only find limited evidence that focused on individual perceptions and experiences of using learning analytics, and a small number of research studies that focused upon the evaluation of learning analytics from an institutional perspective. I could find no literature in relation to the evaluation of learning analytics from a multi- stakeholder perspective. This led me to conclude that this was a relevant and topical area to investigate further, and that there was a potential research gap within published research into learning analytics. To contribute to lessening this gap, the research project reported in this thesis was initiated.

1.3 Overview and structure of the thesis

The thesis is presented in several distinct parts over six chapters. This chapter provides the reader with a broad definition of learning analytics and focuses on the research topic under investigation. The aim of the research and research question are outlined, and the reader is introduced to the conceptual framework which forms the lens through which the results and findings are viewed. Chapter Two focuses on a review of the literature pertinent to learning analytics. This chapter will demonstrate how the literature review was conducted and will provide a critical review and appraisal of the existing body of knowledge in relation to the key focal areas of learning analytics within HE. Chapter Two also provides a detailed account of how the conceptual framework was developed. Chapter Three provides a rationale for the methodological foundations and tools used to execute and evaluate this research study. Consideration for research ethics is also included as part of this chapter content. Chapter Four presents the results of the research from a multi-stakeholder perspective. A full analysis of results and discussion on the research findings in relation to the research questions is presented in Chapter Five. Chapter Six summarises the contribution to knowledge made by this study and provides a review of the wider implications of the study in relation to educational practice, management and policy. Finally, it provides recommendations for additional research into the use of learning analytics within the UK HE context.

We begin by setting the context for the study. To understand the impetus for learning analytics, we need to consider not only individual institutional drivers, but also the overall current HE environment within the UK.

1.4 Background to the research problem

Ensuring student success at university is a high priority for UK Higher Education Institutions (HEIs), with many universities developing and implementing an array of student led interventions to ensure that their students complete their educational journeys and leave university with their intended academic awards. At strategic level, HEI leaders need assurance that specific student led interventions and initiatives show impact and effectiveness. In recent years, HE has undergone a period of significant change; there are numerous factors that have enforced and influenced change, ranging from external drivers governing how HE is funded and functions, to internal initiatives aimed at enhancing institutional effectiveness and the measurement of educational practice and processes. There is an increase in use of technology within the educational arena which brings a new different era of digitally literate university student studying in the twenty first century (Persico and Possi, 2015). Higher Education Institutions are faced with operating under challenging constraints, but at the same time being forced to demonstrate institutional effectiveness, improvement and ensuring student success. Improved data systems within HE institutions present a new opportunity for organisations to consider how they use data, and how they can develop new ways of working to improve strategic performance and the student's educational experience. The background to the research problem is particularly significant as it potentially influences the institutional rationale for considering new innovative ways of working within the educational context.

1.4.1 The fee-paying context of higher education

The context in which UK HE functions and operates has undergone a period of reform and significant change. One of the most significant external contextual changes to date within HE in England was the introduction of tuition fees (Higher Education Funding Council for England (HEFCE, 2012). From September 2012, controversial government policy has allowed universities to charge up to £9,000 per year for undergraduate courses, raising the cap from its 2011/12 level of £3,375 (HEFCE, 2012). The introduction of fees was a controversial step, as it has generated heightened competitiveness among universities, and created a fee-paying culture which positions students as consumers of education in the educational marketplace (Kenworthy, 2003). Institutions need to find new ways to assure educational benefits, as they are under considerable competitive pressure as organisations within the consumer world (Scheffel et al, 2014).

Students themselves have also adopted a consumerist ethos, expecting a quality service, which needs to be understood from a customer's point of view (Slack et al, 2004). Essentially, students want value for money through investment in them as learners, investment in environmental resources and investment in the broader educational community as well as personalised support to enable them to achieve their learning goals (Kandiko and Mawer, 2013). Kandiko and Mawer (2013) believe that students have clear expectations of what institutions should provide to support and enable their learning; clearly students want to be supported by their university, through having a personalised learning experience, with acknowledgement of flexibility and authorship over their degree experience (Kandiko and Mawer, 2013).

Further change to the fee-paying context of HE is anticipated with the recommendations arising from the Augar Review (Department for Education, 2018). At the time of writing this thesis, it was not known whether the proposed recommendations will be adopted. The Augar Review (2018) was conducted to review the post eighteen education system and its funding; which has been informed by independent advice offered from an expert panel consisting of individuals working within post eighteen education, business and academia. The Augar Review (2018) recommendations address four key aspects relating to student choice, value for money, access to education and skills provision to ensure that the current UK post-18 educational system is a joined-up system that meets the needs for students, taxpayers and the business economy. It is anticipated that he Augar Review (2018) will bring about further change to the current HE system once the review recommendations are published, and this places some uncertainty on how HEIs will continue to operate in the future.

1.4.2 The need to improve quality and effectiveness within higher education

Higher education institutions operate within a quality and effectiveness-focused culture (MacFayden and Dawson, 2012, Kavanagh and Ashkanasy, 2006) despite a backdrop of shrinking resources and pressures to improve the quality of teaching and learning (Brown and Diaz, 2011). Clow (2013) identifies that drivers are imposed on institutions in terms of performance management, performance metrics, and higher proportions of students achieving qualifications. Internal and external environments both recognise and value the importance of the student journey and the student experience and, as a result, students entering HE have raised expectations of their university experience and what it needs to offer.

Higher education is operating within a new age of metrics strategically focused towards the measurement, analysis and evaluation of teaching excellence, research excellence and knowledge exchange (Taylor, 2018). In the current climate, academic institutions are rewarded for verifiable teaching expertise, publication output which is used as a measure of research success, and independent achievement (MacFayden and Dawson, 2012). Recent moves by the UK Government support recognition of excellent teaching in addition to recognition of good research practice. The Teaching Excellence Framework (TEF) (HEFCE, 2016) makes universities more accountable for the quality of the academic experience offered by HEIs.

1.4.3 The Teaching Excellence Framework (TEF)

The Teaching Excellence Framework (TEF) is a formal mechanism that assesses educational standards of UK HEIs using a ranking system (OfS, 2018). It provides universities with both a financial and reputational incentive. The TEF awards are decided by an independent panel of experts made up of academics, students, and experts on employment and widening participation in Higher Education. The Office for Students (2018b) states that the TEF provides information about the quality, environment and outcomes of teaching (OfS, 2018b) with metrics being grouped into core areas, which are teaching performance, graduate outcomes, student continuation and overall student satisfaction. TEF (OfS, 2018) considers the mix of student characteristics, entry qualifications and subjects at each HE provider (OfS, 2018b).

TEF assessment is based on what a provider should be achieving within this context. Data taken from the previous three years is benchmarked based on the provider's student characteristics, which results in a unique benchmarking position for the provider relative to the sector. In addition to core metrics, split metrics look at variations in each of the core areas by (amongst others) gender, ethnicity, age and disability. The aim of split metrics is to establish how students from different backgrounds fare on the various measures relative to their peers. TEF in part incentivises institutions to look at and address inequity amongst different student groups; highlighting differences in this way will identify areas for improvement and facilitate the identification of good practice. To some extent the implementation of learning analytics can support institutional TEF activity through the provision of accessible data about students and their performance within a course. Learning analytics can be used as a predictor of potential student failure and indirectly serve to support TEF continuation metrics.

TEF metrics are supplemented by a written narrative provided by the HE provider which contextualises the metrics. This facilitates a more balanced and combined approach to measure institutional quality and effectiveness against competitor HEIs. Implementation of TEF is somewhat overshadowed by the broader challenges and flaws of using metrics. Bols (2015) argues that metrics alone will struggle to reflect diversity across the sector, and that this must be taken into consideration when reflecting on the data. A recent independent report on the use of metrics in research assessment (Wilsdon et al, 2015) concluded that quantitative methods are no substitute for academic peer review. Bols (2015) reflects that it is essential to effectively benchmark data to account for different subjects taught and different types of students studying. Bols (2015) supports the use of the written narrative and believes that the institutional statements should be seen as robust evidence on which to make TEF judgements. Bols (2015) further believes that the narrative submission should be given as much weighting as the data so that TEF panels are able to contextualise the data presented and also identify a wider range of activities beyond the data. Such activities can include the implementation of learning analytics to demonstrate good practice in terms of supporting students to succeed.

1.4.4 University rankings

With the aim of informing potential undergraduate applicants about their preferred university there are published national rankings of universities in the UK based on a range of criteria including entry standards, student satisfaction, staff-student ratio, expenditure per student, research quality, degree completion rates and student destination. These university league tables place considerable pressure on HEIs to improve their quality and performance continually, as do other mechanisms. The National Student Survey (NSS) (HEFCE, 2016) is an independent student survey, but is viewed as an influential element of institutional ranking through the measurement of undergraduate final year students' course experiences and overall student satisfaction. The NSS is used as one of an institution's key performance indicators to measure student experience and opinion.

1.4.5 Universities in the era of big data

With the increased use of online and mobile technologies, large amounts of data are generated and accumulated across industry, business and from a personal domain. What has emerged from this data generation is the use of analytics to process and interpret data to enable individual organisations to develop a better insight and to optimise their processes and organisational outputs. As HE becomes more immersed in the use of technology through electronic student management systems and the use of virtual learning environments (VLEs), data is more easily accessible and able to be better presented than ever before (Arbaugh, 2014). This information includes datasets about student learners, individual learning activities and the learning environments in which students' study. Analytics systems can be employed to exploit data (Booth, 2012) to better understand and enhance aspects of the educational experience as well as helping to solve broader institutional challenges against the pressures described above. However, despite the plethora of data available, Sclater (2014) argues that at strategic level better data relating to student experience still needs to be obtained to enable the institution to identify and address areas of concern to learners, and MacNeill (2012) says that there is a need for a clear and cohesive data source to support student success.

What is becoming apparent from the changing context of HE, is that there is a wide range of challenges from a macro to micro level. Such challenges have the potential to affect the institution in multiple ways, from their strategic performance to the student's educational experience. Key aspects such as increasing student numbers, increased government scrutiny and the TEF all contribute to heightened need for effective decision-making processes at all levels within HEIs. In addition, as Sclater (2017) points out, HE is in a new era of accountability and liability, and with that comes a requirement for a better measurement and quantification of educational processes (Campbell et al, 2007, Clow, 2013).

1.4.6 Ensuring student success

Ensuring student success is a high priority for any educational establishment, as this demonstrates the impact and effectiveness of different education practices in advancing student outcomes. Student success is multi-faceted but is defined by the Higher Education Academy (HEA) (2015) as student access, retention, attainment and progression. Student success requires practical strategies such as an inclusive curriculum, flexible learning, employability, encouragement of student engagement and belonging, and using data driven practices (HEA, 2015). From an institutional perspective, providing excellence in these specific areas influences institutional reputation, student satisfaction levels and potential future institutional sustainability. There are also legal, ethical and moral imperatives for institutions to ensure student success. For students themselves, success is important for their future endeavors and after significant financial and personal investment. HEA (2015) believe that all students should have the opportunity and support to succeed in HE and to develop skills, knowledge and attributes to make the successful transition into and beyond HE. Enabling and facilitating student retention and progression has a positive impact on students' well-being and success at university, and many institutions devise and employ strategies and initiatives to facilitate student success which promote student inclusion and belonging. The HEA (2015) have developed a multi-faceted framework for student success. This framework provides a structure to shape and evaluate developments and practices at local level, and reporting using it helps institutions to demonstrate their commitment to ensure student success.

1.5 Learning analytics as an educational development

Learning analytics as a field has multi-disciplinary origins, and can refer to a specific topic (such as health analytics), an activity aim- through predictive analytics or through on-line data sources. (Sclater, 2017). Definitions of learning analytics appear to vary. Within the educational arena, the term academic analytics was initially adopted by Goldstein and Katz (2005) to describe the implementation of business intelligence in HE. This terminology is problematic, as Goldstein and Katz (2005) believe that it implies that the administrative uses of analytics are not included. The terminology learning analytics is used more for aspects of learning and the educational experience of students (Sclater, 2017) through its relationship with action research, both of which attempt to improve education through cyclical investigation. Junco and Clem (2015) appear to define learning analytics explicitly in terms of using student generated data for the prediction of educational outcomes for the purpose of tailoring education, whereas others (Rubel and Jones, 2016) define learning analytics use as a way to help educators examiners, understand and support student behaviours to change their learning environments. While it is apparent that there is no generally accepted definition of learning analytics, there have been numerous early definitions of learning analytics presented (Buckingham Shum and Ferguson, 2012, Verbert et al, 2012, Clow, 2013). For the purpose and scope of this research, the description offered by Siemens and Gasevic (2012) will be used as a basis of understanding. This definition has become one of the most frequently cited definition of learning analytics, with Ferguson (2012a) recognising that it aptly covers the educational research context.

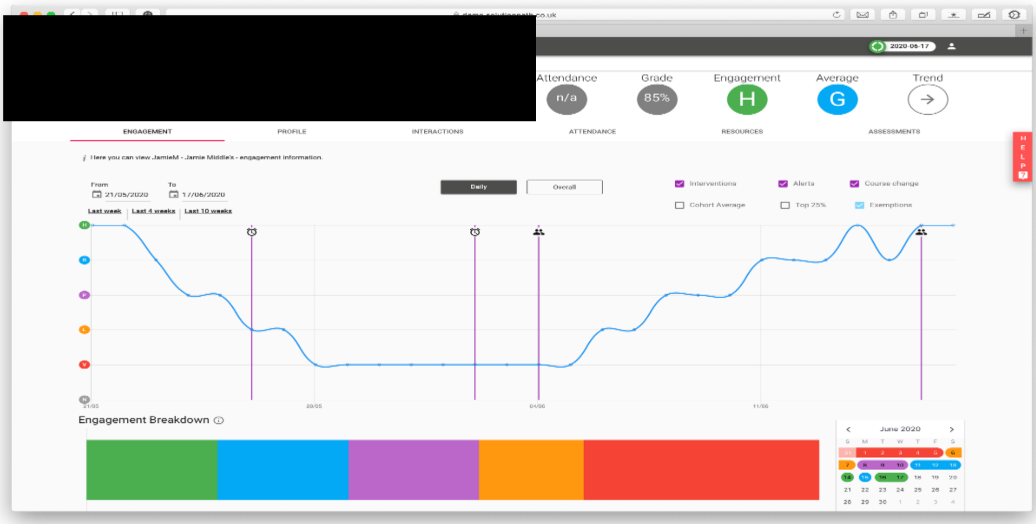
Siemens and Gasevic (2012) describe learning analytics as:

> ***'The measurement, collection, analysis and reporting of data about learners and their contexts for the purposes of understanding and optimizing learning and the environments in which it occurs.'***
>
> (Siemens and Gasevic, 2012, p. 1)

JISC (2016) support Siemens and Gasevic's (2012) definition and believe that learning analytics (or student analytics) refers to the measurement, collection, analysis and reporting of data about the progress of learners and the contexts in which learning takes place. Learning analytics requires the accurate collection of timely data, presented with visualisations of student engagement, outcomes and use of resources. Campbell et al (2007) suggest that analytics is the practice of mining institutional data to produce ‘actionable intelligence’, which clearly implies that taking an action as a result of the insight is key. Clow (2013) supports Campbell et al (2007) and sees learning analytics as the analysis and representation of data about learners to improve learning through the use of predictive models that provide actionable information. Hung et al (2012) believe that learning analytics applies techniques from information science, sociology, psychology, statistics, machine learning, and data mining to analyse data collected during education administration and services, teaching, and learning. Decision making and decisions on how to enhance education are suggested to have better results if they are founded on data, facts and statistical analysis (Sclater, 2017) rather than intuition and presumption. As teaching moves to a more on-line format, there is a potential lack of visual clues that help educators to identify students who were insufficiently challenged, bored, confused or failing to attend (Ferguson, 2012b). Sclater (2017) believes then that the use and interpretation of learning activity data becomes key. Hung et al (2012) believe that one of the main applications of learning analytics is tracking and predicting learner’s performance, with Johnson et al (2011) recognising learning analytics use as identifying potential problematic issues and students at risk. Cooper (2012) suggests that analytics can help educators then answer questions such as what happened, or what is the trend with their students in order to offer a more personalised student experience, and at institutional level to support a philosophy of continuous improvement (Sclater, 2017).

Within my own position within the HE environment, data is obtained about student engagement using class attendance, electronic swipes into buildings, library use, assessment submission and accessed learning materials through the VLE. Banoor et al (2019) describe this to be in the form of access or clicks or number of downloads, but also through time spent on a particular, on-line resource. This data is presented on a visual dashboard. Student engagement is illustrated in Fig. 1. Hogaboam et al (2016) have researched the design and content of visual dashboards so that they incorporate useful features to allow academic staff to identify students' engagement and disengagement, although Hogaboam et al (2016) acknowledge that visual dashboards do not provide understanding for academic staff or provide meaning to student progress.

Fig. 1 Student engagement rating



As a result of the rapid increase in the quantity of data about learners described in earlier sections, learning analytics have come more strongly than ever into focus. Organisations and educators themselves appear to hold high hopes for learning analytics in the assumption that they can support organisations to remain fit for purpose, flexible and innovative (Rienties et al, 2016). Clow (2013) suggests that this is linked to management approaches that focus on quantitative metrics as a strategy for improvement, and to facilitate the effective use of limited resources within the educational arena.

Learning analytics have the potential to offer a different way for educators to understand education and their learners, and a number of uses have emerged which I believe can be categorised into three broad areas:

1. enhancing teaching and course provision through evaluating the usage of taught materials

2. student retention through the identification of students at risk of not returning to study
3. students reviewing their own learning to measure their own success

Within the UK HE context, it seems that institutions are responding to the new environment and are engaging with the development and implementation of learning analytics as a measure to contribute to student success. Within the educational arena, learning analytics is broadly perceived as an educational innovation with the ability to provide stakeholders, academics and students insight into the learning process (Clarke and Nelson, 2013, Buckingham Shum and Ferguson, 2012) and to improve learning and pedagogic practice (MacFayden and Dawson, 2012). However, many institutions need to determine how to design their learning analytics in order to respond to their particular strategic needs. Ferguson (2012b) believes that the concept of learning analytics has different meanings for different people due to historical overlap between academic analytics, learning analytics and educational data mining, and as such, had become a confusing mix of disciplines and terminology.

1.6 Identification of the research problem

In the context of the changing environment facing HE in the UK, learning analytics has promise as a potential solution, despite the issues alluded to above. Current empirical research recognises that its use is still in its infancy (Manderveld, 2015). Tools successfully implemented in Australia and the United States continue to encourage the HE sector in the UK to engage with and develop learning analytics, with nearly 30% of UK HEIs viewing the implementation of learning analytics as a major priority for their institution (Bichsel, 2012). Although developing tools using learning analytics is seen as only one of a range of investments to support students to succeed within their studies, there is a need for further research for institutions to understand how learning analytics can benefit them from both a strategic and operational perspective, as well as to identify potential drawbacks of this approach (Ferguson et al, 2015). Despite claims of learning analytics being an innovative educational development, Strang (2016) recognises that it remains a new field in need of more research, particularly focused towards predicting and understanding student performance. The technology to deliver the potential of learning analytics is young, and the research on understanding its pedagogical usefulness is still in its infancy (Johnson et al, 2013).

Learning analytics has been successfully employed to study and visualise the relationship between student activity and performance in on line courses (Scanlon et al, 2015) but Ferguson (2012) believes it is limited in its widespread use within HE as a predictor of student performance to ensure student success. Ali et al (2013) recognise that research focusing on educators and the required analytics is scarce and note that there are few reports on evaluation studies aimed at assessing developed analytical tools (Ali et al, 2013). Siemens (2012) concurs and believes there is a gap between research and practice, particularly in sharing of information, learning analytics tools and datasets. A scholarly community around learning analytics involving researchers, academic staff and other personnel within the HEI exists, but Sclater (2017) believes that a serious challenge is presented by the lack of connection between the empirical research undertaken by this community, the commercial software tools being developed by vendors, and the needs of end users (Sclater, 2017). As the tools, technology, methodologies and practices within the field of learning analytics continue to grow, there is a need for dialogue between all these groups to ensure the appropriate evolution of learning analytics. Hence, there is a clear need for further research to address the opportunities and inherent challenges of driving forward this educational development from an institutional perspective.

1.7 Research aim, research objectives and research design

During the institutional learning analytics project mentioned at the outset of this chapter, I had begun to gather my research ideas. Initially, my idea was to gather perceptions and experiences of learning analytics from academic staff and students within my own institution using appreciative inquiry (AI) as a research methodology, and my plan was to conduct my research over two time-points to determine whether perceptions had changed. However, the project closed at completion of the pilot phase due to technological infrastructure issues. This encouraged me to reflect on my original research idea, and I decided to broaden my approach to investigate perceptions and experiences of academic staff and students from HE providers within the UK who were developing and implementing learning analytics. This meant that I could no longer use appreciative inquiry as my research methodology as I would not have the opportunity to be able to conduct my research at two time-points. Through further informal conversations with my Ed D supervisor, I decided to expand my initial idea and obtain views and perspectives from learning analytics experts in addition to academic staff and students, to provide a triangulated approach to my research. For the purposes of this study, experts were defined as those participants in non-academic roles who were leading the development and implementation of learning analytics at institutional level. Experts consisted of participants in roles such as learning analytics project managers and technology-enhanced learning experts. An expert at sector level (a commercial software developer) also agreed to participate. Based on my experience during my own university's institutional pilot project, I recognised that the majority of academic staff had not used learning analytics previously, so I consciously did not define this staff group as an expert in this domain, and selected to use academic staff as a separate sample group.

The overall aim of this cross-sectional research study, therefore, is to gather a multi-stakeholder perspective to gain a better understanding of learning analytics as a mechanism informing enhancements designed to further student success within HE. Undertaking a cross-sectional study allows the researcher to collect data from different groups of people who are at different stages in their experience of the phenomenon (Parahoo, 2006). In order to achieve the research aim, the following research questions were identified:

1. What are the opportunities in the use of learning analytics as viewed by students, academic staff and learning analytics experts?

2. What are the challenges in the use of learning analytics as viewed by students, academic staff and learning analytics experts?
3. In view of the findings above, can learning analytics be effectively used within a Higher Education Institution to support student success and if so, how?

All research is based on an underlying philosophical assumption about what constitutes valid research, and which methodology is appropriate to be able to develop knowledge and theory within a specific study (Burrell and Morgan, 1979). A subjective qualitative approach aligned to an interpretivist paradigm lent itself well to the research aim of understanding and gathering meaning from multiple perspectives to explain an experience. Using a qualitative approach also provided a unique dimension to the existing body of knowledge into learning analytics, as the majority of published research is written from a quantitative perspective.

To answer my research questions successfully, it was necessary to gather perspectives from key stakeholders involved with the development and implementation of learning analytics, as well as users of learning analytics within an HEI. Participants were selected from five different post-1992 universities from across the UK. Participants were purposefully selected based on their own experiences of developing and implementing learning analytics within their own institutions. As I wanted to understand the experiences of participants, the research aim, objectives and the development of research questions were structured to focus upon the exploration of participants lived experiences, with a view to understanding the constructed, real world view of learning analytics within educational practice.

1.8 Development of the conceptual framework

As is evident from the discussion above, learning analytics are a relatively new feature in dynamic HE environment with complex interplay between multiple stakeholders. As these factors emerged from the literature, a conceptual framework was devised as an organising device through which to view the results and findings of the research. Silverman (2015) outlines that a conceptual framework allows the researcher to identify research goals, develop realistic and relevant research questions, select appropriate methods and to provide justification of the research. As such, this has the potential to connect all aspects of the research inquiry and to organise ideas to achieve the ultimate research purpose. The conceptual framework devised to frame this research study initially viewed learning analytics as a central aspect, with interlinking factors such as the student, the academic and the institution. Surrounding the framework enabling and challenging factors were positioned as an influence to the interlinking factors portrayed. This framework was further developed as the study progressed, and the progressing thinking around the framework is highlighted throughout this report.

1.9 Methodology

Different methodological approaches were considered, with case study being finally selected for this study as it fitted the focus on the detailed areas under investigation - the need to discover and answer *how* and *why* type questions. Case study focuses on specific populations and events bounded by time and which are well defined (Parahoo, 2006, Yin, 2012). After consideration, as an educational researcher, I felt that face-to-face, semi-structured interview process would be a simple and effective mechanism to generate sufficient data to enable me to respond successfully to the research questions that I had formulated. A face-to-face, semi-structured interview method would enable me to easily gather research participant responses to the questions posed, as well as providing opportunity to ask additional questions, gather points of clarification from participants and enable the observation of non-verbal clues within their responses. In addition to interviewing research participants, I decided to conduct focus groups for student participants, as I felt that a group setting would make student participants feel more at ease with answering the questions that I was posing.

1.10 Significance and outcomes of the research study

This research study is important as the findings contribute significantly to increasing the evidence base for the development and implementation of learning analytics within the UK HE context. My research study provides an original contribution in supporting the development of professional knowledge and practice into learning analytics from a multi-stakeholder perspective; there are limited published research studies focusing on participant perceptions and experiences of learning analytics to date; thus, this research is unique. The findings show the opportunities and challenges of implementing learning analytics as an educational development from a participant perspective, and indicate how challenges can be overcome to ensure effective institutional adoption and success. This research study therefore enhances pedagogic knowledge, increase understanding into the use of learning analytics within HE and supports institutional advancement in this developing pedagogic area.

1.11 Summary of the chapter

To conclude, Chapter One has provided an overview of the background and the origins of my research study and has provided a brief introduction to the study purpose, and the research paradigm and methodological approach that will be used. The research aim, objectives and design have also been briefly introduced along with the conceptual framework which provides an organising mechanism for subsequent information and discussion. The next chapter will demonstrate how the conceptual framework was developed through a critical exploration of the key concepts that influence and underpin this research study as revealed through the thematic areas emerging from relevant literature.

Chapter 2 Literature review

2.1 Introduction to the chapter

As noted within Chapter One, learning analytics as an educational development within HE is a complex and multi-faceted area. To do justice to the literature on the topic, it was felt that an organising tool was required. Therefore, this chapter begins with the development of a conceptual framework. Thereafter, the chapter details how the literature search was undertaken, before using the conceptual framework to analyse critically the key concepts that influence and underpin the main research study as they appear in the literature.

2.2 The development of a conceptual framework for this research study

A conceptual framework is an analytical tool that is used to make conceptual distinctions and to organise researcher's ideas. Miles et al (2013) describe a conceptual framework as a visual or written product that explains (either graphically or in narrative form the key factors, concepts, research variables and the presumed relationships among them. Having a system to organise concepts, assumptions, expectations, beliefs and theories to support the research is a fundamental part of a research study design (Miles et al, 2013). Silverman (2010) emphasises that a conceptual framework is a tentative theory of the phenomena that the researcher is investigating. It helps the researcher to identify research goals, develop realistic and relevant research questions, select appropriate methods and provide justification of the research (Silverman, 2015).

A conceptual framework has the potential to connect all aspects of the research inquiry and to organise ideas to achieve the research purpose. Several types of conceptual framework have been identified and are broadly categorised within Table 2.1 along with their links to research purpose.

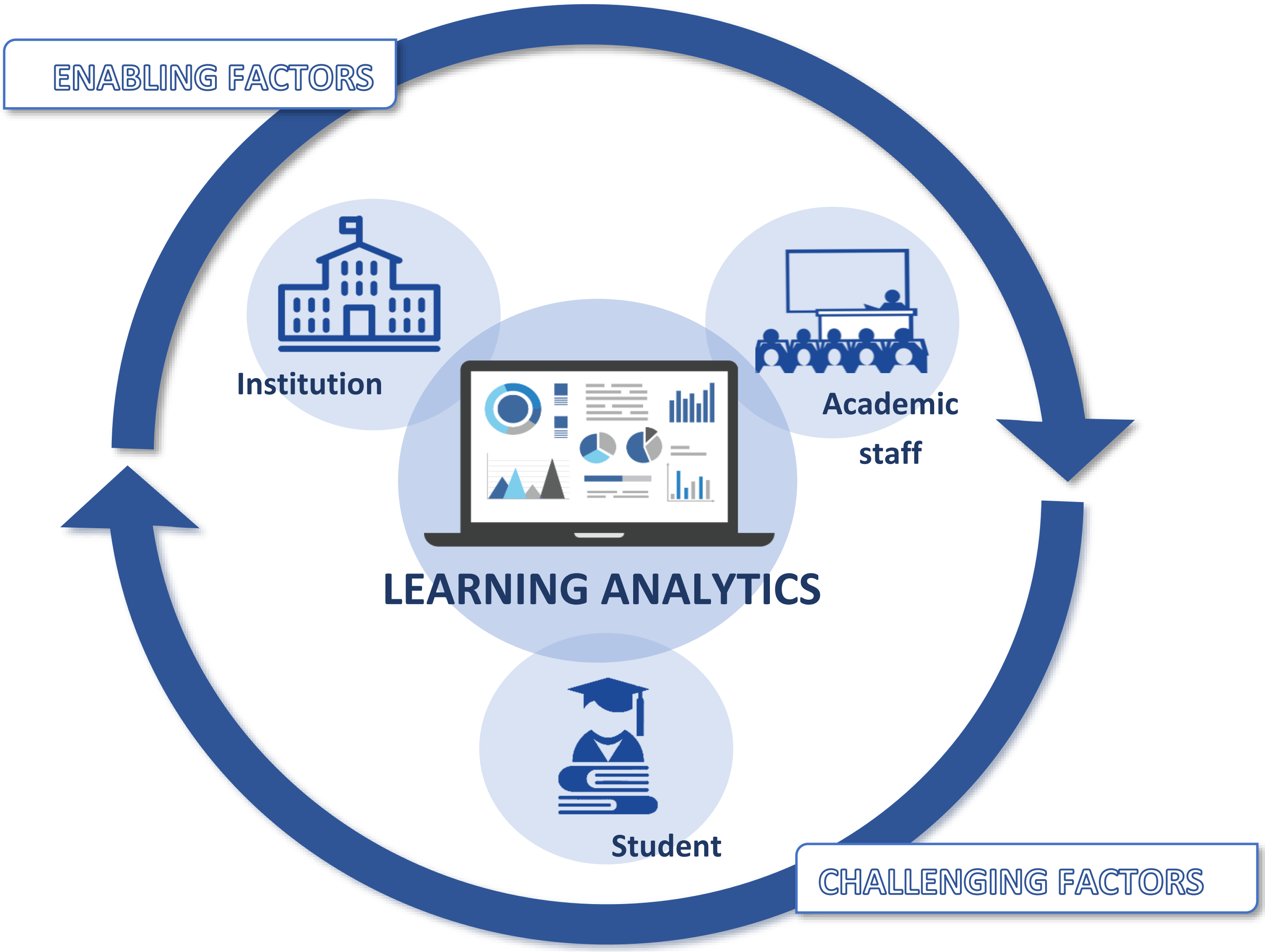
Table 2.1 Types of Conceptual Frameworks

Conceptual framework type	Link to research purpose
Formal hypothesis	Explanation and prediction
Descriptive categories	Description/Descriptive research
Pillar questions/working hypothesis	Exploration or explanatory research
Practical ideal	Analysis

Forging a link between the conceptual framework and the research purpose allows the researcher to develop their own research design. The most common type of research purpose within empirical research is explanation; in this case a conceptual framework acts as a map to organise and provide coherence to any empirical findings (Evans, 2002). My own research will link to the research purpose through an exploratory approach, with the conceptual framework providing broad pillar questions and areas of consideration that need to be addressed to respond to the research aim and objectives.

The conceptual framework for this study emerged organically and was initially created during my literature search as a basis for discussion into the topic area. The development of a conceptual framework allowed me as a researcher to examine the basis of learning analytics from the differing viewpoints of academic staff, students and from an institutional perspective. Learning analytics is placed centrally within my conceptual framework, with influencing factors to its success or barriers to success being identified as the student, academic staff and the institution. The conceptual framework was later refined following the data collection phase of my research study as I discovered that to aid the effectiveness for learning analytics within the professional environment it needed to change. The amendment to the conceptual framework will be discussed within the discussion part of this thesis which is detailed in Chapter Five. I initially viewed learning analytics as central to the conceptual framework, as the majority of literature presented learning analytics as a central theme. While preparing the literature review, I identified that the research into learning analytics was focused from a student or staff perspective or from an institutional perspective. In some of the studies presented, all three of these areas were considered. This new knowledge supported the enhancement of my conceptual framework, as I felt that each of these aspects could be described as areas which surrounded learning analytics, and I recognised that there was a need to consider the relationship between each of them as this could be influential. I acknowledge that the vast majority of the literature used the phraseology ‘opportunities and challenges’ of developing or using learning analytics, so I felt that this was an important distinction for the framework. I translated this to enabling and challenging factors, and I felt that these surrounded all the aspects, as they could determine the success or not of development and implementation of learning analytics. My initial conceptual framework (Fig 2.1) was devised with these considerations, and the recognition that variables can occur at any stage of the process.

Fig 2.1: The conceptual framework for this research study.



2.3 Literature search strategy methods

Conceptually, learning analytics is a relatively new educational development, with its use significantly increasing within UK HE. In order to conduct a wide and detailed literature review of relevant published research, multiple computer-assisted databases such as Education Research Complete (ERC) and EBSCO Host were searched.

2.3.1 Inclusion and exclusion criteria

For the purpose of this research, inclusion criteria were set as any relevant research undertaken within the last 20 years (1999-2019). The aim of this search was to identify relevant and contemporary literature that is reflective of current UK HE policy and practice, as well as related to the development and utilisation of academic analytics, educational data mining as well as learning analytics.

As research focusing on learning analytics is expanding the broad key word and descriptor 'learning analytics' was used as a basis for the initial literature search. This initial search yielded a small amount of research publications that related to both staff and student perceptions and experiences of learning analytics. Some of the studies that were found analysed the implementation of various learning analytical tools that were used in HE, but the majority of them were set within an international context rather than being UK focused. This may show that there may be variance in how international HEIs operate and use learning analytics in comparison to UK institutions, so a positive result from this initial search was the ability to gather an international perspective allowing potential similarities and differences to be identified and considered. The initial search showed that there were limited evaluative studies into the effectiveness of learning analytical tools from staff or student perspectives. A broader search using the key word and sub-descriptors 'learning analytics and 'student experience' and 'learning analytics and 'student experience in UK higher education' and 'learning analytics and student success' was used to yield further published research papers which provided a wider range of relevant literature to consider. A summary of the literature search, which was conducted in 2017 and reviewed in 2018. The number of results is presented in Table 2.2.

Table 2.2 Databases used with keyword searched and number of results (hits).

Data base	Keywords	Results (Hits)
EDUCATION RESEARCH COMPLETE (ERC)	Learning Analytics	444
EDUCATION RESEARCH COMPLETE (ERC)	Learning Analytics + Student Experience	11
EDUCATION RESEARCH COMPLETE (ERC)	Learning Analytics + Student Experience + Higher Education	4
EDUCATION RESEARCH COMPLETE (ERC)	Learning Analytics + Student Success	4
EBSCO Host	Learning Analytics	200
EBSCO Host	Learning Analytics + Student Experience	21
EBSCO Host	Learning Analytics + Student Experience + Higher Education	4
EBSCO Host	Learning Analytics + Student Success	4
Research papers references and bibliography search	Learning Analytics Learning Analytics + Student Experience Learning Analytics + Student Success Learning Analytics +Student Success + Higher Education	10
Internet search	Learning Analytics Learning Analytics + Student Experience Learning Analytics + Student Success Learning Analytics + Student Success + Higher Education	15

2.3.2 Data extraction and management

The results shown in Table 2.2 relate relevant published research material. Each individual publication was reviewed for its appropriateness to the research field, and the key aim and objectives of the research. The review was conducted utilising a framework developed by the Critical Appraisal Skills Programme (CASP, 2013) to appraise the research papers suitability and relevance to the research topic. Using a framework provides a structured mechanism to enable an effective literature review. The Critical Skills Appraisal Programme framework (CASP, 2013) can be adapted depending on whether the researcher is investigating quantitative or qualitative approaches to their investigations.

To increase the volume of published material and to enhance the literature search, references and bibliography sources from individual research papers were reviewed for completeness, and to identify additional work that may add richness to the initial search. Research papers were selected based on the highest correlation to the stakeholder pool and having the most recent publication dates. This method yielded an additional selection of 10 research papers. Lastly, a search of the internet was completed, using the general term 'Learning Analytics' as well as 'Learning Analytics + Student Experience', 'Learning Analytics + Student Success' and 'Learning Analytics + Student Success + Higher Education'. During the process of appraising and selecting relevant research, key themes began to emerge which provided a clear link for the development of the conceptual framework which was used as a lens for the literature review. The key themes gathered in the framework also provided a tool to inform the development and refinement of the research question and research aim and objectives.

2.4 Findings from the literature

As a brief overview, findings from the literature review demonstrate that there are key areas of activity that are engaging researchers and practitioners within the field of learning analytics. Current literature is focused on testing and applying approaches to learning analytics using a convenience sampling approach. The current applications of learning analytics focus on single studies, or a limited combination of case-studies in a single discipline (Arbaugh, 2014). It is apparent that there is research which deals with learning analytics from a conceptual perspective. Further analysis of the earlier literature in relation into learning analytics reveals that the most commonly cited papers are conceptual rather than empirical in nature. Dawson (2008) suggests that this is due to researchers still attempting to define and place analytics within a domain. Although there are a number of evidence-based reviews (Ferguson and Clow, 2017) exploring whether learning analytics improves learning practice in HE, it is noted these are mainly aimed at researchers and not practitioners, nor are they conducted through a multi-stakeholder approach. More recently, Viberg et al (2018) conducted a large literature review of 252 papers published between 2012 and 2018 which looked at the current landscape of learning analytics within HE, and larger scale studies have been focused towards student perceptions of learning analytics (Bals et al, 2019), teacher perceptions of technology acceptance (Rienties et al, 2018) and evaluation of predictive learning analytics at institutional level (Herodotou et al, 2020, Herodotou et al, 2019). Utilising learning analytics to support study success in HE is also a new emerging area of interest (Ifenthaler and Yin- Kim Yau (2020), but as yet, large- scale evidence into the effectiveness of learning analytics in relation to study success is lacking.

Sclater (2017) has studied learning analytics in depth and identifies that there is growth in learning analytics from an institutional perspective in relation to predictive analytics and the identification of students at risk of failing or withdrawal; Sclater (2017) believes that this is a new and exciting domain within the field of learning analytics, and a specific area that researchers are starting to address. Although there are a number of innovations in using predictive analytics, only a few studies were conducted on a larger scale. A notable exception to this is a study by Herodotou et al (2020) which has reported a large scale and long-term implementation of predictive analytics spanning four years at a distance learning university.

Lastly, I identified that there is a considerable amount of published material which is presented in the form of a literature review. The conceptual nature of the studies presented facilitates a discussion on several thematic areas in relation to the broader benefits and impact of learning analytics, as well as the challenges they present, barriers to adoption and differences in the way they are used. The second area of interest within the research is concerned with educational data-mining (EDM) techniques for learning analytics enhancement.

This literature allows for discussion on the thematic areas relating to a changing student body, using data to support students, supporting students, using learning analytics to support student success and ethical considerations of using data. The third area of focus in the research relates to the use of learning analytics within social settings, with a particular focus on massive on-line courses (MOOCs) and supporting learning theory (Sin and Muthu, 2015) which enables a thematic discussion in relation to the purpose of learning analytics within educational design.

2.4.1 A changing student body within HE

Although not directly related to the concept of learning analytics, the notion of a changing student body holds significant influence at institutional level, as university's look for innovative ways to support a wider body of students. As such, it can be described as a challenging factor. Using learning analytics through a data driven approach can provide a mechanism for academics and institutions to support students effectively, and as such may be a key driver for the adoption of learning analytics at institutional level. Evidence suggests that the student body in HE has changed, due to many factors which are described below. As a result of this, there is a greater need for institutions to show that they can effectively support students to succeed within their studies; whilst recognising that todays HE students have different needs and competing demands in addition to their academic learning.

The student body has changed for numerous reasons. Firstly, tuition fees were first introduced across the entire United Kingdom in 1998 under the Labour government as a means of funding tuition to undergraduate and postgraduate certificate students at universities, with students being required to pay up to £1,000 a year for tuition. The introduction of fees, and due to subsequent changes in funding for the HE sector there was potential for student numbers to decline due to fiscal reasons. Despite this, full-time student enrolment numbers continued to rise (Patrick and Gaele, 2007); resulting in a changing student body. In part, the changing student body may be the result of educational policy drivers (HEFCE, 2012b) promoting widening participation and entry into university. Widening participation results in increasing numbers of non-traditional applicants attending university (HEFCE, 2012b), significantly changing the demographic nature of the student body, as well as providing a heightened need for academic staff to adequately support students to succeed in their studies.

A report conducted by Brown et al on behalf of Universities UK (2008) identifies that universities faced a shortfall of 70,000 students by the end of the next decade, as a result of a drop in the number of young people in the UK, known as the demographic dip. Current demographic trends predicted by Brown et al, (2008) recognise that the full-time undergraduate student population with UK HEIs may fall by 4.6 per cent due to this drop. It remains to be seen if this will be the case. That said, the demographic dip will potentially increase the diversity of learners as universities attempt to attract and develop other student markets, such as mature students, part-time study, work-based and overseas students in order to maintain student numbers. On the other side of this, it can be suggested that HE providers will need to show students that their institution offers the best value for money, and could potentially be keen to introduce different educational developments as a method of attracting new students. The development and implementation of different mechanisms (including learning analytics) as part of a multi-faceted approach will become all the more important to demonstrate institutional effectiveness within a competitive HE marketplace.

Most universities are now expected to cater for a diverse student body with students living away from home, mature students returning to education, or those individuals juggling study and a career or family life (Twigg, 1994, Thomas and May, 2010). Undergraduate students are an increasingly diverse population with greater support needs and include a significant proportion of students from black and ethnic minority groups (BAME), students with identified learning differences, and a higher number of mature learners, alongside the more traditionally expected group of young school leavers. This diverse student body has greater support needs than ever before (Gorard et al, 2006).

