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Affordances of Learning Analytics for Mediating Learning

by

Tracie Marie Farrell

A thesis submitted in partial fulfillment for the degree of Doctor of Philosophy

in the
Science Technology Engineering and Mathematics Faculty
Knowledge Media Institute (KMi)

August 2018

Declaration of Authorship

I, TRACIE MARIE FARRELL, declare that this thesis titled, 'AFFORDANCES OF LEARNING ANALYTICS FOR MEDIATING LEARNING' and the work presented in it are my own. I confirm that:

- This work was done wholly or mainly while in candidature for a research degree at this University.
- Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated.
- Where I have consulted the published work of others, this is always clearly attributed.
- Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work.
- I have acknowledged all main sources of help.
- Where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself.

Signed: ____

Date: ____

"Men often oppose a thing merely because they have had no agency in planning it, or because it may have been planned by those whom they dislike"

Alexander Hamilton

Abstract

Science Technology Engineering and Mathematics Faculty
Knowledge Media Institute (KMi)

Doctor of Philosophy

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Learning analytics acceptance and adoption is a socio-technological endeavour. Understanding how learning analytics impact practice is an important part of demonstrating their value. In the study presented in this thesis, "Mediated Learning" provides a framework through which to describe how learning analytics can impact psychological, social and material aspects of learning, from the perspective of educators and learners. It also offers a structure through which to make recommendations for improving the mediatory effects of learning analytics. A qualitative research design, based on "Grounded Theory" was implemented and 10 educators from 3 European universities were recruited through convenience and purposive sampling for exploratory interviews. A subsequent case study of the Open University provided critical perspectives from both educators (n=18) and learners (n=22) about the institutional, departmental, domain-related and epistemological factors that broadly influence perceptions of learning analytics. The study applied "Affordance Theory" to identify what participants were most easily able to recognise as beneficial to their own practice. Participant contributions were open-coded to uncover emerging themes and then organised into thematic categories and subcategories. Respondent validation, as well as triangulation of data between the exploratory interviews and focus groups support the validity of the study. Findings suggested that domain-related epistemological assumptions and previous experience influence how and why an individual could make use of learning analytics insights. Gaining stakeholder acceptance involves targeting the right training and opportunities at the appropriate disciplines. Findings also indicate that learning analytics has the strongest mediatory effect for learners when the technology is capable of exposing them to other learners' strategies, or when it assists them personally, and continually in goal orientation adoption. The implications of the study are important for higher education institutions looking to implement large-scale learning analytics initiatives, in particular, those with a diverse student body.

Acknowledgements

I owe many thanks to my patient supervisors, Dr. Alexander Mikroyannidis and Prof. Harith Alani, for their expertise, guidance and mentorship. Their good humour made supervision an enriching conversation that greatly improved the value of my work. In fact, it is not only my supervisors to whom I owe my gratitude, but to all of my colleagues at the Knowledge Media Institute, for building an inspiring atmosphere in the lab through interdisciplinary collaboration and the opportunity to develop new skills. I thank them for their creativity, optimism and passion for research. In particular, I would like to thank Prof. Zdenek Zdrahal and Dr. Ale Okada, whose early interventions during my probation phase helped to shape my research and give me confidence. I would also like to thank Dr. Anna De Liddo, Dr. Miriam Fernandez, Dr. Allison Littlejohn and Dr. Bart Rienties, for always having their door open and being willing to take time out of their busy schedules to help me to understand the broader context of research. A very special note of thanks goes to Prof. Marian Petre, who truly cares about students at the Open University. She has helped so many post-graduate students, not only through her invaluable guidance through the Post-Graduate forum, but also by opening her home to those of us from abroad. To the educators and learners who took part in my research, I thank you for your time, insight and patience. Your capacities are already stretched and your effort, not only for my own research, but for the research of so many others, is extremely valuable. To Dr. George Gkotsis, thank you for being such a wonderful friend and cheerleader. Without you, I would have never found my way here. I owe you too much to ever repay. To Dr. Brian Plüss, you changed everything about this experience for me. I am so grateful I found you. To Dr. Allan Third thank you for answering all of my messages and going down the rabbit hole with me on so many topics. I treasure both of your beautiful brains. To my dear friends and domestic partners, Ahmed Salmi El Idrissi, Sara Krimou and Mikolaj Wlodarski, thank you for providing the family support that I needed and for making these last three and a half years so special. To my parents, Eileen and Bill, thank you for your constant love and for always believing in me. To my sisters, Janine and Megan, and to their families (especially Mike and Madeline Dwyer, who both consulted at various stages of my research), thank you for jumping in, being patient with me and keeping in touch with me from so far away. Finally, to my new wife, Laura Farrell - you've known me only as a student, with little time, a lot of stress, and significant self-absorption. Thank you for your compassion and love.

Thank you all for your encouragement!

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Abbreviations

TEL	**T**echnology **E**nhanced **L**earning
SRL	**S**elf **R**egulated **L**earning
HEI	**H**igher **E**ducation **I**nstitution
LAK	**L**earning **A**nalytics and **K**nowledge
EDM	**E**ducational **D**ata **M**ining
VLE	**V**irtual **L**earning **E**environment
LMS	**L**earning **M**anagement **S**ystem
ELLI	**E**ffective **L**ifelong **L**earning **I**nventory
PLE	**P**ersonal **L**earning **E**nvironment
OER	**O**pen **E**ducational **R**esource
OLM	**O**pen **L**earner **M**odel
LACE	**L**earning **A**nalytics **C**ommunity **E**xchange
JISC	**J**oint **I**nformation **S**ystems **C**ommittee
GPA	**G**rade **P**oint **A**verage
TAM	**T**echnology **A**cceptance **M**odel
LAAM	**L**earning **A**nalytics **A**cceptance **M**odel
ZPD	**Z**one of **P**roximal **D**evelopment
MLE	**M**ediated **L**earning **E**xperience
UTAUT	**U**nified **T**heory of **A**cceptance and **U**se of **T**echnology
OU	**O**pen **U**niversity
TMA	**T**utor **M**arked **A**ssignment
EMA	**E**nd of **M**odule **A**ssignment

Definitions

Learning Analytics	Measuring, collecting, analysing, and reporting on data for understanding and improving learning.
Social Learning Analytics	Measuring, collecting, analysing, and reporting on social data (interactions, participation, networks, etc.) for understanding and improving learning.
Multimodal Learning Analytics	Measuring, collecting, analysing, and reporting on sensor data (eye-movements, heart rate, sound, etc.) for understanding and improving learning.
Unknown-unknowns	Potential knowledge gaps that inevitably cannot be anticipated.
Mediated Learning	A theory of learning that addresses the many (social and cultural) interactions that contribute to learning success and challenges. In particular, the theory examines how these dynamic relationships influence or "mediate" learning and how this impact can be facilitated.
Mediatory Agent	An entity that stands between the learning and the object of learning, and facilitates the learner's engagement with that object.
Affordance	An action possibility that an individual is able to perceive, given the properties of the object that are most readily apparent.
Metacognition	An understanding of one's own thinking process.
Pedagogy	The broad aim of education, in terms of what is valued and what should be achieved.

Psychological Tools The signs and symbols that human beings use to construct meaning. Psychological tools represent different ways of thinking, inside of which certain concepts are more or less accessible, depending on to which system of psychological tools the individual subscribes. Psychological tools are developed over time through exposure and reinforcement.

Dedicated to teachers and learners…

Chapter 1

Introduction

Time, presence and physical attentiveness are our most basic proxies for something ultimately unprovable: that we are understood. - Tom Chatfield

"Learning Analytics" is a broad term used to describe the tools, technologies, methods and outputs involved in the "collection, measurement, analysis and reporting of data" to "understand and optimise learning" [3]. The term "data" refers to information that can be gathered in educational settings, such as demographic information, digital traces from any activities in which a learner might participate online (in the process of interacting with digital tools or platforms for learning), and performance data (including marks on assignments and exams) [1][3].

Theory and research on learning analytics focus on defining a "closed-loop system": awareness promotes reflection, which leads to action, which then feeds back into future decision-making processes [4]. Learning analytics are intended to shed light on behaviour, helping students to be more autonomous in their learning [5] and contributing to a deeper understanding of the complex interplay between cognition, motivation and behaviour in learning [6]. The potential of learning analytics is seductive for institutions that are searching for innovative ways to empower their staff in providing high quality, accessible education with limited resources. However, the literature shows that the **research community investigating learning analytics does not understand well enough what a quality educational experience really means in practice**.

The following sections of this chapter present a motivating example for this research, which will be expounded upon in chapters 2 and 3. Transition and change are presented as proxies for learning that can help to mitigate this challenge and act as a central hub around which the activity, cognition and emotion of learners can be organised. In addition, the context of contemporary education is briefly introduced, to highlight the necessity of identifying new ways of understanding learners' experiences. In particular, the focus is higher education, as a common environment for learning analytics research, including that which is presented in this thesis. Finally, the chapter summarises the research questions, the chosen learning framework, and primary objectives of this thesis as an entry point to subsequent chapters. The last section presents the structure of this thesis.

1.1 Motivating Example

The literature suggests that learning analytics research still relies heavily on proxies, such as retention and learner marks, as benchmarks for optimisation [7]. Though they are important *indicators* of learning, what they represent is the *performance of learning*, which is different from learning itself. Without the ability to peer into learners' minds and see what knowledge they have acquired, it is useful to look at such proxies. Retention and marks indicate the presence of requisite competencies to achieve adequate results and complete one's studies [8]. This is useful for understanding some aspects of learning. Others, however, may require more investigation.