Demographic changes to the student body mean that a growing number of students are coping with additional commitments as well as academic challenges, such as family commitments, relationships and living arrangements, as well as increasing financial hardship due to university costs, and the need to undertake additional employment while studying (Lee and Choi, 2011). The extent of the demographic change of the student body means that student attrition has become an increasingly significant issue within HE (Tinto, 2012), and that financial or family issues are often cited as the cause of students failing or dropping out of university (Keshavamurthy and Guruprasad, 2014). Learning analytics has the power through data use to be a key predictor if there are student retention concerns or a lack of student engagement on a course and facilitates the ability to have a proactive approach in supporting students to succeed.

Lee and Choi (2011) recognise that a student's decision to drop out is often more complex than simply an academic one. Briggs and Pritchett (2010) report that university attrition particularly within the first year, can be due to changing perceptions about the course, health problems, time management and under-preparedness, and their view is supported by Keshavamurthy and Guruprasad, 2014). More recently, a news article published in the *Guardian* newspaper (Wakeford, 2017) based on an annual student experience survey noted that 87% of first-year students found it difficult to cope with social or academic aspects of university life. Students are unsure of what to expect, with a large proportion saying that the transition from school was a source of stress, with 6 in 10 students reporting that this transition made it difficult for them to cope. Other troubles that featured significantly included isolation (44%), balancing work and study (37%), financial difficulties (36%) and living independently (22%). Research undertaken by Tinto (2009) focusing on student retention indicates that poorer academic performance can be predicted based on demographic, social integration, psycho-emotional and social factors, and that effective systems need to be put in place within institutions so that they can support student success effectively. Learning analytics holds the ability for academics and institutions to easily access this type of data, and through integration of learning analytics with other mechanisms of student support (such as personal tutoring). Once the root cause of attrition has been determined, positive actions and planned interventions can be established to support retention of students (Woodley, 2004). Grau-Valldosera and Mingillan (2014) believe that dropout should be seen as a failure of the educational system to create an outcome (i.e. a successful graduate) after investing a significant amount of resources. As a result of this kind of view, HEIs are experiencing greater demands to retain students (Dietz-Uhler and Hurn, 2013) through both informal and formal mechanisms such as TEF and university league table ranking, as non-continuation of students can have major financial consequences (Griffiths, 2013) and create reputational loss. As such, the adoption of learning analytics may be a potential solution for institutions to be able to proactively focus on student retention activities, grounded in fact provided by tangible data.

Diversity of students within HE is not directly related to the concept of learning analytics, but is an influential factor as it may be a trigger for institutions to adopt alternative approaches (such as learning analytics), and as such, can be described as a challenging factor. As we have previously noted, diversity across the sector means that there is no single student experience and it is the responsibility of the HEI to provide students with transformational academic opportunities, to provide excellence in teaching and learning and to offer activities beyond the set curriculum to transform their lives. The newly formed Office for Students (OfS) as an independent regulator of HE has placed a clear expectation on HE providers within the sector to focus on supporting student success. The OfS strategy objective requires that ‘all students, from all backgrounds with the ability and desire to undertake higher education, are supported to access, succeed in, and progress from higher education’ (OfS, 2018a). A further objective of the OfS is that all students from all backgrounds should receive value for money from their educational experience. Therefore, HEIs need to concentrate on developing their pedagogy to support student learning and successful outcomes for their students. The role and purpose of HE has changed (Buckingham-Shum and Ferguson, 2012) and now concentrates on student success and preparing people for work, and there is a need to for HE to deal with, respond to and benefit from these different requirements. MacFayden and Dawson (2010) argue that there is a need for learning tools at operational level (such as learning analytics) that can support and enhance student engagement with peers, instructors and learning materials. This means that tools to support learning and improve the student experience are now becoming essential enterprise resources (MacFayden and Dawson, 2012) within HE, and maybe indicative of the increase in the implementation of learning analytics within the HE environment.

There is, a broad understanding that learning analytics can provide knowledge about a learner’s activity and engagement within a specific course, which in turn can support academic staff with decision-making processes. This general benefit can be harnessed to support specific groups of learners in improving their educational goals and helping to predict when they are at risk of dropping out of university.

2.4.2 Personal tutoring as a method of supporting students

A fundamental mechanism of support for students which has existed in HE for over a decade is the role of the personal tutor. Personal tutoring is the most common method of student support in HE; and holds a strong assumption that academic staff are a key stakeholder to ensure student success. This suggests that the implementation of learning analytics needs to be clearly integrated into personal tutoring to aid acceptance and effectiveness. Grisciti et al (2005) believe tutoring to be a diverse role, encompassing the academic, clinical and pastoral needs of students. Personal tutoring is felt to increase the sense of belonging for students entering HE, through promoting an institutional relationship by making individuals feel comfortable and settled within the institutional culture (Thomas and Hixenbaugh, 2006). Personal tutors act as a bridge between students and the institution, integrating them into the HE community of staff and students (Thomas and Hixenbaugh, 2006). This role has been defined as integral in ensuring student success (Bowden, 2008), and although personal tutoring has also been described as poorly defined (Braine and Parnell, 2011) it is a role which can significantly impact on the student experience.

To be effective, personal tutors need information to be able to determine how students in the greatest need are identified and how quickly interventions can take place (QAA, 2005). The provision of data allows personal tutors to make informed decisions about their students (Kent et al, 2011) which is particularly important due to an increasing trend of accountability in all levels of education (Dietz-Uhler and Hurn, 2013). Often personal tutoring is based on intuitive processes (Mor et al, 2015), but to support students effectively, academics need to be aware of what students are doing, and how they are interacting with course material (Mor et al, 2015). This is fundamentally important when student numbers on a course are high, or the number of students allocated per personal tutor is large. Academics need assistance and guidance to keep track of student activities, without having to rely on the student asking for help.

Recognising as far back as 1992 that there were no clear guidelines on how personal tutoring systems should be operationalised, Earwalker's (1992) research attempted to address this by devising and classifying personal tutoring into pastoral, professional or curriculum-based models (Fig. 2.2).

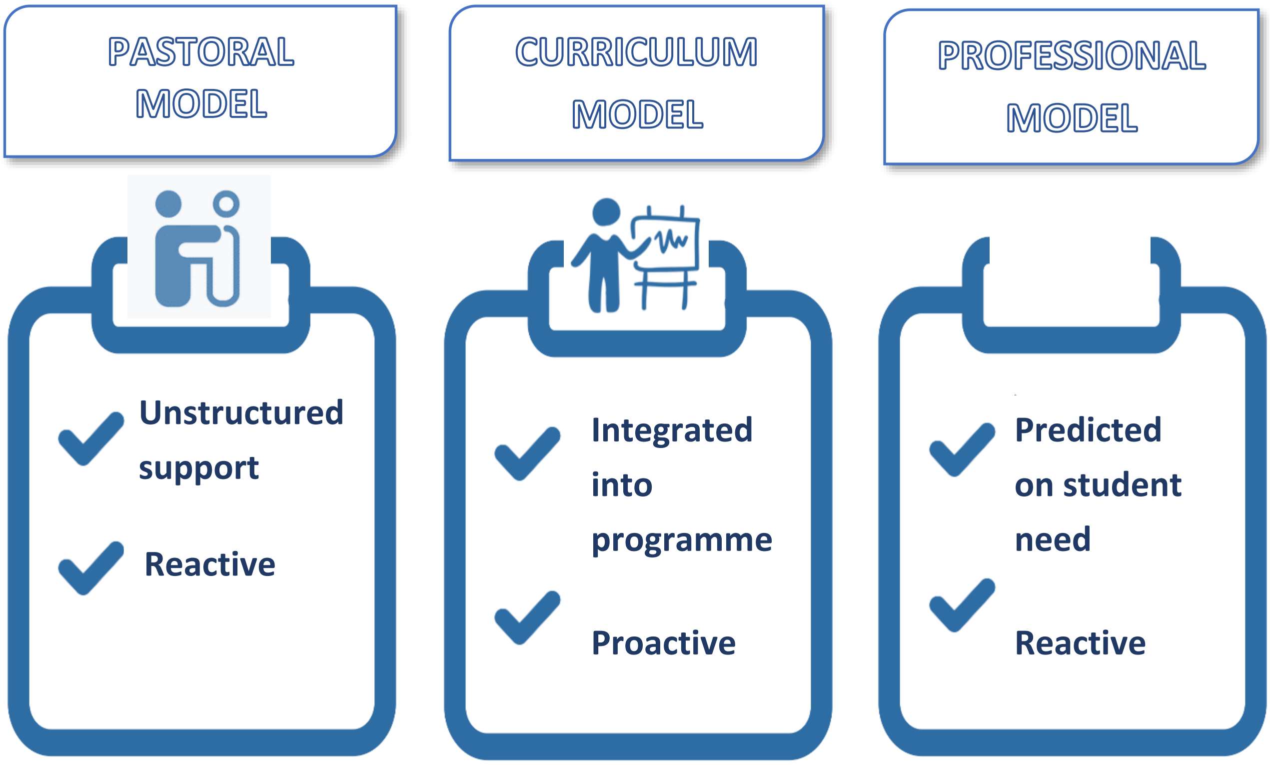


Fig. 2.2 Earwalker's (1992) models of personal tutoring.

Earwalker (1992) reported that there are three personal tutoring models in which student support was categorised as taking either a proactive or a reactive approach. Models vary between providing tutoring for all or for those students identified as being in need, and models vary between being integrated into the curriculum or not, or using a structured or unstructured approach (Owen, 2002). Yorke and Thomas (2003) recognise that models used within institutions are being devised and re-developed to meet the changing needs of the twenty-first century student, and for the diverse student body who do not fit the typical profile where there is still an assumption that students are young with no responsibilities (Yorke and Thomas, 2003).

Crotty (1993) believes that student progress and student success are the most important functions of the personal tutor, and through using a proactive tutoring model (as in Earwalker, 1992) students should be encouraged to take increasing responsibility for monitoring their own progress. Using a student facing learning analytics tool facilitates achievement of this. Phillip's (1994) early work into the personal tutor role identified that personal tutors act as student facilitator, advisor, critic, friend and examiner. The personal tutor role and function involves a balance between assisting students and student facilitation (Phillips, 1984). Gidman (2001) recognises that the personal tutor is in an ideal position to encourage students to accept responsibility for their learning, as well as facilitating their individual development, as the personal tutor is able to develop an effective relationship with the student throughout their course of study. However, Gidman's (2001) study found that there is a gap between what the students expect in terms of their support compared with their actual experience.

Smith's (2008) literature review into personal tutoring identifies that the provision of a responsive and supportive personal tutoring system can do much to enhance the student experience through the identification of problems, helping to improve retention, progression and completion. Smith (2008) perceives that good models of support for students exist, but recognises that questions still need to be answered to determine their impact on the student experience. Using Smith's (2008) literature review as a basis, it further supports the idea that having an indicator (i.e. through using data) to instigate and direct a conversation between a student and their personal tutor allows for a more proactive approach to personal tutoring as a method of supporting students.

With the move to a more on-line learning environment and reduced face-to-face teaching interaction, there is now a need to re-evaluate and consider how academic staff can support students to achieve success. Learning analytics can enhance personal tutoring mechanisms when a staff-facing analytical tool is used. Learning analytics enhance the ability of academic staff to make decisions based on data rather than on human indicators such as a hunch, intuition or presumption. Sclater (2014) believes that learning analytics provide a platform for personal tutors to have actionable insights into student performance, as well as watching individual performance dips to trigger pastoral or academic interventions (Griffiths, 2013). This in turn supports personal tutors and allows for the gathering of more detailed information about their students (Clow, 2013). Learning analytics is entangled with the evolving changes of the increasingly accountable role of academics due to the management of the education system (Griffiths, 2013).

Mor et al (2015) believe that, as a concept to improve student support, learning analytics can be used to improve the student experience and to support student learning by putting digital tools in the hands of staff (particularly personal tutors) who work directly with learners. To be effective, the designer of the learning analytics tools needs to understand how personal tutors' intuitive processes can be made visible, shared and consequently made more effective and efficient (Mor et al, 2105).

2.4.3 The digitally literate learner

Although digital literacy is not a pre-requisite to the implementation of learning analytics, it can influence use and acceptance of learning analytics by students and staff as key stakeholders, and is a broader consideration for institutions when adopting learning analytics to support student success. The digital revolution has become a key force that is shaping the emerging educational landscape (Buckingham-Shum and Ferguson, 2012). The educational landscape has changed, specifically due to the increased use of digital devices and the adoption of technology by learners within the educational environment (Pardo and Siemens, 2014) with learning management systems (LMSs) or virtual learning environments (VLEs) becoming a common element of the toolkits for educators today (Schroeder, 2009).

In conjunction with this, research recognises that learners within HE now arrives at university with different skills; there is a new wave of digitally literate learner and this has a bearing on how an institution can effectively provide student support, as well as acceptance of use. Widespread use of technology may also be a factor when a potential student is making their university choice, and in a competitive marketplace, universities need to be responsive to this consideration. Long and Siemens (2011) believe that technology is shaping the way that the student learns, and as new learners become more trained in the use of technology, there is a more apparent and identified need for new systems that are configurable to suit the demands of a particular cohort or learner (Casquero et al, 2014). Persico and Pozzi (2015) point out that younger students now live in a digital and technology-rich environment, and that they quickly learn how to handle tools and media. They propose that student needs are changing, mainly because learning strategies have changed as a result of the pervasiveness of the digital tools in our society. However, it must be borne in mind that this may not always be true from a mature learner's perspective, with Persico and Pozzi's (2015) study which analysed current research into informing learning design using learning analytics focused on the traditional school-leaver, rather than the broader and diverse body which is reflected within HE today. It can be argued that the development and implementation of learning analytics within the HE context could be a potential barrier for mature learner groups in terms of learning analytics use and acceptance if they cannot demonstrate digitally literacy, an aspect that warrants further exploration within my study.

2.4.4 Using data to support students

Studies by Greller and Drachsler (2012) demonstrate that learning analytics holds out the promises of offering new methods to diagnose learner need in a technology-enhanced environment, where personalised instruction can be developed to address those needs. They do, however, admit that it is still not clear whether learning analytics will actually lead to a more personalised learning experience, or will cluster learners and change the socio-cultural approach.

While Cooper et al's (2013) review finds that staff and student acceptance of learning analytics is not an issue, studies by Levy (2003) and Persico and Pozzi (2015) find that there is some resistance to change by academic staff in the use of technology to support education. Resistance in the use of technology have previously been highlighted as an issue and a cause of concern for the development and adoption of learning analytics (Persico and Pozzi, 2015), particularly when analytics are implemented as a method to enhance student retention. Persico and Pozzi (2015) find that educators will use technology in education, in the belief that it will improve teaching, their relationships with their students and their ability to engage with students to ensure effective educational experiences. On the other hand, empirical research does not support or refute the notion that either technology or application of learning analytics improves the student experience. Johnson et al (2013) recognise that the technology used to develop learning analytics tools is young, and research to support its use is still in its infancy. Pozzi and Persico (2015) identify that there is a significant gap in the promises of technology-enhanced learning research and current practice within HEIs due to both expense and learning analytics not yet demonstrating impact of effectiveness. Campbell (2017) believes that a broad but fundamental challenge of learning analytics relates to acceptance of using data to improve student success. Further research within this emerging development is required to be able to improve and inform future pedagogic practice.

Added to the issues above is the resistance to the use of learning analytics which has been seen within the institutional setting, including during the learning analytics pilot project within my own institution. The concept of 'big brother' and the notion of 'monitoring' are terms used to describe data-gathering for supporting students. Staff perceptions and experiences vary on a spectrum from cautious use to negativity. MacFayden and Dawson (2012) believe that a focus on data alone is not sufficient, and that learning analytical data needs to be presented and contextualised in ways that can drive development. Overarching concerns identified by Clow (2013) and Ellis (2013) within their research studies relate to the need to use the insights gathered from data to make interventions, and to generate actionable intelligence, rather than policing teachers and students.

Kent et al (2011) recognise that understanding the use of data is a process that requires an understanding of the data itself, and what it means. Duval's (2011) conference presentation concludes that there is a lack of clarity about what analytics measure and how that provides an understanding of how learning is taking place. There may be institutional limitations in terms of data availability or reliability which can affect the implementation of learning analytics. Dringus's (2012) study points out, for instance, that learning analytics can be considered harmful if the number of postings or time stamps are used as a singular measure to evidence student participation. Dringus (2012) further clarifies that these become direct measures of evidence of persistence which Slade and Prinsloo (2012) suggest can lead to potentially intrusive advising rather than using data to inform and improve a learner's experience (De Frietas et al 2014).

Boyd and Crawford (2011) believe that analytics can unintentionally disempower learners by making them reliant on institutions to provide them with feedback on their learning and overall performance, while Subotzky and Prinsloo (2011) describe a need for reciprocal sharing of appropriate and actionable knowledge between students and the institution to allow the facilitation of customised support, which in turn will allow educators to act accordingly. Ferguson (2012a) takes this even further, indicating that the focus of data must be from the learner's perspective if it is to address their needs effectively.

West et al (2015), who conducted a survey exploring 276 teachers early experiences of analytics in New Zealand, provide evidence that the resistance to using data to support students stems from a lack of data understanding by both academics and students. For educators to use analytical tools effectively, they need to be to be able to evaluate their implementation effectively (Ferguson et al, 2015), and ensure that they are fit for purpose. This also indicates to me that institutional data owners as key stakeholders need to support academic staff and students in understanding the analytics that are used as measurement predictors. Learners need convincing that learning analytics are reliable, and that their use will empower learning (Clarke and Nelson, 2013) without intrusion (Ferguson et al, 2015).

2.4.5 Learning analytics within education

Considering the different challenges described above, it can be suggested that new and innovative ways to effectively support students to succeed need to be adopted by HEIs. As a prospective answer to this, learning analytics may hold promise in responding to the differing educational needs of the student body. Learning analytics is established within educational practice in the United States and Australia, but in the United Kingdom widespread development and implementation of learning analytics can perhaps be described as emerging more widely within HE. A recent survey conducted into learning analytics within HE (HeLF, 2017) shows that there has been a rapid change into the implementation of learning analytics within the UK over the last two years with double the number of HEIs now working towards implementation (66% of UK HE providers). Figures also show that nearly a third of these institutions are making quick progress in their rate of implementation, but that 46% of those surveyed consider themselves to be making slow progress (HeLF, 2017).

This echoes findings by Viberg et al (2018) who discovered in their literature review of 252 papers on learning analytics in HE that most studies into the adoption and uptake of learning analytics at institutional level are at a macro level (Dawson et al, 2018, Ferguson et al, 2016). To date, larger-scale studies are minimal. Some of the literature reviews presented focus explicitly on the use of learning analytics in HE (Avella et al, 2016, Sin and Mathu, 2015); whereas others focus on the educational context in general (Ferguson et al, 2016, Papamitsiou and Economides, 2014). Across all of this work Knight et al (2020) believes that there is the argument that learning analytics have the potential for a tangible positive impact on student learning by supporting effective teaching and learning strategies. Despite the emergence of evidence of impact, it still seems that adoption has not been widespread (Ferguson et al, 2016), and to date, only a handful of HE institutions have adopted learning analytics as a main organisational approach (Herodotou et al, 2020).

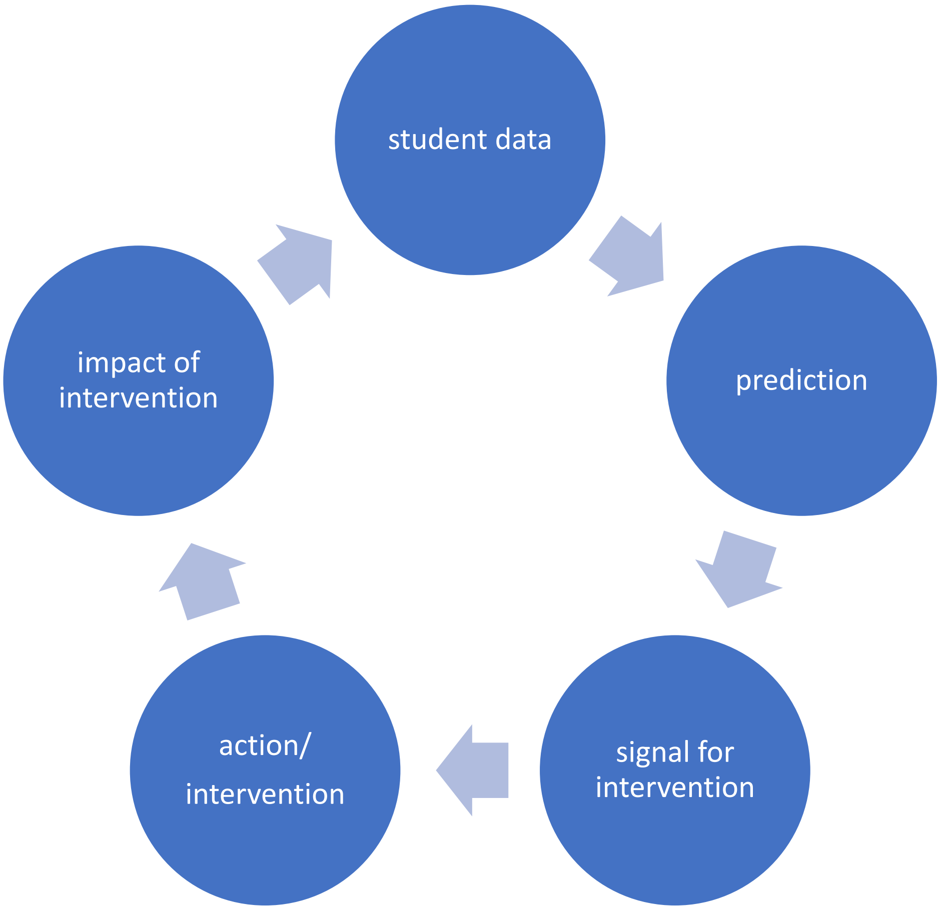
Globally, Rienties et al (2016a) believe that institutions and organisations have high hopes that learning analytics can play a major role in helping their organisations remain fit for purpose, flexible and innovative. Rienties et al (2016b) recognise that there has been substantial progress in learning analytics research relating to identifying at-risk learners using advanced computing techniques to predict which learners are likely to fail (Calvert, 2014, Tempelaar et al, 2015).

The term analytics refers to a science of logical analysis and is not a new concept (Van Barnevold et al, 2012). A case study conducted by Dietz-Uhler and Hurn (2013) explores the ways in which learning analytics can assist HEIs to support their students effectively by providing a more personalised learning experience through the use of data to respond to student's needs (Smith et al, 2012). Learning analytics is viewed as a tool which could benefit both students and educational organisations (Keshavamurthy and Guruprasad, 2014) through improving quality of learning, and potentially the competitiveness of the institution (Fladhi, 2014).

Gasevic et al (2015) and Van Harmelen and Workman (2012) believe that analytics builds on ideas from data processing, information retrieval, educational data mining and data visualisation (Scheffel et al, 2014). The shift to developing and using data within the educational context has largely emerged from two trends: the increased use of technology through virtual learning environments (VLE) and the application of educational data mining (EDM) techniques (Agudo-Peregrina et al, 2014, Papamitsiou and Economides, 2014). A systematic literature review into learning analytics and educational data mining was conducted by Papamitsiou and Economides (2016) which sought to discover the impact on adaptive learning in practice. Although institutions hold a wealth of data about individual students, taking-action as a result of data use has only recently found a place within education (Johnson et al, 2012). Data retrieval (the process of identifying and extracting data from a database based on a query), plus the ability to analyse data hold substantial promise (Greller and Drachsler, 2012) with Rienties et al (2016b) and Johnson et al (2011) highlighting that learning analytics is becoming an effective approach to analyse the wealth of available information related to learner activity. The areas of learning analytics (LA) and educational data mining (EDM) explore the use of data with the focus covering a wide spectrum in relation to instructional design, tutoring and student success, to increase insight about learning environments and improve the overall quality of experience for students (Lang et al, 2017). Ochoa et al (2014) observe that learning analytics is an expanding field that grows at the confluence of learning technologies, educational research and data science. As the fields of learning analytics and learning design mature, the convergence and synergies between the two areas are becoming important for research (Mangaroska, Giannakos, 2019).

Learning analytics are created through sophisticated analytical tools and processes analysing data generated through virtual learning environments (VLEs), library systems and student record systems (Griffiths, 2013) to produce actionable intelligence (Buerck and Mudigonda, 2014). Wagner and Ice (2012) believe that learners leave behind ‘digital breadcrumbs’ which provide data such as viewing, reading, course engagement and institutional interaction. The implementation of a tool such as learning analytics provides a simple process for academics and institutions to use their data to better understand their students. Siemens (2005) believes that information provided from gathered data can be mined to predict, evaluate and draw conclusions and suggest potential courses of action (Picciano, 2012) which in turn may enable student success. What is needed to do this are institutional data experts, and these are key stakeholders in the development of learning analytics at institutional level. Campbell et al (2007) refer to this as ‘actionable intelligence’. Most of these sources imply that a fundamental part of learning analytics is the need to take-action in response to the insights they provide. The process of effective learning analytics is diagrammatically depicted in Fig 2.3.

Fig 2.3 Diagrammatical representation of effective learning analytics.



A number of uses of learning analytics has emerged as institutions across the globe develop and explore possibilities, with each area of learning analytics having different benefits and which may be perceived by different learning communities in different ways. Three broad key areas are evident within the literature presented:

1. Enhancing teaching and course provision - learning analytics can provide information on the quality of educational content through the measurement of student engagement and student experience
2. Student retention through the identification of students at risk of not returning to study - a high accuracy of analytics is needed to enable focused academic interventions to retain students

3. Students reviewing their own learning- learning analytics can show how students are performing against their own educational goals and support understanding of student learning patterns by comparison against benchmark data.

To date, anecdotal evidence by MacFayden and Dawson (2012) suggests that all three approaches need to be considered by an institution to see which serves the institution best, depending on the purpose for which the learning analytics will be required. The second example, using learning analytics as a mechanism to support student retention, has the highest risk potentially, as it may be perceived as intrusive by both students and academic staff. This approach is, therefore, controversial. What is evident from the identified approaches above is that no single approach can be developed and implemented without multi-stakeholder input. There is a requirement for institutional strategic planning services as data holders and data experts to be able to design and develop a learning analytics tool for institutional use, and for academic staff and students to use and implement information gathered from learning analytics.

JISC (2016) is a not-for-profit organisation which provides digital services and solutions to UK HE and FE. To support HE providers with the development and implementation of learning analytics, they published a report (JISC, 2016) which contributes to existing knowledge within the field of learning analytics by providing case study examples of learning analytics implementation across the USA, Australia and the UK. An additional JISC report published in 2017 looks at assessing the impact of these case studies from an institutional perspective. Publications by not-for-profit organisations enable institutions to view and understand the best practice available within the current market place. JISC (2018) have more recently launched a technological solution through an application (app) that enables HE providers to pilot learning analytics within their institution even if they do not already have all the required technological infrastructure.

2.4.6 Theoretical perspectives on learning analytics

The literature base surrounding learning analytics appears varied which reflects the differing interests of researchers in the field. Within published research there are conflicting conceptual viewpoints in relation to the theoretical position of learning analytics (Knight et al, 2013).

On the one hand, there is a strong belief that learning analytics are data-driven and their use is viewed by many educational researchers as 'atheoretical' (Clow, 2013, Dawson, 2006). Clow (2013) further clarifies that educationally, the field of learning analytics does not claim to be explicit about its theoretical basis. In the analytics discourse, there is little mention of pedagogy, theory, learning or teaching (Ferguson, 2012a). Ferguson (2012b) recognises that further development and research is needed in this area.

In contrast, other researchers believe that activities using learning analytics need to be grounded clearly within existing educational research (Gasevic et al 2015). Dawson (2008) suggested that researchers had started to work to link learning analytics to pedagogical theory but recognise that existing research remains inconclusive. Many researchers (for example Greller and Drachsler, 2012, Gibbs, 2010) believe that the use of learning analytics does not support or ignore specific pedagogic theories, but that it is an abstract concept that aims to be neutral- Greller and Drachsler (2012) argue that pedagogy should drive analytics while Van Barnevold et al (2012) and Ali et al (2013) who conducted comparison qualitative studies evaluating how a learning analytics tool can influence educators beliefs refute this view, and suggest that learning analytics may be a driver for pedagogic change, allowing the researcher to identify how learning analytics can support the particular pedagogy being used. Dringus (2012) suggests that more empirical research is needed to identify which pedagogic theory serves learning analytics best as there is currently conflicting opinion from key researchers within the discourse of analytics.

Knight et al (2013) critically examined the relationship between learning analytics and pedagogy is important epistemological consideration as individual epistemological beliefs differ. Persico and Pozzi (2015) believe that teacher-centric pedagogical approaches do not seem to meet learners' needs, and that analytics works best when they are learner-focused. Knight et al (2013) suggest that analytics focused on student progression is bound to a constructivist approach and hold the notion that learning occurs through the experimentation of the learner. Duffy and Cunningham (2001) disagree and state that there is little research to support constructivist approaches. Greller and Drachsler (2012) believe that data obtained from a content-sharing platform will reflect a behaviourist and cognitive pedagogy and be attached to learning behaviour. They draw this opinion from the pedagogic models underlying the use of technology in learning, rather than specifically from research into learning analytics (Greller and Drachsler, 2012). Quantitative research into student use of learning management systems conducted by Pardo and Kloos (2011) supports the successful use of learning analytics for behaviourist and instructive approaches to student learning.

Within the domain of learning analytics as a discourse, there remains little consensus from either the empirical research, or among researchers themselves. Greller and Drachsler (2012) recognise that the introduction of learning analytics within education supports different approaches to evaluation, which in turn provides evidence to develop pedagogical theories of learning and knowledge. They state that technology itself is not pedagogically neutral, and hence evaluation of any application of learning analytics will be influenced by the delivery approach chosen. MacFayden and Dawson (2010) concur with this viewpoint and recognise that learning technologies within HE has brought about educational change, and they need full utilisation within the education environment to support a pedagogical practice of engagement that will ultimately enhance the learning experience for students.

2.4.7 Educational change

One of the fundamental issues within educational research and policy relates to educational change. Educational change aims at improvement in one way or another and has been described as improvement of student learning, learning conditions and/or learning processes (Hargreaves, 1998). The introduction of learning analytics is one such example of educational change that appears to be emerging at institutional level within the HE environment. To be effective, it is suggested that educational change needs to occur from a multi-stakeholder perspective, as many different types of staff (both academic and non-academic staff) are integral to the change process. Educational change has been widely researched within the literature (Hargreaves, 1998, Fullan, 2007, Burner, 2018). Burner (2018) recognises three reasons for educational change being necessary: increased globalisation, with education needing to meet the needs of the globalised classroom; advancements in technology leading to new ways of doing, learning and to new types of knowledge; and development in research into teaching and learning approaches, leading to increased knowledge about the effectiveness of teaching and learning approaches. Burner (2018) believes that driving forward educational change is often difficult, and that there is a need to make educational change effective (Burner, 2018). According to Macredi and Sandom (1999) the ability to manage change successfully has become a vital asset for organisations to stay competitive in an unstable environment, although Biesta (2012) points out that the quality of change still requires thought, rather than merely focusing on change for its own sake.

Timperley and Parr (2005) point out that educational change often fails to achieve the desired impact. From this, it is clear that the need for any impending change resulting from the development of learning analytics needs to be considered carefully, with Fullan (2007) believing that the enablers of effective educational change are strong leadership, building a shared vision and a collaborative environment to develop learning in and across education. Chapman (2002) reinforces this, stating that change needs to embrace the attitudes, beliefs and values of the employees to be effective.

The concept of leadership has been extensively studied in the literature; one classic work being by Kotter (1995). Kotter researched effective leadership when specifically applied to the change process, and identified eight steps to leading effective change, which are presented as:

1. Establishing a sense of urgency
2. Creating a guiding coalition
3. Developing a change vision
4. Communicating the vision for buy in
5. Empowering broad-based action
6. Generating short term wins
7. Never let up
8. Incorporating the changes into institutional culture.

Kotter (1995) depicts leadership from a generic perspective, and it might be that this application to leadership may not be sufficient to promote effective change in relation to the development and implementation of learning analytics within an institution. Arnold et al (2014) reinforce that leaders should possess domain knowledge, and that a leader needs to have a deep understanding of learning analytics principles and practices to create institutional success in addition to the steps proposed by Kotter (1995). Within the educational context, only a few individuals within an organisation have awareness and knowledge about learning analytics, so this may be difficult to achieve. Sclater (2017) believes that it is essential to have leadership at all levels, but to use advocates at subject or school level to drive forward educational change, as this will have more impact than a pronouncement from senior management.

Appreciative inquiry (AI) has been viewed within literature as an effective methodology for change. AI is an approach that focuses on identifying what is working well within an organisation, analysing why it is working well and then doing more of it (Cooperrider and Whitney, 1999). Interventions in AI focus on imagination and innovation instead of on the negative, critical and spiralling diagnoses commonly found in organisations (Cooperrider and Whitney, 1999). Organisations and institutions adopting AI are viewed as entities seeking solutions, rather than as entities focusing on problems (Cooperrider and Whitney, 1999).

2.4.8 Purpose of learning analytics within HE

In the relevant literature it is acknowledged that the development and implementation of learning analytics within institutions should have a purpose. As I considered the development of my conceptual framework, I recognised that the institution needs to be an integral consideration, as learning analytics will fundamentally direct how the institution develops, and implementing learning analytics can be a critical mechanism for student success. An early literature review conducted by Manderveld (2015) indicates that the use of learning analytics within HE is still in its infancy but that it is one of the key emerging trends across the UK. Later studies conducted by MacFayden and Dawson (2012), Buckingham Shum and Ferguson (2012) and Clarke and Nelson (2013) recognise that the use of learning analytics is an educational innovation that has the ability to provide stakeholders, teachers and students with insight into the learning process and has potential as a mechanism to improve learning and pedagogic practice within education. Romero and Ventura's (2010) literature review into educational data mining (EDM) shows that many institutions state that the core objective and purpose of developing and implementing learning analytics tools within the educational arena are broadly linked to enhancing institutional decision-making processes and potentially helping to allocate resources effectively. Romero and Ventura's (2010) literature review does not specifically declare a specific purpose for the implementation of learning analytics, which concurs with Slade and Prinsloo's (2012) literature review into the ethical issues and dilemmas that face learning analytics. This clearly shows that before embarking on the implementation of learning analytics, institutions must decide themselves what their main purpose is - for example to maximise student numbers, to improve completion rates, or to maximise profits.

A review into the uses of management information and technology in HE conducted by Goldstein and Katz (2005) recognises that one purpose of learning analytics within education is that they can be used as a mechanism to improve decision-making processes through the identification of students who are the strongest prospects for admission or through predicting and improving student success and graduation rates (Olmos and Corrin, 2012, Smith et al, 2012). Using predictive learning analytics as part of a student retention strategy appears to focus in many of the evidence-based reviews presented (Ferguson and Clow, 2017), and there is an emerging body of evidence suggesting that learning analytics can be effective in some cases, but not others (Herodotou et al, 2020). This raises the need for more robust and longitudinal research beyond a single context (Herodotou et al, 2020). (Gasevic et al (2016) have identified alternative purposes for the development and implementation of learning analytics within HE, which is to address learning problems.

Gasevic et al (2016) and Banoor et al (2019) believe that learning analytics provide opportunities for educators to analyse which on-line aspects of courses students are visiting, the time spent there and the tools that they are using, as well as the frequency of their use. Learning analytics based on learners' interactions, experience and engagement with course material and content can enable evidence-based changes to resources, activities and other aspects of the curriculum (Lockyer and Dawson, 2011) or can be used to increase knowledge about a learner's behaviour (Slade and Prinsloo, 2012).

Sclater (2014) believes that the vast majority of institutions are interested in developing learning analytics to identify students at risk of leaving university, as student retention and continuation is clearly linked to financial reward for the institution (Sclater, 2014). The pressure may in part be the result of the contextual challenges at institutional strategic level described in Chapter One. Crede and Niehorster's (2012) quasi-experimental research focused on the transition and academic adjustment into HE supports the fact that learner's performance can be rationally predicted in terms of social, psycho-emotional and demographic factors by using learning analytics, a perspective that is reinforced by Richardson (2012) and Ritos and Roberts, 2014). MacNeill (2012) suggests that learning analytics allow HEIs to have measurable, positive impacts in areas such as retention and attrition from university or to strengthen the university support systems through monitoring student progression, retention and continuation. Calvert (2014) and Sclater (2014) find that substantial progress has been made in learning analytics research relating to identifying at risk students, but a literature review into learning analytics conducted by Viberg et al (2018) postulates that that there is little evidence to suggest that learning analytics supports student outcomes and student success. Sclater (2014) recognises that the motivations for implementing learning analytics tools within institutions vary, but the majority of HEIs mention a desire to enhance the student learning experience, improve institutional achievement and empower students to become more reflective learners. Tempelaar et al's (2015) longitudinal research investigated the factors that enhanced students learning processes, and clearly demonstrated that learning analytics applications within education are expected to provide institutions with opportunities to support learner progression, as well as providing personalised rich learning on a large scale.

Griffiths (2013) suggests that algorithms rely on capturing relationships between explanatory variables and the predicted variables from past occurrences and exploiting them to predict an unknown outcome. Accuracy and usability of results depends on the level of data analysis and on the quality of assumptions made. Algorithms used by analytics tools have the power to react to the present but can also predict futures trends (Griffiths, 2013), thus enabling academic staff to respond accordingly. This enables organisations to have a strategic focus on retaining students, identify students that are at risk of failure (Jayaprakash et al, 2014) and identify those students likely to succeed and improve their learning (Fiaidhi, 2014).

Sclater (2017) recognises that much of the existing work into learning analytics is focused on presenting data analytics to academic staff and the wider institution so that an intervention can be made. More recently, interest has been growing in the provision of student-facing predictive learning analytics to help empower students in their learning (Corrin et al, 2015) by helping them to be aware of the impact of their actions and allowing them to reflect on their behaviour (Sclater, 2017). Ritos and Roberts (2014) suggest that student-facing tools which help learners review effect, impact and outcome and look at consequences, facilitate progress from novice to experts and from shallow to deep thinking. Student-facing learning analytics systems may support student's individual goal-setting and progression towards these goals (Sclater, 2017) and may allow them to tap into their competitive spirit to progress (Ritos and Roberts, 2014).

Goldstein and Katz (2005) conducted a review into the uses of management information and technology in HE which recognised five stages of best practice in using learning analytics. These are: data extraction; performance analysis (through algorithms); 'what if' decision support; predictive modelling (which can be used to estimate how likely it is that a student will complete a course (Clow, 2013)), and developing automatic response triggers. Dringus's (2012) research concurred with Goldstein and Katz's (2005) findings but he pointed out that extracted data needs to be meaningful to support successful use. Long and Siemens (2011) emphasise that HE has traditionally been inefficient in its use of data because of ineffective institutional data management systems which can lead to a substantial delay in analysing data. Long and Siemens (2011) believed that poor quality or inaccurate data could potentially compromise effective optimisation of the information provided by analytics. Dringus (2012) concurs with Long and Siemens (2011) through recognising that there needs to be a good level of performance analysis (or good algorithms) for effective and efficient data use. Efficient use of data is reliant upon appropriate interpretation - often data can be masked or adapted to mean different things. Kent et al (2011) state that data needs to be accurate and interpreted in context so that it is meaningful, and it should have visualisations that are understandable for those using it without data-mining knowledge (Dyckhoff et al, 2012). Dringus's (2012) literature review suggests that learning analytics could even be harmful if such requirements are not met.

2.4.9 Benefits of learning analytics

Literature broadly suggests that there are many benefits to the implementation and development of learning analytics within the educational arena. Before any institution embarks on the development and implementation of learning analytics, it can be considered that there need to be clear benefits to adopting this approach. Benefits are viewed as enabling factors and are included in the conceptual framework for this study as an aspect that surrounds the drivers for learning analytics. Early studies undertaken by Butler and Winne (1995), Long and Siemens (2011), Greller and Drachsler (2012) and Mor et al (2015) categorise the benefits of learning analytics into three broad groups: benefits to the faculty, to the institution and to the student. A systematic literature review by Avella et al (2016) examined learning analytics methods, benefits and challenges in HE and identified that targeted student learning, outcomes and behaviour were potential benefits of learning analytics, which are fitting to the groups described above. Manderveld (2015) additionally acknowledges the professional role of the academic staff member as a supporter of students by clearly identifying that using learning analytics allows lecturers to design appropriate interventions for either an individual or a group of students. Manderveld (2015) states that 'functional groups' can also benefit; these are described as educational development teams wanting to improve or develop the curriculum.

Within UK HE, the area of curriculum development may be the responsibility of a faculty, or of individual lecturers as an area of responsibility. From a faculty perspective, use of learning analytics is desirable due to the benefits that analytics can provide, such as increasing student retention and progression rates (Long and Siemens, 2011). When learning analytics are used as part of educational curriculum design, faculties can use them to provide a performance comparison (Greller and Drachsler, 2012), or to inform them about gaps in student knowledge (Greller and Drachsler, 2012). Thus, it can be argued that learning analytics could be used as a mechanism to inform future pedagogical approaches (Butler and Winne, 1995).

From an institutional perspective, Slade and Prinsloo's (2012) review emphasises that one of the benefits arising from the implementation of learning analytics is that they can demonstrate institutional successes and challenges, and they also have the potential to increase organisational productivity and knowledge. Long and Siemens (2011), Butler and Winne (1995) and Mor et al, (2015) share Slade and Prinsloo's (2012) perspective. Extrapolating from this, we might suggest that learning analytics provides the opportunity to unveil and contextualise information for different stakeholders, both at strategic level to improve university league table placings and influence future institutional TEF (OfS, 2018b) rankings, and also at an operational level as a quantitative evidential agent to measure quality and effectiveness to support localised quality assurance processes.