For example, retention is a macro figure, relating to the "big picture". At the macro level, one can improve retention through improving processes that have macro level results, such as improving a learning design [9][10][11] or assessment procedure [12]. These are decisions that are made at the institutional or faculty level that involve changes to the structure around the learning process, such as which materials are most useful or which assignments cause the most difficulty. At the micro level, however, factors influencing retention include various attitudes, behaviours and contextual realities that have different types of impacts, such as lack of orientation, poverty, illness, other employment or family commitments, and learning disabilities that have gone unnoticed or ignored [13].

1.2 Change as Proxy for Learning

In learning analytics research, it is difficult to document impact [4]. Learning is personal, and difficult to define and represent [14], which is why the reliance on proxies is so important. In addition, learners can be difficult to access and understand, given the private nature of their motivations and personal assessments of their own learning [3] [15]. Without understanding the motivations and goals of learners, it is difficult to use learning analytics to influence their behaviour more directly. Moreover, it is challenging to examine emotional or psychological factors in learning analytics research.

For example, in the Learning Analytics Acceptance Model [2], issues related to defining value in learning and resistance to change appear to be dealt with in terms of technology acceptance and pedagogical role within the institution. The model has mostly been validated with individuals working in computer science. In addition, the psychology and emotion around learning analytics is reduced to one influencing factor of “perceived usefulness”.

This thesis argues that **perceived usefulness is a more complex category that warrants further qualitative investigation in the field**. What factors influence perceived usefulness? Starting this investigation from the point at which learning analytics does or would change behaviour, it is possible to distil what aspects of learning analytics are inspiring to different stakeholders and hold significant value for their practice. Uncovering trends or patterns in perceived usefulness may help to target learning analytics approaches and identify blind-spots within the field.

1.3 Research Questions

As the subsequent chapters will demonstrate, educator and learner perspectives have been underrepresented in the literature. Thus, the central research question of this thesis addresses this gap explicitly:

> **What impact is learning analytics having on practice and how can it be improved for educators and learners?**

This question involves an exploration of how impact is currently understood (described in chapter 2), and how that compares with perceptions of what should or could be done with learning analytics tools and technologies (presented in chapter 3). At the heart of the question, however, is uncovering the aspects of learning analytics tools and technologies, or the environments in which they are implemented, which appear to enhance or increase positive impacts.

The challenges in learning analytics research are accurately measuring impact, ensuring relevance, avoiding unnecessary complexity and gaining stakeholder acceptance. To help gain a wider perspective on these issues, the additional guiding questions of this research are the following:

How does what learners perceive as being important fit with other stakeholders' perceptions? How do wider institutional perspectives fit in?

What of different stakeholders' perceptions is shared? What can be agreed upon as useful for practice?

When do learning analytics really assist educators and learners with their work as they describe it? How do learning analytics actually support teaching and learning?

How do educators and learners view their role in learning analytics research? Do they view themselves as partners? As experiments?

All of these questions surround learning analytics research, but do not make up a large part of its process of self-reflection in the literature. The purpose of asking these questions is to **provide orientation on the issue of optimisation and some direction to institutions, educators and learners on how to make the best of the power of learning analytics.**

1.4 Introducing Mediated Learning and Affordances

To address difficulties in assessing impact and exploring psychological and emotional factors, the study presented in this thesis focuses on transition and change in learning, applying Mediated Learning [16][17] as **a framework for examining impact potential**. Mediated Learning has a long history in both philosophy and education that involves **capturing dynamic relationships between humans, materials and the different ways of thinking they develop to make sense of one another and the world around them** [16]. It is an appropriate theory of learning for examining transition and change, but it also provides a structure to assess the potential of learning analytics.

The protagonists of Mediated Learning, whose work is presented in this thesis, are Lev Vygotsky and Reuven Feuerstein, whose respective contributions were grounded in understanding the influence of others on our learning processes [16][17][18] and the necessary mechanisms to produce fruitful outcomes of this influence [19][20]. Mediated Learning was determined to be appropriate for organising the ways in which learning analytics can illuminate certain patterns, identify important relationships, and act as an intermediary between the goals of the learner and their achievements. The purpose of this application was to test **learning analytics as a potential mediatory agent in learning, delivering transition and change toward achievable goals**.

To help gather information about the current and potential impacts of learning analytics on practice, Affordance Theory [21] guided the development of the research design, in terms of how to address the subject of learning analytics with its stakeholders. “Affordances” are properties of an object that are perceived by a potential user, presenting action potential for what can be done with that object[21]. Using a hammer as an example, one can perceive the qualities of a hammer, that it is hard, that it is heavy, that it can be held in one hand. What can be done with that hammer is limited by its properties, but also by the creative observation and consideration of the user. Affordance Theory made it possible to **understand and categorise what different stakeholders perceive as being the *recognisable action potential* in learning analytics tools and technologies**.