Siemens (2013) believes that the use of learning analytics allows institutions to predict and model learner activities and can be a foundation to inform change within HEIs. Greller and Drachsler (2012) believe that when learning analytics are used as a mechanism to support university retention drivers, this can lead to earlier intervention to prevent student drop-out. Mor et al (2015) argue that institutions can improve resource allocation through the implementation of learning analytics, although offer no tangible evidence to identify how this can be achieved. Anecdotal evidence presented by JISC (2017) highlights that analytical tools are an expensive resource, so a clear purpose must be identified as a driver for adoption and implementation.

Numerous studies such as those conducted by Butler and Winne (1995) and Lang and Siemens (2011) focus on supporting academic decision-making as one of the key drivers for the adoption of learning analytics and indicate that when responding to broader strategic challenges, learning analytics is a potential solution. Greller and Drachsler (2012) argue that this is one of the dangers of using learning analytics as a solution-based approach, but Campbell et al (2007) highlights the importance of institutions having an obligation to act on knowledge gained through analytics.

Slade and Prinsloo's (2012) review identifies that learning analytics are most beneficial when institutions and students collaborate as stakeholders, and when students themselves are not simply recipients or customers paying for an education. Buckingham Shum (2012) reports that across stakeholders- at institutional, departmental, and individual and student level- there is interest in how data can inform learning. Manderveld (2015) believes that when analytics are used with learning as a focus, students are provided with personal information about their current needs. Analytics can identify patterns of learner activity, interaction and conversation to support the student (Mor et al, 2015). Scheffel et al (2014) recognise that students can compare their performance with others but also that learning analytics provide ways for learners to improve and develop whilst their course is progressing. Dawson et al (2008) believes that this can increase students' sense of community and student engagement (MacFayden and Dawson, 2010). Scheffel et al (2014) highlight that one of the key benefits of learning analytics is that their use allows the student to develop reflective skills, as well as the ability to link ideas with others. Bolton (2010) believes that reflection is often an area that goes unnoticed, but Scheffel et al (2014) believe that the reflection encouraged by learning analytics can lead to an improvement in learning behaviour. Verpoorten et al (2011) also imply that learning analytics can be used to foster awareness and thus reflection on learning behaviours. A qualitative survey examining aspects of student experiences conducted by Verpoorten et al (2011) agreed that improved reflection is an important aim of learning analytics but recognised that it is hard to measure.

2.4.10 Challenges presented by the use of learning analytics

The literature reveals numerous challenges with the implementation and development of learning analytics. I reflected that if my conceptual framework was considering enabling factors to the development and implementation of learning analytics as a mechanism, then it would also need to identify the potential challenges to using learning analytics, and that these could potentially be viewed from all stakeholder levels - the student, the academic and the institution. Studies conducted by Mor et al (2015), Greller and Drachsler (2012), Long and Siemens (2011) and Butler and Winne (1995) indicate that adopting learning analytics in education is an exciting development, and one that potentially holds benefits for students, academic staff, the faculties and the wider institution, but Dietz-Uhler and Hurn's (2013) literature review reports a wide range of challenges when learning analytics are used to support student success, with these being categorised as technical, political, cultural and ethical (Dietz-Uhler, Hurn, 2013). Roger's (2000) research into systems theory focused on specific factors which stopped individuals from using technology, citing socio-cultural aspects (economics and location), personal factors (such as age, gender, beliefs) and extent of exposure. Rogers (2000) believes these inhibiting factors are clearly linked to the level of technical support and training offered. Although this research focused on the broader context of technology use, this perspective can be applied to the implementation and use of learning analytics by students and academic staff. Gamdi and Samarji's (2016) research study which investigated the challenges of adopting e-learning in HE in Saudi Arabia collected quantitative data from 214 participants through a questionnaire survey design using multivariate analysis of variance (MANOVA) as a method of analysis. This study corroborated Rogers's (2000) findings but also showed that educational level and educational background are factors that influence acceptance, and to a lesser extent, so does individual attitude (Gamdi and Samarji, 2016).

More recently, Reinties et al (2018) conducted a case study which explored teacher's readiness of learning analytics visualisations, with findings indicating that teachers were sceptical regarding the perceived ease of use. Rienties et al (2018) recognised that most of the 95 staff who participated in the research indicated the need for additional training and follow up support when working with learning analytics tools. This can be considered to be critical factor for institutions to consider when developing learning analytics to ensure that academics as key stakeholders are confident and competent to use the tools with which they are presented. This may in part, encourage acceptance from this stakeholder group.

Literature identifies that to effectively develop and implement learning analytics effectively within HEIs, consideration should be given to a number of significant strategic and operational factors, and that there needs to be capacity within an organisation before embarking on the development and implementation of learning analytics. Norris and Baer (2013) have devised a model of organisational capacity for learning analytics. Norris and Baer's (2013) model is based on an assessment of the activities and processes that leading institutions used to optimise student success. They found that success was dependent upon certain distinct factors for organisational capacity. These are: commitment and effective leadership from a senior level, investment in the technological infrastructure and technical skills to support analytics development, as well as assurance that there are clear processes and practices in place which support institutional commitment. Norris and Baer (2013) advocate that organisational change needs to occur through the nurturing of organisational culture and changing staff behaviours, and through ensuring that the values of staff and students include the willingness to participate in such a culture change.

2.4.11 Barriers to institutional adoption

Empirical research links the broader challenges of learning analytics with more specific barriers to adoption by HEIs. This focus on institutions provided confirmation that the institution warranted inclusion as a factor in my developing conceptual framework. Bichsel's (2012) report into learning analytics in HE identifies fundamental concerns relating to institutional adoption of analytics, such as the overall institutional culture and leadership culture and affordability of learning analytics tools. HEI's are suggested by Reinties (2014) to be characterised by resistance to change, and that this resistance is often linked to organisational culture and sustained clear expectations exerted by academic and professional services staff in long standing positions (Chandler, 2013). The introduction of learning analytics may go deeply into the core roles of academics, which in turn could cause passive or actual resistance to change (Herodotou et al, 2017). Similarly, Cooper et al's (2013) study identifies the greatest concern over the use of analytics as the financial cost of implementation. Sclater (2017) believes that successful implementation of institution-wide learning analytics requires the organisation to be ready in various ways, and if the ground is not properly prepared, institutions run the risk of alienating stakeholders, destroying confidence in the potential of learning analytics and wasting significant resources. Studies by Herodotou (2019a, 2019b) and Van Leeuwen (2018) have shown that adoption of predictive learning analytics at institutional level could be facilitated through the provision of institutional effectiveness, promotion of effective communication across stakeholders to reduce perceived barriers of implementation by key stakeholders.

In their study, Powell and MacNeill (2012) use the term 'institutional readiness' to encapsulate this idea, and propose three key institutional considerations in order for learning analytics to be effective. Greller and Drachsler (2012) contend that the factors identified by Bichsel (2012) are more widely linked to institutional change, and found that organisational, managerial and institutional processes often place constraints on the effective use of learning analytics. A study of uptake of learning analytics within HEIs was taken by Dawson et al (2018) who interviewed 32 senior leaders. Dawson et al (2018) found that institutions either followed a top down approach to learning analytics implementation, or used emergent innovators through a consultative bottom up approach. Despite this, most institutions had limited adoption of learning analytics and used them on a small scale. Dawson et al's (2018) study indicates that the change process needs to be managed effectively to avoid potential barriers for adoption at either strategic or operational level. To overcome this at operational level, MacFayden and Dawson (2012) suggest that data needs to be presented and contextualised in ways which drive and support organisational development and adoption of learning analytics more widely.

Ferguson et al (2015) believe that to motivate behavioural change, greater attention needs to be paid to accessibility and the presentation of analytics processes. Bichsel's (2012) research identified another barrier to adoption which relates to staff expertise in using analytics to support decision-making. Academic workload is commonly cited as a reason for lack of adoption to technology focused solutions (Bates, 2000), however this is questioned by Ellis (2013) who believes that learning analytics provide a methodology and a tool to help staff carry out their tasks more effectively and can alert staff if a student is not engaging with the institution. A question arising here is whether this approach to supporting student success is understood by staff to be reactive rather than proactive, or whether lack of adoption relates to staff confidence in making decisions and initiating student support based on data findings. Bichsel's (2012) review identifies concerns over institutional access to quality data, and Swan (2012) indicates that the right data must be used, with learning analytics tools needing to employ good algorithms and transparency. If data is interpreted wrongly or the analytics cannot be used in a positive way, this can create a fundamental barrier to adoption (Bichsel, 2012).

2.4.12 Ethical considerations

One of the key challenges for the implementation of learning analytics identified within the literature relates to ethical issues and data privacy, and this consideration is reflected to some degree within all the research studies discussed within this chapter. Within a digital context, ethics relates to the systematisation of correct and incorrect behaviour by all stakeholders in virtual spaces. To be effective, learning analytics require large quantities of data collected to be collected on students, and HE providers need to be cautious about privacy, data profiling and the rights of the students in terms of recording their individual behaviours (Picciano, 2012). Learning analytics tools allow institutions and educators to make use of the data they hold about students, and Campbell et al (2007) recognise that it can seem threatening to students to know that someone can watch and track all that they do. Greller and Drachsler (2012) recognise that predictive analytics, in particular, can pose ethical problems in that early judgements about a learner could potentially limit their potential and could be a disabling factor rather than one enabling student success. Within evidence, there are a handful of studies that directly explore issues of ethics and privacy. Slade and Prinsloo, (2013) acknowledge ethical considerations in learning analytics research; whereas Rubel and Jones (2016) argue that learning analytics poses moral and policy issues for student privacy, and that these are areas that require resolving to ensure that learning analytics are in line with student's privacy and autonomy.

Strang and Sun's (2015) literature review into learning analytics found that ethical issues have arisen in many research studies into analytics use and recognise that ethical principles must apply to future research and researchers (Strang and Sun, 2015). Willis et al (2013) believe that prior to the implementation of learning analytics, institutions need to consider the ethical issues that can arise from holding the data, and balance this against the use that it could be put to in enhancing student retention and academic success. Ferguson (2012a) supports the need for an ethical framework which can help institutions make decisions regarding ownership and stewardship of learner's data to ensure that ethical issues are adequately addressed prior to institutional adoption. Greller and Drachsler (2012) suggest that without addressing ethical issues, there may be a backlash from users who feel that their privacy is endangered, and therefore the development of learning analytics within HE may be hindered.

2.4.13 Learning analytics student experience and student success

Literature broadly identifies the concept of learning analytics as relating to both student experience and student success. The HE student is a key stakeholder within my research study, so I felt that my conceptual framework needed to address student perspectives as an important aspect. Notably, Shelton's (2018) study shows that diversity across the university sector means that there is no single student experience and that students each have their own individual experience. Shelton (2018) states that it is the responsibility of the HEI to provide students with transformational academic opportunities, and excellence in teaching and learning, and to offer activities beyond the curriculum which will transform their lives. A consequence of the rising consumerist ethos is increasing student expectation, with Slack et al (2004) believing that students now expect a quality service and a high standard of educational material and support from academic staff. Students are mindful of disparities between their expectations and the reality of service delivery (Durlaston-Jones et al, 2003). Shelton (2018) recognises that academic staff working within educational institutions need an understanding of the twenty-first century student experience, so that student learning is successfully facilitated and supported, and allows for an effective university education.

Slade and Prinsloo (2012) believe that student success is the result of multi-dimensional, interdependent interactions between the student, institution and broader society at different phases. Tinto (2009) concurs but expands on this to highlight four conditions which enable a student to succeed within HE: high student expectations, an acceptable level of support, provision of effective feedback, and high student involvement (or engagement) with their course of study. To address student expectations, a literature review conducted by Clow (2013) examines the view that students need to take personal responsibility for their own situation and make appropriate decisions about support that they receive. Slade and Prinsloo (2012) suggest that students should become agents of their own learning through making their own choices and through collaboration with academics and the institution (Giroux, 2003). Glasser (1998) describes learner agency as the capability of individuals to make choices and act on these choices in a way that makes a difference. The notion of agency relates to the cognitive processes involved in learning where knowledge is seen as constructed through a process of taking actions in an individual's environment and making adjustment to existing knowledge structures based on the outcome of those actions. Learner agency is known to lead to increased feelings of competence, self-control, self-determinism and higher emotional intelligence (Bandura, 2001). This viewpoint supports the need for predictive learning analytics systems that are both staff- and student-facing so that students have the information they need to support their success.

From a student's perspective, Deakin-Crick et al (2004) suggests that previous experience, motivation and intelligence are key factors in an individual's capacity for learning. Further, an individual's response to the learning opportunities offered can determine their success as a student. The use of learning analytics is one mechanism that can inspire a student to be a collaborator in their learning, rather than positioning them as a passive recipient of educational intervention and services (Buchanan, 2011). As agents, students need to collaborate with institutions in providing data and access to data to allow learning analytics to serve their learning and development (Slade and Prinsloo, 2012). Hence there is a need for students to understand the use of learning analytics to improve their experience and chances of success. Roberts et al (2016) conducted qualitative research into student perceptions towards learning analytics in HE. Forty-one HE students participated in one of six focus groups. Through a thematic analysis, it was concluded that students had a lack of knowledge about learning analytics prior to the research, with student perceptions illustrating that learning analytics were either a help or a hindrance to learning, and that analytics impeded independence in learning. Roberts et al (2016) noted the absence of student voice in decision-making about learning analytics, and that there is a further need to engage students prior to the development and implementation of it.

Interest regarding student perceptions of learning analytics is increasing, with additional research being conducted. One of the most recent qualitative study into student perceptions of learning analytics in Scotland (Bals et al, 2019) asked 29 students to participate in focus groups to investigate their perceptions and experiences of using analytics. The study was conducted across four HEIs in Scotland. The study concluded that students welcomed the opportunity to view their academic path and recommendations for future performance (Bals et al, 2019). This study did not ask students how they used the learning analytics tool, however a literature review conducted by Gasevic et al (2015) shows that care should be taken not to rely on trivial measures in learning analytics, such as an increasing number of logins, in learning management systems being used to self-evaluate learning progression. Negative perceptions of learning analytics can result in skewed power relations with academics, and analytics have been linked with the notion of a monitoring and surveillance type approach (Andrejevic, 2011) rather than being seen as a tool used to support learning and development. Ferguson (2012a) provides the overview that a significant amount of learner activity takes place externally to institutionally gathered data sets, and therefore she believes that it remains a challenge for analytics to be used as a reliable measure of learner activity, success and engagement.

2.4.14 The role of academic staff

The role of the academic is central for student success, and I recognised that my conceptual framework needed to consider academic staff as a key stakeholder in terms of their relationship with students as this could potentially be a key factor in the development and implementation of learning analytics within an institution. Academic staff need to view their role holistically, and with the provision of learning analytics as a mechanism, value needs to be seen using a data driven approach. Gidman (2001) believes that the role of academic staff within HE is multi-faceted, with many individuals holding responsibility for providing student support and ultimately student success. Gidman’s (2001) literature review into personal tutoring in HE finds that course leaders, module leaders and personal tutors all in some way have responsibility for providing student support, and this can create a situation where students are unclear about who to go to for what (Gidman, 2001). On the opposing side, this links to the development of learning analytics and the need to understand the purpose of why learning analytics is developed, and to ascertain how it can be used for different academic groups. What is essential, is that students feel adequately supported by academic staff as they progress through their studies. The provision of effective student support is potentially more crucial than ever before, due to the diverse student body with complex needs we have already discussed. Positive interaction with students is seen as a crucial component of the academic’s role (Romero-Zaldivar et al, 2012), with personal tutoring being an integral aspect.

What is embedded in the notion of supporting students, is the presumption that academics as key stakeholders will use learning analytics as a mechanism to support their students if it is adopted by institutions, and perceptions into learning analytics use by different stakeholders is starting to emerge. A study by Rienties et al (2018) suggested that as a key stakeholder, academic staff were sceptical about learning analytics tools ease of use, and recognised that they required additional training and follow up support for working with analytics tools. Further studies by Herodotou et al (2019a, 2019b) in which 20 education stakeholders were interviewed regarding perceptions of learning analytics were positive, but yet noted challenges in relation to management priorities, teachers and evidence of effectiveness. These perspectives link to the need for institutional readiness and the effective implementation of change discussed above.

2.4.15 Learning analytics and academic accountability

Interestingly, the notion of academic accountability is not explicitly identified within the literature reviewed, but there is often concern conveyed by academic staff in relation to this, along with the perception that new educational drivers are being implemented to increase academic accountability and to monitor academic performance. This can potentially lead to staff negativity towards educational advances (such as learning analytics) through initiative fatigue. The area of academic accountability and staff monitoring (whether an enabling or a challenging factor) was, therefore, a critical aspect to consider for the development of my conceptual framework, and for the research study described in this thesis, through questioning research participants to determine whether this is a true reflection of staff thought and opinion. Campbell (2017) believes the notion of academic accountability is intrinsically linked to the broader ethical question of whether academic staff are obliged to act on the basis of learning analytics. Sclater (2017) believes that learning analytics should be seen in the wider context of support offered to students, and that the accountability and responsibility from an academic staff's perspective is related to being able to draw from available resources and to their use in an advisory capacity only.

2.4.16 Impact of learning analytics

While developing my conceptual framework, I believed that learning analytics was a central aspect of my research idea, and as such, should be the central part of the conceptual framework. The literature search undertaken for this thesis shows that limited research has been conducted into the impact of learning analytics, and that researchers are moving into this domain of educational research following the steady growth of the implementation of learning analytics within education. Notably a study conducted by Knight et al (2020) attempts to develop a model to measure impact used in Australia to address key challenges encountered when implementing learning analytics at institutional level. The added value of learning analytics for learners and educators has been recognised (Long and Siemens, 2011), but there is little research being conducted to compare the findings of empirical learning analytics studies and evaluating whether the tools for using them are having a desirable effect on learning (Scheffel et al, 2014). The development and evaluation of learning analytics dashboards shows that learning analytics can provide value for learners and educators (Rienties et al, 2016b). There is, however, not as yet sufficient hard evidence for or against different types of learning analytics, and it is difficult to compare the results of different tools and methods. Scheffel et al (2014) have developed a proposal for a framework of quality indicators for learning analytics that supports standardisation in evaluating learning analytics tools and makes it more systematic for key stakeholders to evaluate and measure the impact of learning analytics more broadly. This framework will provide a means of capturing evidence of the impact of learning analytics on educational practices in a standardised manner. At the time of conducting my research this framework was not yet published and so could not be included as part of the research discussion. In addition to Scheffel et al (2014), Rienties et al (2016b) recognise that there is an urgent need to develop an evidence-based framework if more institutions are going to adopt learning analytics as a mechanism. Rienties et al (2016b) believe that the research community needs to provide a clear conceptual model that can accurately and reliable identify learners at risk, identify learning design improvements, deliver intervention suggestions that work for students and teachers, operate within existing learning and teaching culture and be cost effective.

2.5 Highlighting the gaps within the literature

The critical appraisal as presented here of the current literature in relation to learning analytics highlighted to me as an educational researcher that some pertinent studies have already been undertaken in relation to learning analytics as a mechanism to enable student success. Clearly from the literature, learning analytics is a rapid growth area within UK HE and is seen as an educational development that has the ability to build on established pedagogic practices and findings. However, there are fewer reports on evaluation studies aimed at assessing the learning analytics tools and approaches that have been developed, and this presents a gap within current published research as there has been minimal evidencing of the impact of adopting learning analytics. In this, Ali et al (2013) echo Siemens and Gasevic (2012) who believe there is a gap between research and practice, particularly in the sharing of information, learning analytics tools and datasets, although it is identified that the literature base in this area has increased over the last couple of years. However, I would argue there is still a need for further research to address the opportunities and challenges of driving forward this innovation within the context of HE.

That learning analytics will continue to evolve can in some ways be predicted from analysing current literature, and the fact that interest is expressed by researchers across the educational sector. However, the published research at this stage fails to show significant impact of learning analytics interventions. Early literature reviews focus on learning analytics from a conceptual nature, and it is only fairly recently that studies based on institutional implementation have been published. To date, there is a minimal amount of literature covering large scale applications. From undertaking the literature review and reviewing the evidence base, it appears that research into learning analytics will continue to evolve and allow it to establish its own distinct identity.

As this literature review has shown, there are research gaps within the published studies, particularly in relation to the theoretical perspectives on learning analytics, but equally from an operational perspective addressing the impact of learning analytics and the approaches to learning analytics used. There are some systematic reviews emerging that focus on either staff or student perceptions of learning analytics, but this shows to me that there is a clear research gap, which needs to consider the relationship between key stakeholders and the lived experiences of participants which can be used to reflect on the purpose and implementation of learning analytics as a mechanism to enable student success. The research conducted for this thesis will add to the empirical research in this area and will contribute to addressing some of the gaps in the literature identified in this chapter.

2.6 Study Rationale

Through my own professional and personal involvement with the development and implementation of learning analytics, and through undertaking a literature review into learning analytics, I established a clear rationale and direction for undertaking this study. I have recognised that although there are more recent published studies that have been conducted to examine perceptions and experiences of different stakeholders, these are focused on either academic staff or students. I have identified there is currently no published research that has considered a multi-stakeholder perspective conducted through the eyes of different users of learning analytics. I can also conclude that the majority of published studies have been conducted at a single institutional level. Due to the cessation of the learning analytics pilot project within my own institution, it was necessary for me to research the development and implementation of learning analytics within other HEIs across the UK, and attempt to close the knowledge gap in this area. These reasons provide me with a clear rationale for conducting my study, but more importantly will afford me a unique opportunity to provide an original contribution to research through enhancing the knowledge base in the field of learning analytics from a unique perspective, as well as offering the ability for me to be able to develop and inform my professional practice.

2.7 Development of the research questions following the literature review

As a result of reviewing published empirical research and relevant evidence relating to the development and implementation of learning analytics, it is evident that there is clear academic interest and a drive to develop and implement learning analytics within the UK HE arena. Undertaking a literature review has enabled me to begin to develop a conceptual framework for this research. The conceptual framework places learning analytics centrally but also recognises that there are key relationships (the student, academic and the institution) that surround and can influence learning analytics. Undertaking the literature review has also shown me that there are broad enabling and challenging factors that surround the relationships already identified, and that addressing these would provide me with justification for the research and a basis on which to develop the research questions.

In response to the literature review, my research will investigate the opportunities and challenges inherent in the use of learning analytics within HE from a multi-stakeholder perspective. An important consideration for this research will be to investigate and show how the challenges identified in the literature review can be overcome if any are seen. The results of the literature review and the creation of a conceptual framework have informed the development of three pertinent research questions. After the literature review, the original research questions were re-visited. Although a greater understanding of the area was in place, it did not appear to necessarily change the research questions as they were still pertinent.

Therefore, the research questions for this study have been confirmed as:

1. What are the opportunities in the use of learning analytics as viewed by students, academic staff and learning analytics experts?
2. What are the challenges in the use of learning analytics as viewed by students, academic staff and learning analytics experts?

3. In view of the findings above, can learning analytics be effectively used within a Higher Education Institution to support the student success and if so, how?

The research reported here will contribute to increasing our understanding of the development and implementation of learning analytics at institutional level from a multi-stakeholder perspective. This will benefit strategic planning teams who are tasked with developing learning analytics and will also benefit academic staff who are involved with supporting students and facilitating student success on an operational basis. Finally, this research will contribute to student success through adding to the body of knowledge which allows institutions to give them the tools to learn effectively.

2.8 Summary of the chapter

This chapter has identified how the literature search was undertaken. Using a conceptual framework as a basis to frame the thematic ideas, this chapter has provided a critical discussion and analysis of the key thematic areas in relation to learning analytics. The next chapter will discuss the methodology used to address the research questions and will outline the pilot study that was conducted in preparation for the main research study.

Chapter 3 Methodology

3.1 Introduction to the chapter

Through the process of critical analysis and reflection, this chapter will explore the explicit relationship between the purpose of the research, the research paradigm and the research design for this study. I will discuss how an appropriate research approach, research design and methodology were chosen, and how they fared in an initial pilot study. Thereafter, I will explore how the main study was carried out. Data collection methods are presented, and an example will be used to demonstrate how research data was analysed. The chapter also covers the ethical considerations pertinent to this study, and quality indicators that are integral to any research.

3.2 Research approach

Research approaches are plans and procedures for the research that detail the methods of data collection, analysis and interpretation (Cresswell, 2014). Bryman (2008) provides the viewpoint that the main distinction between qualitative, quantitative and mixed methods is framed in terms of using words rather than numbers, or a combination of the two.

Because, as noted in the literature review, most research studies conducted are quantitative in nature, I sought from the beginning to use a qualitative approach for this research study to provide a new perspective and insight into the subject matter. My previous experience in undertaking research showed that I had a natural preference towards qualitative approaches, and that I am comfortable with using words to attach meanings. Cresswell (2014) describes qualitative research is an approach for exploring and understanding meaning from individuals or groups in relation to a social or human problem. In contrast, quantitative research is seen as an approach for testing objective theories by examining relationships among variables, which this research study was not seeking to do.

Slife and Williams (1995) believe that philosophical ideas influence the practice of research, as it is the researcher's beliefs that guide action (cited in Cresswell, 2014). Cresswell (2014) argues that there are three components involved in a research approach: philosophical assumptions and its distinct methods and procedures.

My previous involvement with a pilot into using learning analytics, and the development of a conceptual framework and critical appraisal of relevant literature for this study, provided a clear purpose for my research, as it was evident that there was a significant gap in learning analytics research in terms of qualitative explorations of perceptions and experiences from a multi-stakeholder perspective. As a result of this, I devised the research questions that were discussed in Chapter Two. The research questions were designed and structured to focus upon the exploration and description of the perceptions and actual experiences of research participants, with a view to understanding the constructed 'real world' of learning analytics within educational practice. The initial research questions did not change significantly apart from minor wording amendments as I felt that the questions remained broad enough to be able to address the research aim appropriately.

3.3 Research design

Parahoo (2006) believes that qualitative research relies on research methods that allow researchers into the personal, intimate and private world of participants, so the research approach and the research design for this study were required to elicit research participants' perspectives and experiences in order to provide data to respond successfully to the research questions posed. Upon appraisal of the differing research designs, it was decided that a cross-sectional approach would fit naturally with the research aim. A cross-sectional study is a type of descriptive observational study that involves measuring different variables in the population at a single point in time (Lindell and Whitney, 2001). Although literature claims that the major disadvantage of cross-sectional studies is that they lack in-depth analysis when compared with other research designs (such as a longitudinal research) as data is only collected at a single point in time, it appears that the advantages of this approach outweigh negative criticism. Parahoo (2006) recognises that the key advantage of using a cross-sectional study approach is that it offers a quick and easy way to gather data from the selected participant group, and that it can be used as a springboard to expand or inform the research question. Lindell and Whitney (2001) and Bordage and Dawson (2003) suggest that a cross-sectional research design enhances participant response rates in comparison with other designs; this is thanks to the data being collected all at once, meaning that research participants are less likely to opt out of the study before data is fully collected.

Using a cross-sectional research design allowed me as a researcher to conduct research participant interviews and focus groups within a relatively short space of time. With cross-sectional research, it is acknowledged that there is a risk of bias due to a lack of follow up with participants (Lindell and Whitney, 2001) and potential participant bias due to me being an insider to the research. As a novice researcher, I felt that the benefits of this approach outweighed the potential risks displayed. In terms of lessons learnt from my pilot study, I had identified there was a limited time-frame in which to interview academic staff without conflicting academic demands jeopardising the interview process. Likewise, student focus groups could be planned and delivered only at an appropriate point in the teaching calendar to ensure maximum participation and accessibility. This would also make other research designs (such as longitudinal research) difficult to conduct.

Another advantage of using a cross-sectional research design is related to cost. Parahoo (2006) points out that the costs involved in this approach are low due to the ease of gathering and collecting data. In terms of this research study, the only costs are related to researcher time and travel for data collection.

3.4 Paradigm rationale

A research paradigm is a set of assumptions, concepts, values and practices that constitute a way of viewing reality (McGregor and Murnane, 2010). Essentially, a research paradigm is a belief system that guides the way researchers do things, through establishing a set of guidelines for carrying out the research. Across (and within) disciplines there are often varying views of what research is and how knowledge is developed. By identifying a paradigm to guide the research, and through the proper application of methodological principles, researchers enhance the integrity of their scholarship (McGregor and Murnane, 2010).

All research is based on an underlying philosophical assumption (that is, a paradigm) about what constitutes valid research, and which methodology is appropriate to develop knowledge and theory within a specific study (Burrell and Morgan, 1979). Guba (1990) believes that research paradigms can be categorised by their ontology (knowing what is reality), and their epistemology (how you know something). Consideration of ontological and epistemological perspectives creates an holistic view of how knowledge is constructed and how researchers see themselves in relation to it (Burrell and Morgan, 1979). Heron and Reason (1997) argue that an inquiry-based research paradigm must also consider axiology. Axiology is concerned with the nature of value and captures the values question of what is worthwhile. Dudovskiy (2018) believes that this is an important consideration as a researcher's values affect how research is conducted and what the researcher values within their research findings. From appraising the relevant literature on research paradigms, I have collated a summary which informs Table 3.1. The table is based primarily on work conducted by Patel (2015).

Table 3.1. Relationship of research paradigms to ontology and epistemology.

Fundamental belief	Positivism	Postpositivism	Interpretivism	Pragmatism
Ontological perspective	External, objective and independent of	Objective. Exists independent of human thought,	Socially constructed, subjective, may	External, multiple. View chosen to best

	social actors- real ordered and real world (Welford et al, 2012)	belief or knowledge of their existence but is interpreted through social conditioning	change. Open to new ideas with no fixed assumptions (Welford et al, 2012)	achieve an answer to the research question
Epistemological perspective	Only observable phenomena can provide credible data and facts. Focused on causality and generalisations (Houghton et al, 2012)	Only observable phenomena can provide credible data and facts. Focused on explaining within a context or contexts (Welford et al, 2006)	Subjective meaning and social phenomena. Focus upon the details of the situation, the reality behind these details, subjective meanings and motivating actions (Guba, 1990)	Observable phenomena and subjective meaning can provide acceptable knowledge dependent upon the research question (Holloway and Todres, 2007)
Axiology	Value free Researcher is independent of the data and maintains an objective stance	Value laden Researcher is biased by world views, cultural experiences and upbringing	Value bond Researcher is part of what is being researched, cannot be separated and so will be subjective	Value bond Researcher adopts both an objective and subjective points of view. Values play a large role in the interpretation of results

Methodological approach	Quantitative	Quantitative or Qualitative	Qualitative	Quantitative and Qualitative (or mixed method design)

Burrell and Morgan (1979) and Guba (1990) propose that each component of a philosophical assumption can be represented on a continuum of approaches from subjectivist to objectivist. Objectivist approaches seek to conduct research reflecting a scientific paradigm, which rests upon theoretical frameworks that can be tested by experimentation, replication and refinement (Cohen et al, 2003). Subjectivist approaches recognise the importance of the subjective accounts of individuals, seeking to explore and validate their understanding. From an ontological perspective, adopting an objectivist approach would imply that there was an independent or objective truth waiting to be discovered, and that reality can never fully be known (Cohen et al, 2003), whereas a subjective approach considers the lived experience of individuals, people and culture. Through engagement with relevant literature and consideration of the research aim, a subjective approach was considered the most appropriate for the investigation being undertaken here, as I was seeking to understand the lived experience of individuals who were familiar with using learning analytics. An interpretivist paradigm lends itself well to my research aim of understanding and gathering meaning from multiple perspectives to explain an experience.

3.5 Interpretivism as the selected research paradigm

Interpretivism attempts to explain human and social reality (Crotty, 1993), embedded within social interaction and interpretation of the real world. Within this setting, interpretivists assume people’s behaviours and actions are shaped by their environment (Creswell, 2009), and the cultures in which they live and work. Interpretivists emphasise the importance of participant perception, intention and beliefs and the opening up of possibilities rather than finding truth (Lincoln and Guba, 1985 cited in Creswell, 2009). The intent is to make sense of meanings that others have about the world, in this instance in relation to how learning analytics can be used to improve student experience and success. Rather than starting with theory, Interpretivism is inductively developed (Creswell, 2009) to find meaning. Creswell (2009) recognises that researchers' experiences and backgrounds shape interpretations, so researchers must position themselves within the research to acknowledge personal, cultural and historical experiences. As an educational researcher, therefore, I need to be mindful that I am an insider to the research, and my personal experience is that of immersion within an environment where technology is an institutional strategic driver for improving the student's educational experience. Interpretive researchers need to adopt an exploratory orientation to arrive at an understanding of the distinctive orientations of the people concerned, and hence gain insight (Parahoo, 2006) into how and why participants use learning analytics.

3.5.1 Epistemological and ontological considerations within Interpretivism

Interpretivism assumes a relativist ontological position (Houghton et al, 2012), i.e. that more than one truth exists, and reality is socially and experientially based (Guba, 1990). This position holds that everyone experiences their own reality, and that realities can be multiple and relative. Knowledge is acquired and socially constructed rather than being objectively determined. Flexible and personal research structures need to be adopted to capture meaning when interacting with research participants and attempting to make sense of what is perceived as reality. When working within this paradigm, the researcher remains open to new ideas, and lets knowledge emerge and develop through the participants themselves. As a researcher, my ontological position in education is that of someone sharing knowledge with others to understand the world around us. The use of an emergent and collaborative approach is consistent with the interpretivist belief that humans have the ability to adapt, and that no one can gain prior knowledge of time- and context-bound social realities (Hudson and Ozanne, 1988).

Interpretivism acknowledges a subjective epistemology, with the stance that the participant holds a relative position in the way that they see the world. In other words, as Bowling (2009) explains, interpretivists are not concerned with whether knowledge is true in the absolute sense, since truth depends on the knower's frame of reference.

Epistemologically, knowledge is gained through reason, is constructed at an individual level and exists in multiple formats. Lave (2008 cited in The Open University, 2013) perceives that different views of the everyday have underpinned views of knowledge, and that learners move towards knowledge of a high cultural value. Laves's (2008) theory of knowledge describes our experiences of the world as a way of deriving new knowledge and places a dual emphasis on theory and the development of practice. Epistemology questions relationships between the researcher and what can be known (Welford et al, 2012) and requires the researcher to be aware of the impact of their perception on the research (Houghton et al, 2012) as this may affect the reliability of their studies. Epistemologically, this study is based on the view that the participant is the expert, and that the subjective data provided by participants will reveal reality in terms of what is recognised and valued.

The epistemological position considers the cultural context in which learning takes place, whether this is home, the educational or clinical environment. In the case of this study, factors such as student monitoring, usability, level of technical support available and the level of technical ability of the user may influence or hinder the use of learning analytics. Another determining factor in using technology more broadly can be age - the younger generation is immersed in technology; hence the new digital generation of learner may potentially be more at ease with learning analytics (Helsper and Eynon, 2010). This research with its emphasis on experiential use will help us to understand the phenomenon of using learning analytics within the educational context.

Burrell and Morgan (1979) believe that in addition to ontology and epistemology, there should be consideration of human nature assumptions (the way in which study subjects respond to stimuli). The researcher needs to use a strategy to discover such information; thought needs to be given to whether the methodological approach provides a reproducible study and is able to capture data efficiently and effectively (Burrell and Morgan, 1979). As noted previously, we should also consider axiology, i.e. the question of value. Within interpretivist paradigms, research is value-bound, being subjective as the researcher is part of what is being researched.

3.6 Selection of the research methodology

My original intention was to use AI as a methodological basis for the research study. Due to the change in research direction discussed in Chapter One, I reflected that AI would no longer be a helpful methodology to use as the AI approach is better suited as a change methodology rather than a research methodology.

A fundamental requirement for this study was for me to select a research approach, research design and suitable methodology that would capture the unique experiences of research participants, in response to the research questions. In addition, the research design and methodological approach would also need to be able to address the third research question of how potential challenges could be overcome. Having considered different approaches that lent themselves to an interpretivist paradigm, I identified that using case study, a mixed methods approach or the Delphi technique may potentially be suitable to use. Using a mixed methods approach was soon dismissed, as although it can be used for qualitative research to inductively seek an emerging qualitative theory or pattern (Cresswell, 2014) more commonly it is used when collecting, analysing and integrating both qualitative and quantitative data. As I had consciously made the decision to solely use a qualitative approach at the start of this study due to my prior experiences and professional background, this approach was soon dismissed. I reflected that my area of expertise in relation to statistical analysis was weak, and that it would take me a long time to be able to understand and apply statistical analysis. As is evident in the literature review chapter (Chapter Two), I had identified that previous published research was mainly quantitative in nature. In order to bring some uniqueness to this study, I felt that using a qualitative approach would offer new insight and ideas into the topic area. The Delphi technique was also a considered alternative; this method is frequently used when researching participants that are subject level experts within a chosen subject area. The Delphi technique is described by Cohen et al (2003) a systematic forecasting method that involves structured interaction and communication amongst a group of subject experts. The Delphi Technique typically includes at least two rounds of experts answering questions and giving justification for their answers, providing the opportunity between rounds for changes and revisions. Due to my lack of knowledge surrounding the Delphi technique, and considerations on the time factors allocated in which to complete this study, I also decided that this approach may take too long within my timeframe for completion.

I wanted to use a research approach that works to define a problem, so case study was selected as it fitted the aims of this study in terms of the richness of data required and the need to discover and answer *how* and *why* type questions.

Yin (2009) describes case study as a research methodology that:

> **'…investigates a contemporary phenomenon (the case) within its real-life context, when the boundaries of phenomenon and context are not clearly evident.'**
>
> (Yin, 2009, p. 13)

Stake (1995) further defines case study as a design of enquiry where the researcher develops an in-depth analysis of a case, which may be a programme, event, process or one or more individuals. For my study this meant focusing on a research participant group that had direct involvement with using learning analytics within the HEI context.

Yin (2014) believes that one advantage of the case study approach is that it is flexible and broad. Case study approaches can range from brief descriptive summaries to more detailed accounts. This is suggested by Cresswell (2014) to allow the researcher to present ideas, explore what has happened and why it has happened. Other advantages, as suggested by Yin (2014) is that the case study method is able to give an account of the human side of a project, explain goals, explore project dynamics, investigate particular phenomenon, and present outcomes in their complexity without being subject to the confines inherent in most other evaluation methods.

The defining characteristic of the case study approach is its focus on one instance of the element to be investigated, which I recognise fits well with using a cross-sectional research design, my intended design approach. Due to time limitations in which to complete the thesis, I consciously made the decision not to use a longitudinal approach. Using a longitudinal approach would involve interviewing the same participants over a period of time, and through conducting my pilot study I recognised that time was a distinct limitation in which to conduct my main study due to availability of both academic staff and student participants. Using a longitudinal approach would be advantageous for post-doctoral study if I decided to conduct further research in this topic area. The use of a case study methodology is also a strategic decision relating to the scale and scope of the investigation (Denscombe, 2010), and is seen to work best when the researcher wants depth to be an outcome of the investigation (Bryman, 2012) rather than breadth. Using a case study approach is advantageous as it allows the researcher to study participants holistically rather than in isolation, and within natural settings rather than artificial situations (Denscombe, 2010). Yin (2009) suggests that using case studies is appropriate for researchers who want and need to understand the real world, as they capture contextual conditions relating to the case that facilitate an understanding of relationships and processes rather than outcomes and end products (Denscombe, 2010). Yin (2014) believes that this is one of the key strengths of case study research.

Although literature emphasises numerous advantages to using case study as a research method, there are also disadvantages, with the case study method traditionally considered to have several major limitations as an evaluation tool (Yin, 2014). Descriptive case studies are suggested by Lohen et al (2013) to be qualitative and unreliable. Yin (2014) believes that case studies typically relate to single projects, and as such, their results usually cannot be generalized. One of the biggest disadvantages of case study method is related to validity as the researcher often does not have control over variables. However, that criticism is suggested by Yin (2014) to be directed at the statistical and not the analytical generalization that is the basis of case studies. As a consequence, the researcher must be content with the notion that their findings may only be applicable to similar cases, thus losing some external validity. Another disadvantage of the case study method is in relation to the potential of researcher subjectivity. Yin (2014) proposes different solutions to counteract this, such as using multiple sources of evidence, establishing a chain of evidence, and having a draft case study report reviewed by key informants.

For the purposes of this study, I decided on a case study approach with an exploratory focus. The rationale for using a case study approach was that it afforded me as a novice researcher breadth and flexibility for the study. As I was hoping to discover the human side of learning analytics and to investigate learning analytics as a phenomenon within an institution, the case study approach fitted in well with my research aims. The exploratory focus allows me as a researcher to investigate the key issues and themes affecting participants (Cresswell, 2014), in this case aiming to elicit problems and opportunities that participants encountered in relation to the use of learning analytics. Best practice in the use of case studies indicates that cases should be selected on the basis of known attributes that are significant in terms of the theoretical issues that the researcher wants to discover (Denscombe, 2010).

3.7 Data collection method

When deciding on a suitable data collection method, I did initially consider using a questionnaire, which Parahoo (2006) describes as the most frequently used survey tool. Questionnaires can easily collect information on facts, attitudes, knowledge, perceptions and experiences of participants (Parahoo, 2006) and have the practical advantage of being quick to administer and allowing for participant anonymity and confidentiality (Parahoo, 2006). Parahoo (2006) acknowledges that using questionnaires as a data collection method is more appropriate for quantitative approaches to research. However, because my study was based on an interpretivist paradigm and would be conducted qualitatively, I needed to understand the research problem in depth. Response rates from questionnaires are typically poor (Denscombe, 2010) and time limitations on my research meant that it would create a problem if the data collection phase became a lengthy process through participants failing to return the required information within a timely manner. There was also a significant risk in not receiving sufficient information on which to base data analysis if my questions were not formulated correctly, with the attendant problem of having to collect a large amount of data from a variety of people in order to ensure validity (Parsell and Bligh, 1999, Denscombe, 2010). For these reasons, the use of a questionnaire did not fit with the principles of my research and the practical requirements for my study, so I felt that a more appropriate data collection method was required.

3.7.1 Interviews as a method of data collection

After dismissing the idea of a questionnaire, I turned to the option of interviews. This was a logical choice as interviews allow for the verbalisation of important beliefs, attitudes, experiences and perceptions of participants (Newby, 2014). Gathering this type of information was central to achieving my research aim, and I felt that interviewing participants would allow for open discussions and provide valuable insight into how learning analytics were implemented and utilised within each HEI. When considering the type of interview to be conducted, I selected a face-to-face, semi-structured interview rather than a telephone interview approach. Holbrook et al (2003) conclude that telephone interviews are completed more quickly but have a lower response rate compared with face-to-face interviews. As a low response rate could affect the validity and reliability of this research, in order to maximise responses, the researcher chose to meet face to face with individual participants, which would have the added benefit of allowing for clarification and discussion of the key points raised, thus enhancing validity. Parahoo (2006) believes that face-to-face interviews allow for the researcher to observe non-verbal signs which can alert them if participants are experiencing difficulties understanding questions, and they also allow for additional discussion when framing a question response.

A semi-structured interview has been described by Bowling (2009) as:

> ***'…verbal questioning of study participants using a combination of pre-set questions without response codes.'***
>
> (Bowling, 2009, p. 285)

Barriball and While (1994) point out that every word does not mean the same to each participant, and every respondent does not have the same vocabulary. Using interview questions and follow-up clarification and probing would provide me with the opportunity to change the words but not the meaning of questions (Woods, 2005). Parahoo (2006) states that this enhances research validity, as participants are helped to understand interview questions, and researchers can ask for clarification on points and probe for further responses if required.

3.7.2 The development of the semi-structured interview questions

Interviews were developed through the selection of pre-determined, open-ended questions which provided a broad structure and standardisation to the interview process. Each participant was directed to provide information about learning analytics from their own perspective and viewpoint. Leininger (2000) believes that this type of interview is an important approach, as it allows participants' perceptions and ideas to be revealed. This allows the researcher to get inside participants' heads (Leininger, 2000). This approach was designed to understand how learning analytics experts, academic staff and students viewed and experienced learning analytics within their own HEIs, and allowed me to gain an insight and understanding into how learning analytics and analytical tools had been developed and were being implemented within each organisation. I noted that all institutions that had chosen to adopt learning analytics were at discretely different phases of development and implementation – a factor which could impact and influence individual participant responses.

Parahoo (2006) recognises that in qualitative interviews, the degree of control and structure on the part of the interviewer needs to be minimal to allow topics and perspectives to emerge. Ryan et al (2007) believe that this allows for integration between the researcher and the participant and demonstrates the value and relationship between the researcher and the research participant. This further allows for the researcher to be guided by what participants say (Denscombe, 2010), and enables appropriate themes to be drawn together in preparation for the data analysis phase of the research study.

Interview questions were devised to act as a starting point for conversations with research participants. Questions sought to identify participants' attitudes and opinions in relation to the opportunities and challenges of using learning analytics within educational practice. Questions were tested with research participants as an integral aspect of the pilot study to ensure that they would elicit the types of responses that I was searching for to provide relevant data for the research aim. Minor wording in two of the questions was changed following the pilot study, as I found that during the pilot the questions originally elicited similar responses from participants, and additional clarification was needed.

3.7.3 Development of focus groups stimulus for student participants

Kitzinger (1995) believes that focus groups are useful in allowing participants to explore their views and to generate questions in ways that they would find more difficult in face-to-face interviews. Kitzinger (1995) also recognises that focus groups can be used to examine not only what people think, but how they think and why they think in that way, their understandings and priorities. Bowling (2009) recognises that by making use of group dynamics, discussion can be stimulated, insights can be gained, and ideas generated to pursue a topic in greater depth. The focus group approach seems a logical choice to gather a satisfactory level of conversation and discussion so that the topic of learning analytics can be explored in more depth.

Student perspectives are crucial to this research, to develop our understanding of what students want from their university experience with a view to influencing future educational direction and practice within the domain of learning analytics. As I was proposing to interview students from HEIs across the UK, I was conscious that my participant response rate may be adversely affected if the student participant group did not want to meet with a stranger outside of their own institution. Secondly, students may feel uncomfortable with disclosing information to someone that they do not know. I felt that conducting focus groups for student participants would provide a better solution than individual interviews to maximise the response rate and encourage student participation in this study.

Bowling (2009) defines a focus group as:

> ***'…unstructured interviews with small groups of people who interact with each other and the group leader.'***
>
> (Bowling, 2009 p.424)

Focus groups have been described by Smithson (2000) as particularly useful at an early stage of research as a means for eliciting issues which participants think are relevant, which can then be used to inform design of larger studies (Vaughn *et al.* 1996). The method therefore seemed appropriate for an exploratory investigation. For all the reasons discussed above, the focus group approach seems a logical choice in order to generate a satisfactory level of conversation and discussion so that the topic of learning analytics can be discussed in more depth. Focus groups are not without limitations, and as Bowling (2009) identifies, even with an experienced researcher, one or two people may dominate the group and sway the opinions of the others. Some participants may not wish to publicly share their views on sensitive topics, but these can be important views that need to be included. This is an important consideration for the researcher to acknowledge whilst questioning student research participants. As we have seen, the purpose of a focus group is to explore specific issues, and to do this it uses a stimulus as an exploratory tool. The stimulus can be a shared experience or something specific introduced by the leader of the focus group at the beginning of the session (Denscombe, 2010). For my focus groups, I considered that it was appropriate to use wording that was familiar to students. For the purposes of my research, therefore, I decided to select the wording 'student dashboard' and, where appropriate, to use the specific product name as students would be familiar with these words. I felt that if I used the wording 'learning analytics' it could potentially be unfamiliar terminology to student participants. Kitzinger (1995) recognises that focus groups can be used to examine not only what people think, but how they think and why they think in that way, their understandings and priorities.

In order to align with the analytic expert and academic staff interviews, I concluded that I would use a stimulus first, and then use a similar questioning method as in the interviews, i.e. use questions to guide the discussion, and in this way, ensure that there was parity across the research findings from all participants. As a basis for discussion, the same semi-structured questions that were developed for the interview process would therefore be used for the focus group discussions.

3.8 Reliability, validity and quality criteria

For any methodological approach, it is essential that there is credibility of the research study with the bases for judging this as validity, reliability, objectivity and generalisability which are viewed as quality criteria for any research study. Denscombe (2010) recognises that the credibility of the research needs to be demonstrated as part of the research process itself, and that this can be achieved through basing findings on the principles of good research. Silverman (2010) stresses that this applies both to qualitative research and to quantitative research. According to Parahoo (2006), validity refers to the accuracy, appropriateness and precision of data, and ensuring that the data is the right kind of data for the topic under investigation. Reliability is seen as whether the research instrument is neutral in its effect and is consistent across multiple occasions of use (Denscombe, 2010). Objectivity is seen as the absence of bias within the research, denoting that the research is impartial (Parahoo, 2006) with generalisability referring to the prospect of applying research findings to other examples of the phenomenon to explain similar research findings, rather than being something unique (Denscombe, 2010).

Parahoo (2006) and Denscombe (2010) believe that credibility in qualitative research is not easily judged using the criteria proposed above. Within scientific experimentation using a quantitative method, the research can be easily replicated which checks the quality of the research as well as that of the research findings. Silverman (2010) makes the point that qualitative research is not be able to be verified in the same way as quantitative methods; none the less, there is still a need for researchers to address verification within social research methods.

Yin (2014) believes that tests can be used to establish the quality of empirical social research, namely construct validity, internal validity, external validity and reliability. Yin (2014) provides a comprehensive account of how case study research can achieve compliance with these tests. Application of Yin's (2014) account provides the reader with a structure to demonstrate credibility, transferability and dependability within my research study, and is shown in Table 3.2.

Table 3.2 Case study tactics for design tests (adapted from Yin, 2014).

Test	Case study tactic	Phase of research in which tactic occurs
Construct validity	Establish chain of evidence Have key informants review draft case study report	Data collection- Interviews with staff Interviews with students Interviews with Learning Analytics experts Analysis and results reported using transcript details Participants provided with copy of transcript and results for comment/review purposes
Internal validity	Pattern-matching	Data analysis

	Explanation-building Address rival explanations Use logic models	
External validity	Replication logic in multiple case studies	Research design Theory informing research design
Reliability	Use case study protocol Develop case study database	Data collection Production of transcripts, direct quotes from transcripts used as part of data analysis and discussion

As a methodology, case study is vulnerable to criticism in relation to generalisability of research findings (Denscombe, 2010). Denscombe (2010) argues that the value of a case study approach is that it has the potential to deal with the subtleties and intricacies of complex social situations, and that case study is worthwhile in its own right as a depiction of a unique or specific situation (Denscombe, 2010). This perspective is embraced in the cross-sectional case study research design of this study. None the less, it is acknowledged that findings from this case study can be generalised only to cases similar to this one.

While my research sample was gathered from universities from different geographical locations across the UK, there were similarities in terms of the type and size of the organisations participating, as well as the ethnic grouping, social class and ages of the student population. This allows for some comparison between this study and other institutions of this type. Yin (2014) identifies that having a theory or a theoretical proposition plays a critical role in generalising lessons learnt using case study research. Yin (2014) proposes that generalisation is based on modifying, advancing or rejecting the theoretical concepts referenced in the case study design, or through the identification of new concepts that arose upon completion of the case study. Yin (2014) argues that generalisation using case study research is at a conceptually higher level than other qualitative approaches and can be used directly to inform theory or policy. This makes the conceptual framework which has emerged from this study an even more important contribution.

As a researcher, I acknowledged that there is a limited sample size in this study. Using participants' perceptions and experiences as a basis can make generalisability problematic. In order to address this potential problem, I suggest my research is warrantable rather than using the description generalisable. Hammersley (2010) suggests that to support validity and reliability within research, the researcher needs to be guided by (or guided to) a coherent conceptual framework which supports the research process. Weston (n.d.) adds to this by acknowledging that researchers need to be skilled to avoid pitfalls within the research, such as missing observation detail and possibly introducing bias during data collection and analysis. I recognise that triangulation of data is difficult to achieve in this study as I am only using a single method of data collection (interviews). Normally, methodological triangulation takes place when the researcher uses case study gathered from multiple sources of data from interviews, documents and observation**.** It can be considered that perspective triangulation has been applied to this study through the use of multiple, rather than singular perspectives to examine the topic under discussion (Roulston, 2018). Hammersley (2010) believes that reliability and validity of results depend on creating a strong research design, choosing an appropriate method and conducting the research carefully and consistently. To improve reliability of the analysis for this qualitative study, records of interviews and focus group observations were made which formed part of the process of analysis. Construct validity was enhanced through research reporting using the transcript details and then research transcripts and findings being fed back to participants to provide them with the opportunity to confirm they provide a reasonable account of their experience. Participant reactions to the emerging research data (Oakley, 1974) then became part of the research findings. Finally, as an educational researcher it was essential that I considered the role of the insider as part of the research process.

3.8.1 *Considerations when undertaking insider research*

As this research specifically relates to my own work-based practice, it is important for me to acknowledge my position as an insider to the research, and therefore to explore issues around insider research. The origin and purpose of this research were based on my own involvement in the development and implementation of learning analytics within my own institution. This placed me as a researcher in the position of 'insider', as I have gained specialist knowledge about the concept of learning analytics through working with this particular issue in depth. Costley (2010) believes that insider researchers are in a prime position to study an issue in depth, as they have insider knowledge and easy access to people and information that can further enhance that knowledge. Although my own research expanded from my institution to involving participants from other UK HEIs, I did have insider knowledge and felt that my own experiences allowed me to investigate and to challenge from an informed perspective.

Besides insider knowledge allowing for depth in the research, Reed and Proctor (1995) believe that insider research provides the ability to focus upon aspects of practice in which the researcher can initiate change, and therefore it is a process that is likely to yield insights which can be conveyed in a form which make them worthy of interest to a wider audience. Costley (2010) recognises that for insider-led research the sample size is likely to be small. This is certainly the case for the research project for this report, as there are relatively few HEIs currently involved with the development and early implementation of learning analytics, a factor which is compounded by the timing considerations in conducting the research. Costley's (2010) also suggests that the nature of the project is likely to be specific, a perspective which is echoed within my own research, where an important consideration is specifically to identify the opportunities and challenges presented by the development and implementation of learning analytics, but also to provide recommendations to identify how challenges identified can be overcome. Answering these specific questions allowed for the evaluation of practice and will enable other UK HEIs who are considering developing and implementing learning analytics to be more fully informed prior to implementing institutional change, although it does need to be recognised that work-based research concerned with specialised practice may not provide results that can transfer exactly to another situation. Bassey (1999) describes this as ‘fuzzy generalisation’ but feels none the less that broad generalisations that arise from one particular research project may have general application in a similar context which has usefulness as well as the potential to generate theory. Nixon (2008) demonstrates that undertaking insider-based research can make significant contributions to work-based practices and can encourage engagement in reflection at work. Costley (2010) believes that insider-based research has the potential to make an impact, not only at local level through the influence of policy and decision-making processes, but also at national and international level through the provision of an evidence-based research perspective.

At a more micro level, it is important to recognise, as Costly (2010) does, that the unique perspective of the researcher makes a difference to the research, and that an important aspect of work-based research is the researcher’s own situatedness and context. Vygotsky (1962) initially put forward the concept of ‘social situatedness’, recognising that situatedness arises from the interplay between the researcher (agent), the circumstances and the researcher’s position (the situation) and the context of the research. Costly (2010) further asserts that organisational, professional and personal contexts will affect the way in which a piece of research and its development is undertaken, and how these contexts interact will ultimately shape and individual researchers work. Costly (2010) also indicates that when researchers are insiders, they draw upon shared understandings and trust of their research participants when social interactions are developed.

While Costley (2010) recognises the positive impact that the insider-based research can make, she also points out that negative impact needs to be considered. Therefore, as an insider-based researcher, I am obligated to reflect on the research process and to demonstrate criticality of my own work. Insider-based research is subjective in nature, and as such researchers need to consider that there may be a vested interest in certain results being received. As this research is being undertaken externally to my own organisation, I am able to exert a higher level of impartiality than would be the case had I been interviewing participants from my own institution. None the less, as an insider researcher, I have specific responsibilities to ensure that careful consideration is giving to the development of interview questions as well as the gathering of data to ensure that questions are not biased and do not impair the validity of the study (Murray and Lawrence, 2000). To guard against bias within this research, careful attention was paid to the feedback provided by participants when they viewed the initial evaluation of data, and also to the final report of the findings of this project.

3.9 Ethical considerations

Ethical issues were considered through all stages of the research process, from the initial research planning through the design of the research instrument, participant information and consent, to final viewing of the report. This process was applied to both the pilot study and the main research study. Permission to conduct my research was granted by the Open University Human Research Ethics Committee (HREC) (Appendix 2) following the completion of the HREC project registration and risk checklist (Appendix 1). No additional formal permissions were required as the host institutions granted permission simply on the basis of the research not hindering the daily business of the institution. I also made it clear to research participants that their contribution was voluntary and would be anonymous.

From an ethical perspective, the fundamental areas of consideration that were applicable to this study related to risks and safety of the researcher and research participants, and data protection and confidentiality. To adhere to ethical principles, when inviting participants to be interviewed I provided information detailing the research aim and objectives, and an outline of the research process (Appendix 3). Participants were informed by this document that their participation was voluntary, and that they had the freedom to withdraw from the study at any time. Participants were advised that data would be captured and retained through audio-recording (via Dictaphone). Data from the audio-recording would later be transcribed for the purpose of data coding. Following completion of each interview, the audio-recording was transferred onto an encrypted memory stick, and the Dictaphone recording deleted. Participants were reassured that there would be restricted access to captured data and it would be seen only by myself. Stored data will be kept until publication of my research study, after which it will be destroyed. During the semi-structured interviews and focus groups, I advised participants that I would be making additional handwritten notes which were used to provide me with key words of the main points raised. This information was purely for my benefit in order to write down thoughts and further points for clarification during the interview and was not used as part of the data coding process. The handwritten notes served to support validity in the data collection process through documenting how each institution was using learning analytics (e.g. if it was staff-facing or student- and staff-facing) and indicated whether there was some generalisability in how learning analytics was operating at each institution. There was written assurance that a pseudonym would be used to protect participant identity for note-taking, data transcription, analysis and presentation of the final thesis. At the commencement of each interview, research participants were provided with a written copy of the participant information sheet and were verbally reminded that they had the right to withdraw at any time. In addition, written consent (Appendix 4) was obtained from each participant confirming that they consented to taking part in the study and allowed me to use the information that was elicited during the interview process.

To ensure the safety of research participants, interviews were conducted within each host institution. This meant that participants would be aware of safety procedures in the event of emergency which minimised the risk to them. As I was to be travelling to different institutions, there was a risk to myself in relation to personal safety, so I provided my destination information to an identified colleague prior to my meeting with each research participant. The exact location of the proposed interview was agreed with the research participant when arranging the interview. I telephoned my colleague immediately prior to the interview taking place so that they were aware of the venue and my arrival time. Upon completion of the interview, I telephoned again so that they knew that the interview had concluded. For the focus groups with students, a pre-determined location within the institution was agreed, and I was met and introduced to the students by their lecturer. The lecturer was not present during the focus group but provided me with their contact details in case of concerns and then met me after the focus group concluded so that any potential risks were reduced. Allowing the students' lecturer to be present for the focus group discussions could have influenced the data collection and research findings as it may have had a restrictive influence on the responses given by participating students.

Following transcription of the data, research participants were provided with a copy of the transcript for comment and to ensure that the transcription accurately reflected their experiences. This supports construct validity and reliability for the study (Yin, 2014). Research participants will also be able to access the final research findings and thesis in its entirety which Yin (2014) believes supports validity of a research study. Ten research participants have requested to see the final thesis to support advancement of learning analytics within their own HE institutions.

3.10 Pilot study

The interview questions were designed to elicit responses in relation to the enabling and challenging factors that were identified in my conceptual framework. Interview questions were devised as an expansion from the broad research questions that I had already developed and sought to identify participant's attitudes and opinions in relation to the opportunities and challenges of using learning analytics within educational practice. Once I had constructed potential interview questions and the participant information and participant consent forms, I decided to conduct an initial pilot study. The main purpose of the pilot study was to test the semi-structured interview questions (Appendix 7) in preparation for the main research study. This gave me with the opportunity to sense-check the interview questions to ensure that answers were open and would lead to further discussion about the topic under investigation. Six academic staff from within my own institution were contacted to participate in the pilot study. Academic staff were selected who had contributed to the institutional learning analytics pilot project. Therefore, a purposeful sampling technique using these academic staff was used. Expert purposeful sampling has been defined by Crossman (2020) as a form of sampling when the researcher needs to capture knowledge rooted in a particular form of expertise. Crossman (2020) recognises that this approach is often used at the beginning of the research process, when the researcher is seeking to become better informed about the topic at hand before embarking on a study, and that using expert-based research can shape research questions and research design (Crossman, 2020).

Staff were asked to participate based on their actual experience of using the institution's manufactured learning analytical tool during the institutional pilot. Participants were contacted by e-mail inviting them to take part. A personal touch was used to recruit participants, which could increase the potential for coercion (Baxter et al, 2006). To reduce this risk, as recommended by Parahoo (2006), I provided research participants with a written participant information sheet which contained detailed information about the study, the research aim and objectives, the potential risks involved, ethical considerations and the opportunity for participants to opt out. Four participants responded to the e-mail request, and three agreed to be interviewed. At the interview stage participants provided me with written consent to participate in the pilot study.

The pilot study was conducted during a peak marking and assessment period over early Summer 2017, which meant that interviews needed to be re-scheduled due to changing academic workload demands. This was an unexpected benefit of the pilot study, as lessons learnt was the recognition of time limitations for academic staff became a fundamental consideration for the main research study, and it was clear that I would need to select appropriate time-periods within the academic calendar to avoid delay with the data collection process and avoid the potential impact of poor-quality data that would result in rushed responses from research participants.

Following the interview process with research participants at the pilot study, minor amendments were made to the structure and wording of two of the questions to improve their clarity and meaning for respondents (Appendix 8). At this stage, the pilot project showed me that I had sufficient questions from which to draw appropriate responses from the participants for the main study and that they would elicit a satisfactory level of data to analyse and to achieve my research aim.

3.11 The main study

I had planned to conduct the main study in Summer 2018. From the outset of this research study I was aware that there may be some limitations with the accessibility of suitable research participants due to the topic area being a developing domain within the HEI context. Although I had some insight into the topic area due to my personal involvement within my own institution, I was unaware as to how widespread learning analytics was developing within the UK HE context or how quickly this was happening. Prior to undertaking this study, I was unaware of how developed learning analytics was within different educational institutions, nor how many UK HEI's has implemented and has established learning analytics as a tool for student success. This could potentially limit the number and types of institutions that I wanted to access and the number of potential research participants that could contribute to my study. To draw upon the largest possible pool for my sample, I first conducted a broad internet search to see which universities were promoting learning analytics as a mechanism for supporting students, and I contacted the key individuals through directly acquiring contact details. I had also established some contacts through external networking with HEI colleagues, so I contacted them directly via e mail to see if their institution was developing learning analytics. This did not yield any research participants due to the development of learning analytics being at an early stage in their institutions, and I felt that no evaluative information could be gained which could inform my research. I also had contact with a commercial software developer, who agreed to support me with my research and who was independent from any of the institutions that I had contacted. My internet search was initially limited to institutions within a 150-mile radius from my home to facilitate travel to interviews. This provided me with five different institutions within the Midlands and to the Northern and Eastern parts of the UK (Appendix 9). As I wanted to interview learning analytics experts, academic staff and students from within each of these institutions I believed that this would provide me with a large enough participant sample size on which to base my findings. Although not intentional, the type and size of each of the institutions drew some similarity to that of my own, and there were similarities with the ethnic grouping, proportion of disability and the ages of the student population. I considered that Russell group universities may not see the need to develop learning analytics as a mechanism to ensure student success, as this group of universities consist of high performing students and therefore areas such as student retention, progression and student success may not be such a concern for them in comparison with post-1992 universities, but this is personal opinion and cannot be backed up by evidence.

3.11.1 Staff participants

In qualitative research, study sample sizes are often quite small, typically comprising research participants who are purposefully recruited to a study because of their exposure to or experience of the phenomenon in question (Ryan et al, 2007). From my internet search of institutions, I found contact names of key individuals who were involved in learning analytics within their institution. These names provided a useful starting point. Fossey et al (2002) believe that purposeful sampling ensures that there is richness in the data gathered. Once the institutions were identified as outlined above, I contacted these potential participants via e-mail, creating a purposeful sample group. Additional research participants were sourced through contact names provided by the software developer which had supported my institution's pilot project, and through additional contacts known by my Ed D supervisor. Once I had directly contacted some interested participants from the selected institutions, these participants provided suggestions for additional people that were involved in learning analytics and would potentially be interested in supporting my research study. Bowling (2009) refers to this approach as the snowballing technique. This technique typically involves the researcher asking an initial group of respondents to recruit others they know that are in the target group. The disadvantage of this method is that it includes only members of a specific network (Bowling, 2009). The snowballing technique was beneficial to me as it resulted in my accessing additional participants and which I felt would enhance the study. This resulted in my accessing participants from five different post-1992 universities within the UK, and allowed me to generate a manageable sample size of twenty participants at the beginning of the study. Although it was not planned, my case study sample provided me with universities that were all post-1992 education establishments, and all universities that had a diverse body of student learners in terms of ethnicity and learning needs. This correlates to the student make-up within my own institution.

Twenty initial e-mails were sent to learning analytic experts and academic staff from a variety of UK HE institutions (Appendix 5). Of these, 14 participants responded and agreed to participate in the research. Five participants failed to respond to my initial request. One participant responded but refused to be interviewed due to time limitations and a heavy workload. From the 14 participants that agreed to participate in my research, I was provided with the contact details of five additional possible participants, who I contacted directly via e-mail to request their participation in the study.

This process provided a participant population of 19 academic staff and learning analytics experts to interview. When trying to arrange specific dates/times in which to conduct the interviews, a further seven participants failed to respond or were unable to meet with me; this provided a final participant population of 12. Although I recognised that this was a small sample size, and may provide some limitations to my research study, this was broken down into six learning analytics experts and six academic staff. The learning analytics expert participants job roles are shown in Table 3.3, and the academic staff's subject specialities are shown in Table 3.4. Detailed information about each different institution can be found in Appendix 9.

Table 3.3 Learning analytics expert participants' job roles.

Learning analytics expert participant number	**Job role**
Participant 1 (Commercial software developer)	Learning analytics platform developer

Participant 2 (Institution 5)	Head of Learning and Digital Technology
Participant 3 (Institution 1)	Deputy Registrar (Project manager (for the institutional learning analytics project)
Participant 4 (Institution 4)	Learning Analytics Project manager
Participant 5 (Institution 2)	Learning Analytics Project team member
Participant 6 (Institution 3)	Head of Learning and Digital Technology

Table 3.4 Academic staff participants by subject speciality.

Academic staff participant number	**Subject speciality**
Participant 1 (Institution 4)	Education
Participant 2 (Institution 1)	Sports Science
Participant 3 (Institution 4)	Nursing/Health
Participant 4 (Institution 5)	Business Studies
Participant 5 (Institution 3)	Nursing/Health
Participant 6 (Institution 2)	Psychology

Once the interview schedule was determined and finalised, data collection with both the learning analytics experts and the academic staff was scheduled to take place over a period of two months during the summer when students were on vacation. Lessons learnt from the pilot study showed this to be the most convenient time for participants to meet. It also enabled the data collection phase to occur quickly.

At the beginning of each interview, each research participant was catalogued and indexed with a unique number. I also assigned a label which allowed me to identify participants in terms of the interview number and their role within this research (i.e. whether the research participant was a learning analytics expert, member of academic staff or a student research participant). The labelling would be used to reference participant quotations within the research findings and is discussed in Chapter Four. Cataloguing and labelling interviews supports anonymity of the data and assisted me in the identification of referencing information which was required for transcribing, data coding and analysis. Notes made during each interview were anonymised with the same labelling technique as the Dictaphone recordings so that specific individuals cannot be identified. Participants were advised that my hand-written records taken at the time of the interview would be kept solely for the purpose of information giving and that any information obtained following transcription would be held securely within a locked cupboard in my office. These would be destroyed following the completion of the research.

3.11.2 Student participants

Once the data collection phase had concluded with learning analytics experts and academic staff, I reflected on my study progression to date. Through my early observations I recognised that may of my research participants were reporting similar findings, so I made a conscious decision not to recruit more learning analytics experts or academic staff participants at this stage. I realised that finding students to participate could prove challenging. Through the data collection phase involving the analytics experts and academic staff, I had identified that some of the learning analytics tools used across HEIs were not student-facing and were accessible only by academic staff. Likewise, many of the institutions were at a project phase with learning analytics, with many systems in development and not yet being implemented. I reflected that this could limit access to student participants and could potentially pose major limitations on the research study. In an attempt to overcome this problem, I contacted academic staff from institutions that used student-facing learning analytics systems to request their support in recruiting student volunteers.

This resulted in academic staff from two different HEIs being asking for their support in inviting student participants to take part in my research study. Students nominated themselves through direct contact back to their tutors. Using similar criteria to the other research participants, student participants were selected on the basis of their familiarity with learning analytics and their experience of its use in supporting their own learning. I devised an e-mail for personal tutors to send to their tutees, inviting them to participate in the research (Appendix 6). This approach could have raised issues of coercion and either encourage students to participate to impress their personal tutors or encouraged students who had had a particularly bad experiences using learning analytics to come forward. Each personal tutor arranged for interviews to be conducted with students at their own institutions and provided a date, time and location for the focus groups to take place. This process provided me with three focus groups in which to conduct discussions. Selection for the focus groups is detailed in Table 3.5.

Table 3.5 Student participants allocated to each focus group.

Focus Group (FG) number (number of students in focus group)	**Institution**	**Year of Study**	**Subject studied**
FG 1 (2 students)	Institution 2	3	Health
FG 2 (4 students)	Institution 4	2	Business Studies
FG 3 (4 students)	Institution 2	3	Education

As the student research participants were scheduled to be interviewed over the Autumn, using first-years would not have been appropriate due to the short time that they would have been at university. First year students may not yet have been introduced to the learning analytics tool or may not have used it. Therefore, I purposefully selected students from their second and third years of study, as I wanted to ascertain when and how the learning analytics tool was implemented during their course of study, how effective they felt using learning analytics was, and also whether they felt that this was a suitable approach to support student learning and enable their success. During the focus group interviews, I found out that the students that I interviewed were high users of the learning analytics tool, but they also reported that many students chose not to use it. Some of these thoughts and observations have been included in the findings chapter (Chapter Five).

3.12 Data analysis

Analysis of qualitative data within educational research can take many forms, reflecting the particular kind of data being used and the particular purpose for which it is being studied (Denscombe, 2010). Denscombe (2010) believes that there is no single approach to the analysis of data, but that coding data should be regarded as an iterative, evolving process rather than a one-off event, as well as an inductive process arriving at generalised statements about the topic. He also recognises that analysis of the data is researcher-centred, with the values and experiences of the researcher being factors that influence analysis.

Qualitative data can be captured through different media, such as spoken or written words or visual images depending on the research methodology being followed (Bowling, 2009). As my research participants were interviewed, audio-recordings were taken to form the qualitative data for analysis. Each interview and focus group meeting was transcribed in its entirety, thus providing written words from which to distil the meanings of each discussion. The handwritten notes that were taken during each interview and focus group provided factual information and gave broad descriptive account to inform me how learning analytics was operationalised within each specific institution. As part of the transcription process, each participant interview was catalogued and indexed with a unique number. This allowed me to record participant information for reference purposes while maintaining anonymity of the participant and their data.

Saldana (2015) believes that a fundamental part of analysis is to code and annotate raw data to help support navigation through research findings. Adler and Adler (1987) believe that you need to consider your research position or lens when coding, as your level of personal involvement will filter how you perceive, document and code your data. Using an interpretivist approach to my research meant that I was immersed within the fieldwork and was an active participant within the data collection process as an insider to the research.

Basit (2003) attests that coding and analysis are not synonymous, though coding is a crucial part of analysis. Richards and Morse (2007, p. 137) further add that ‘coding is linking; it leads you from the data to the idea, and from the data pertaining to that idea’. On the other hand, Miles et al (2013) believe that coding is analysis, and state that most qualitative researchers will code their data both during and after data collection (Miles et al, 2013).

Saldana (2015) describes a code in qualitative research as a word or short phrase that symbolically assigns an attribute or a summative, salient, essence-capturing point for written data. Coding is seen as a method that enables a researcher to organise and group similarly coded data into categories that share the same characteristics (Saldana, 2015). Ranney et al (2018) suggest that most research projects increase rigor by using double-coding, with more than one researcher independently assigning pre-specified codes to the data. Once the coding structure becomes well defined, some research projects will proceed using a single coder for remaining transcripts, being sure to check in to avoid coder drift throughout the coding process. For this study, using multiple researchers was not an option, so data gathered from participant interviews was manually coded by myself to draw out key categories and sub-categories which aligned with the conceptual framework and to the research questions. An illustrative example taken from one of my participant interviews is shown in Fig 3.1. Table 3.6 provides an example to demonstrate how the codes, categories and the identification of a theme link together.

Fig. 3.1 Example of coding technique.

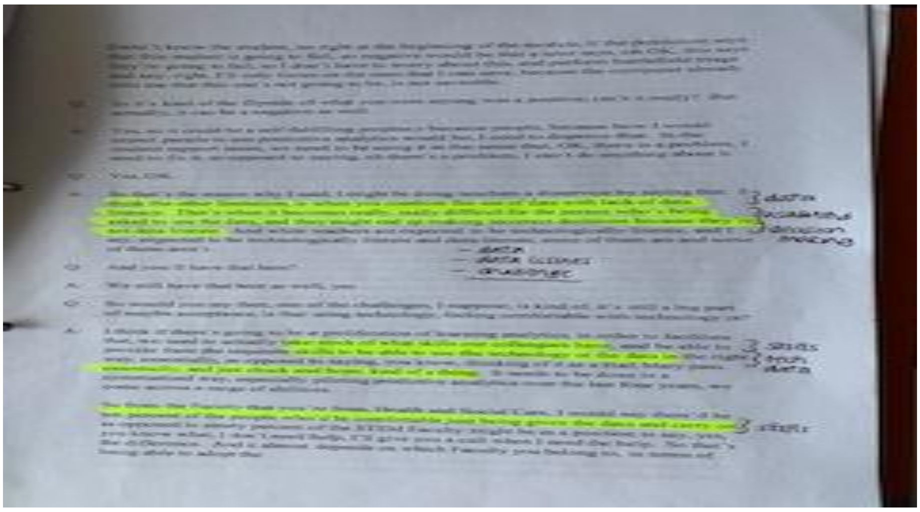


Table 3.6 Coding, categories and identification of themes.

Participant response	Code	Category	Theme
'analytics is useful to incentivise attendance and engagement on a course' (Participant Int 9, AS)	-Student engagement -Student attendance -Course belonging -Incentive -Reason -Direction -Monitoring -Assumption -Increasing chance of success	-Beneficial -Using data -Using learning analytics tool	Context and purpose

An alternative to using a manual coding process was to use computer-assisted qualitative data analysis software. Such software systems are the preferred approach as they are designed to ensure that qualitative data is organised and stored appropriately (Denscombe, 2010). Such systems also take advantage of the computers abilities to manage the storage, coding and retrieval of data (Denscombe, 2010). As a researcher with no previous experience of using computer-assisted qualitative data analysis software, I felt that the time required to learn how to use such software would be a significant limitation in completing the study. Besides this, as Denscombe (2010, p. 279) points out 'the researcher still needs to decide the codes and look for connections within the data' whether using a computerised or a manual approach to coding. Therefore, I made the decision that using a manual coding process was achievable as this was a small-scale study, and was indeed beneficial in that manually coding data would allow me to submerge myself within the data and formulate effective codes.

Saldana (2015) believes that coding requires meticulous attention to language and deep reflection on the emerging patterns and meanings. For my study, coding was done once, and then was undertaken for a second and third time to ensure that the codes and categories that emerged were coherent and reflective of participant responses, and would provide me with sufficient information to convey the lived experience of my research participants. Saldana (2015) feels that the second and subsequent cycles of coding further manage, filter and highlight the qualitative data record for generating categories, themes, concepts and the building of theory. Rubin and Rubin (2005) recommend that the contents of each category are refined (working within) from your data before they are compared with each other (working across). This allows for emerging categories to evolve as concepts rather than the codes becoming merely descriptive (Saldana, 2015).

3.13 Summary of the chapter

This chapter has identified the relationship between the purpose of the research, the research paradigm and the research approach and design to show how they align to create a coherent foundation for this study. The selection of an appropriate research methodology and data collection tools is discussed, and justification for the choices is provided. The processes used to carry out the data collection are outlined, along with information about the sample and participants. Finally, the data coding technique is discussed and the process of analysis is illustrated. This provides the context for the next chapter in which the key research findings are presented.

Chapter 4 Findings

4.1 Introduction to the chapter

This chapter reports the key research findings that were discovered following the data collection phase of my research study. Findings are presented thematically from the perspectives of the different key stakeholders identified within this study. Direct quotations gathered from participant interviews have been used throughout this chapter as they generated the thematic categories from which theory emerged. The subsequent chapter will provide a thematic discussion and critical analysis of the findings in relation to existing knowledge.

4.2 Findings from learning analytics experts

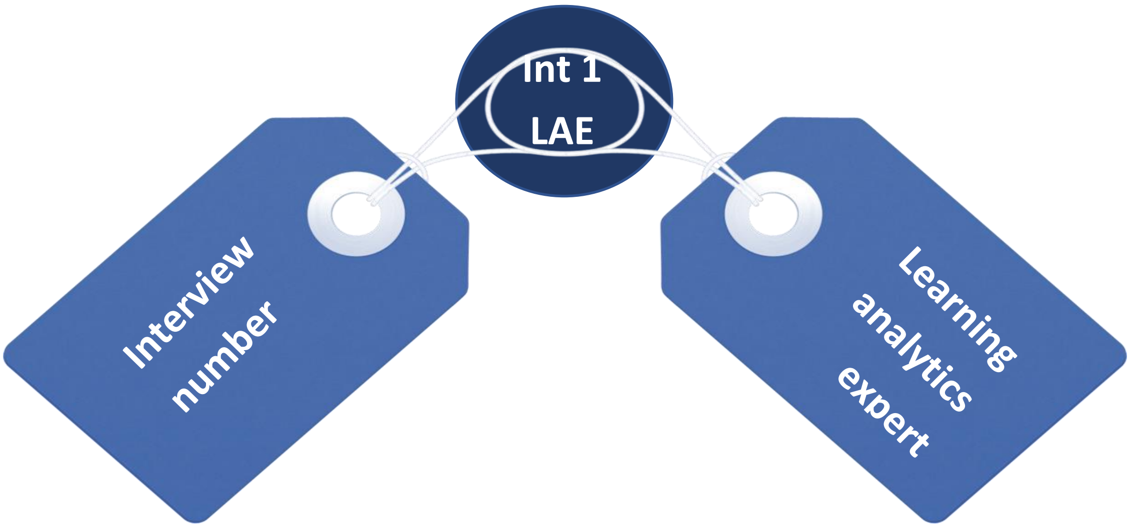
Six learning analytics experts participated in this study. Each participant was selected based upon their professional role in relation to the development of learning analytics, and their direct involvement with the development of learning analytics within the selected institution. Selected participants were a mix of commercial software developers, Project managers with the responsibility of implementing learning analytics within an organisation, and those from a technological background working within the HEI as learning technologists (rather than being from an academic background). Through coding the qualitative data gathered from research participant interviews, six broad but distinct themes were identified. These were: the context and purpose of learning analytics, the change process, role of the educator, student perspective, educational design considerations and finally disparities or 'gaps'

To add context to participant quotations, I have labelled each quote using a convention system. This is illustrated in Table 4.1. Figure 4.1 provides an illustration to demonstrate participant quote labelling and shows clearly how each participant can be identified.

Table 4.1 Descriptor abbreviations for direct quotes.

Label Item	
Int	Interview
FG	Focus group
LAE	Learning analytics expert
AS	Academic staff
St (*)	Student participant (number)

Fig. 4.1 Illustration of participant quotations labelling.



This example (Fig. 4.1), therefore, indicates that the quote was obtained from a participant at first interview and was with a learning analytics expert.

4.2.1 The context and purpose of learning analytics

One of the central aspects identified within my conceptual framework was the institution. From an institutional perspective, organisations need to consider a rationale for the development and implementation of learning analytics- which relates to the context and purpose of using it as a mechanism. All six participants identified a different combination of reasons for implementing learning analytics within their organisations which were explored. The six participants from all of the different institutions believed that learning analytics were beneficial and held a place within education. They felt that it ***'makes sense to use technology to be part of a system that could support students'*** (Int 1 LAE), but this view maybe reflected from these participants job roles which were intrinsically linked with either technology or as project managers for the development of learning analytics within each institution, and the commercial software developer. When questioned on the fundamental reasons for the institutional development and implementation of learning analytics; three out of the six research participants cited reasons which included student retention and student continuation, grade improvement or as part of a wider institutional strategy to support students. This seemed to be a common response from those participants from institutions which had recently implemented learning analytics within the last 18 months, and could potentially be linked to driving forward institutional improvements as a result of internal and external performance metrics. Participants did not reveal as to whether this was the case.

> ***'It was always about student support, it was always about retention, progression, helping our students to understand their engagement with the university…. It very much started out around supporting students for retention and progression.'***
>
> (Int 5 LAE)

One participant stated that one reason for the development of learning analytics was in response to ***'poor student retention within some areas of the institution'*** (Int 3 LAE). Again, within this institution the implementation of learning analytics was very recent in 2017/8. Another participant reported that in their experience as a commercial software provider, that many institutions:

> **'…had always struggled with demonstrating timely interventions and timely student support. Learning analytics enables us to see, very quickly whether a student is struggling, sometimes before they know that they are struggling themselves, and for us to initiate a conversation'.**
>
> (Int 1 LAE)

It was identified that this participant was a commercial software developer and, as such, could have a vested interest in developing learning analytics as an approach within the HEI. (Int 3 LAE) identified that the key driver for wider institutional implementation within their university was more broadly related to student support and improving support mechanisms, but had also alluded to poor student retention within their institution. This respondent believed that:

> ***'I wouldn't necessarily separate retention and support, because the provision of the right support helps with retention…. It's providing the right support for the students, with the intention being improving our retention, and improving progression.'***

(Int 3 LAE)

In contrast, another one of the participants felt that when considering the purpose of implementing learning analytics, it was their perception that there was a mix of drivers for their a HEI. This participant had experience as a commercial software developer, and has to date provided a manufactured software platform to 10 UK HEIs:

> ***'At the highest level, we are looking at core deliverables but more generally we are recognising the amount of data that we have and the ability to interrogate that is an important principle, and that drives the outcome.'***

(Int 1 LAE)

This participant recognised the influence at strategic level that the implementation of learning analytics can potentially have (Int 1 LAE), and there was a similarity from all institutions in this response. (Int 1 LAE) reported that there were pockets of poor retention and poor student progression within their university but suggested that ***'if we improve the retention slightly across our eight biggest courses, we would improve our league table positions and we would improve our financial position'.*** This participant emphasised that the financial costs for student losses were high and that:

> ***'every student lost is not just one year's fees lost but its three years potentially for an undergraduate degree'***

and

> ***'the financial aspect alone should make university leaders want to consider that if you provide students with support, it ultimately helps with student retention and eventually success.'***

(Int 1 LAE)

Although this response provides a financial rationale, rather than a pedagogical one, what was apparent through the interviews was that these participants working in HEIs were given no clear purpose or direction as to why learning analytics was being implemented within their organisation, despite the fact that five of the participants cited the use of learning analytics as an identified strategic priority. Although these participants believed that every institution's motivation for using learning analytics was different, what was evident was that the directive to employ this educational development appeared to be based on student retention, student progression and student support at a secondary level. All six respondents reported similarities across institutions, in that the driver to develop learning analytics within their institutions came from a strategic or senior level, which could be a financial rationale, rather than a pedagogic one, and as such, a potentially hidden agenda to learning analytics development. With the exception of two participating institutions, the implementation of learning analytics had occurred within 2017/8 so it very recent. This perceived 'directive' approach could potentially influence and affect the other factors identified in the data gathered from the learning analytics experts, such as how the change process occurred, and the perceived disparities of learning analytics use.

On an operational level, three out of the six participants highlighted that data allowed for a decision-making process to be made by academic staff, and that ***'learning analytics allows academic staff and personal tutors with another lens through which to view the student'*** (Int 3 LAE). This alluded to learning analytics being part of wider student support, rather than supporting students based on data alone. A second participant summarised this as ***'using data allowed for academics to make a decision based upon the data presented, and that data helped to support academic decision-making processes'*** (Int 2 LAE). All of the institutions included in this research had similar student numbers, with the exception of one (Institution 5) which was significantly larger. It was identified that there were very different ratios of staff to student numbers in terms of student support, which may reflect the variance in responses from participants noted above. The similarity from all six of these participants felt that learning analytics provided additional information about each individual student, in relation to what they already knew through developed staff-student relationships. Based on this perception (Int 1 LAE) believed that learning analytics ***'enabled personal tutors and wider academic staff to make a decision, as they are the person that knows the student best'*** Four out of the six research participants believed that this then pointed academic staff towards having a conversation with a student, with (Int 2 LAE) suggesting that ***'learning analytics provided staff with an opportunity and a reason to have a chat with a student'.*** (Int 1 LAE) reinforced this view and further added that ***'the positives of learning analytics allow for creating better connections between academic staff and their students'*** These four participants recognised that a general conversation as a starting point could direct honest conversations and discussion towards ***'retention, supporting grade improvement or to even encourage student withdrawal in some situations'*** (Int 4 LAE).

From an opposing perspective, using data to direct conversations with students was viewed as negative, with two out of the six research participants (Int 5 LAE) and (Int 6 LAE) reporting that academics may choose to ***'ignore conversations'*** if the analytics identified that a student may fail. Having positive conversations with students was cited as one of the beneficial elements and demonstrated the opportunities that learning analytics could provide- but it was identified that positivity was often inter-linked with the analytics tool used, and the decision-makers to have trust in the data being presented to them. One participant recognised that ***'there are negatives in the staff that don't use it for the purpose in which is intended - that is that the engagement rating is an indicator, but not the truth'*** (Int 1 LAE).

One research participant whose institution was the most developed in terms of learning analytics suggested that:

> ***'A good analytic package needs to allow you to have enough of a rounded understanding of the student to actually ask them, because it can open up a personal conversation…. This creates a different dynamic with the student and they're much more likely to turn around to you and go, do you know what, I'm really struggling with this thing here ….'***

(Int 2 LAE)

Participant responses were also around users needing to be data literate and competent in data use. Participants (Int 2 LAE and Int 6 LAE) felt that staff may make incorrect or ill-informed decisions if they were not data literate themselves, or even not use the learning analytics tool for this reason. Four out of the six participants felt that decisions and subsequent actions should not be data-driven, due to potential unreliability with the data presented. It was interesting that five out of the six participants reported poor institutional data management systems, with many system errors or difficulties in obtaining data. (Int 2 LAE) noted that ***'we have lots of different data but it's not in all in the same place'***. These five research participants felt that they had insufficient information stored within institutional management systems to make accurate analytic predictions, and as such reported that institutional roll out was problematic. This was particularly pertinent for Institution 1, which implemented learning analytics in 2017/8, but made a deliberate decision not to make the system student facing due to data inaccuracy. Participants from Institution 4 which had a staff and student facing learning analytics tool and which implemented learning analytics in the same academic year also recognised that data unreliability was an issue. (Int 6 LAE) believed that ***'the reliability of the data and of information causes concern from academic colleagues, which has made us hold off making learning analytics available to students'*** It was suggested that data issues or problems with data presentation strongly impacted upon the accuracy and reliability of the analytics platform or analytics tool used; these factors are considerations and potential challenges in the development and implementation of a learning analytics tool within an institution.

One research participant recognised that learning analytics was not a panacea, and that learning analytics only ***'provides the ability for an academic to make a decision to provide an intervention or instigate a conversation'*** (Int 1 LAE). The need for academic staff to take action and to make an intervention on the data presented was also raised by research participants (Int 1 LAE) and (Int 5 LAE); this links to the discussion in the disparities section of this chapter.

Of the six research participants, one from an institution that implemented learning analytics in 2017/8 stated that:

> ***'…selected student interventions were potentially linked to the notion of targeting resources and focusing and streamlining academic effort, ultimately to target students that were most in need before they reached crisis point.'***
>
> (Int 3 LAE)

Other research participants, (Int 4 LAE) and (Int 6 LAE), concurred with this perspective voiced by (Int 3 LAE), and also mentioned that their institutions were generally concerned with identifying and targeting specific students at risk of failure or dropout from university.

4.2.2 The change process

Learning analytics experts participating in this study (Int 2 LAE and Int 6 LAE) agreed that change was required, and that an effective change process was fundamental to successful implementation but more importantly for acceptance of learning analytics within the HEI. Applying my conceptual framework this relates to the institutional aspect and can be applied as an enabling or a challenging factor. Of the six research participants, one took the view that there is some general reticence from educational providers to purchasing commercially available learning analytics tools; this was suggested as being ***'largely due to the sense of analytics being an expensive resource that remains untested'*** (Int 2 LAE). This participant elaborated to say that there was ***'little evidence of the impact or effectiveness of learning analytics to date'***, which made some institutions cautious with a financial investment (Int 2 LAE). At the time that my research was conducted, in Summer 2018, there were limited evidence-based reviews focused on successful institutional implementation of learning analytics which could be a reason for this response. Three out of the six participants (Int 6 LAE, Int 4 LAE, Int 5 LAE) felt that their individual organisation had the capability and technical ability to build an individual organisational learning analytics tool, rather than buying in a commercial platform. Institutions 1, 3 and 5 had chosen to adopt this approach, but Institution 1 and 3 recognised that progress was delayed due to conflicting fiscal and time pressures in which to develop a suitable tool. Data reliability was also a cause for concern for these institutions. Despite this, all agreed that manufactured versions had a higher presentation standard although they were expensive. Adopting a user-friendly version with better presentation was considered more important if the student was also going to access the analytics tool. Staff and student facing learning analytics tools were in place in Institutions 2 and 4.

One research participant whose institution was the most developed in terms of learning analytics concluded that learning analytics provides:

> ***'an opportunity for institutions to be able to build on some good creativity within a learning context.'***
>
> (Int 2 LAE)

Participants appeared to hold differing epistemological positions regarding the concept of learning analytics, with this viewpoint being echoed from participants across all of the institutions. Two of the six participants (Int 4 LAE, Int 5 LAE) felt that more generally amongst the academic community there was limited knowledge about learning analytics, and there is still a sense of disbelief amongst academic staff that technology and artificial intelligence are now able to manipulate data and thus provide information that was once hidden. These research participants expressed the view that this may be the result of different experiences of HE, different job positions within the organisation or disciplinary background. Differing epistemological positions can affect the development and implementation process for embedding learning analytics within an organisation; three of the participants cited some strong resistance to change from both academic and professional services colleagues at the institutional development phase. Two of the participants (Int 1 LAE and Int 4 LAE) reported that staff wanted a ***'proof of concept'*** and more ***'rigorous testing before acceptance of analytics'*** could be reached. One of these participants (Int 4 LAE) were from institutions that had implemented learning analytics in 2017/8, with (Int 1 LAE) being the commercial software provider. Two other participants (Int

2 LAE and Int 6 LAE) linked acceptance of learning analytics with the need for '***data maturity and data reliability'*** before it could be embraced and embedded operationally within academia.

Three of the learning analytics expert participants (Int 1 LAE, Int 4 LAE, Int 6 LAE) felt that an influential factor for the successful implementation of learning analytics was how the change was introduced and embedded within an institution. Despite the fact that the move to use learning analytics was often mandated or informed by senior university staff and was viewed as a directive approach (as pointed out by five of the participants) two out of six participants (Int 4 LAE and Int 6 LAE) still felt strongly that the language used when helping academic and professional staff to understand and accept learning analytics had to be very carefully gauged.

All six learning analytics expert participants in my study identified that successful development and implementation was related to both having effective change and an open organisational culture, and that the move to using learning analytics as a mechanism needed to be viewed and treated as an organisational culture change programme. One participant (Int 1 LAE) believed that ***'learning analytics needs to sell itself… we have scenarios of a personal tutor using it and saying, I've used this, it's really good…and then the project team are invited to a school team meeting to talk about analytics'*** This participant believed that the best change approach within an organisation was when an academic said ***'this works really well and its helped me, and then other academics will follow. But it's a slow change in organisational culture'*** (Int 1 LAE). It is noted that this response came from a commercial software provider, so could be a slightly biased perspective. From other respondent's perceptions, it can be considered that there is a lack of academic acceptance. It was unclear as to whether this related to using learning analytics as a mechanism to support students, acceptance of using technology per se, or the academic acceptance of using technology (and data) to support student success. This perspective seems to refute suggestions identified within literature which support acceptance of learning analytics. It is noted that for 4 of the institutions, the development and implementation of learning analytics remains fairly new, and may not yet be fully understood or embraced.

The implementation of learning analytics was likened more broadly to implementing educational change. It is not known to what extent change is occurring within institutions as this may reflect the response provided. This research participant whose institution implemented learning analytics in 2017/8 more broadly summarised educational change this way:

> ***'There is a group of people who see change as an essential part of life, and it goes to the heart of individuals… there are those who embrace change and see that analytics allows organisations to unlock a platform for innovation, then there are the negatives. So, people feed on negativity and create an echo chamber that then becomes reality.'***

(Int 2 LAE)

This participant took the position that an effective institutional approach to change was essential. Triggers for success from that specific institution were noted to be ***'keeping the definition tight, keeping the project team small, and having a willing set of volunteers'*** (Int 2 LAE). This links to the philosophy of changing organisational culture through effective change agents using ***'volunteers as effective change agents to energise others'***. (Int 2 LAE). This has a ripple effect, creating impetus for the adoption of learner technology. Other research participants (Int 1 LAE, Int 6 LAE) concurred and suggested that a ***'slow burn change effect'*** (Int 1 LAE) was perceived as the most effective method to encourage change within their own institutions. This could be suggestive to be reflective of their own experiences to date. Research participants recognised that effective change agents were needed at operational level to demonstrate a ***'proof of concept approach [i.e. using an illustrative example of what the data is showing about a tutor's individual student] to encourage staff behaviour to use analytics and encouraging acceptance of it'*** (Int 1 LAE). All six of the participants indicated that the 'slow burn' approach needed to happen by convincing people one or two at a time, based on their own experiences within their institutions, although it is recognised that at strategic level, this would not be the preferred adoption approach.

It seems apparent that from the research participants interviewed as part of this case study that learning analytics has not been mandated, as and such, could be a perceived barrier to successful implementation. The implementation of learning analytics is quite recent within the majority of the participating institutions, and as such, may not be fully embedded across each organisation. One of the research participants summarised their perception and experiences as a commercial software developer as follows:

> ***'With the emergence of new technology, you have to change the way you work. And one of the difficulties in the academic community is, I've always done it this way, why do I need to change now? Because it's a slightly better way of doing it. So, embedding change from that perspective is more difficult because they are entrenched with ways of working which are already in place. You have to try the slow burn always to get the best results.'***

(Int 1 LAE)

All six of the learning analytics expert participants highlighted that effective change was one of the key challenges for the development and implementation of learning analytics within their own institutions, and this perspective was identified even when learning analytics had been implemented for a longer period of time. Linked to this was the recognition by all the participants that the slow burn approach to embedding change, by definition, takes time. Research participants (Int 1 LAE and Int 2 LAE) also pointed out that a clear approach and strategy needed to be adopted institutionally to promote successful implementation of learning analytics as an educational development within HE. Four of the participants believed that this was not always in place, notably for institutions 1,2, 3 and 4.

One of the participants from Institution 2 who implemented learning analytics in 2014/5 summarised using learning analytics as part of institutional change as follows:

> ***'Analytics is not the panacea, it's what you do with it that counts. And, until you know what you want to do with it institutionally, you might want to stay off from spending loads and loads of money, essentially because you can get loads of fancy systems off the shelf, but do they actually fit with what you need for?'***

(Int 5 LAE)

4.2.3 The role of the academic

Participants felt that the role of the academic (or educator) would change with the emergence of learning analytics into the educational arena. Academic staff were identified in my conceptual framework and can be either an enabling or a challenging factor. Two of the six participants (Int 3 LAE and Int 6 LAE) felt that analytics now provided the ability for academic staff to have a deeper, more holistic view of their students; a view that had perhaps not been seen possible previously as the only perspective gathered was from staff-student relationships which maybe variable. These participants (Int 3 LAE and Int 6 LAE) believed that the power of learning analytics came from the provision of a transparent balanced and 'un-biased' view of the student. Expert participants felt that this worked in theory, however they did not believe it always happened in fact, because they felt that there was sometimes bias towards some students. Two of the six participants (Int 3 LAE and Int 6 LAE) pointed out academic staff need to view the analytics tool, decide to contact a student, and also act based on that decision. With the slow burn change effect that most participants identified within institutions, this was not always happening effectively across all courses. Four of the six participants (Int 1 LAE, Int 3 LAE, Int 4 LAE and Int 6 LAE) believed that this was difficult to achieve as there were differing perceptions from academic staff, and they recognised that not all staff engaged with learning analytics as they did not understand the purpose or the need for it. One research participant from Institution 2 who implemented learning analytics in 2014/5 stated that:

> ***'…staff need to understand that it is about helping them to do their job better, and therefore, engaging with and using it.'***

(Int 5 LAE)

Two of the participants (Int 3 LAE and Int 5 LAE) found that there was better engagement with the adoption and use of analytics from some academic disciplines compared with others. The engagement split appeared to be linked to professional background and was found at school or faculty level. Two other participants (Int 1 LAE and Int 6 LAE) supported this view, in that they conveyed that teams from Health and Social Care appeared to be more comfortable with using the data and showed initial interest and acceptance in using learning analytics tools in comparison to other academic staff from other academic disciplines. These two participants could not identify a specific reason for this, but anecdotally suggested that this may be due to these staff groups being more used to using data than other academic disciplines. Interestingly, one participant (Int 1 LAE) cited that academic staff from a technology background appeared more hesitant in engaging with new systems and ways of working. This perception could not be substantiated as there was a different mix of academic disciplines from each of the different organisations participating in this study.

The learning analytic expert participants (Int 1 LAE and Int 6 LAE) could not specifically identify whether decreased engagement in using learning analytics was the result of a lack of skills (and feeling comfortable with using technology as a decision-making process) or whether this was linked to overall acceptance of using learning analytics as a mechanism for student success. Five of the six participants interviewed felt strongly that there was a need to address a (potential) skills gap and develop staff to use the technology and data in the right way.

An interesting observation made by two of the expert participants (Int 2 LAE and Int 3 LAE) concerned the inclusion of professional services colleagues as part of the decision-making process when considering contacting students. One expert (Int 2 LAE) reported that within the majority of organisations each school had an administrative team, and ***'they have responsibility for looking at the engagement rating and the trends on the cohort. They then provide leads to the personal tutors or course leaders to say these students might be at risk'*** These two participants identified that it was professional services colleagues within their own organisations who were prompting academic staff when student engagement was low. One of the expert participants whose institution had implemented learning analytics in 2017/8 stated that:

> ***'It would be quite interesting to see if that worked or if it was more developed, because actually then it would perhaps take those academics who were reluctant to use it, to have a peep and see what it was all about.'***

(Int 3 LAE)

Two of the participants (Int 1 LAE and Int 3 LAE) believed that academic staffs' reluctance to engage with learning analytics was linked both to increasing academic accountability and to perceived activity monitoring of academic staff. Two of the participants (Int 3 LAE and LAE 5) felt that academic staff were still sceptical about the use of learning analytics as it had the potential to redefine and change the academic role. These observations were mirrored from participating institutions that had both new and established learning analytics tools in place. Anecdotal reports from three out of the five participants (Int 5 LAE, Int 7 AS, Int 12 AS) indicated that reluctance to engage with analytics systems came from the fact that staff felt that they were being monitored, and hence their academic autonomy was being altered and potentially lost. This will be further explored within the academic staff interviews.

4.2.4 Improving educational design and educational outcomes

Students were identified as a central aspect and surrounded learning analytics in my conceptual framework. This singular aspect can be identified to have enabling or challenging factors. Participants (Int 1 LAE, Int 2 LAE and Int 6 LAE) mentioned that the implementation of learning analytics allowed a move to a proactive rather than reactive approach to supporting student success and also to improved educational design. One participant (Int 1 LAE) suggested that this was linked to having course and module information readily available- thus giving educators the ability to make changes to their modules or courses in real time if student engagement was poor.

Improving educational design was illustrated by another research participant whose institution had implemented learning analytics in 2017/8 saw it this way:

> ***'You are not waiting for a module evaluation before you are understanding that students are not engaging with the course material. We can see how well (or not) resources are being used, and we can understand what is working and what's not working around that.'***

(Int 3 LAE)

Participants Int 3 LAE and Int 5 LAE agreed, and suggested that learning analytics could easily aid both module and course development, as it allowed academics the ability to measure instantly the impact of learning materials provided, and also to identify how positively a module or course was being received by students. Int 1 LAE concurred with the opinions of other participants above, and summed up this benefit as an enabling factor for learning analytics as ***'We can easily understand what is working for students and what's not'.*** Academics were also able to see what course materials were being accessed by their students so would be well placed to make changes if it is was felt that the materials were not effective. Participant Int 3 LAE felt that this approach was beneficial as prior to the implementation of learning analytics staff would need to wait for the end of module or course evaluation to ascertain how effective the learning materials had been.

4.2.5. Disparities

Three learning analytic expert participants (Int 1 LAE, Int 4 LAE and Int 6 LAE) agreed that there were fundamental disparities or 'gaps' in the development and implementation of learning analytics within individual organisations. Using my conceptual framework as a basis, this can be seen as a challenge in all the aspects of the model, i.e. learning analytics, students, academic staff and the institution. Some of the disparities have already been identified - the fundamental problem of a lack of breadth of information available within institutional data systems to support effective predictive analytics was identified by all of the institutional experts interviewed. This is clearly one of the fundamental challenges when attempting to develop and implement learning analytics within an institution. Without accurate data and therefore accurate predictions about students, one participant suggested, there may be ***'further reluctance from academic staff to engage and see the potential benefits that learning analytics has to offer'*** (Int 3 LAE). Three of the six participants perceived that many academic staff had a ***'technical skills gap'*** which needed addressing prior to the implementation of learning analytics so that academics could effectively use the learning analytics tool. It is considered that this aspect can be easily overcome through the provision of staff training prior to implementation. It was apparent that there was a strong presumption at the start of development of the learning analytics initiative that academic staff would be able to use and interpret data presented; in reality, this may not be the case, and there maybe additional staff training requirements needed.

Possibly the most important challenge identified by participants (Int 1 LAE, Int 3 LAE) was a gap identified in 'loop closing' at operational level. Participants Int 1 LAE and Int 3 LAE identified that while the use of learning analytics was reliant on the academic or professional services staff to use data, make a decision to approach a student and implement an intervention, there was also a need thereafter to evaluate that intervention and assess what difference the entire process had made. Evidence presents the need for academics to take- action, but this goes against suggestions made by learning analytics expert participants who believe that this may be a potential framework gap in operationalising learning analytics within institutions. This concept was summarised by one of the research participants whose institution implemented learning analytics in 2014/5 and who recognised that:

> ***'There is a reliance on academic staff to 'do something', a student remains your responsibility.'***

(Int 5 LAE)

Two of the participants (Int 2 LAE and Int 5 LAE) indicated that they felt that staff were still not using the data available to them to its full advantage; this viewpoint was made from both institutions that had new and established learning analytics tools in place. Although the learning analytics would identify to staff that there was an area of concern about a student or students, these participants felt that staff needed to intervene, and that those interventions needed to be documented as additional data and also elsewhere (such as student records). Evidence of impact using learning analytics as a singular mechanism would only be seen in terms of improvement to a student's engagement score. Participants Int 3 LAE and Int 5 LAE felt that isolated information gathered from just using learning analytics may not be the best approach to measure the effectiveness of academic staff interventions, and this linked back to earlier discussions about how learning analytics are only one lens through which to see a student.

4.3 Findings from academic staff

A total of six academic staff participated in this study. Each participant was selected based upon their direct actual experience of using an learning analytics tool. Academic staff interviewed had a range of academic experience ranging from 5 years (participant 12) to over 25 years (participant 9). All those interviewed have had extensive teaching experience, and from casual conversations with them, appeared dedicated to providing effective student support, and seeing this as a central aspect to their academic role. Participant 10 came from the institution that was most developed in terms of using learning analytics, and was clearly an advocate of this approach. All of the other participants had had no direct experience of using learning analytics prior to their institutional implementation. The exception to this is participant 12 who was new to the institution, and although learning analytics was established within this institution (institution 2) they had not used the tool prior to joining the university 12 months before. Through coding the qualitative data gathered from these participant's interviews, three broad themes were identified. Broad themes were identified in relation to the context and purpose of learning analytics, students and the role of the academic. Two of these themes- the context and purpose of learning analytics and the role of the academic were parallel themes to those gathered from the learning analytics expert participants.

4.3.1 Context and purpose of learning analytics

Applying my conceptual framework to these findings it is identified that the context and purpose of learning analytics relates to all of the aspects (learning analytics, students, staff and the institution) and can be either an enabling or a challenging factor. All six of the academic staff research participants had a general awareness of the context and the purpose of learning analytics within their own institutions.

One participant an experienced academic of ten years, and whose institution implemented learning analytics in 2017/8 recognised that:

'Its early days for the learning analytics thing. We are still trying to understand what does what and we are still working on that… We used Blackboard analytics for a time but that didn't work, so we went to a commercial provider which has provided a more user- friendly dashboard… What we have never done is to provide anything student facing.…'

(Int 8 AS)

A second participant whose institution also implemented learning analytics in 2017/8 and who has been a member of academic staff for over 20 years recognised that there was an overarching need for learning analytics and suggested that it was:

'…essential, and I think if we don't do it, we're doing our students a disservice'

(Int 9 AS)

Three of the six academic staff participants (Int 7 AS, Int 8 AS, Int 9 AS) all came from institutions that had implemented learning analytics in 2017/8 and strongly believed that learning analytics could not be used in isolation and that their use needed to be integrated clearly with other student support systems (such as personal tutoring) to provide the most effective approach to improving the student experience and ensuring student success.

Participant (Int 7 AS) has been an academic member of staff for 15 years, and believed that:

'learning analytics needs to be part of a package of student support. We are never going to know what the student does outside of university, or even what they are looking for on-line, so as a package it's good to have the data and information'

(Int 7 AS)

Participant (Int 8 AS) who has been an academic for 10 years stated:

'You can't just use it on its own, and our learning analytics system wasn't sold like this, it was supposed to help personal tutors… I feel it needs integrating with everything else from face to face tutoring to putting things on line to build up a picture of the student.'

(Int 8 AS)

This alludes to the findings from the learning analytics expert participants who believed that learning analytics should not be used in isolation, and can be used to support academic decision making. This research participant felt that despite their institution only adopting learning analytics in 2017/8 that learning analytics' use was linked to a clear purpose (i.e. to help personal tutors support students) and that a clear institutional steer was provided when the learning analytics system was initially implemented. This participant noted that the implementation was mandated by senior staff within the institution, for reasons that were not communicated, but acknowledged that acceptance among academic staff was not commonplace across the university, and that some academics did not support the implementation of learning analytics, as they felt that it went against their professional beliefs and values and increased academic accountability.

This participant who has had 10 years' experience within academia also stated:

> ***'As a package it's good to have that data and information, in a modern world we can't really not have some sort of system, we have the data and while we have technology, we should use it as well.'***

(Int 8 AS)

Another participant (Int 9 AS) who was the most experienced academic that participated in my research summarised the purpose of learning analytics from a personal academic perspective as being dependent upon the academic's role (i.e. whether they were supporting student success as a personal tutor, module leader or course leader capacity). This participant suggested that this changed the lens through which analytics was viewed. (Int 9 AS) believed that as a module leader, it was apparent that ***'analytics is useful to incentivise attendance and engagement on the course'*** and that it ***'could support pedagogic development through tracking virtual learning environments to see materials that students were viewing and using within courses'.*** Participant In 9 AS went on to say that as a course leader, the use of learning analytics needed to be different and ***'focused on the peaks and troughs of student engagement, to see if there are any areas of concern. As a course leader you are looking at student retention as an overall picture of course performance'***

This participant summed up the use of learning analytics in this way:

> ***'Everyone has a different need. Not everyone wants the same thing and not everyone wants the same thing in the same way. To have an institution provide a top down set of parameters around the information you are going to have is nonsensical. If people can't***

> ***identify with the bits that they need, they will disengage pretty quickly, and then be quick to say its rubbish.'***

(Int 9 AS)

These findings show that for the academic staff participants interviewed, the need for learning analytics was clear from a personal perspective, however precise institutional direction for using and implementing learning analytics was not necessarily apparent. This participant believed that the reasons for implementation were multi-faceted, but suggested links to student retention and continuation. One of the six research participants stated specifically that within their institution there were no parameters set to use learning analytics and that ***'we did not have a coherent strategy for it'*** (Int 12 AS), which they felt could lead to staff and student resistance in adopting learning analytics as a mechanism. Another participant (Int 10 AS) identified a ***'lack of academic ownership'*** within their own institution, despite this institution using learning analytics for the longest period of time out of all of the participating institutions. This belief concurs with the findings of institutions that are developing learning analytics more recently, with participants commenting that there is a lack of purpose and a lack of direction for their use.

While academic staff participants had mixed views regarding the 'real' purpose of implementing learning analytics, they were clear on their own epistemological position. Four of the six academic staff participants (Int 8 AS, Int 9 AS, Int 10 AS, Int 12 AS) felt that broadly the drive and implementation of learning analytics within education was a positive way forward, the other two research participants felt that this approach shouldn't be forced- the other two participants felt that this approach shouldn't be forced, and those who wanted to use it should (Int 7 AS, Int 11 AS). This could potentially create inequalities from a student experience perspective, but also indicated to me as a researcher that there is potentially some institutional resistance and some hesitance in adopting and driving forward learning analytics as a mechanism to support student success. For one participant (Int 7), the implementation felt like a ***'dictated mechanical process to push academic and student relationships, rather than developing the culture of student support to inform student success'***.

Another research participant (Int 10 AS) observed:

> ***'We paid those [academic staff] to train to use analytics, we paid for a de-briefing, and I piloted it with a small group of tutors in advance. Out of two hundred tutors, around eight engaged with it. This should have been a scandal. And the fact that no one in the academic staff were troubled by this.'***

(Int 10 AS)

This observation questions the value of implementing learning analytics if it is not to be adopted by academic staff, considering the financial investment and perceived strategic need. The statement raises other issues which relate to having an effective change process and the organisational culture which was raised by learning analytics experts' participants. This participant went on discuss their institution's approach and explained that a senior manager had discussed with staff that ***'analytics are to be used in an "opt in" fashion'*** (Int 10 AS) which gave academic staff a signal that they had no obligation to use it, although the institutional driver for implementation of learning analytics was based on student performance and student retention. An optional approach to using analytics calls into question its purpose and a challenge in getting it adopted, especially considering that this particular institution has implemented learning analytics for the longest period of time.

This participant further noted:

> ***'My perception is that learning analytics is a hugely powerful tool that is not taken up by frontline staff, as they don't understand the value of it. The pressure to get tutors to use analytics is remarkable.'***

(Int 10 AS)

This is evidently a strong statement to make, but it was noted that academic staff participants provided similar responses to the expert participants when questioned about resistance to change; but the notion of power and a power shift was also raised as part of this discussion. As observed by the learning analytics experts, some academic staff participants (Int 10 AS, Int 11 AS) felt that resistance to change was linked to academic culture and academic autonomy. One participant (Int 7 AS) who had been in academia for 15 years felt that academics ***'like to deconstruct every practice and talk about why they***

shouldn't do it' One of the academic staff participants (Int 9 AS) felt that learning analytics allowed ***'the computer to make a decision'*** and suggested that analytics gave 'power' to both the institution and the member of academic staff, rather than there being an equal relationship between staff and students. Two of the research participants (Int 7 AS, Int 9 AS) felt that this promoted an organisational culture shift and changed the power dynamics between academic staff and the student.

> ***'it's too easy to make assumptions from analytics, and it's too easy to read into things that isn't there because that's what happens with statistics, you know, you really need to interpret them and make sense of them in certain ways.'***
>
> (Int 7 AS)

This statement also alludes to the perception from both learning analytics experts and academic staff that learning analytics should not be used in isolation, but in conjunction with other methods and systems of student support. Two of the six academic staff participants (Int 7 AS, Int 12 AS), who held distinct differences in terms of their time within academia, yet felt that organisationally we were creating a student culture of dependency and a culture of institutional and academic staff power which may be contributing factors to academic resistance. One participant (Int 7 AS) who has been an academic for 15 years believes that ***'It's all about university standards I know, but it's a game the university is playing to formulate an appearance'***. This participants perception was that learning analytics was moving education to a **'product thing'** but although they strongly recognised that a university now has more of a business focused approach, and that universities ***'have things to prove to people, or that they need to prove things in a logical, formal way'*** (Int 7 AS). From an academic perspective, this participant felt that ***'the more we transfer power to the lecturer…there's always the risk it just becomes about ticking boxes and outcomes rather than about student experience'*** (Int 7 AS). This again was a strong statement to make, but could be reflective of the amount of time spent within the academic setting.

4.3.2 The role of the academic

The role of the academic was identified by all the participants (regardless of their level of academic experience) to be one of the key areas that challenged the concept of using learning analytics. Two of the academic staff research participants (Int 9 AS, Int 11 AS) identified that there was some change to their role with the implementation of analytics; this can either be linked to the notion of embracing analytics and seeing this approach as an opportunity, -or to seeing it as something negative, and therefore as a challenge. A third participant identified that it didn't change their role but ***'it re-affirmed what I thought I already knew'*** (Int 8 AS). This participant was an experienced academic member of staff, and prided themselves on the close relationships that they held with their students. This participant felt that academic staff need to think about ***'how it can help the personal tutor's role',*** rather than hold a negative perception. Three of the six participants (Int 7 As, Int 8 AS, Int 10 AS) that had over 40 years of experience between them within HE felt that academic and student relationship dynamics changed when analytics was used.

One of these participants summed up the changing staff student relationship in this way:

> ***'I believe that the relationship between the lecturer and the student should be as equal as you can get it… when I look at analytics, I kind of get this straight serious adult/child look about it.'***

(Int 7 AS)

Two of the participants (Int 7 AS, Int 11 AS) felt that analytics forced a mechanical process to drive the academic and student relationship and forced power onto the academic. Another had the view that ***'the role of the academic should be about building adult relationships so that people can come and talk to you as equals and treated as an adult'*** (Int 12 AS). Another participant who has had 15 years' experience within academia emphasised that in this relationship the focus should be on the student as ***'this is their degree, this is their time to learn, this is their time to take responsibility, before they go out to work'*** (Int 7 AS). In contrast, other participants felt that analytics provided the opportunity for a more nurturing approach by opening up conversations with students.

This participant believes that learning analytics can be used:

> ***'…as a fuel for discussion. So, if they hadn't been to the library or looked at any information, it gave me the ability to say, have you looked at databases for this assignment… I could tailor what I said to the student by looking at the dashboard.'***
>
> (Int 8 AS)

This approach promoted independent learning, ***'by nudging them, meeting what they need to do'*** (Int 10 AS). It might be suggested that the student would need to be able to view the dashboard themselves in order to promote independence in their learning; from the participant responses from my study it can be concluded that this did not happen broadly across the sector. Notably, only two institutions included in this study had student-facing learning analytics systems. As identified by Int 1 LAE student-facing learning analytics systems were not widely used because of data availability and reliability. It might be suggested that institutions are fearful of incorrect data being visible to students. Whether respondents felt that learning analytics promoted dependence or independence in learning, half of the academic staff participants agreed that it was ***'the student's learning experience, and they should be in charge of it'*** (Int 7 AS, Int 8 AS, Int 11 AS). This perception could necessitate the need for learning analytics tools to be made available for students to access.

Two of the six academic staff participants (Int 8 AS, Int 12 AS) agreed that learning analytics could not be used in isolation and ***'should be used as part of a broader package of student support'*** (Int 12 AS) to enable student success. Some of the learning analytics expert's participants agreed with this view; recognising that embedding learning analytics into existing models of student support (such as personal tutoring) would be beneficial. Additionally, Int 10 AS and Int 12 AS felt that to avoid resistance, learning analytics needed to be framed positively to keep the human perspective when implementing it into HE. They felt that this would encourage wider staff and student adoption. This response made me reflect on my previous experiences when piloting learning analytics within my own institution, and the recognition that there were mixed opinions regarding its place and use within HE. From an operational perspective, there was recognition that academic staff ***'need to be careful to interpret analytics and not to have a knee jerk response to it'*** (Int 10 AS), and this observation to me emphasised the need not to rely on what the analytics are saying in isolation. One participant (Int 7 AS) believed that ***'analytics give us the perception of awareness but not the actual awareness. It's too easy to read things into them that aren't there… You need to interpret them and make sense of them in certain ways and then speak to the student'.*** Another participant-Int 12 AS- held the view that learning analytics were able to ***'support learner independence as well as academic decision-making'*** through the provision of a rounded approach to supporting students.

Academic staff participants Int 10 AS and Int 11 AS both recognised that decision-making was still needed despite using learning analytics. Their perception was that data alone was not a sufficient basis to decide an approach to take with a student. One of these participants stated, for instance, ***'you can gather as much information, but you still have to make a decision. It's decision-making that's hard. What people tend to do is displace attention on the data'*** (Int 10 AS)*.* This participant was an experienced member of academic staff, whose institution had used learning analytics for the longest. What is interesting about this perception is that this participant had already identified that not all academic staff used learning analytics, but it seemed that this participants experience was suggestive of a reliance on data by those users who advocated learning analytics use. Decision-making was raised as a fundamental challenge by academic staff within the context of providing effective student support. This viewpoint was not raised by learning analytics expert participants, but this may be suggestive of differences in job roles. Five of the academic staff participants indicated that some academic staff within their institutions were reluctant to make decisions based on the presented data, while, in contrast, some academic staff relied on presented data to make their decision before contacting their students. This data reliance issue means that academic staff are waiting for a dip in student engagement scores or for negative aspects to show up in the data before they respond, rather than using data to take pro-active steps. This was summed up by one participant who believed that ***'there is a need for academic staff to be pro-active to situations that are presented'*** (Int 12 AS). Notably, this participant was new to using learning analytics at their institution, but obviously recognised the importance of it as an approach to supporting students to succeed. A second research participant believed that using learning analytics in isolation ***'can make***

analytics negative and give them a public image problem' (Int 10 AS). Again, this participant was from the institution that had used learning analytics for the longest period of time. These findings show that there is still the need for academic staff to make sense of the analytics, decide what to do, and take-action based on that decision, which is potentially challenging for academic staff.

A further challenge for the effective introduction and development of learning analytics is the issue of academic accountability. Two of the six academic staff participants (Int 8 AS, Int 11 AS)- one of which was experienced, and the other being in academia for approx. 5 years felt that the implementation of learning analytics increased their academic accountability but were unsure of the place learning analytics held in relation to individual, module or course performance monitoring. One participant stated: ***'with analytics we can act on performance sooner… and a module that is not performing should be asked to address it'*** (Int 10 AS). Analytics present statistical information that has not been previously available, and this raises questions from academic staff about their use and the direction that the institution is heading in terms of monitoring individual staff performance. All six of the academic staff participants interviewed were unclear about whether learning analytics was being used to increase their accountability or ultimately to monitor their performance as an academic. One participant clearly stated that ***'it is not a disciplinary tool, it is an enabling tool, and the university needs to frame it clearly as that'*** (Int 12 AS). This may show a reason for reticence from some academic staff to use learning analytics. Another participant spoke about module performance specifically, saying that ***'we still respect academic autonomy, but academics are the autonomous and accountable agent in this, and we need to work together to sort it out'*** (Int 10 AS). This viewpoint was related back to the purpose of analytics, with the strategic direction needing to be clear that ***'analytics is part of the job',*** (Int 10 AS) and staff need to be empowered to embrace it as a concept.

4.3.3 Students

Academic staff participants in this study linked the use of learning analytics to students and recognised that one of the key enabling factors of learning analytics in relation to students is that ***'it is useful to use as a bit of a stick to incentivise student attendance and engagement on the course'*** (Int 9 AS). Four of the six academic staff participants (Int 7 AS, Int 9 AS, Int 10 AS, Int 11 AS) who had a high level of academic experience across the different institutions agreed that poor classroom attendance was a common issue across institutions, but the majority of research participants interviewed appeared to separate student attendance from student engagement and felt that the two areas should not be linked together (Int 7 AS, Int 8 AS, Int 11 AS, Int 12 AS). This is a wider debate within the HE context, and one that still hasn't been entirely clarified at operational level.

One participant noted that:

> '***We have dabbled with analytics in areas like student attendance, but we have just introduced different systems that captures all of our virtual data about student engagement. Understanding the student body using all of this information is something that we are very new at.'***
>
> (Int 9 AS)

This perception exemplifies the different positions and stages of development that different institutions are at. It also re-enforces learning analytics expert's perspectives in relation to poor data reliability and accessibility. It is interesting to note that two of the institutions who participated in the study (institution 2 and 4) did not include attendance as part of the learning analytics tool due to poor attendance data quality. On a positive side, academic staff research participants felt that learning analytics was useful in relation to improving the student experience and supporting students to succeed in terms of curriculum design and development, rather than with a focus on student retention and continuation. One of the participants believed that learning analytics enabled academic staff to ***'look at which learning tools are being used or not used by students on our virtual learning environment'*** (Int 8 AS). This was considered a useful aspect in supporting academics to develop their teaching pedagogies to help to develop a positive student experience. One other participant stated: ***'I am interested in what is happening in the curriculum, what's the experience for the student so that we can have immediate impact'*** (Int 12 AS). This viewpoint was linked to the opportunities that learning analytics provided in making available real-time data and information about course and individual student performance. All six of the academic staff participants recognised that prior to the implementation of learning analytics information was gathered from different sources and through end of module and course evaluations. As end of module or course evaluations are only useful for the next cohort of students and not the current cohort, this was perceived to be a reactive rather than proactive approach to curriculum development. It was also judged to be a significant barrier to ensuring student success as ***'the formats we got information back weren't accessible and not easily understandable, so we couldn't use them as part of a bigger picture'*** (Int 9 AS). Participants agreed that the implementation of learning analytics mechanisms allowed academic staff to have all of the required information about a student in one place (i.e. being able to see what learning materials students have accessed and how many times they have accessed materials), and this was seen as an enabling characteristic for learning analytics use.

Two of the participants (Int 8 AS, Int 9 AS) specifically identified that the factors which make learning analytics as an enabling mechanism related to improving the level of student support to enhance a student's chances of succeeding at university, and the promotion of independent learning for students. These perceptions were also alluded to by learning analytics expert participants. For those institutions that used student-facing learning analytics tools, participants interviewed stated that the tool was not always viewed by students alongside staff or discussed as part of face-to-face discussions with academic staff and personal tutors. Academic staff participants (Int 8 AS, Int 10 AS) felt that learning analytics were generally an acceptable mechanism to support students, and that their use raised awareness of a student's situation so that an academic could offer a student additional support.

One participant felt that analytics gave the perception of supporting students rather than actually doing so. This participant explained:

> ***'I'm not particularly positive of using learning analytics in terms of supporting learning, but in talking about the student experience, in the perception that I am being supported and we [personal tutors] are supporting then I can see the point of them.'***

(Int 7 AS)

Academic staff participants' opinions as to whether analytics promoted dependence or independence in learning was mixed-and it was noted that this participant response was derived from a colleague working in Education Studies, and who held a research interest in student motivation and learning theory. All six of the academic staff participants felt strongly that as adult learners, students needed to take responsibility for their learning. One participant expressed this as follows: ***'I want to let the student take some responsibility for their own learning, and when they fail; I want to have a reflective conversation with them about why'*** (Int 9 AS). Another of the academic staff research participants recognised that ***'by the time students leave university they are twenty-one at least: if they don't have a level of responsibility for themselves and are independent learners, we have done them a disservice'*** (Int 7 AS). Two of the participants (Int 7 AS and Int 9 AS) that used student facing learning analytics tools felt that this approach was a factor enabling students to take responsibility for their learning; However, Int 9 AS recognised that not all students chose to use the analytics tool which purported to show their level of engagement, or to take action based on the information presented to them. (Int 7 AS) identified that they remained cautiously about the widespread implementation of learning analytics across their institution, and was not entirely positive about its use.

Academic staff participants (Int 9 AS and Int 10 AS) recognised that some students chose not to use or infrequently use the learning analytics tool within their institution, and it was clear that practice varied. This will be addressed within the student participation section of these findings to see if student's perceptions are similar. Some of the variance in my study data about this aspect is related to the fact that not all institutions were using a student-facing learning analytics tool, (research participants Int 7 AS and Int 12 AS used a student facing learning analytics system; whereas the others did not). Implications of this may indicate disparity of practices in relation to learning analytics use within HE, and questioning importance and need to implement learning analytics as an approach to support student success. One academic participant whose learning analytics tool was available to students shared *that* ***'when I launched it to my students, they were fine and took it with a positive stance. They had made their pre-judgement about analytics'*** (Int 7 AS). This participant did not elaborate to say whether their students continued to engage with analytics after its launch. Another participant (Int 12 AS) who was also aware of launching learning analytics to students had some concerns about its use, which they expressed as: ***'I don't know whether they think it was big brother-ish, I don't know'*** (Int 12 AS). This response may be in part due to their relatively new experience in using learning analytics as a new member of academic staff within the institution. Participant (Int7 AS) was from an institution that had implemented learning analytics in 2017/8; whereas the institution that (Int 12 AS) was from had implemented learning analytics in 2014/5. This observation can be suggestive of the need to clearly explain the learning analytics tool to students to support student engagement with it. The area of student reaction and continuing views may be a potentially fruitful area for exploration as part of the student participant interview process.

4.4 Findings from student focus groups

A total of 10 students participated in this study. Each participant was selected based upon their previous experience of having access to a learning analytics tool as part of their studies. I purposefully selected students from their second and third years of study, as I wanted to ascertain when and how the learning analytics tool was implemented during their course of study, how effective they felt using learning analytics was, and also whether they felt that this was a suitable approach to support student learning and enable their success. I recognised that the student participants that agreed to support my research were high users of the learning analytics tool, and appeared to be very engaged students. As students were invited to participate in my research through their personal tutors, it would seem typical that engaged students would be those who would be more likely to respond to such a request and take part in the research. As mentioned in the methodology chapter (Chapter Three), I made a conscious decision to conduct student focus groups rather than to use interviews as the data collection method, as I felt that a focus-group would help students to feel more at ease in answering my questions, and it would be less intimidating than participating in one-to-one interviews. Through coding qualitative data gathered from participant focus groups, four broad themes were identified. It should be noted that findings presented from the students provided limited breadth of responses in comparison to the other research participants interviewed, in some part because at those institutions where there was no student-facing learning analytics tool, the students would not have any knowledge or experience of the concept so could not be included as part of my study. It would be interesting to explore student perceptions and experiences on a wider scale to see if my findings could be more generalisable to the student population.

4.4.1 Purpose of Learning Analytics

Students were identified as one aspect of my conceptual framework, and there would be enabling or challenging factors in relation to this identified area. Similarly, to the other participants interviewed in this study, students were not clear about the purpose of implementing learning analytics within their institution, and this can be seen as one of the key challenges to implementing this approach. In all three of the focus groups, students knew that an analytics system had been implemented and they had been aware of it since the beginning of their courses but felt that it was not well promoted. A student from FG 1 (St 1) for instance stated that '***we were not introduced or guided on how to use the learning analytics tool, we just got on with it'***, and upon further probing it was apparent that there was no institutional launch to promote the learning analytics tool for new students. This institution implemented learning analytics in 2014/5, and academic staff participants reported that it was launched to students, so it seems that there is a disparity in responses between the two participant groups. Another student in FG 1 (St 2) reported similar experiences and did not seem to have been guided nor encouraged to use the learning analytics tool by course leaders as part of induction into their educational experience. One student participant from FG 1 (St 1) believed that the use of ***'learning analytics appeared to be instigated by silos of academic staff working within the capacity as a student's personal tutor'*** rather than believing that it was part of a wider institutional perspective. Based on this perception, it may be the considered that individual academic staff are the advocates of learning analytics and choose to launch it to their students rather than the launch coming from course, faculty or institutional level.

This contradicts the view that the development and implementation of learning analytics is strategically top down driven, but seemingly it can be suggested that operationally using learning analytics as a mechanism to support student success is only being used by a small number of students within this particular institution. This may be a failure on the institutions part to communicate this approach to students more widely, or that only small pockets of academic staff are pushing the use of learning analytics to their individual students, which in part is reflective of both academic staff and learning analytics expert participants who suggest that the implementation works best as a slow burn approach to change. Some of the student participants reported that they found their learning analytics tool by chance when browsing the VLE. Anecdotal conversations among the student participants in the focus groups indicated that student perceptions echo the slow burn change that was identified with learning analytic experts and academic staff participants. When questioned on what they felt the purpose of learning analytics was, students varied in their responses, ranging from believing that analytics had the ability to support students with their learning (FG 2 St 3*): **'it is there to increase support for students'** through to* ***'providing a support network between students and their tutors'*** (FG 1 St 1), to believing that learning analytics supported institutional student retention and continuation activities, as well as providing the ability to monitor students more easily.

FG 1 St 2 commented that:

> ***'The university wants students to attend and get good grades. Obviously, they don't want their students dropping out as it looks bad on them.'***

(FG 1 St 2)

It was also highlighted by FG 2 St 1 that ***'the university will do anything to keep students, so if that means monitoring it, they're going to do it'.*** Students in this focus group came from an institution who had implemented learning analytics in 2017/8. Within FG 2, monitoring was actually seen as a positive element, rather than a negative one. Expanding on FG 1 St 1's perceptions that learning analytics was more supportive in nature, FG 2 St 2 suggested that ***'although they are monitoring you and it's kind of big brother, it does help because you can talk to them and they can find out what's going on and help you'***. In contrast, students in FG 3 felt that the monitoring of students was wrong and was providing academic staff with an element of 'control' over students- something that was viewed more negatively than it was in the other two focus groups. One student in FG 3 (FG 3 St 2) commented that ***'they want to know what we are doing and how hard we are working on our course so that we pass it'.*** Two students (FG 1 St 1, FG 3 St 2) pointed out that the monitoring on students tended to be specifically in relation to their classroom attendance, rather than their wider engagement with their studies. Although the students in FG 3 themselves were engaging with learning analytics, and chose to use the learning analytics tool, they felt that many students within their cohort did not use it, and they were aware of some students within their cohort who had never accessed the tool. One student in this focus group (FG 3 St 2) said that using the learning analytics tool was not a requirement, and in their experience, it was not encouraged by personal tutors. It was therefore something that was not seen as particularly important or influential. This correlates with findings portrayed by some academic staff participants.

Two students (FG 1 St 1, FG 3 St 4) indicated that there was variance in how both staff and students used the analytics tool within their institution. This sense of variation was in fact evident in conversations with the students in all of the focus groups. One student participant commented ***'I don't think the tutors really talk about it, some more than others do but it wasn't really pushed'*** (FG 1 St 1). A second student expanded on this commentary to suggest ***'there's a tab that says student dashboard; I didn't know anything about it until I clicked on it myself and had a look'*** (FG 1 St 2). Within FG 3 (St 4) observed: ***'I use the dashboard myself, but it's never been brought up when I meet with my tutor, but I haven't had any issues this year so that's probably why it's not been talked about'.*** This student explained that her tutor ***'brings up the dashboard on her computer when we meet, and we talk about my engagement and the attendance system, and then she will make notes'.*** This comment was in complete contrast to FG 1 St 2's experience.

These students' experiences and perceptions give some idea of the broader challenges and barriers to implementing learning analytics, as well as demonstrating the variation both within and across institutions when adopting learning analytics. FG 1 St 1 and FG 1 St 2 both suggested that the learning analytics tool needed to be promoted more broadly and felt that adoption should be encouraged to enable learning analytics to be an effective mechanism to support students to succeed. FG1 St 1 said, for instance, that staff should ***'go through it with us, show us how it works, this is how you do each thing'.*** This view was confirmed by other students, with FG 1 St 3 stating: ***'the tutors need to talk about it more, they need to say, 'don't forget to check your dashboard, and do this or do that'***.

4.4.2 Student motivation

My conceptual framework shows students as one of the key aspects. As an enabling factor, some students appeared to be more motivated and 'reliant' on the data than other students. This was particularly true with FG1 where it was evident that St 1 and St 2 were actively engaged and were high users of the learning analytics tool; their perception was that analytics was motivating in terms of improving their educational outcome. FG 1 St 1 commented: ***'I can see how much I am engaging, then I can see where I can improve… maybe I'm not looking at enough resources, but it shows me how many times I'm swiping in and coming into university'.*** This institution has purchased a commercial learning analytics tool which has been in use since 2014/5; an engagement rating is generated which provides students with a daily score. The daily score ranges from 'no engagement' to 'excellent engagement'. It was evident from this focus group that the scoring element was important; these students felt that a higher score led to an improved degree outcome.

FG 1 St 2 put it this way:

> ***'I use it every day. I like that a certain level of engagement is like an educational grade and you should be working through at that. A high engagement and you could get a 2:1 and if you're partially engaged it's a third… I like knowing where I'm standing and seeing if my grade actually comes out at that.'***

(FG 1 St 2)

It cannot be determined how accurate or likely this would be. Although it is widely acknowledged that engaged students have reported higher academic outcomes within relevant literature, there is no guarantee. This can indicate the importance of getting factors right to feed into the learning analytics tool to ensure accuracy and reliability of data, or else universities put themselves at risk if this the impression given by students, an aspect that was noted by learning analytics expert participants. FG 1 St 1 agreed with FG 1 St 2's perception and felt their high level of engagement was reflected in their actual grades received. Both students identified that they used analytics to push them to work harder, with the aim of achieving a higher degree award, with FG 1 St 1 even stating ***'that it scares me to do a bit more work'.*** Although FG 1 St1 and 2 felt that analytics was motivating, FG 1 St 2 did suggest that one of the challenges of analytics was that other students might perceive learning analytics as mostly being about ***'lecturers trying to get you to do more work'*** (FG 1 St 2). Both of these FG 1 students also acknowledged that analytics ***'can make people feel bad if the engagement rating is low… because they're like, oh I tried really hard but it's still not enough'***. This shows that students also recognise, as do other participants in this study, that learning analytics can potentially be demotivating for some students in comparison with others. All four of the student participants from FG 3 indicated that the learning analytics tool itself was quite complex and was confusing to use, which did not encourage them to engage. FG 3 St 4 stated: ***'I can't make head nor tail of it, it's not that I don't want to use it, I just don't understand it.'*** This perception emphasises the need to ensure that students are fully informed about how to use learning analytics tools so that they can get the best use out of the data presented.

4.4.3 Technological ability

Students in all three of the focus groups suggested that one of the fundamental challenges of using learning analytics was the technology itself. As noted above, all four of the students in FG 3 felt that the analytics system was complex to use, which was linked with their overall motivation to engage with the tool. Although not reflected within this research study, most academic staff perceived the opposite and identified that their learning analytics tool was simple to use. FG 1 St 1 and St 2 also recognised that not all students in their course engaged with analytics and pointed out that there was a diverse range of learners within their course. FG 1 St 1's view was that **'some mature students just don't get it'.** This perception was gathered from anecdotal conversations with other students from the course cohort. FG 1 St 2 recognised that ***'there are loads of different tabs for loads of different things, so if you don't know what's in them then you might not understand it'.*** Being comfortable with engaging with learning analytics was not solely related to mature learner groups, with FG 2 St 4 recognising that ***'some people our age [21] do still struggle, maybe because they have not used it before.'*** Another potential issue was pointed out by FG 2 St 2 who noted that ***'there is a lot of jargon around it',*** so it may be that issues such as system complexity, lack of system understanding and well as aspects of digital literacy and technology acceptance are a fundamental issue for some student learners when it comes to working with learning analytics.

Two of the student participants in FG 2 (St 3 and St 4) recognised that there were errors with the system in terms of the information that was actually presented. This again echoes findings from learning analytics expert participants in terms of data accuracy and reliability. FG 2 St 3 provided an example of this where they had attended class, but this was not reflected within their daily attendance record. FG 2 St 3 reported that this was not an isolated episode. In FG 1, St 2 reported that there had been an occasion when another student had logged in, but ***'it was not their personal information that was on screen'.*** It was interesting to observe that the majority of students in FG 1 and FG 2 appeared accepting of system errors, despite the fact that students in FG 1 had demonstrated a level of reliance on the data presented. When students were questioned about whether their engagement scores might be wrong because the information was incorrect, they did not consider this a concern or recognise that there may be a link. FG 2 St 2 responded ***'I hope not, I don't know but it could be wrong'.*** Students FG 1 St 2 and FG 3 St 2 and St 3 broadly concluded that there was some inaccuracy of data particularly in relation to card swiping into buildings, and that this was a negative of the learning analytics tool used within their institution, which had been implemented in 2014/5. Students appeared to be accepting of the flaws within the learning analytics tool presented to them and did not consider this to be a particular concern. It should be noted here that there are links to the ethical considerations identified within the literature review chapter, particularly as concerns the wrong student information being attached to a student account, but ethical considerations will not be considered as part of this research study explicitly.

4.4.4 Ownership of learning analytics

Students in FG 1 (St 1 and St 2) felt that the implementation of learning analytics within the institution was positive, and that the ownership of and responsibility to engage with the analytics tool lay with the student. In the context of my conceptual framework, this can be regarded as an enabling factor for learning analytics, and echoes the perceptions by academic staff participants. Across all three of the focus groups, students noted that they were adults and, as such, should make their own decisions about their learning needs. FG 1 St 2 indicated that she took responsibility and control using the analytics system, although she did also allude to potential over-reliance on the data.

She observed:

> ***'I get funny with mine…. I check it a good couple of times a day… and then I check the ins and out of it, so I check what resources I've used, what I've downloaded, everything… it's my responsibility to use this, not my tutors.'***

(FG 1 St 2)

This perception can be related to an over-reliance on presented data; which again can show similarity with academic staff participants. Students did not expect academic staff to take responsibility for forcing them to use the learning analytics tool, but they did feel that academic staff should do more to promote learning analytics to encourage its adoption by students across the institution. The view of students is in distinct contrast to those viewpoints presented by academic staff participants who felt that learning analytics tools were well promoted to students. All four of the students in FG 3 acknowledged that it was the student's responsibility to use learning analytics, but also pointed out that academic staff should promote and engage with the system themselves to ensure that it was effectively used.

4.5 Summary of the chapter

This chapter has reported the key research findings that were made following the data collection phase of the research study. My conceptual framework has guided presentation of findings, with the findings presented thematically from the perspectives of the different key stakeholders identified within this study. To summarise the main themes, learning analytics expert participants and academic staff participants identified that the context and purpose of learning analytics and the role of the academic were either enabling or challenging factors in the use of learning analytics. Learning analytics experts participants suggested that other challenging factors were the change process and disparities with learning analytics use. These participants identified that the enabling factors were in improving educational design and educational outcomes. Academic staff saw that students themselves were an enabling factor. Student participants raised the purpose of learning analytics and their technological ability as challenging factors for learning analytics and recognised that student motivation and ownership of learning analytics were enabling factors for this specific group. A thematic discussion and critical analysis of the findings in relation to relevant literature will be presented in the next chapter of this thesis.

Chapter 5 Discussion

5.1 Introduction to the chapter

This chapter places the research reported in Chapter Four into context and discusses it in the light of the literature and conceptual framework presented in Chapter Two. In addition, this chapter focuses on a critical analysis of the thematic findings linked to the research questions forming the basis for this study. Some judgements will be made about whether the research findings support or contradict existing information.

5.2 The research question

This research study set out to gather a multi-stakeholder perspective to gain a better understanding of using learning analytics as a mechanism to increase student success within HE. The pilot study conducted as part of this research had the main purpose of confirming the research direction and research design. As a secondary consideration, I also wanted to test the semi-structured interviews as a data collection method. The pilot study allowed me to sense-check interview questions to make sure that they would open lines of discussion relevant to my study. Interview questions were designed to be exploratory in nature due to the small scale of the research study. Questions were designed to identify common patterns and themes from the participant responses and sought to identify participant attitudes and opinions in relation to the opportunities and challenges of using learning analytics within educational practice.

Through using case study as a methodological approach, research findings were portrayed though the lived experiences of the individual research participants through a cross sectional research study design.

To reiterate, the research questions were:

1. What are the opportunities in the use of learning analytics as viewed by students, academic staff and learning analytics experts?

2. What are the challenges in the use of learning analytics as viewed by students, academic staff and learning analytics experts?
3. In view of the findings above, can learning analytics be effectively used within a Higher Education Institution to support student success and if so, how?

5.3 The conceptual framework

As part of the literature review into learning analytics, I devised a conceptual framework which evolved organically after reviewing pertinent literature in relation to the subject area. The conceptual framework was used to frame the literature review and, therefore, was introduced within Chapter Two. The conceptual framework showed the mechanism of learning analytics as a central theme, with students, academic staff and the institution as factors intersecting and linking with learning analytics. Surrounding all of this were both enabling and challenging factors. To link the information emerging from my research findings with the existing body of knowledge and apply it to the conceptual framework, I shall explore each of the research questions in turn in relation to the thematic aspects identified.

5.4 Opportunities in the use of learning analytics

The first research question asked participants about what opportunities, from their perspective, were opened up by the use of learning analytics. Participants felt that as a concept, the development and implementation of learning analytics was an opportunity, although there were differing views on the exact rationale and purpose of learning analytics. The thematic areas relating to this were identified as decision-making, student ownership and the role of the academic.

5.4.1 Developing learning analytics for a purpose

Both academic staff and learning analytics expert participants in the study identified numerous drivers for the development and implementation of learning analytics in their institutions, with many identifying that developing this approach provided opportunity. What was apparent through the participant responses from both these groups was that there was a mixed rationale and reasoning about the purpose of using learning analytics, ranging from student retention and progression issues, through the ability to improve educational design, to the provision of a different way to support students to succeed. It was identified that the majority of institutions included in my sample group had only implemented learning analytics in 2017/8, so this may in part provide explanation for this as the implementation was fairly new. One of the benefits of an institutional learning analytics initiative that Sclater (2014) identified, is the breaking down of silos through forcing data owners to co-operate for the benefit of the organisation and the students, and this emphasises the need for a multi-stakeholder approach for learning analytics to be effectively implemented. However, my study shows that this benefit is not necessarily being realised, with the overarching view of participants being that the development and implementation of learning analytics was coming from a top-down strategic directive with little consideration for defining a real purpose for development and implementation. This is reflective in part of findings in Dawson et al's (2018) study who found that there were limited levels of adoption regardless of how the approach was defined. The lack of a clear reasons for developing and using learning analytics confirms the findings of relevant literature, notably studies conducted by Butler and Winne (1995) and Lang and Siemens (2011) who directly concur with this view. Lang and Siemens (2011) felt that learning analytics was often used to either drive or enforce strategic decisions, with the imposition of a decision-making process being one of the key drivers for the adoption of learning analytics within an institution. My participants were of mixed opinion, with some agreeing that learning analytics supported decision-making processes while others felt that data simply reinforced what they knew already.

5.4.1.1 Supporting institutional improvement

Some research participants that were academic staff or learning analytics experts believed that while development and implementation of learning analytics provided many different opportunities to support institutional improvement, these would be dependent upon different academic roles. It was suggested, for instance, that a personal tutor, module leader or course leader would have different individual interests for the application of learning analytics depending on whether they wanted to access data and information about one student, or whether they were reviewing a module or course performance. Because different roles may approach learning analytics differently, to encourage academic buy-in, different ways of promoting learning analytics to different staff groups may be required dependent upon their individual needs. There was a perceived training and support need noted, particularly by academic staff, and this is reflective of a study undertaken by Rienties et al (2018) who recognised that staff required explanation of the learning analytics tool as well as follow on support in order to encourage use.

5.4.1.2 Improving curriculum design and delivery and tracking student activity

Some of the academic staff and learning analytics expert participants felt that learning analytics provided opportunities in relation to improving curriculum design and enhancing educational opportunities for students, this was suggested across different institutions that participated in this study, and was reflective of both academic staff and learning analytics expert participant views. This correlates with findings by Greller and Drachsler (2012). The availability of immediate information about courses was seen as facilitating proactive course development rather than waiting for end-of-module or course evaluations. This viewpoint echoes Sclater (2017) who believes that learning analytics provide unprecedented opportunities to discover whether the curriculum is functioning as intended. Morris et al (2005) suggest that learning analytics provide educators with the ability to analyse the places students visit online, the time they spend there, what tools they are using and how frequently they are using them. This information allows educators to see in real time whether curriculum content is facilitating the students learning process and addressing learner need (Morris et al, 2005).

While my academic staff research participants saw learning analytics as a mechanism to support improvements in students learning, the literature discusses the opportunities offered by learning analytics only in the broadest of ways, without offering suggestions for specifics. Manderveld (2015) believes that when learning analytics are used with learning as a focus, students are provided with personal information about their level of need (Manderveld, 2015). This builds on the findings of Greller and Drachsler (2012) who suggest that learning analytics allow for a highly personal, competence-driven educational system. Greller and Drachsler (2012) recognise that more importantly learning analytics allows ways for learners to improve and develop whilst their course is progressing, thus leading to improving student success. Research participants highlighted the notion of enhancing educational design as an impetus, a view that is supported by Scheffel et al (2014) who recognise that students can compare their performance with others, which can provide a competitive perspective and can be a motivational factor to drive individual improvement. Dawson (2006) summarises that this can then increase a student's sense of community, and enhance student engagement (MacFayden and Dawson, 2010).

On the whole, both academic staff and learning analytics expert participants felt that learning analytics was beneficial and provided a more proactive approach to improving educational design. Again, it is to be noted that the implementation of learning analytics within the majority of institutions was new, so was interesting to discover that participants were able to see the benefits at such an early stage of implementation. This reflects the existing literature, with Lockyer and Dawson (2011) believing that learning analytics based on learner's interactions with a course of study enable academic staff to undertake evidence-based changes in relation to resources, learning activities and other aspects of the curriculum. Using analytics in this way makes use of Dawson et al's (2008) findings that 80 per cent of student interactions involved the discussion forum tool, while quizzes, wiki's and blogs showed lower levels of adoption. In this study, differences in student performance were found to correlate with their on-line behaviour, with each individual student's online sessions being of a similar duration in time, but higher performing students accessing the on-line systems more frequently than lower performers (Dawson et al, 2008). It can be considered that it is futile to know this information unless something is done to make improvement either for current or future students, with learning analytics expert participants in particular recognising that this approach offers a powerful approach to develop student learning. Dyckhoff et al (2012) provide another dimension to using learning analytics for enhancing educational design by suggesting that analytics can be used to convince academic staff to change their pedagogic practice and to increase their use of on-line learning, and that academics are more likely to attempt innovation if they can see a beneficial impact for their learners. For this to happen, it can be assumed that there needs to be widespread adoption of learning analytics at institutional level, yet studies by Herodotou et al (2020) opine with this perspective.

5.4.1.3 Improving student support

While all categories of participant saw supporting students as fundamental to the academic staff role, academic staff themselves appeared to hold conflicting views as to whether learning analytics should be used as a mechanism to do this. This viewpoint was held regardless of level of academic experience, but it was noted that the newest academic in this study saw learning analytics more positively than others. From an academic perspective, the literature shows that learning analytics can identify patterns of learner activity, interaction and provide a trigger to start a conversation to support the student (Mor et al 2015). As education moves to an on-line platform with less interaction occurring within the classroom setting, Ferguson (2012a) suggests that academic staff may lack the visual clues to identify insufficiently challenged students or those students who are bored confused or are failing to attend (Ferguson, 2012a). This may be one reason why Sclater (2017) feels that learning analytics can be positive and provide opportunities through using data to understand learner behaviour and can glean issues about learners not previously identifiable. This perspective does not take an holistic view of the student, and considers data as the single method of predicting student success. In contrast, all of my participants recognised that academic staff need to consider the holistic view of the student, and that learning analytics tools should be used as part of a broader package of student support, rather than being used in isolation. This would position the student as the central focus with other support mechanisms surrounding them, and enforces the need for learning analytics to be developed in conjunction with existing student support systems (such as personal tutoring).

5.4.1.4 Using learning analytics as a foundation for change

Siemens (2013) believes that using learning analytics provides opportunities to predict and model learner activities which can be used as a foundation to inform change within HEIs. Mor et al (2015) believe that institutions can improve on resource allocation through the implementation of learning analytics, although offer no tangible evidence to identify how this can be achieved. An investigation conducted by JISC (2017) highlights that analytical tools are an expensive resource, so a clear purpose for developing learning analytics (whether this is to facilitate institutional improvement, improve student retention activity or support student success) must be the driver for adoption. Although all of my participants from across the different stakeholder groups understood the need for learning analytics, they were not always aware of their purpose within their institution, either because they were not properly informed, or because they felt that the reason had not been thought through by strategic leaders. This also links to the earlier discussion on supporting institutional improvement. In terms, then, of the opportunities provided by learning analytics, my study shows the same kind of variety of opportunity and potential that is revealed in the current literature. However, it also shows that students should be the central consideration, and that the potential opportunities and the practical abilities to use this data to realise these opportunities has not yet been fully forged.

5.4.2 Supporting academic decision-making

A number of the academic staff and learning analytics expert participants believed that learning analytics were beneficial in supporting decision-making processes; with literature supporting the key benefits of learning analytics as the ability for academic staff to base their decision-making on data (Sclater, 2017), data visualising and prediction (Avella et al, 2016). While Campbell and Oblinger (2007) and Bischel (2012) believe that decisions based on student enhancement will have better results if they are founded on data, fact and statistical analysis, the academic staff participants in my study felt that their interactions with students were still frequently based on hunches or anecdotal evidence. These participants felt that a holistic view of the student was more important, and that learning analytics cannot be used in isolation. This perspective supports the findings by Sclater (2017) who believes that human factors such as experience, expertise and judgement was also a fundamental aspect of gathering the holistic view of the student. Many of the academic staff participants recognised that, in practice, data generally reinforced what they already thought or knew about a student. Student participants recognised that learning analytics tools were used by some personal tutors but not all, which suggests variance in decision-making processes, and indeed when using learning analytics as a mechanism for student support. In fact, some participants from all groups interviewed acknowledged that there was a varied level of staff engagement with the learning analytics tool across their institutions, but it not known if this is linked to confidence or competence in using learning analytics. All the participants agree on one thing—there is patchiness of use of learning analytics (by staff and students) which was seen across all of the institutions that had implemented learning analytics, and there is a need to target each group to provide reasons for using the learning analytics tool so that the full benefits and the purpose of learning analytics already discussed are realised.

5.4.3 Student ownership

Most of the participants from both the academic staff and student groups agreed that the implementation of learning analytics promoted independent learning, and that learning analytics allowed students to increase their responsibility for and ownership of their learning. Student participants felt that learning analytics was a positive move forward within the educational setting to enable student success as it provided them with a clear motivation to improve their grade outcomes. Although Sclater (2015) proposes that much of the research into learning analytics centres on the presentation of data to staff and students so that an intervention can be made, in my study only two institutions used staff- and student-facing learning analytics tools, meaning that students could see their own level of course engagement through an on-line platform. One of the institutions had made a conscious decision at the development of their institutional learning analytics programme that it would not be visible to students, only staff. This correlates with findings from a study conducted by Verbert et al (2013) who examined 15 dashboards across HEIs and found that only four of them were specifically designed for learners. The dashboards observed by Verbert and colleagues enabled students to see visualisations on social interactions, time spent on activities, and the use of documents and tools (Verbert et al, 2013).

Sclater (2015) has discovered that learning analytics is continuing to advance from a technological perspective, and student visibility of systems is a growing area. This growing trend has meant, for instance, that UK HE institutions have requested mobile applications for their students to use. In response to this request, JISC (2015) have developed a free, evidence-based learning analytics application which allows students to see figures relating to their engagement, compare themselves with other students, track their academic progress and assessments, and record their progress towards career aspirations. This could potentially increase the implementation of learning analytics within HEIs as the work, done by JISC (2015) may support a more resource-effective option for HEIs than having to purchase a commercial version of an analytics tool.

In one of the focus groups (FG 1), in which the institution had implemented learning analytics in 2014/5 student participants discussed that they used learning analytics tools as an incentive to make improvements and to study harder, and they believed that this would support them to improve their degree outcome. It was noted that all of the students that contributed to this research could be considered as high users of learning analytics, and as such, could be a reason for this particular response. Although this perception is not directly dealt with in the literature, Corrin et al (2015) do recognise that a student-facing learning analytics tool can empower students so that they can become aware of their own actions related to their learning, and be able to reflect on and alter their behaviour (Sclater, 2017; Wise, 2014). My findings support the case-study examples published by JISC (2017) which showed that when students become aware of their risk level, they alter their behaviour with resulting improvements in their performance. A funded empirical research study conducted by JISC (2017) with a student control group who used a pilot version of a learning analytics tool found that students in the control group sought help earlier and more frequently than those in the experimental group who did not use the tool.

The concept of student ownership can be placed more broadly within the educational context within the theory of learner agency (Glasser, 1998). Glasser (1998) describes learner agency as the capability of individuals to make choices and act on these choices in a way that makes a difference. The notion of agency is seen relating to the cognitive processes involved in learning where knowledge is seen as constructed through a process of taking actions in an individual's environment and making adjustment to existing knowledge structures based on the outcome of those actions. Learner agency is known to lead to increased feelings of competence, self-control self- determinism and higher emotional intelligence (Bandura, 2001). Clearly, those student participants who had access to a learning analytics tool felt that it played a role in providing them with agency over their own learning, which implies that learning analytics should be student facing to enable student success. As there were only a small number of student participants in my study, no assumptions can be made about whether this perception would be reflective of the wider student body.

Shwartz and Okita (2004) proposed a theory for the agency of learning which recognises that a high agency learning environment (which increases an individual's capability to make choices and act on these) is an environment that is student centered, and therefore an environment which allows students to have control of their learning and participation. Chia-Jung (2011) believes that from a teaching and learning perspective, using technology also gives the opportunity to directly enhance learner agency and emotional intelligence by reflecting the student's personal learning pace and style. The flexibility afforded by digital tools enables students to learn based on the way that they feel comfortable, which directly correlates with learner agency. Chia-Jung (2011) believes that technology allows for supporting a connection to content or other people to learn better, whilst allowing the student provision of space to explore difficult issues (Chia-Jung, 2011). Lindgren et al (2012) reiterate the idea that technology presents a new and different opportunity for leveraging learner agency and the learning environment through personalising the student experience. Hence, from observations cited in the literature, it can be seen that providing student-facing learning analytics would be a positive move, increasing learner agency and increasing control. From a wider perspective, Sclater (2017) states that at its simplest, that learning analytics should be for the benefit of the student.

5.4.4 Role of the academic

Learning analytics experts and academic staff participant believed that the development and implementation of learning analytics changed the role of the academic and allowed for the development of positive staff and student relationships. This perception of a change in role was observed despite the length of time that learning analytics had been in place at the institution sampled. Conversely, this aspect was also identified as a challenge to the widespread adoption of learning analytics, because of the different relationships between staff and student, with a possible threat of power to the academic being cited by my participants. The findings of my study show that key stakeholders believe that learning analytics can have a positive effect on the staff–student relationship is encouraging in that Baker et al (2008) firmly believe that teachers play an important role in the trajectory of students, and recognise that teachers have the opportunity to support students' academic and social development (Baker et al, 2008). A positive staff and student relationship has been aligned to attachment theory (Ainsworth, 1982) with the recognition that positive teacher-student relationships having the presence of closeness, warmth, and positivity (Hamre & Pianta, 2001) which can serve to encourage students to succeed. These positive relationships enable students to feel safe and secure in their learning environments and provide scaffolding for the development of social and academic skills (O'Connor et al 2011). Although O'Connor et al's (2011) research was conducted within a school-based setting, it none the less has relevance to HE.

It can be concluded that the development and implementation of learning analytics provides numerous opportunities for both students, academic staff and for the institution. Through the discussions, it is apparent that for learning analytics to work effectively there is a need to have effective relationships between these three stakeholders. What has become apparent is that the development and implementation of learning analytics is not considered with the student in mind, and from that, it has raised questions in terms of the original conceptual framework that I presented.

5.5 Challenges in the use of learning analytics

The second research question related to identifying the challenges in the use of learning analytics as viewed by students, academic staff and learning analytics experts. The findings resulting from this question indicated that there were in fact more challenges comparison than opportunities. The findings will be discussed thematically and in relation to the conceptual framework. This section will address the context and purpose of learning analytics, institutional readiness, technological considerations, digital literacy, staff and student relationships, staff and student engagement, decision-making and academic accountability. Participants have presented both opportunities and challenges which can be seen as two faces of the same coin, and it is apparent that there is a matter of interpretation involved in whether these issues are seen as an opportunity or challenge.

5.5.1 Purpose of learning analytics within the educational domain

Although research participants identified that broadly speaking learning analytics provided opportunities to make improvement within HEIs, they indicated that not knowing the context and purpose for the development of learning analytics was a challenging factor. The findings show that all participant groups in this study were unclear about the reasons for the development and implementation of learning analytics within their institutions. Participants identified increasing student support and student retention strategies as being key drivers for learning analytics implementation, and recognised that these differing goals were interlinked. This finding that the true purpose of introducing learning analytics is vague or unclear to those actually using them correlates with other findings in the existing literature pointing to a lack of clarity for adoption (Romero and Ventura, 2010, Manderveld, 2015). At operational level a study by Avella et al (2016) reported challenges in terms of accurate data tracking, data collection and evaluation. Recently, there has been extensive literature into learning analytics written by Sclater (2014, 2015, 2016, 2017). A large volume of Sclater' s work relates to the context and purpose of learning analytics and is focused towards finding out how best learning analytics can be embedded operationally within organisations, so is pertinent to use this as part of this discussion. It is Sclater' s (2017) belief that each institution will develop learning analytics based on their own specific purpose. However, this may lead to confusion among stakeholders if they believe that there should be an overarching, common reason within HE for their introduction. Literature cites numerous motivational reasons for the development of learning analytics to overcome specific student and institutional challenges, such as using it as a tool to identify students who are the strongest prospects for admission, to predict and improve institutional graduation rates (Olmos and Corrin, 2012, Smith et al, 2012), or to identify students at risk of dropout (JISC, 2014).

The wide range of purposes cited in the literature may add to users' confusion. These include: to address teaching and learning problems (Gasevic et al, 2016), to monitor the performance of underperforming groups (such as students from a BAME background) (JISC, 2014), to improve the students educational experience more generally (JISC, 2018) as a response to external drivers such as the National Student Survey, and to obtain and address issues of concern to learners. My research findings from academic and learning analytics expert participants support the idea that there is a lack of clarity about the purpose of developing and implementing learning analytics. This is a significant challenge because, as

Slade and Prinsloo (2012) show, to encourage adoption of this approach and facilitate effective change, institutions must decide what their main purpose is in using learning analytics.

5.5.2 The change process

My study provides confirmation that the most fundamental challenge to the development and implementation of learning analytics within participants' institutions is related to the change process and how change is managed. When the change process is placed into the conceptual framework devised for this study, it can be considered either as an enabling or a challenging factor when implementing learning analytics. My findings indicate that how the change is implemented correlates with the level of success of the introduction of learning analytics. The concept of change and the management of effective change in organisations has been extensively researched, and there is an array of classic authors (Lewin, 1947, Kotter, 1995) who have researched change and devised models and approaches to direct and guide the change process. The negative effect of change can be aligned to the existing body of knowledge with Kotter (1995) claiming that there are eight fundamental mistakes that organisations make that will result in unsuccessful change. Kotter (1995) highlights mistakes in relation to a lack of vision, an under communication of the vision, not removing obstacles to the vision and not anchoring change within a corporation's culture as key areas that can influence the success or failure of the change. Participants' responses correlated with Kotter's (1995) perspective and is reflective of studies by Rienties (2014) and Chandler (2013) who argue that HEIs are often characterised by resistance to change and adaption. All participants, although particularly the academic staff explicitly identified that there was a lack of vision and an under-communication of the vision. This then made them question the purpose of the development of learning analytics within their own institution.

Kotter (1995) believes that not anchoring change within a corporation's culture can be linked to wider debate into organisational culture. Sclater (2017) recognises that for learning analytics to be successful, leaders need to be mindful of the organisational culture, and that resistance to change is often linked to organisational culture (Chandler, 2013). It would seem fitting then that learning analytics initiatives should be built around an institutional strategic plan to encourage adoption by all stakeholders. This is an important consideration to address when developing a response to the third research question, which asks in view of the research findings how learning analytics can be effectively implemented within an HEI to support student success. Sclater (2017) identifies other challenges when developing learning analytics as maintaining openness and transparency at all stages, ensuring that processes are robust, and upholding the privacy of data. He also firmly believes that this approach will help to build confidence with learning analytics as an educational development and will support an effective change management process within the institution.

Radovic and Markovic (2008) identify that rapid and continual innovation in technology is driving changes to organisational systems and processes, and that relentless change has become a fact of organisational life. The effects of organisational change can be seen as being detrimental to organisational culture, with Radovic et al (2008) recognising that failed organisational change initiatives leave cynical and burned-out employees, making the next change objective more difficult to accomplish and making staff and organisations ‘change averse’. Sclater (2017) concurs with Radovic et al (2008) and describes how institutions are now suffering from ‘initiative fatigue’ with learning analytics seen as another example of an educational development foisted upon them by strategic leaders. In addition, Sclater (2017) takes the view that organisations may struggle to achieve large-scale institutional change, particularly where faculties or departments have high levels of autonomy.

As a potential solution, Sclater (2017) believes that student and faculty advocates may have more impact on the successful development of learning analytics than a directive enforced by strategic leaders; that is, in the HEI environment, a bottom-up approach may be a more effective change process. It is evident from the findings of this study that participants were generally unclear of the rationale for developing learning analytics and felt that a slow burn change approach was the preferred way of implementing the new concept and tools. To respond to and overcome the challenge of resistance to change, therefore, it is critical to apply a carefully considered change methodology at both a strategic and an operational level when implementing learning analytics within HE. An organisational study conducted by Chandler (2013) supports this notion and has found that the uptake of new innovations need to be supported from both a senior management level as well as from the 'shop floor'.

5.5.3 Institutional readiness

The findings from my study show that the reasons and motivation for developing learning analytics within each HEI differ, with some participants not believing that the motivation was clearly articulated. Development was often perceived to be driven from a top-down strategic directive, without consideration of whether this was the ideal approach to use. Sclater (2017) believes that successful implementation of institution-wide learning analytics requires the organisation to be ready in various ways, and if the ground is not properly prepared, institutions run the risk of alienating stakeholders, destroying confidence in the potential of learning analytics and wasting significant resources. In their study, Powell and MacNeill (2012) use the term 'institutional readiness' to encapsulate this idea and propose three key institutional considerations in order for learning analytics to be effective. For institutions to assure an 'analytics ready context', Powell and MacNeill (2012) believe that the first consideration is related to the logistics of the provision of effective data and the need to have a variety of accessible data sources to inform the analytics. The second consideration is ensuring that data is presented in an accessible and informative way; and finally, insights require actioning and therefore there should be clear processes by which academic staff and learners can turn insights into actions in their context.

5.5.4 Technological readiness

Research participants (and, in particular, student participants) identified the wider theme of technology as being a significant challenge in the development and implementation of learning analytics within an institution. Sclater (2017) believes that institutions need to be 'technologically ready' before embarking on institutional wide learning analytics projects which reflects Bichsel's (2012) perspective. Powell and MacNeill (2012) agree with Bischel but recognise that technological readiness forms part of broader institutional readiness. Although participants' in my study did not talk about technological readiness specifically, they did report issues with institutional data systems and inaccuracy of presented data. From a data perspective, Sclater (2017) believes that existing data sources within institutions may not be adequate or understood, or that data may not be collected in a systematic way for incorporation into a learning analytics solution.

Dell (2013) identified that integrated interoperable data systems are key to a greater management efficiency to empower learning analytics development and operationalisation. This is not easy to achieve, and a study by Norris and Baer (2013) found that to overcome this issue, large institutions were selecting different learning analytics tools from different vendors and in so doing, trying to keep up with the still-developing field. Siemens et al (2013) and Arnold et al (2014) point out that in addition to interoperable systems, technical expertise is required to develop, integrate, co-ordinate and use data inputs from various institutional data systems and to develop a means of synthesising data for mass consumption, particularly within a pedagogical context (Siemens et al, 2013). This supports the notion that learning analytics development and implementation within an institution needs to be designed and delivered through a multi-stakeholder perspective. Sclater (2017) found that some institutions are developing their own systems or customising analytics tools in an attempt to overcome this issue. Norris and Baer (2013) recognised that the development and certification of individuals skills in analytics and overall institutional competence needs to be put in place to overcome a lack of technical skills in this area. However, in 2014 Arnold et al reported that the required technical skills do not exist in many institutions, and as recently as 2017 Sclater was still reporting a challenge for institutions in this regard.

5.5.5 Digital literacy levels in learners

The information from student participants across the two institutions sampled indicated that digital literacy of learners was a challenge in implementing learning analytics. This finding correlates with empirical research that demonstrates that there is a new generation of digital literature learner. As discussed in Chapter Two, in today's HE environment, learners range from the typical young school leaver to the mature student. In terms of technology use, this means that learners entering HE are from a variety of generations with different learning styles and varying characteristics which has implications for teaching and learning. Monaco and Martin (2007) proposed that learners could be categorised into different types. Traditionalists born before 1945, are learners who favour a structured 'command and control'-oriented learning Programme. Learners born between 1946 and 1964 are baby boomers, a type of learner who expects a personally focused learning structure. This generation, according to Monaco and Martin (2007), tend to favour participation, reflection and feedback. Generation X learners are those born between 1965 and 1980 and are the most independent of the four groups. Generation X learners prioritise self-directed educational opportunities and programmes that enable them to learn on their own schedule. Monaco and Martin's final group of learners are known as the millennials. Bullen et al (2011) describe this generation, born from the 1980s to the late 1990s, as fundamentally different, a notion that is seemingly now displayed as a self-evident truth within literature (Bullen et al 2011). Millennial learners favour highly personalised training on a self-directed schedule (Monaco and Martin, 2007). The next generation entering HE are post-millennial learners, and unlike the millennial group, they are unlikely to have any experience or any memory of a time without mobile phones, laptops and digital technology. Researchers argue that this generation, have been immersed within a digital world of technology, will behave differently and have different expectations of life and learning (Oblinger and Oblinger, 2005). Bullen et al (2011) refute this proposal and claim that there are no meaningful generational differences in how learners use technology or their perceived behavioural characteristics. Despite the view of Bullen et al (2011), it appears that differences in experience and expectations from these groups, and how they associate and learn from technology poses a challenge for the introduction of learning analytics. Another dimension to consider is that academic staff and students may come from different generational groups, with academic staff trying to keep up technologically with millennial and post-millennial student groups. The technical capability of academic staff is another issue to consider, with acceptance of using learning analytics may be problematic from both academic staff or student user groups. Therefore, crucial aspects to address when institutions are considering the implementation of learning analytics is to reduce technical skills gaps at operational level, and ensuring that effective training in learning analytics is provided for staff and students as part of an institutional implementation programme to ensure that the technological capability of both parties is addressed. This view is echoed by Rienties et al (2018) who endorsed that training and follow up support for academic staff in the use of learning analytics tools is essential.

5.5.6 Ownership of learning analytics

Student participants felt strongly that ownership of learning analytics should be student-centred, and that efforts should be made to increase learner agency through allowing students to be part of their self-development and self-renewal (Bandura, 2001). Student participants in this study were clearly motivated to use learning analytics, and were high users of the analytics tool, however they did concede that this was not always the case across the wider student body. Student participants felt strongly that ownership of learning analytics should be driven by the student body. Limitations of this study are that student facing analytics tools were only used in two of the institutions sampled, so this cannot be considered a widespread viewpoint. This presents an opportunity and a challenge for the introduction and use of learning analytics. Literature does not specifically address whether or how students are consulted about their needs for different learning analytics information, or whether the learning analytics tool presented meets their needs, with research only just starting to emerge into student perceptions of learning analytics use (Bals et al, 2019). Students participating in this study used a manufactured learning analytics tool, so it is not known how much student consultation was held before the manufactured product was launched. Academic staff research participants make the claim that the learning analytics tool was launched to students at the beginning of their course, however the opposite viewpoint was portrayed by student participants. Data used to generate analytics and the students' engagement rating tends to be derived from numerous sources (e.g. on-line learning, attendance, swipe access to buildings, electronic assignment submissions) but this is variable depending upon institutional data-sets, and can make student ownership problematic if there are limited data sources from which to draw and generate an analytics algorithm. Student participants within my research reported inaccuracies in the data that was used as a prediction; but interestingly they did not see this as a cause for concern, or recognise that inaccurate data may affect their predicted engagement rating.

5.5.7 Student motivations and unexpected consequences

Student research participants within my study indicated that they were motivated to use learning analytics and saw their engagement as being related to their degree outcomes. These students held the perception that if they had a high level of course engagement, their predicted degree outcome would be improved. Literature reinforces the view that monitoring could improve learning (Sclater, 2017) but on the other hand, it also indicates that this could increase students' stress levels and encourage non-participation (Sclater, 2017) which could be a challenging factor. Sclater (2017) also points out that continual monitoring of students may have a negative effect on motivation and may lead to students changing their behaviour either consciously or unconsciously if they believe that they are being watched. Labelling students 'at risk' may motivate some learners to improve, but increased awareness and labelling may have consequences for other students who are less fortunate and have life circumstances that prevent them from engaging more fully (Swenson, 2014). This too can be seen considering the diversity of students at HE and the changing nature of the student body as identified in Chapter Two. Willis et al's (2013) study expressed concerns that labelling students 'at risk' could lead to loss of confidence and dropping out from university. This then becomes an ethical argument, if in an endeavour to protect students, institutions do not inform students if they are at risk of failure or drop out (Willis et al, 2013, Slade and Galpin, 2012).

Although this concept was not raised by research participants specifically, linked to the literature to student ownership and student motivation is the issue of 'gamification', i.e. creating competitive comparative elements among students in terms of engagement, attendance, etc. to improve engagement scores and ratings (Bollier, 2010). As one of my student research participants (FG 1 St 2) identified they were high users of the learning analytics tool, and frequently viewed their engagement rating as a method to improve, and potentially relied on the learning analytics tool too much. There is little evidence to support or dispute the benefits of gamification in relation to learning analytics (Morris et al, 2005, Sclater, 2017), however anecdotal reporting by some of my participants indicates their concern with this. Literature also indicates that students may also deliberately manipulate data and not apply the learning analytics if they want to obtain additional support (Slade & Prinsloo, 2012). Suggestions by Slade and Prinsloo (2012) reflect that if factors triggering an intervention by academic staff are known to students, they might act in ways that ensure this occurs. The findings from my research illustrate the need for broad adoption and engagement with learning analytics within HE generally before this aspect is addressed in more detail.

5.5.8 Staff and student engagement

It was clear from the information provided by all stakeholders participating in this study that staff and student engagement with learning analytics was variable. This was viewed as varying by those participations across all of the institutions that participated. However, it must be borne in mind that each institution is at a different stage of development and implementation when it comes to learning analytics, and that a limitation of this research was that only two institutions had used learning analytics tools for a longer than five years. As such, this could have influenced the responses provided by participants. A significant consideration in the development and implementation of learning analytics within the HE environment is related to staff and student engagement with analytics as well as adoption by all stakeholder users, but I recognise that encouraging staff and student engagement is intrinsically linked to institutional readiness, technological readiness as well as the change process and how the move to using learning analytics is implemented within the institutional setting.

Participants reported that there was generally a lack of staff engagement with the learning analytics tool across their organisations, but this was perceived to be due to the approach being an opt in approach with no penalty for opting out. This again links to a study by Dawson (2018) that found differing approaches in how learning analytics was being implemented in the HE setting. Participants suggested that in order to increase staff engagement, examples of good practice and demonstrations of the usefulness of learning analytics were the tools most likely to have a positive effect. This perspective is also echoed by Viberg et al (2018) in their literature review into learning analytics in HE. Student participants also indicated that amongst their peers, learning analytics use was not widespread. They indicated that they had found it by chance (which in contrast to what academic staff research participants had stated) but saw the usefulness of the approach. A lack of staff and student engagement to present a fundamental challenge to the development and widespread implementation of learning analytics within HE. Institutions need to consider the most positive approach for driving forward this development within their own institutions in order for it to be effective as an approach to support student success.

5.5.9 Using data for decision-making

Academic staff participants raised the point that decision-making was a fundamental challenge when providing effective student support within the context of learning analytics. Decision making was not raised as an area of discussion by learning analytics expert participants, reasons for this may be linked to the non-academic role that these individuals are in. Contrasting views were presented by academic staff participants: some suggested that academic staff did not use learning analytics as a basis for their decision-making, while some participants held an opposing view and said that engagement and intervention with students was instigated based solely on the information that the learning analytic tool presented. This perception was held from across the different institutions that participated, which suggests that there remains variance in practice despite the length of time that learning analytics has been implemented within an institution. Campbell et al (2007) claim that decisions founded on data and fact are likely to have better results, and Cooper (2012) further reinforces this claim by suggesting that learning analytics can help to answer questions of information and fact. Despite these views, Sclater (2017) recognises that most decision-making is based on intuition, anecdotes or presumptions as was reflected in some participant responses. Many of the academic staff participants stated that learning analytics supported what they thought, and strongly believed that learning analytics could not be used in isolation.

Cooper (2012) believes that institutions are at a strategic risk of being left behind by more innovative institutions if they do not offer a better and more personalised educational approach. At operational level, one reason for an academics' reluctance to engage with data- driven decision-making may be because learning analytics appear to be a crude measure compared with details of their experiential knowledge (Rienties et al, 2016). One way to help overcome this issue is by providing a thorough understanding of the learning analytics tool itself. This perspective is identified by West et al (2015) who believe that resistance from some academic staff to using data to support students may stem from a lack of data understanding from an academic perspective. This is a factor that needs to be addressed at the introduction of the change and through communicating and understanding the change vision (Kotter, 1995) within an institution as identified previously. Developing this level of trust in the data and the tools is important because, as Ferguson et al (2015) point out educators need to be able to understand and evaluate analytical tools in order to use them effectively.

Participants recognised that there is a need for those using learning analytics to take-action based on the information they provide, however there is limited literature which reports on how this is achieved within the context of learning analytics and education. Picciano (2012) believes that analytical techniques should be a supplementary mechanism, and that the human qualities such as experience and judgement should not be replaced. Picciano' s (2012) perspective is reinforced by Clow (2013) and Ellis (2013) who recommend that academic staff use the insights gathered from data to make interventions. Literature pertaining to the opportunities that are presented by learning analytics tools recognising that they can provide data-informed decision-making and actionable intelligence (Buerck and Mudigonda, 2014; Campbell et al, 2007) but Johnson et al (2013) believe that taking-action based on educational data has found a place within education only recently. JISC (2017) have developed a case study portfolio which supports their belief that it is only when actions are taken with students on the basis of the data that the true value of learning analytics becomes clear. It is to be noted that the case studies were developed in America rather than in the UK HE environment. The case study examples used control and experimental groups to identify the impact of learning analytics as a result of actions taken. JISC (2017) believe that these case studies demonstrate the most convincing evidence for learning analytics as a measure of achieving student success.

In the study reported here, participants indicated that interventions were primarily academically led, and that at an operational level it was the academic or professional services staff member who used the analytics, and then decided on whether or not to intervene. It is to be noted that not all participating institutions reported that professional services staff engaged with learning analytics tools, but that the primary focus was for academic use. JISC (2017) believe that using data to measure student engagement in near-time allows institutions to examine how effective an intervention is proving. Research participants alluded to a similar idea to that of JISC (2017) by recognising that an improvement in a student's engagement rating was currently the only signifier in the learning analytics tool of improvement as a result of using data. Student success can be measured in other ways (such as improving grade outcomes or improving a students' self-confidence) but they are not seen in the learning analytics tool. A surprise finding from this study is that participants identified a potential gap when operationalising learning analytics within the educational arena. Participants felt that there was not only a need to make an intervention based on information provided by learning analytics, but there was also a need to take- action after the intervention. A crucial point to raise is that learning analytics lacks the ability to know or record whether an action has been taken by academics, and there is no evaluative factor in relation to the effectiveness of that intervention, which may be critical to the future success of the student. This clearly demonstrates that learning analytics must not be used in isolation, and that there is a need for academic staff to use learning analytics alongside human insights and to document their interventions to see how this has had a positive effect on the student engagement rating.

Sclater (2016) recognises that there is as yet no literature regarding the effectiveness of the interventions educators take with learners as a result of learning analytics data, but he supports the notion that this is a vital part of the analytics process. This study, therefore, has highlighted a gap in the research and in the operationalisation of learning analytics in institutions as the learning analytics cycle is failing to 'close the loop' upon any interventions made. The only way that loop closure is determined is through reliance on staff to document their interventions and their outcome and effectiveness. Recognising this gap is an original contribution from this study, and alerts those involved with the development and implementation of learning analytics within an HEI to consider how this gap can be rectified within institutional mechanisms.

5.5.10 Staff and student relationships

Staff–student relationships were recognised by my study participants as a potential challenge to the development and implementation of learning analytics although there were varied and conflicting views. Some academic staff and student participants from across the different institutions felt that there using learning analytics provided an opportunity for students and staff to develop relationships through a nurturing approach; other academic staff participants suggested that learning analytics created an unequal power relationship in favour of the academic member of staff. This response was received from an experienced member of academic staff who had been at the institution for a number of years. The overall perception of learning analytics from this member of staff was negative, but could be reflective of Chandler's (2013) study findings which reported resistance to change from this particular staff group. No empirical research focusing on power relationships between academic staff and students from a negative perspective could be found. Academic staff participants in the study did worry that their academic accountability would be increased with the implementation of learning analytics, with concerns raised that its use could potentially be linked to staff performance monitoring. Therefore, one suggestion is that staff–student relationships may be improved or constrained depending on whether an academic perceives that they will be made more accountable as a result of the implementation of learning analytics, and whether there is resistance from staff in adopting this approach.

5.5.11 Academic responsibility and accountability

Participants recognised that the role of the academic would change with the development and implementation of learning analytics within HE. Academic staff participants felt that implementation of learning analytics would potentially increase their accountability and responsibility and were largely sceptical of the place that learning analytics held in relation to their academic role. Many of the academic staff participants were unclear whether the implementation of learning analytics was a measure to increase individual academic accountability or to monitor academic performance. This concern could potentially increase resistance in using learning analytics, and reassurance from institutional senior leaders at the development stage of learning analytics would be needed to avoid speculation. A further suggestion to fuel this argument could be if institutions adopted a top down directive, which could cause further resistance. A study by Macfayden and Dawson (2012) acknowledges that learning analytics maybe used as a measure of performance and may facilitate comparison with academic peers. Macfayden and Dawson (2012) further indicate that an additional concern is the reduction of academic autonomy which may have a negative impact on willingness to adopt learning analytics. Although this aspect is raised both within the literature and in my study as an area of concern, the literature does not seek to answer this issue. Sclater (2017) found that academic stakeholders have additional concerns regarding the impact of learning analytics in relation to their workload and working practices, and that this may cause resistance. Diaz and Fowler (2012) also recognised this challenge, and they suggested that it can be overcome through the management of academic staff expectations and through clearly conveying the benefits of learning analytics and the workload implications. My findings indicate that how the change process is managed is another important consideration in addressing the concerns of learning analytics users.

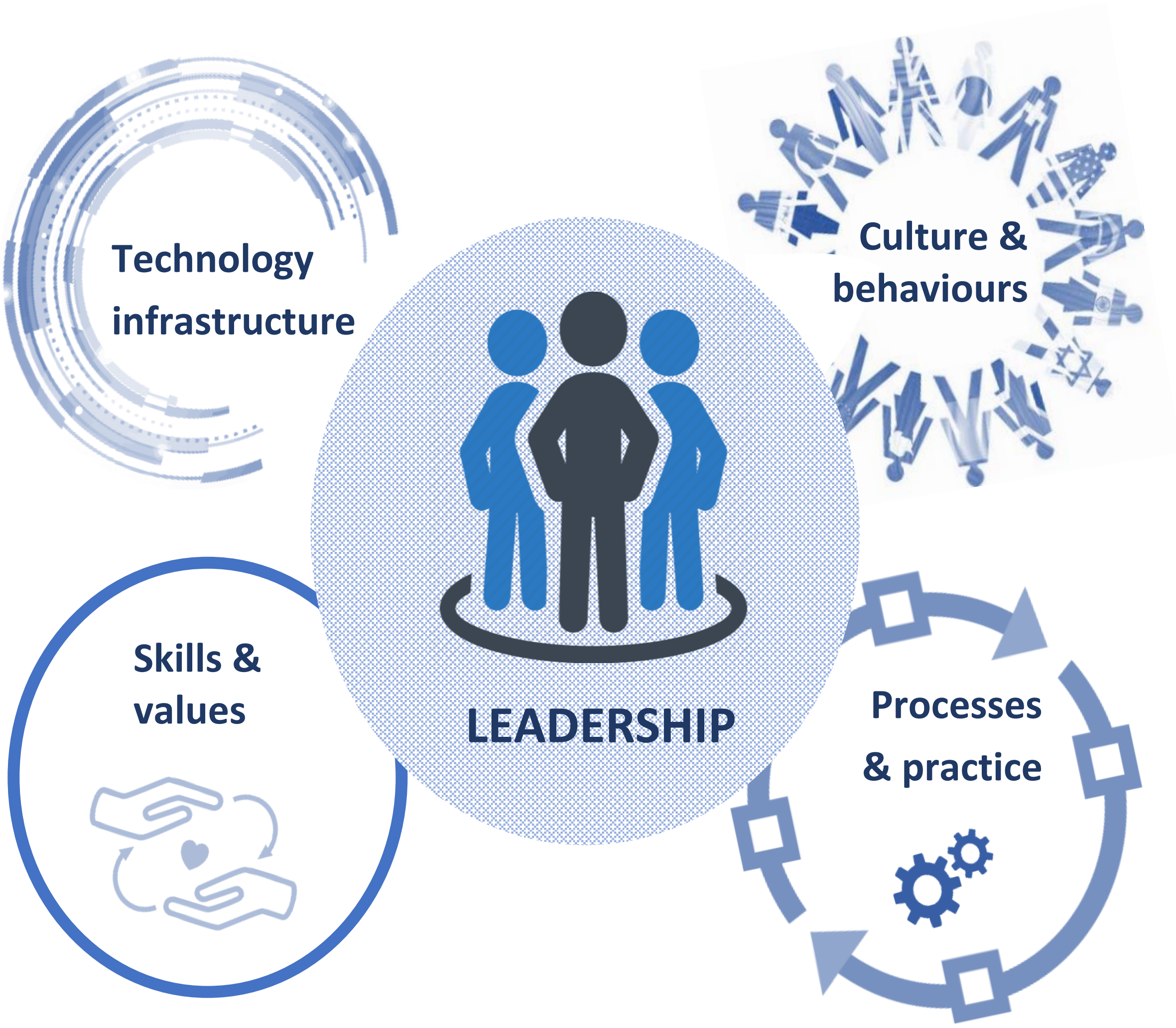
5.5.12 A lack of data reliability

Findings from my research indicate that data issues, and reliability of institutional data management systems in particular, were often a barrier for the implementation of learning analytics. This factor should be included in the conceptual framework as one of the broader challenging factors which surrounds learning analytics development and implementation. Unreliable data management systems were reported by all participants at varying degrees across all of the participating institutions. Although students did not see that the presentation of incorrect data was an issue, learning analytics expert participants and academic staff felt that data unreliability was a perceived barrier to the implementation of learning analytics. This would seem to indicate that there is a lack of institutional readiness to support the development learning analytics as a new educational approach. Although literature clearly shows institutional approaches to the development and implementation of learning analytics, research in this area is not widespread or on a larger scale. JISC (2018) recognise that institutions should monitor the quality, robustness and validity of their data to maintain confidence in learning analytics. These findings are reflective of a study conducted by Bichsel (2012) who uses categories to analyse institutional readiness and demonstration of an institutions maturity for implementing learning analytics. Bischel (2012) believes that culture/process, quality data and data reporting, investment, expertise and governance/infrastructure are of paramount importance when developing learning analytics within the HE arena. Aspects identified by Bichsel (2012) and JISC (2018) will be critical in responding to the third research question which asks how can learning analytics be used effectively within an HEI to support the student experience.

5.6 Using learning analytics effectively within an HEI to support student success

The third research question sought to consider, in view of the findings presented, whether learning analytics could be effectively used within an HEI to support student success, and if so, how. When considering the information conveyed by all of my study participants, and with regard to the conceptual framework structuring the literature review and findings, it can be concluded that in order to develop and implement learning analytics within HEIs, consideration should be given to a number of significant strategic and operational factors in order to effectively achieve this. It is identified that 4 of the participating institutions in my study had only recently implemented learning analytics, and this may be reflective of some of the responses received. The findings of this study relate to the concept of organisational capacity for analytics developed by Norris and Baer (2013). Norris and Baer's (2013) model is based on assessment of the activities and processes that leading institutions used to optimise student success; they found that success was dependent upon five factors. This model accurately depicts some of the fundamental issues raised by my study participants and has informed the conceptual framework for this study. The model is illustrated in Fig. 5.1.

Fig. 5.1 Organisational capacity (Norris and Baer, 2013, p. 30).



My research participants identified the need for a clear purpose for learning analytics, Norris and Baer (2013) argue that commitment and leadership from the senior level of an institution is critical for the implementation of learning analytics within an HEI. Colvin et al (2016) conducted research across 28 Australian universities and concluded that a major theme emerging was the importance of senior leaders in creating a successful initiative through setting strategic direction and indicating the institutions commitment to learning analytics. Although it is recognised that Australian HE system differs from UK educational practice, Colvin's (2016) findings are reflective of original work conducted by Cooper (2012) in the UK, who recognised that the most effective users of learning analytics select techniques that best match their operational or strategic targets in terms of data, technology, organisational culture and skills including leadership.

Norris and Bear (2013) recognise that few institutions make substantial progress in elevating the importance of learning analytics without executive commitment and investment in new tools, solutions and practices, particularly in relation to changing organisational culture and behaviours. This emphasises the need to address or change organisational culture issues and to foster positive staff behaviours to implement learning analytics successfully within an HEI. Norris and Baer (2013) state that a human and fiscal resource investment plan must be developed and should include long-term institutional commitment to launching, resourcing, scaling and sustaining effort when developing and implementing learning analytics. My study participants did not indicate whether a long-term institutional plan was developed within their own areas but alluded to the idea that sustaining effort in implementing learning analytics remained a challenge.

5.6.1 Leadership

Research participants strongly emphasised that there was a need for effective strategic and operational leadership to implement learning analytics successfully within their institution, and this is central to Norris and Bear's (2013) model of organisational capacity. The concept of leadership has been extensively studied within literature; one classic work by Kotter (1995) researched effective leadership when specifically applied to the change process.

Kotter (1995) believes that there are eight steps to leading effective change, which are presented as:

1. Establishing a sense of urgency
2. Creating a guiding coalition
3. Developing a change vision
4. Communicating the vision for buy in
5. Empowering broad-based action
6. Generating short-term wins
7. Never letting up
8. Incorporating the changes into institutional culture.

Kotter (1995) discussed leadership from a generic perspective, so it might be argued that this description of leadership for change may not be sufficient to promote effective change in relation to the implementation of learning analytics within an HEI. Arnold et al (2014) found that, in addition to the steps proposed by Kotter (1995), leaders should possess domain knowledge, and that a leader needs to have a deep understanding of learning analytics principles and practices to create institutional success. However, the findings from my study show that within the educational context, awareness and understanding of learning analytics is often present in only a few individuals in each organisation, so this may be difficult to achieve. What this does support is the development and implementation of learning analytics within a HEI should be considered from a multi-stakeholder perspective to bring together individuals from across the institution to achieve the goal. Learning analytics expert participants recommended the use of change agents to reinforce the positives of learning analytics to sceptical staff, to encourage a successful change effect within and across the institution. Sclater (2017) believes that it is essential to have leadership at all levels, but to use advocates at subject or school level, as this is likely to have more impact than a directive from senior management.

5.6.2 Culture and behaviour

As noted previously, study participants realised that effective organisational change was needed within their institutions, and this is linked to the culture and behaviour of staff, which in turn is linked to institutional and technological readiness. Although the learning analytics experts and academic staff perceived the implementation of learning analytics as a top-down directive from senior staff, it was apparent that the application of learning analytics was not reinforced at an operational level, and that academic staff and students were given autonomy to use it if they wanted to. This creates a culture of believing that the learning analytics tool is optional rather than a requirement, with attendant staff behaviour.

Norris and Baer's (2013) model for organisational capacity posits that organisation culture and behaviour is an essential aspect to optimising learning analytics for student success. Norris and Baer (2013) believe that organisations need to embrace the power and value of data and move towards a changed culture which values the fact that analytics can provide actionable intelligence that provokes action and intervention. Sclater (2017) believes that from a strategic perspective, there needs to be shared values and beliefs about what is best for the organisation, staff and students. Sclater (2017) also believes that learning analytics initiatives should be built as part of an organisation's strategic plan to promote acceptance, but does acknowledge that this is not apparently the case within the current UK HE context.

5.6.3 Technological infrastructure and readiness

The findings from this study clearly convey that there is a skills gap in terms of technological readiness and technological acceptance, a perception which is reflected by Rienties et al (2018), Norris and Baer (2013) and Sclater (2017) who recognises that is a task that organisations should put effort into developing readiness before embarking on an institutional learning analytics project. Norris and Baer (2013) advocate that an appropriate technological structure which includes infrastructure, tools and applications is critical to enable users to access accurate data and thus improve their decision-making. Norris and Baer (2013) believe that this should include a combination of data, information, reporting and analytics capabilities. Indeed, without effective data, such as when data sources are lacking or are incomplete, the purpose of learning analytics cannot be fulfilled, and trust in learning analytics can potentially become damaged. Again, this necessitates the need for a multi-stakeholder approach to be implemented to ensure that expertise is gathered and used positively from across all areas of an institution. Powell and MacNeill (2012) suggest that institutions need to ensure that there are staff with appropriate skills in data-handling and the ability to interpret and visualise data, and that academic staff and learners have the ability to take actions based on the information presented. Despite Powell and MacNeill's early observation, Sclater (2017) recognises that existing data sources and systems may not be adequate or properly understood or are being collected in a systematic way that allows for data to be incorporated into a learning analytics system and this was a significant barrier that learning analytics expert participants alluded too. My study confirms that without these mechanisms being in place, an organisation is not ready to embark on the development and implementation of learning analytics, as it may not be the most reliable mechanism to support student success, and this has knock-on effects on other challenges.

5.6.4 Skills and values

Norris and Baer (2013) believe that to achieve effective organisational capacity for learning analytics, staff and students need to be willing to participate in a culture change, focused through a co-ordinated and continuous approach. Siemens et al (2013) have identified that there is a shortage of skills and capabilities of people being able to apply analytics within a pedagogical context and learning analytics expert participants in this study confirmed that there was an operational technical skills gap among some staff and students. Siemens et al (2013) believe this skills gap is why case studies have failed to translate innovations into institution-wide practice and suggest that offering courses in learning analytics would help to resolve this issue. Student participants in this study reported that they were not introduced to the learning analytics tool, nor were they provided with guidance as to what it was used for or how it could support their educational success. Although it is not stated in the literature about learning analytics, it is recognised generally that effective change requires training through what Kotter (1995) describes as broad-based actions. Therefore, the training needs of both staff and students should be identified, after which appropriate support and training should be designed and implemented so that use of the learning analytics tool is promoted within the organisation, and there is a clear understanding of the learning analytics tool.

5.6.5 Processes and practices

My study participants did not indicate whether there were any policies and practices in place for learning analytics within their institutions. Literature appears to support this, with only one study by Rienties et al (2018) acknowledging a clear strategy with consideration of ethical issues being put in place within one institution. Taking this into account, it appears that the development and implementation of learning analytics is occurring without clear procedural strategic or operational policies and processes. Norris and Baer (2013) emphasise that policies and practices need to be embedded within an institution and used effectively at all levels to promote a data-driven mind set. They also point out that operationally, policies and processes need to be audited to see what supports student success and what has become impediment. Sclater (2017) recognises that structure and governance of learning analytics need to be put in place across all levels for an organisation to achieve learning analytics success. He suggests that data ownership should be considered from both a technological perspective as well as an academic perspective.

5.6.6 Supporting the process of change

Although the elements described by Norris and Baer (2013) can be considered essential to address organisational capacity to ensure student success in learning analytics, one of the key challenges to overcome identified within my study relates to the change process and how change is effectively introduced. Staff and student reluctance to embrace or accept changes in their approach to student success need to be managed carefully for change to be effectively implemented.

According to Macredi and Sandom (1999) the ability to manage change successfully has become a vital characteristic of organisations which wish to stay competitive in an unstable environment. It stands to reason, then, that any impending change resulting from the development of learning analytics needs to be considered carefully, with Chapman (2002) reinforcing that transformational change requires changes in the attitude, beliefs and values of employees to be effective. As an effective change methodology, appreciative inquiry (AI) has been used to facilitate effective change within organisations, and has more recently been applied to research within the social sciences, health and education (Cooperrider and Whitney, 2005). Within recent years, AI has emerged to become an approach that supports and facilitates educational or organisational change during a transitional period or innovation, and as such, seems naturally fitting to the focus of this research. As the implementation of learning analytics is viewed sceptically by some staff within organisations, AI could potentially be an effective change mechanism by those advocates of learning analytics within an institution to encourage key stakeholders to adopt learning analytics and encourage acceptance.

5.7 Appreciative inquiry as a change methodology

Appreciative Inquiry is a well-researched change management approach that focuses on identifying what is working well, analysing why it is working well and then doing more of it (Cooperrider and Whitney, 1999). Interventions in AI focus on imagination and innovation instead of on the negative, critical and spiraling diagnoses commonly found in organisations (Cooperrider and Whitney, 1999). Organisations and institutions adopting AI are viewed as entities seeking solutions, rather than entities focusing on problems (Cooperrider and Whitney, 1999). Using AI as a model for change starts with the major assumption that in every organisation something works, and that effective change can be managed through the identification of what works, and working out how to do more of it (Annis-Hammond, 2013). However, as we have noted in earlier discussions, there should be a belief that there is institutional and technological readiness, as well as accuracy of data before this approach can be implemented effectively with regards to learning analytics.

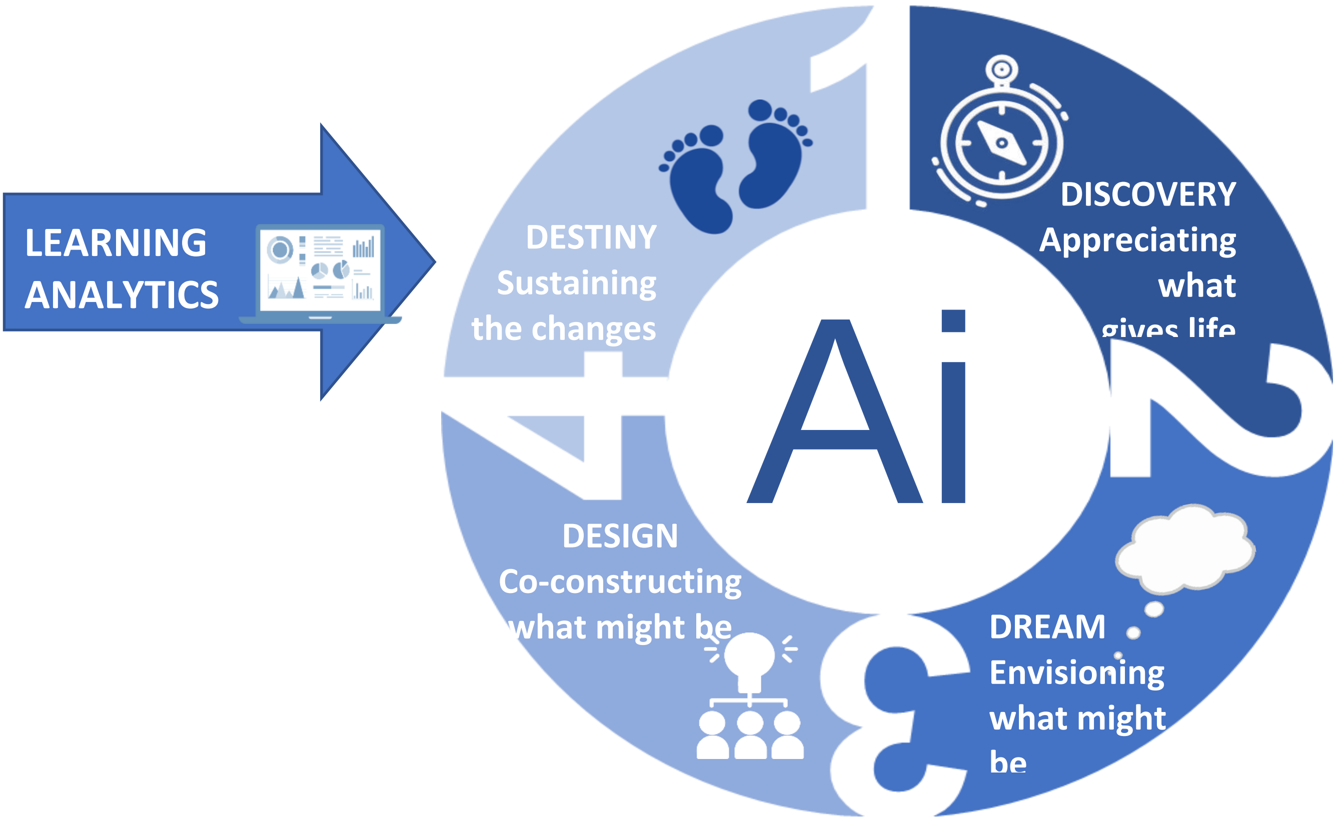
Critics often refer to AI as looking through rose-tinted glasses (Carter, 2006) because of the perception that if positive elements are looked for, then they will be found. Using positive opinions and experiences of learning analytics to drive forward development within an institution could be used proactively, rather than focusing on negative considerations. According to Reed et al (2008) AI is a useful approach when addressing issues that can easily become focused on difficulties and negativities, rather than on strategies to respond to them. This was borne out in reflective responses from the participants that contributed to my study, who recognised that there was negativity and scepticism to using data as a basis to support student success, which could easily perpetuate a strong resistance to change and future development. However, Nyaupane and Poudel (2012) warn that if the process is not carefully followed, AI can be no more than a daydream or provide false hope.

When using AI, all stakeholders have an equally important role within the process, although it is recognised that there may be different levels of understanding of the AI process. A stakeholder is a person, group or organisation that has a direct or indirect stake in an organisation, someone who can affect organisational processes (Nyaupane and Poudel, 2012). In the case of implementing learning analytics, stakeholders would be students, academic staff and technical experts and senior leaders within the organisation. Messerschmidt (2008) believes that the success of the AI approach relies on the understanding of social relationships, social conflicts and a broad knowledge of the social-cultural, historical, political and economic underpinnings of the learning community. Using a breadth of key stakeholders as a project development group would go some way to achieve this aim. This is reflected in my conceptual framework which shows all these stakeholders within a common environment with common opportunities and challenges.

5.7.1 The AI cycle

The AI process uses a 4-D model (Cooperrider and Srivastva, 1987) to direct and implement organisational change. This is illustrated in Fig. 5.2.

Fig.5.2 4-D Appreciative Inquiry Framework (reproduced from Cooperrider and Srivastva, 1987, p. 26).



The object of the discovery phase would be to identify the positive elements and opportunities of using learning analytics as a mechanism to support student success. To develop learning analytics, representatives of all stakeholders need to be gathered together (technological experts, academic staff, students and senior managers) to act as a project group to steer the development of learning analytics forward. There is a clear requirement for leadership within this phase with the ideal being that the leader should have expertise in learning analytics (Arnold et al, 2014). The leader would need to act as an active facilitator during the discovery phase, with the main function of steering the enquiry process and encourage project participants to share their stories and thus elicit the positives to adopting learning analytics as an approach to support student success.

The next phase of the AI process is known as the dream phase. Applied to the learning analytics context, the dream phase would need to consist of all stakeholders taking collective ownership to create an ideal image of the preferred future based on information collected in the discovery phase. This phase is designed to help stakeholders to think beyond short-term problems. In this phase, it is essential that stakeholders think about the 'ideal' for the implementation of learning analytics and identify how perceived challenges to the vision could be overcome. As my study has clearly demonstrated, numerous challenges are associated with adopting learning analytics. All these challenges would need to be considered from both a strategic and an operational perspective. Therefore, strategically the dream phase would need to involve the development and implementation of an organisational strategy to support learning analytics, as well as the development of clear policies and practices to embed the new approach. The most likely dream would be that learning analytics becomes normal practice within the HEI, with the aspiration that new data sources can be gleaned to improve the level of analytics offered. From an operational perspective, the dream phase includes student ownership of the learning analytics tool, and the provision of a personalised learning experience for students, enabling them to set goals for their university career, monitor their progress more closely and to make changes based on data-informed reflection (Wise cited in Sclater, 2017).

The design phase refers to the planning and implementation of activities to accomplish the dream. A number of factors, such as technology, human and financial resources, and governance would need to be considered as an inherent part of this phase (Norris and Baer, 2013), since these factors would affect the implementation of the change process. An effective approach to planning and carrying out the design phase is proposed by Chatti et al (2012) who recommends that a *what, who, why* and *how* approach is frequently used as an effective mechanism to support the development and implementation of learning analytics. Chatti et al (2012) believe that for the *what* phase objectives concerning the data, environment and context need to be set, with the key stakeholders forming the *who* part of the process. The objectives set for the project form the *why* part of the project, and the final step of Chatti et al's (2012) process is identification of *how* the objectives will be met. The outcome of the design phase would be a detailed plan of activities that articulates responsibilities of stakeholders to achieve a common goal.

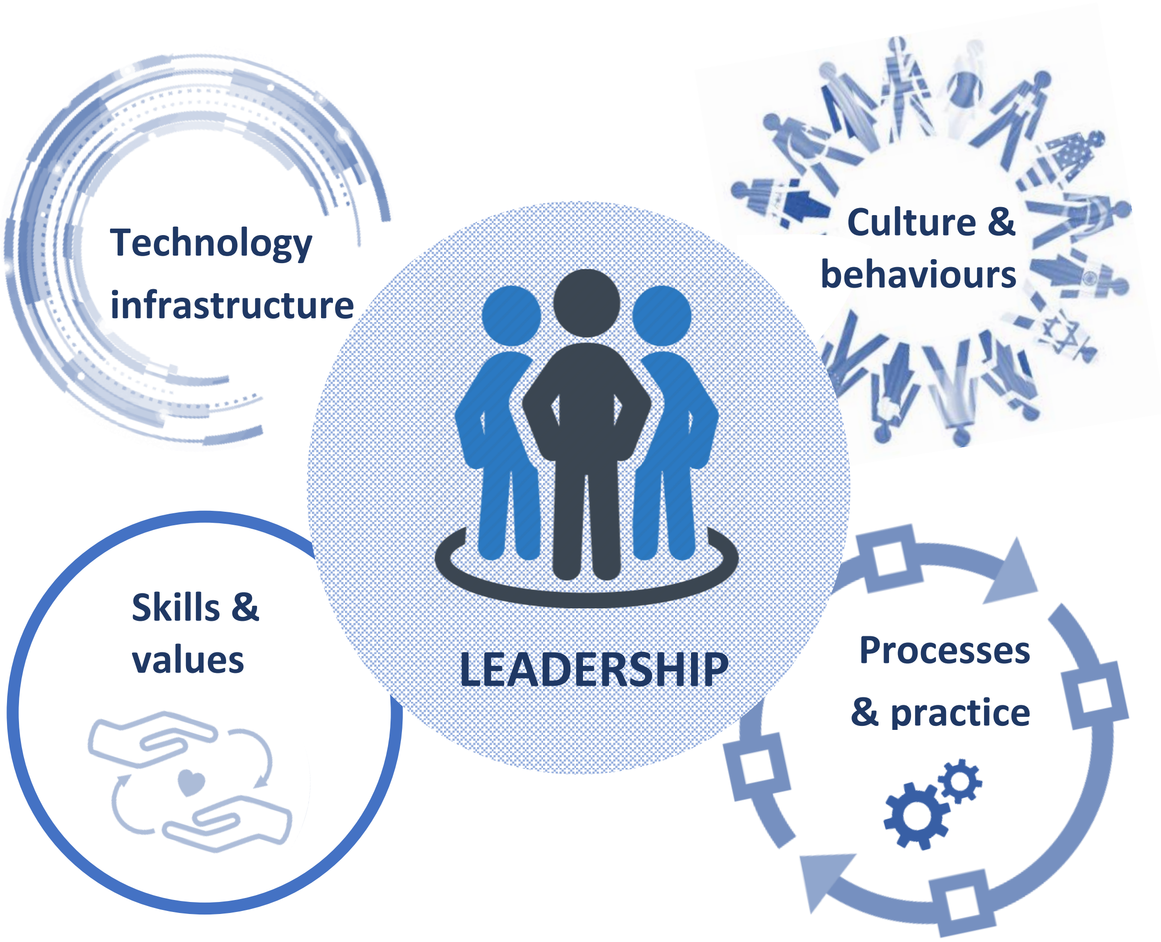
A key aspect of objective-setting in the design phase, is that a clear strategic purpose for the development and implementation of learning analytics needs to be determined. In addition, as proposed by my study participants, a clear step-change approach needs to be designed to manage the organisational change. Study participants believed that the change should be implemented slowly, using selected courses or users from specific faculties. From an operational perspective, objectives need to be set to ensure clear communication so that academic staff can understand their role in relation to using learning analytics. From the findings of my research, it was identified that academic staff required reassurance that learning analytics was not intended to be a performance management tool, but rather would allow them to undertake their role more effectively in supporting students to succeed. Secondly, it was clear that the implementation of learning analytics would need to be embedded as part of organisational student support systems (such as personal tutoring) to be effective, and to ensure understanding of its use. A third objective is to reduce the technical skills gap, so that staff and students can use the learning analytics tool effectively as part of daily practice. One approach to student training might be to launch learning analytics formally to students as part of course induction and at personal tutor meetings. This approach would also seek to support student ownership and provide students with motivation to use the learning analytics available.

The final phase of the AI process is the destiny phase. The destiny phase is associated with sustaining positive outcomes and taking-action on positive accomplishments. In a true AI framework, a reflective session would be conducted to evaluate what stakeholders had learnt from applying the AI sessions. In the case of learning analytics, this would serve to widen the knowledge of learning analytics and to determine the level of impact that learning analytics can have within the institutional setting.

5.8 Refinement of the original conceptual framework

Following the presentation of the research findings and as a result of the discussion, I have reflected on the conceptual framework that I previously devised for the literature review, and which was used as a basis to examine learning analytics from differing viewpoints. As a result of this reflective process, I realised that I had placed learning analytics centrally within the conceptual framework with students, academic staff and the institution linking around it as other influencing factors. Through discussing the findings in Chapter Four and linking them with the literature discussed in Chapter Two, I recognised that learning analytics should not be central. Learning analytics is a single mechanism to support student success so it seems apt that the student should be central to the process rather than analytics, and that analytics should take its place as a part of the whole institutional environment. The proposed amended conceptual framework is represented in diagrammatical form in Fig. 5.3.

Fig. 5.3 Revised conceptual framework



5.9 Summary of the chapter

This chapter has provided a discussion of the thematic findings that emerged from the information provided by participants at interview, and how they address the research questions. The chapter has linked the key findings and themes to the existing literature in order to ascertain whether this new data supports or contradicts existing information. This chapter also presents an amended conceptual framework which was felt to be a better reflection of how learning analytics should be developed and implemented within the HE setting, and also provides a more useful tool for learning analytics developers moving forward.

Chapter 6 Conclusion and recommendations

6.1 Introduction to the chapter

This concluding chapter will bring together the overarching conclusions drawn from the key findings in this study. This chapter will then identify and discuss the wider implications of this study in relation to educational practice, educational management and educational policy. Key recommendations are made for future practice and the acquisition of new knowledge, with suggestions for further research to support the development, understanding and implementation of learning analytics within the HE context.

6.2 What has been learnt?

My study has contributed to the wider knowledge base in relation to the development and implementation of learning analytics within the HE context. It has achieved this through the exploration of individual perceptions and experiences of learning analytics from a multi-stakeholder perspective involving academic staff, students and learning analytics experts. The interpretivist approach taken to this research resulted in the accumulation of rich qualitative data from which different themes and perspectives emerged.

6.2.1 Responding to research question 1

In order to achieve the overarching research aim, three research questions were selected. The first research question asked participants:

> **What are the opportunities in the use of learning analytics as viewed by students, academic staff and learning analytics experts?**

Analysis of the data from interviews conducted with academic staff and learning analytics experts showed some similarities in their views relation to the opportunities that learning analytics provides. These opportunities were related to the fundamental concept of learning analytics per se, and to the idea of using data as an information source for supporting students to succeed within HE. What was evident across these two research participant groups was that participants from different institutions had different drivers and different purposes for developing learning analytics within their areas. There was a mixed response from participants in terms of the reasons for the implementation of learning analytics within their institution. The purpose of developing and implementing learning analytics reflected suggestions made within the existing literature and included reasons such as student retention, improving educational course design and improving levels of student support. Participants felt that the opportunities afforded by learning analytics included offering a holistic view of the student and providing academic staff with a tool to aid and improve their decision-making. This was broadly related to having data as an information source on which to base an academic decision rather than relying on their own experiences, personal judgement or a 'hunch'. Learning analytics was, at times, used as a decision maker by some academic staff, but the question as to whether reliance on learning analytics will increase as experience of it continues to evolve within educational practice. Issues arose from this data which were pertinent to the second research question, which asked about the challenges in the use of learning analytics. While participants generally agreed that the development and implementation of learning analytics provided opportunity, there were also fundamental challenges raised.

Interestingly, students viewed the opportunities of learning analytics differently from other study participants and felt that the opportunity that learning analytics provided was related to student success- more specifically to helping students to improve their degree outcome through encouraging ownership and motivation for students to take responsibility for their own learning. Student participants felt that learning analytics allowed students to develop learner agency. Despite this, in the student focus group interviews it was acknowledged that although students saw value and opportunity and were motivated to use the learning analytics tool, some did not, and this links to the second research question which addresses the potential challenges of using learning analytics.

All participant groups felt that the opportunities that learning analytics provided changed the role of the academic staff, and, that when learning analytics was implemented effectively within an institution it supported driving forward the development of academic staff and student relationships. Learning analytics was strongly embedded as part of the role of the personal tutor in providing student pastoral and academic support, and there was a clear expectation from study participants that when it was linked to student success, the personal tutor was best placed to take ownership of learning analytics. It appears that the predictions derived from a learning analytics tool can provide academic staff with a reason or purpose to engage with their students, and this provides impetus for forging and improving staff–student relationships.

6.2.2 Responding to research question 2

The second research question was:

What are the challenges in the use of learning analytics as viewed by students, academic staff and learning analytics experts?

Unsurprisingly, given the rapid growth and development of learning analytics within UK HEIs participants within the study reported many challenges when questioned on this particular aspect. Findings from the interviews with academic staff and learning analytics experts showed that the evolution of learning analytics within education was in different stages of development across institutions, and that some institutions had to stop implementing learning analytics initiatives as a result of organisational issues and technical data challenges. Academic staff and learning analytics expert participants clearly felt that learning analytics could not be used in isolation, and that systems needed to be effectively combined with other student support mechanisms (such as personal tutoring) to ensure a successful student outcome.

The greatest challenge for the development and implementation of learning analytics within the HE environment is that it represents a significant change. Both academic staff and learning analytics expert participants expressed that this challenge was linked to the change process, including how the move to using learning analytics was implemented (i.e. from a strategic top down approach), how the change was managed and conducted, and the level of perceived 'institutional readiness' to a move to using data to support student success.

Many of the challenges presented came from the academic voice rather than from the student participants. Academic staff and learning analytics expert's participants felt that the development and implementation of learning analytics challenged the role of the academic, and in particular they cited issues such as a potential power shift in the staff–student relationship when using data to support students. Other academic challenges were related to the fear academic performance being monitored, the loss of academic autonomy and the concerns over the potential for increased academic accountability. Although academic staff generally welcomed the idea of using data to support their decision-making, many negativities were identified when this was linked to monitoring academic staff performance.

Student participants generally felt that motivation was the biggest challenge in the development and implementation of learning analytics within an institution. Some students wanted to be responsible for their learning and take ownership of this. They also recognised that not all students were motivated to use learning analytics tools to support their successes. The challenge remained that students were of two opposing viewpoints- those that freely engaged with learning analytics and used it to their advantage, or those that did not engage with it at all.

The final important challenge that was elicited from participants was technologically related. This area could include fitness for purpose of the systems and the data, and also technologically ability of the users. This was viewed differently among the participants, learning analytics expert participants, for instance, cited data unreliability as a cause for ceasing learning analytics' implementation, and they and others questioned the reliability and accessibility of data within institutions. Student participants raised questions regarding the digital literacy of student peers, and more broadly, participants perceived technical skills gaps among academic staff and learners. It is clear that it is essential to overcome reliability issues and to provide students and staff with training and development to use and interpret analytics information.

6.2.3 Responding to research question 3

The final research question to be answered was:

In view of the findings above, can learning analytics be effectively used within a Higher Education Institution to support student success and if so, how?

This study has identified numerous opportunities and challenges for the development and implementation of learning analytics within an HEI. The suggestions that my study participants have given show the way forward to overcome challenges, to ensure that institutions focus on student success effectively using learning analytics as one mechanism among others. When discussing how learning analytics can be best be used, the study shows that we need to approach the issue from both a strategic and an operational perspective.

From a strategic perspective, a warrantable claim from study participants, supported by the literature is that there needs to be a clear purpose for learning analytics, which strengthens the position in existing literature that learning analytics is the preferred approach to support student success. This clear purpose and reason for the development and implementation of learning analytics needs to be defined by strategic leads, outlining specifically what aspect an institution wants to improve and address through the use of learning analytics. In addition, this purpose needs to be effectively communicated with all stakeholders within the institution (learning technology teams, managers, academic staff and students) with clearly defined parameters so that it is possible for all to see how it will support strategic direction and strategic need. A clear purpose will provide institutions with goals in terms of the internal and external drivers against which to measure the impact and effectiveness of the initiative. Finally, institutional readiness is essential. This requires confirmation prior to the development phase to ensure effective implementation. It is clear from the study and from the more general organisational learning analytics literature that institutional readiness is frequently related to data and the need for effective data management systems to ensure reliable, well informed analytics tools. Poor data reduces validity, and may provide students and staff with inaccurate predictors, which in turn renders learning analytics unreliable, open to criticism from academic colleagues and student users, and therefore ultimately unreliable.

From a strategic institutional perspective, a warrantable claim from this study data is that an inclusive policy for the development of learning analytics should be co-created by key staff groups and students within an institution to ensure effective development and adoption of this approach. This will ensure that there is strategic alignment with other institutional initiatives, and that there is a whole-institution approach and commitment to use learning analytics. The policy should pay particular focus to student-centeredness, student ownership student ownership and inclusion. Through the provision of effective strategic leadership, there should be engagement from all stakeholders at the objective setting, the design, development and roll out phases, and also in future monitoring of learning analytics. This will serve to empower individuals to adopt a planned step change process. The key individuals involved with analytics development and their responsibilities should be clear. It is important that learning analytics is developed and understood in its wider context and is combined with other student support mechanisms (such as personal tutoring) to ensure that institutional and local level decision-making is not taken in isolation. This approach will serve to engage staff and students, encourage open and honest conversations as well as understanding the broader purpose for change.

The largest strategic issue to deal with is management of the change process within an organisation. This study indicates that a slow burn change is viewed as effective in the implementation of learning analytics in HE, although it is recognised that this may not have a quick and effective financial or reputational effect for an institution. There is also the risk that using learning analytics will be seen as optional within academic workload rather than this mechanism being embedded in the organisation.

Operationally, institutions need to consider how learning analytics can be linked with existing student support mechanisms. For learning analytics to be operationalised effectively, a warrantable claim is that it needs to be embedded and integrated with personal tutoring to allow for a holistic view of the student. The personal tutor is potentially the academic staff member that knows the student best, so this person needs to be able to interpret the learning analytics appropriately to know when to prompt a conversation and make a positive intervention if the student engagement rating changes. Learning analytics can help predict student performance and under-performance, but even with the tools in place, there is still a need for academic staff to take-action based on what the learning analytics predictions show them. Without action, learning analytics serves no further purpose than to inform rather than to support student success. Once a prediction is generated, academic staff need to be educated on the importance of taking-action based on a holistic view of the student. It is also crucial that learning analytics has the facility to document academic staff actions and interventions so that this information can be used as an additional factor in student engagement data.

Operationally there is the important consideration of ownership of learning analytics. For learning analytics to be effective, this study shows that it should be driven by students to enable them to take ownership of their own learning progress. It is useful to define what student success looks like to an individual student so that students are aware of the level of effort and motivation that is required for them to succeed in their studies. Ownership of learning analytics by students also contributes to a successful change process through helping to embed the use of learning analytics even if academic staff are reluctant to engage. Ideally, ownership of learning analytics should be shared between academic staff and the individual students to ensure that there is an appropriate level of autonomy in decision-making and the taking of actions relating to students learning.

A slow burn change was viewed to be effective in the implementation of learning analytics; organisational culture and a stepped organisational change methodology (such as AI) could be an appropriate approach to drive forward effective change. Operational measures such as using academic, professional services staff and student ambassadors as change agents may serve to support sceptical academic staff who need reassurance that learning analytics provides a valuable tool in enhancing student success. This also links with the need to encourage both academic and staff engagement: through the use of practical examples academic staff and students can see how learning analytics are used in a positive way rather than as a way of monitoring the academic member of staff or student.

During the development phase, the change process will need to include the identification of staff and student development needs during the development phase. Practical training in using the learning analytics tool should be provided for staff and students, as should explanation and interpretation of the data sources to ensure that users are appropriately informed and have confidence in the tool. Students also need to have the learning analytics tool demonstrated at course induction activities and in personal tutor meetings so that they are aware of the purpose of the learning analytics tool and how to use it.

6.3 Recommendations

Following the discussion in Chapter Five, a number of recommendations that can be identified which will facilitate successful development of learning analytics within the HE arena. The changing context of HE remains a challenge for HEIs who need to consider carefully how they can ensure a successful educational outcome for their students in a dynamic and different environment. Although influencing government policy in relation to the drivers of HE sits outside of the scope of this research study, it must be acknowledged that this will indirectly influence the strategic development and implementation of learning analytics. The following recommendations will enhance further empirical research into learning analytics as well as providing a unique contribution to the existing knowledge base.

1. There needs to be a clear strategic direction for learning analytics in the institution, and the purpose and rationale for developing learning analytics must be clearly identified and conveyed to ensure that all stakeholders are aware of the institutional vision and ethos in relation to how institutions want to achieve the purpose

2. Once the purpose for the development and implementation of learning analytics has been defined and understood, the change process needs to be decided to determine how the change will be directed (i.e. to use AI or an alternative change methodology)

3. The change needs to be implemented carefully and effectively to ensure that staff and students engage with the change process

4. Operationally, the development of learning analytics should be clearly integrated with student support systems (such as personal tutoring) to ensure that analytics is embedded and that a holistic view of the student is provided.

5. The technological capabilities of both academic staff and students need to be addressed to avoid a skills gap and potential avoidance of using the implemented learning analytics tool.

6. Action needs to be taken. Action should not be based on the information that learning analytics presents alone but should be based on the learning analytics alongside staff–student communication to ensure that academic staff support each student effectively.

7. Learning analytics tools needs to have the facility to record actions taken so that the effectiveness of the intervention is known. Effectiveness maybe indicated by an improvement in the student engagement rating on the analytics system but also through documented evidence to create a body of evidence supporting the positive impact of informed decision-making and intervention.

6.4 Limitations of the research

While this study has contributed important additional insights into the development and use of learning analytics in HEIs, it is recognised that it has limitations. Firstly, the small sample size is a consideration. As we established in the methodology chapter, using a case study methodology means that generalisations are difficult to make due to the nature of the research methodology itself, so I although I have made claims resulting from my research findings, these are warrantable rather than generalisable. Although it was not an intentional part of the sampling strategy, the organisations that participated in this research turned out to be similar in terms of the diversity of learners, student population and institutional size.

As an insider to the research, I needed to be cautious in my approach to reduce the risk of bias. A starting point for this research was originally through my professional involvement within a learning analytics pilot project within my own institution. None the less, I came into this research process with no pre-conceived ideas, as I had experienced many different and conflicting views regarding learning analytics. Through drawing upon the experiences and thoughts of the distinct groups of study participants, my opinions regarding learning analytics changed and expanded as the project progressed. While I would consider that some participants' perceptions and experiences of developing learning analytics are similar to my own, ultimately, I recognise that there remain very different perspectives and experiences. Learning analytics is viewed as a positive educational development in theory, however operationalising this as a mechanism to enhance student success needs careful consideration.

6.5 Contribution to wider research

This research study has provided the opportunity for me as an educational researcher to build upon the existing knowledge base around the learning analytics domain. Although learning analytics has already been researched from a conceptual perspective, it is recognised that the development and implementation of learning analytics within HE is evolving, and, it remains an under-researched activity within published material. Although research exists in relation to concepts and challenges, educational data mining techniques and the use of learning analytics within social settings, there is currently limited published research into the perceptions and experiences of stakeholders developing and implementing learning analytics within HE. Undertaking this study has allowed me to investigate the development and implementation of learning analytics within other HEIs from the perspective of different stakeholders. Analysing the impressions, perceptions and reactions of the participants in this study has enabled me to bring together some of the overarching themes that are pertinent across UK HE and to contribute to existing knowledge to inform and support others to develop their pedagogic practice. The research findings may promote closer examination of the development of learning analytics within a singular institution as well as across the HE sector, and, more importantly it may serve to stimulate and promote discussion and reflection about this approach.

Within my own institution, we are beginning to re-visit the development and implementation of learning analytics some three years after the completion of the original pilot project. As an integral part of the strategic project development group which has taken the responsibility and ownership for the development, implementation and future monitoring of learning analytics, I am able to use my study to inform the strategic approach within my own HEI, particularly with regard to demonstrating impact. The evidence-based perspective of the study also helps to provide insight and learning for others from within the HE sector from an evidence-based perspective to support successful implementation. In the wider context, my research was presented at the 28th World Congress on Nursing Education and Research conference, and the 4th Nursing World Conference, and thus is starting to have an impact on the way institutions think of and plan for learning analytics.

6.6 Suggestions for further research

As learning analytics continues to evolve and develop within HE, empirical research into this educational development will increase. As we have noted previously, at present learning analytics remains relatively untested and under-researched. This makes advocating for the concept of learning analytics a struggle as there is little research informing practice, and little practice informing the evidence base. The study reported here has highlighted many further research questions that need to be addressed. Further research into these specific areas would help to support expansion of the current evidence base for the development and implementation of learning analytics within HE.

- student perceptions and experiences to understand learning analytics from a student voice perspective

- an action research approach into the development and implementation of learning analytics within a single HEI

- a study into perceptions and experiences of using learning analytics as part of a change process within a single institution

- comparative longitudinal studies across different HEIs and across different subject areas to ascertain benefits, challenges and outcomes of learning analytics

- the creation of practice-based examples relating to the development and implementation of learning analytics within an institution to avoid a mismatch in the field between research and practice

6.7 Personal reflections

Having entered academia from a Nursing background, my natural tendency is to explore research from a qualitative perspective; as I stated to my supervisor at the beginning of this research journey, my ambition in succeeding with the Ed D was to explore the 'touchy feely' side of data and link that clearly to my inherent professional practice. Upon reflection, undertaking this research study has supported my personal and professional development as an academic, but equally as an educational researcher, and I have been able to develop a deeper understanding of the complexity and value of the research process. Broadening my research focus following the suspension of learning analytics at completion of my institutional pilot project meant that the purpose of the research changed as my study progressed. Upon reflection, this has been positive at is has enabled me to consider more broadly the opportunities and challenges that learning analytics presents on a wider scale within UK HE provision. At times I had concerns that I would not be able to achieve my research goal, as I started this project with a lack of awareness of how developed learning analytics was within HE, and whether this was an area of strategic importance in other universities. However, I feel that ultimately the change in research direction to collect data from other HEIs has enhanced and enriched this study through providing me with a broader perspective from which to work with. Undertaking this study has enhanced my professional knowledge through firstly giving me a wider understanding of the diverse HE sector and secondly through providing me with an insight into the many pedagogic challenges that are faced across similar institutions to my own. In some areas the development and implementation of learning analytics was seen as an area of significant strategic importance, and there was a drive to implement this approach quickly, whereas other areas were still at early stages of development and trying to develop learning analytics through using their own strategic planning teams and through the use of their own institutional software, rather than buying in an expensive product through a commercial developer. Many of the teams had the necessary knowledge and skills to develop their own learning analytics software, but felt that they were competing with other strategic priorities and could not produce a professional product compared to manufactured versions, so I saw the reality that progress in terms of development was frequently hindered.

Networking with colleagues in other HEIs supported my professional understanding through the recognition that all institutions are at different stages of learning analytics as an educational development, and I saw very clearly from both reading through relevant literature and through speaking to people that there was a distinct willingness from both academic colleagues and project managers keen to develop learning analytics within the institution, equally I saw many barriers to the development and implementation of this approach. There was a sense of frustration from colleagues who frequently reported a lack of reliable data, and that this factor alone appeared to halt or limit institutional approaches to learning analytics development and implementation. Through reflection by undertaking this research, and further discussion of learning analytics more recently at strategic level within my own institution, I have too recognised that my own institution is not ready to embark on the development of learning analytics. This is largely due to the implementation of a new institutional data system two years ago which has not yet proved its reliability and continues to provide inaccurate data. Within other institutions, and from what I had seen myself when I was involved in my institutional pilot project, some staff were very keen to use data to support their students to succeed, but there was also a high reluctance from both academic staff and students to engage with using learning analytics, and in some sense, their perception was this was another educational change that was being dictated by senior managers. Within my job role, this was important in terms of lessons learnt, as I recognised that staff needed to be open and embrace change in order to make any educational change effective (not just learning analytics). As a result of this, I have changed my practice to ensure that more widespread views of users are sought through any educational change that I am asked to lead, and I have recognised that effective communication across both academic and professional services staff is fundamental to ensure success.

My personal views of learning analytics changed during my involvement with our local institutional pilot, and I felt that I moved from a positive stance embracing the concept of learning analytics to questioning whether the implementation of learning analytics was actually the right approach to ensure student success. Even at the completion of this research project I still remain undecided. I feel strongly that using learning analytics is a great innovation and can be an effective educational development; yet at the same time, I sense that UK HEIs may not quite be ‘ready’ strategically and operationally truly to embrace this approach, and that there are significant barriers that need to be overcome in order for learning analytics to be truly effective. Within my own institution, this remains the case. After conversations with academic colleagues within my own area, I once described the concept of learning analytics as like Marmite- you either love it or hate it. Though I have learnt much through this study, I still stand by my original analogy.

For me, there were some surprises in the findings from this work, and excitement in finding something new and original within this research field, such as the need for academic staff to take-action and ensure that they record and document their findings. I also quickly recognised that there is a strong sense of similarity across institutions in relation to the challenges presented. In particular, it is clear that no matter what the initiative is, academics tend not to view change positively. Academic culture has particular characteristics and perhaps the way it interacts with change is another research study in itself. I am indebted to the research participants that contributed to this study who willingly gave up their time and talked to me openly about their perceptions and experiences within their own areas. I hope that this research study gives something back on their own journeys within the world of learning analytics development.

Undertaking this research has informed my own professional practice significantly and I feel that I have developed both as a researcher and through me informing pedagogic practice. I have presented my research findings at international Nursing conferences, and I am keen to publish my work moving forwards. As a result of undertaking this research, and through my previous experiences with using simulated practice within Nursing, I have led as an academic and clinical advisor with colleagues at the Open University in the development of a virtual reality teaching tool, on taking blood sampling. This experience has allowed me to directly inform future practice, through working with colleagues outside of my own subject area to devise, develop and create a commercial product for widespread use. The development of this teaching tool holds promise to create a safe simulated environment in which students can practice blood taking skills prior to practising on a real patient. Aside from the development of this as a teaching tool, my involvement in this project has also allowed me to see learning analytics from a different side, as I have directly led the development of the critical predictive analytics that support effective blood sample taking.

My acquired expertise in the field of learning analytics has also resulted in me negotiating consultative work for a Northern public university. This institution implemented learning analytics eighteen months ago, through a manufactured software provider. This is underutilised within the university, and I have been tasked with devising an institutional policy and work with academic staff to embed learning analytics with the universities personal tutoring system to ensure that it is used by both academic and professional services staff. My work will also include working with the Student Union to drive forward student utilisation. Although this work is at very early stages, this has enabled me to establish a clear relationship between this research and developing my professional practice. Following the completion of the Ed D, I would like to progress my work within the field of learning analytics further and potentially re-direct my academic career within this domain.

When reflecting on the research process in detail I will reflect on the methodology, the tools and techniques used and identify the strengths and limitations of this approach. These personal reflections could be useful to other researchers if this study were to be repeated. When reflecting on the participant sample size, I recognised that due to both time and geographical limitations that this sample would not be truly representative of all academic staff and student perspectives within the UK. Through a purposeful sampling approach, my original sample size was evenly balanced between academic staff and learning analytics experts, but this could have been different if there had been a lack of response from some participants when I invited them to take part in this research study. This could have happened as I contacted them by e mail, which can be easily ignored. Upon reflection, the use of a different medium such as an initial telephone conversation may have provided more of a personal touch when inviting individuals to participate. From the initial responses it appeared that the learning expert participant group were more willing and more easily engaged with my request to interview them. My small initial sample size was overcome with the help of some participants themselves, as they provided me with additional names of additional staff to contact which had a snowball effect on my participant sample. In the relevant section above, I also acknowledge some further limitations to the sample size as some institutions were in a similar position to my own and had suspended the implementation of learning analytics due to internal institutional challenges. This may have resulted in a biased perspective from participants, which potentially could have affected the overall findings of the study. Upon reflection, the findings from this study feel provide a balanced perspective from all research participants has allowed me to consider a holistic view.

As I entered into this study my concerns were that I would not be able to recruit student research participants as they did not know me personally and would question why they should take part. As academic staff approached their students on my behalf asking for their participation in the study, I was easily able to easily gather volunteers, and I found that students were willing to share their experiences with me. This method of recruitment could have affected the results through attracting students that were keen to impress their personal tutors, or only those who held a particularly strong view on learning analytics leading to a skewed perspective. My decision to conduct focus groups with students rather than to conduct individual face to face interviews was an effective way of mitigating potential issues, as it enabled students to talk freely during the interview process. Despite my initial concerns, students provided a wealth of interesting data from different viewpoints, and I was able to gather sufficient student perspectives which I feel have enriched this study and has provided a triangulated response to the research question under consideration.

When commencing my research study, I recognised that I needed to meet research participants face to face to enable the development of a professional relationship with this cultural group of individuals and to glean their honest responses. The semi-structured face-to-face interview process allowed me to observe both the verbal and the non-verbal cues that research participants provided. The interview approach enabled me to understand how learning analytics was developing within each participants area of work and ascertain information about the learning analytics tools used. There were many areas where clarification of understanding was needed, and upon reflection I do not feel that this could have been achieved using a different data collection method. In addition, these meetings allowed me to engage in sector wide discussions with academic staff and learning analytics experts on educational developments across different HEIs and also to network with new colleagues.

The interviews themselves were conducted over a short space of time for me as a researcher, I was conscious of students entering summer vacations and not being available to participate, while simultaneously recognising that summer months with little teaching activity and no student assessments were potentially a better time for academic staff to be interviewed. This created a small but suitable time frame in which to collect data. While the interview approach was time-consuming for me as a researcher, upon reflection, I realise that the benefits of this process was that it allowed me to submerse myself within the data collection phase and provided good impetus for moving forward with my study.

The participants' readiness to engage in discussion and conversation about learning analytics led to interviews lasting up to two hours which in turn generated a large volume of data. At times, it was difficult to keep the interview focused, as some responses naturally led to more questions. The quantity of data that was generated and my relative lack of experience with coding data meant that the process of coding was initially difficult to grasp. It was not possible to present all of the aspects that emerged from the rich data collected, and as a result the findings are to some extent a reflection of my own experience and what I felt was important to address. Throughout the process of data analysis and developing the discussion I found that I was already identifying potentially influential areas which could benefit from post-doctoral study, as noted above in the suggestions for further research section of this chapter.

As mentioned in Chapter Three and the section on limitations in this chapter, I came to this research with my own views and perceptions, and therefore there is a risk that I may have influenced participant responses through my existing knowledge base in relation to learning analytics. Despite this risk, using an interpretivist approach afforded me a valuable opportunity to be integral to the research process and immersed with the research participants. I was able to probe the views of participants as well as explore how learning analytics was developing both strategically and operationally within different HEIs.

Overall, upon reflection I feel that the approach that I have taken the research method and the data collection tools were suitable for this piece of small-scale research, and appropriate for me to use and develop as an inexperienced educational researcher. My study, conducted through the eyes of multi-stakeholders developing and implementing learning analytics has shown an innovative approach for research within this field. The extensive and rich data gathered from my study participants have enabled me to take the field forward in the domain of learning analytics, and to enhance the wider evidence base into learning analytics. My conceptual framework adds a new dimension by providing a way for those developing learning analytics to think about the challenges and the key stakeholders that they need to engage.

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Appendix 1- HREC Project Checklist (copy)

Human Research Ethics Committee (HREC)
Project Registration and Risk Checklist

If you are planning a research project that involves human participants (including data and/or biological samples), you should complete and submit this checklist so that the HREC Chair can decide the level of ethics review that is required. If you have not already done so, refer to the ***OU Ethics Principles for Research involving Human Participants***.

Once you have completed the checklist, save it for your records and email a copy to Research-REC-Review@open.ac.uk, with any relevant documents e.g. a questionnaire, consent form, participant information sheet, publicity leaflet and/or a draft bid. You should receive a response within 7 working days as to whether your research will need full HREC review, but please indicate if you require a more urgent decision. It is essential that no potential participants should be approached to take part in any research, until you have submitted your checklist and, where required, obtained a HREC review.

To meet internal governance and highlight OU research, the titles of all projects considered by the HREC (whether by HREC checklist or proforma), will be added to the Research Ethics website - http://www.open.ac.uk/research/ethics/human-research. If you would prefer for your title **not** to be made public or have any queries, please email the HREC Secretary on Research-REC-Review@open.ac.uk.

Section I: Project Details

Project title	Data Changes Everything- An investigation into the acceptance of learning analytics to support the student experience		
Brief description (100 words maximum)	The use of Learning Analytics is an innovative educational development, and its implementation is steadily growing within UK Higher Education Institutions (HEI). This research aims to explore opportunities and challenges of using Learning Analytics from a multi-stakeholder perspective. The research will use a case study design frame using longitudinal interviews to explore students and staff perceptions and experiences of using a learning analytics tool. Thematic analysis gathered from data will provide a broad understanding of opportunities and challenges that are presented using Learning Analytics within HE.		
Is your research part of an application for external funding?	N/A	If yes, please provide the name of the funding body and/or your Awards Management System (AMS) reference	Funding body: AMS ref:
Will your research proceed if external funding is not awarded?	N/A	Is your research being assessed by the Student Research Project Panel or Staff Research Project Panel?	N/A

Section II: Applicant Details

Name of Primary Investigator (or research student)	Nicola Brooks	Status	Student
Email address	NBrooks01@dmu.ac.uk	Academic unit	De Montfort University, Leicester
Telephone number	07940 311133		
Other researcher(s)	N/A		
Date	14th September 2016		

Section III: For students only:

EdD/MA/MPhil/MRes/MSc/PhD	EdD	Supervisor's name	Dr Liz Marr
Supervisor's email address (Your supervisor will need to email a brief endorsement, before, or at the same time this checklist is submitted)	Liz.marr@open.ac.uk		

Section IV: Risk Checklist

Please assess your research using the following questions and click yes or no as appropriate. If there is any possibility of risk please tick yes. Even if your list contains all "no"s you should still return your completed checklist to ensure your proposed research can be assessed and recorded by the HREC.

		Yes	No
1	Does the study involve children (under 16 years old), or those aged 16 and over who are unable to give informed consent. E.g. participants who are potentially vulnerable, such as people with learning disabilities, those with cognitive impairment, or those in unequal relationships, e.g. your own students?	☐	*☐
2	Will the study require the co-operation of a gatekeeper for initial access to the groups or individuals to be recruited? (e.g. students at school, members of a self-help group, residents of a nursing home)	☐	*☐
3	Will it be necessary for participants to take part in the study without their knowledge and consent at the time? (e.g. covert observation of people in non-public places)	☐	*☐
4	Will the study involve discussion of sensitive topics (e.g. sexual activity, drug use, or politics)?	☐	*☐
5	Are drugs, placebos or other substances (e.g. food substances, vitamins) to be administered to the study participants or will the study involve invasive, intrusive or potentially harmful procedures of any kind?	☐	*☐

6	Will the research involve the sharing of data or confidential information beyond the initial consent given?	☐	*☐
7	Is pain or more than mild discomfort likely to result from the study?	☐	*☐
8	Will the research involve administrative or secure data that requires permission from the appropriate authorities before use?	☐	*☐
9	Could the study induce psychological stress or anxiety or cause harm or negative consequences beyond the risks encountered in normal life?	☐	*☐
10	Will the study involve prolonged or repetitive testing?	☐	*☐
11	Will the research take place outside the UK?	☐	*☐
12	Does the research involve members of the public in a research capacity (participant research)?	☐	*☐
13	Is there a possibility that the safety of the researcher may be in question? (e.g. in international research: locally employed research assistants)	☐	*☐
14	Will research involve the sharing of data or confidential information beyond the initial consent given?	☐	*☐
15	Will financial recompense (other than reasonable expenses and compensation for time) be offered to participants?	☐	*☐
16	Will the research involve participants responding via the internet or other visual/vocal methods where participants may be identified?	☐	*☐
17	Will the study involve recruitment of patients or staff through the NHS or the use of NHS data?	☐	*☐
18	Will tissue samples (including blood) or other human biological samples be obtained from participants?	☐	*☐

If you answered 'yes' to questions **17** or **18**, you will also have to submit an application to an appropriate National Research Ethics Service ethics committee). Please note that it is your responsibility to follow the University's ***Code of Practice for Research*** and the ***Ethics Principles for Research involving Human Participants,*** and any relevant academic or professional guidelines in the conduct of your study. Also, to provide appropriate participant information sheets and consent forms, and ensure secure storage and use of data. FAQS offering advice and guidance on these issues are available on the Research Ethics website.

Appendix 2- HREC favourable opinion (copy)

The Open University

From Dr Louise Westmarland
Chair, The Open University Human Research Ethics Committee
Email Louise.westmarland@open.ac.uk
Extension 52462

To Nicola Brooks, Education.

Subject Data Changes Everything- An investigation into the acceptance of learning analytics to support the student experience

Memorandum

Ref HREC 2016 2390 Brooks
AMS (Red)
Submitted 19/09/2016
Date 11/10/2016

This memorandum is to confirm that the research protocol for the above-named research project, as submitted for ethics review, **has been given a favourable opinion** by the Open University Human Research Ethics Committee by **Chair's action** as it is thought to be low risk. Please note that the OU research ethics review procedures are fully compliant with the majority of grant awarding bodies and their Frameworks for Research Ethics.

Please make sure that any question(s) relating to your application and approval are sent to Research-REC-Review@open.ac.uk quoting the HREC reference number above. We will endeavour to respond as quickly as possible so that your research is not delayed in any way.

At the conclusion of your project, by the date that you stated in your application, the Committee would like to receive a summary report on the progress of this project, any ethical issues that have arisen and how they have been dealt with.

Kind regards,

Dr Louise Westmarland

Chair OU HREC

Appendix 3- Participant information (copy)

Nicola Brooks
Room 3.36 Edith Murphy Building
De Montfort University
LEICESTER
LE1 9BH

Further information (Q&A) about:

Data Changes Everything- An investigation into the acceptance of Learning Analytics to support the student experience

What is the aim of this research?

The purpose of this study is to understand the perceptions and experiences of staff and students who use a learning analytics tool to support student success. The study will focus particularly on answering research questions on potential opportunities that learning analytics offer, challenges of using learning analytics, and how potential challenges can be overcome to ensure effective implementation within Higher Education.

Who is conducting the research and who is it for?

Nicola Brooks is carrying out this research on behalf of the Open University. This study will form part of original research that is being undertaken as part of the Doctorate in Education thesis. Written permission has been granted from Human Research Ethics Committee (HREC) at the Open University in order to conduct this study.

Why am I being invited to participate in this research?

You have been identified as either a student or member of staff within the university who has had experience of using a learning analytics tool within higher education. For this reason, I would like to invite you to participate in my research, so that I can gain an insight and understanding of your experiences of using learning analytics as a mechanism to enhance the student experience. Although taking part in this research will not benefit you personally, the results will provide information which will inform my Doctoral thesis, and further potential research.

If I take part in this research, what will be involved?

Following your consent to take part in this study, I will be conducting individual semi structured interviews throughout November 2017. The interview will take approximately 45 minutes and would be conducted on the university campus, on a date and time that is convenient for you. To ensure your safety, I will carry photographic identification. It is up to you to decide whether to take part. If you do decide to take part, you will be given this information sheet to keep, and asked to sign a consent form. You will be given the freedom to withdraw from the study at any time, and without giving a reason.

What will the semi-structured interview be like?

I will be asking you a series of open-ended questions regarding your perceptions (your beliefs and opinions) and your current experiences of using learning analytics. There will be opportunity for you to provide additional comments and observations as you see fit as part of the interview process. A pseudonym will be used to protect your identity, and to anonymise any data that is collected. In order to capture data, a Dictaphone will be used to record the interview. Data gathered will be transcribed and kept on an encrypted computer and stored in a locked place.

What will we be talking about?

I will be asking you about your general beliefs and opinions in relation to using learning analytics within your university to enhance the student experience. This will include open ended questions regarding the positive and negative elements of using learning analytics to support the student experience, as well as discussing whether learning analytics and using data meets your individual need. There will be opportunity for you to provide additional comments and observations. Any identifiable information that you may give will be removed and anonymised. There is currently no qualitative research that is focused towards the opportunities and challenges of using learning analytics within higher education, so this research will be unique.

Is it confidential?

Your participation will be treated in **strict confidence** in accordance with the Data Protection Act. No personal information will be passed to anyone outside of the research team. I will write a report of the findings from this study as part of my Doctoral thesis, but no individual will be identifiable in published results of the research.

What happens now?

Over the next few weeks, I may contact you by telephone to ask if you would like to take part and, if so, ask you a few questions about yourself. I need to make sure that a cross-section of people with different experiences are included in the study and for this reason, I cannot guarantee that I will see everyone who volunteers to take part, although I would hope to include most. If you would prefer not to be contacted about this research, please use the phone number below to let me know and I will not contact you again. Your participation is entirely voluntary, and you are free to withdraw at any time without reason.

What if I have other questions?

If **you have any other questions about the study, I would be very happy to answer them. Please contact Nicola Brooks** on (0116) 201 3860 or by e mail to NBrooks01@dmu.ac.uk. If you prefer, you can contact my doctoral supervisor, Dr. Liz Marrs by e mail (Liz.marrs@open.ac.uk). I would like to thank you for agreeing to take part in the study.

Appendix 4- Participant Consent Form (copy)

The Open University

Centre for Research in Education and Ed Technology (CREET)

Consent form for persons participating in a research project

Data Changes Everything- An investigation into the acceptance of learning analytics to support the student experience

Name of participant:

Name of principal investigator(s): Nicola Brooks

---

1. I consent to participate in this project, the details of which have been explained to me, and I have been provided with a written statement in plain language to keep.

2. I understand that my participation will involve semi-structured interviews and I agree that the researcher may use the results as described in the plain language statement.

3. I acknowledge that:

   a. the possible effects of participating in this research have been explained to my satisfaction;

   b. I have been informed that I am free to withdraw from the project without explanation or prejudice and to request the destruction of any data that have been gathered from me until it is anonymized at the point of transcription point on 7th January 2019. After this point data will have been processed and it will not be possible to withdraw any unprocessed data I have provided;

   c. the project is for the purpose of research;

   d. I have been informed that the confidentiality of the information I provide will be safeguarded subject to any legal requirements;

   e. I have been informed that with my consent the data generated will be stored in a locked cupboard in Room 3.36 Edith Murphy Building, De Montfort University, Leicester. LE1 9BH and will be destroyed after five years;

   f. If necessary, any data from me will be referred to by a pseudonym in any publications arising from the research;

g. I have been informed that a summary copy of the research findings will be forwarded to me, should I request this.

I consent to this semi structured interview being audio-taped/video-recorded □ **yes** □ **no**
(please tick)

I wish to receive a copy of the summary project report on research findings □ **yes** □ **no**
(please tick)

Participant signature: Date:

Principal Investigator

Nicola Brooks

Room 3.36

Edith Murphy Building

De Montfort University

Leicester

LE1 9BH

NBrooks01@dmu.ac.uk

Doctoral Supervisor

Dr Liz Marr

Director

Centre for Inclusion and Collaborative Partnerships

The Open University

First Floor

Wilson B

Walton Hall

Milton Keynes

MK7 6AA

Liz.marr@open.ac.uk

Appendix 5 Copy of participant invite (staff)

Dear XXXX,

I hope that you are well?

Apologies for contacting you out of the blue, I am looking for academic staff who are involved with the implementation of learning analytics within HE and who would be willing to assist me with my doctoral research. I'm currently a second-year student at the Open University studying a Doctorate in Education. The overall aim of my research is to capture different multi-stakeholder perspectives regarding the opportunities and challenges of using learning analytics to support the student experience, and I'm looking to recruit academic staff, students and experts within the LA field to support the data collection phase of the study.

My research aims to answer the following research questions:

1. What are the opportunities in the use of learning analytics as viewed by students, academic staff and learning analytics experts?

2. What are the challenges in the use of learning analytics as viewed by students, academic staff and learning analytics experts?

3. How can challenges be overcome (if any) to ensure the effective implementation of learning analytics within an HEI?

I'm looking to recruit individuals who would be willing to take part in a face to face semi-structured interview to discuss their perceptions and experiences of using learning analytics. I have attached some participant information, for further information about the study I can be contacted via e mail (NBrooks01@dmu.ac.uk) or by telephone (07940) 311133.

I do hope that you will be able to consider supporting me with this, and I look forward to receiving your response. If you feel that you are not best placed to assist with my research, I would be grateful if you could either advise me of their name, or forward this onto the most relevant person.

Kind Regards

Nikki

Nikki Brooks
Associate Dean (Academic)
Faculty of Health and Life Sciences
Tel (0116) 201 3860

Appendix 6 Copy of participant invite (students)

Dear XXXX,

I hope that you are well?

Apologies for contacting you out of the blue, but I have been given your contact name by XXXX. I am looking for some students to interview as part of a focus group that use learning analytics, and I wondered if it would be possible for you to help me access your students? I would only need between 4-6 of them?

The overall aim of my research is to capture different multi-stakeholder perspectives regarding the opportunities and challenges of using learning analytics to support the student experience, and I'm looking to recruit academic staff, students and experts within the LA field to support the data collection phase of the study. I've already conducted the academic staff and learning analytics experts interviews, so I just need to find some students to complete my data collection.

My research aims to answer the following research questions:

1. What are the opportunities in the use of learning analytics as viewed by students, academic staff and learning analytics experts?

2. What are the challenges in the use of learning analytics as viewed by students, academic staff and learning analytics experts?

3. How can challenges be overcome (if any) to ensure the effective implementation of learning analytics within an HEI?

Do you think that this is something that you can help me with? I just need the student's honest opinions and need to pinch them for no more than an hour just to talk to me about their perceptions and experiences of learning analytics… I can be pretty flexible with dates- so can accommodate times/dates to suit you.

Kind Regards

Nikki

Nikki Brooks
Associate Dean (Academic)
Faculty of Health and Life Sciences
Tel (0116) 201 3860

Appendix 7 Interview questions devised for the pilot study

Q1. What are your perceptions of using learning analytics as an approach to support the student experience?

Q2. What are the positive elements of using learning analytics to enhance the student experience and student success?

Q3. What are the negative elements of using learning analytics to enhance the student experience and student success?

Q4. Do you think that institutional adoption of a learning analytics tool will support or hinder student experience and success? How?

Q.5 Do you think that learning analytics improves student engagement compared to other methods? How?

Q.6 Do you think that using learning analytics to support the student experience changes the role of the academic staff? How?

Q.6 How could learning analytics be improved within your institution?

Appendix 8 Interview questions devised for the main study

Q1. What are your perceptions of using learning analytics as an approach to support the student experience and student success?

Q2. What are the positive elements of using learning analytics to enhance the student experience and student success?

Q3. What are the negative elements of using learning analytics to enhance the student experience and student success?

Q4. Do you think that institutional adoption of a learning analytic tool will support or hinder student experience and success? How?

Q.5 Do you think that learning analytics supports student engagement compared to other methods? How?

Q.6 Do you think that using learning analytics changes the role of the academic staff? How?

Q.6 How do you feel that learning analytics could be improved within your institution?

Appendix 9 Participating institutions (anonymised)

Participating institution	Brief description of institution
Institution 1	Public university in Northern England Student population of 32,000 Staff numbers 3,000 Offers 150 UG courses- TEF SILVER rating Multi-campus university 60% female students 16% BAME 5% Disability 21% overseas students 11% students over age of 21 Institutional roll out of LA in 2017/8- staff facing only
Institution 2	Public research university in East Midlands Student population of 33,000 Staff numbers 4,000 Offers 200+ UG courses- TEF GOLD rating Multi-campus university 57% female students 30% BAME 16% Disability 15% overseas students 15% students over age of 21 Institutional roll out of LA in 2014/5- staff and student facing
Institution 3	Public university in East Midlands Student population of 34,000 Staff numbers 3,500 Offers 300 UG courses- TEF GOLD rating Multi-campus university 56% female students 17% BAME 12% Disability 5% overseas students 63% students over age of 21 Institutional roll out of LA in 2017/8 as one- year pilot project- staff facing only

Institution 4	Public university in Central England Student population of 12,000 Staff numbers 3,000 Offers 60 UG courses- TEF GOLD rating Single-campus university 64% female students 51% BAME 12% Disability 5% overseas students 36% students over age of 21 Institutional roll out of LA in 2017/8- staff and student facing
Institution 5	Public research university in Central England Student population of 174,000 Staff numbers 8,000 Offers 300 UG courses Single-campus university 60% female students 11% BAME 19% Disability 4% overseas students 76% students over age of 21 Institutional roll out of LA pre-2014-staff facing