1.5 Thesis Objectives

Given the complexity of the research question and the context in which it is situated, this thesis has the following objectives:

- To explore learning analytics more concretely from the perspective of educators and learners, drawing from their own experiences of practice.
- To investigate the action potential that educators and learners can perceive in having access to different types of educational data, and how this would improve their practice.
- To analyse the potential of learning analytics tools and technologies toward meeting the expressed needs of educators and learners.
- To translate the needs of educators and learners into software requirements and metrics, which learning analytics developers and researchers can consider in the development of learning analytics platforms or tools.

1.6 Potential Impact

These objectives were pursued within the context of contemporary developments in education. First, the learner-as-consumer model, brought about by changes to university funding structures, has both shifted learner expectations of the learning experience and institutional perspectives on what retention means to the institution's financial sustainability [8]. Second, university degrees "no longer last a lifetime" [22]. The pace of a knowledge-based society requires more and more professionals to return to educational environments for retraining and other types of certification [22].

The personal nature of retention and performance, and the pace of change and development in education, are confounding factors in learning analytics research. **This thesis explores learning analytics from an entirely different perspective, less connected to traditional benchmarks like retention or performance. Rather, the study presented in this thesis emphasises the recognition of choice, transition and change.**

This thesis will demonstrate that it is important to be able to understand and utilise learning analytics in more subtle, sophisticated ways. Building trust and widening the scope of learning analytics research and development, increases the value of affordances.

1.7 Thesis Structure

This chapter has already presented some of the challenges that impact learning analytics research and development. In chapter 2, these issues are outlined in further detail, alongside a critical review of the literature related to the genesis of learning analytics, contemporary educational challenges, and the differentiation between learning analytics and its close companion, Educational Data Mining [1]. In addition, the chapter presents some of the techniques and outputs of learning analytics that are relevant for the higher education context, in which the research presented in this thesis was conducted. Finally, the chapter closes with a discussion on the Open Learner Model [23] and the potential contribution of learning analytics to support the future direction of education toward increased personalisation.

Chapter 3 explores the motivations for the research presented in this thesis, including a lack of attention to contemporary educational theory [11] and the socio-technological factors involved in learning analytics research and deployment [24]. It also explores difficulties related to the assessment of impact and the attempts within the field to record and catalogue experiences with learning analytics [25]. In particular, the thesis addresses the issues of relevance and evaluation as two key problems of learning analytics research. Finally, the chapter addresses learning analytics acceptance, including actual use and the development of learning analytics literacy.

In chapter 4, Mediated Learning is presented as a theoretical framework for examining impact potential. As has been discussed above in the introduction, the thesis incorporated the theories of Vygotsky and Feuerstein to explore how learning analytics could contribute to raising the awareness of learners and driving action toward transition and change. The chapter focuses on exposure to the "other" [18][26] and human cognitive modifiability [19][20] as the primary forces of transition and change, along with a set of universal criteria [16] that all experiences of mediation in learning should share. In addition, the chapter includes a discussion on technology mediated learning as a contemporary addendum to the philosophies of Vygotsky and Feuerstein, which helps to shape the discussion around learning analytics acceptance. Finally, the chapter closes with a vision of learning analytics as a mediatory agent, acting as a more knowledgeable entity that can scaffold learning experiences.

Chapter 5 presents the research question in more detail, alongside arguments for investigating learning analytics within the qualitative research paradigm. It introduces the use of Grounded Theory and the "Case Study" [27] as a way of avoiding repetition of themes in learning analytics research and giving way to participants' perspectives, while acknowledging the perspective of the researcher. The chapter concludes with an introduction to Affordance Theory [21] and its contribution to capturing perceptions around action potential, which is relevant for understanding impact.

Chapter 6 builds on the previous chapter to go deeper into the methods that were used to implement the research approach and design. In particular, it presents qualitative interviewing and focus groups as the chosen mechanisms for harvesting data from the participants. It also describes the analytic procedures that were performed on the data to produce reliable evidence.

Findings from the exploratory interviews are presented in chapter 7, which helped to guide the subsequent case study. The chapter describes the participants, procedures and analyses that resulted in a tentative suggestion that departmental epistemology was impacting learning analytics acceptance. In addition, it begins the discussion on the indicators that educators use to recognise that they are successful in their endeavours (*i.e.* that students are learning). The chapter explores affordances of learning analytics in terms of both actual and imagined use, connected to authentic challenges that educators experience. The last sections of the chapter outline how the exploratory interviews informed the design of the subsequent case-study.

Chapters 8 and 9 present the findings from the case study, in which educators and learners from the Open University participated in focus groups and "focused interviews" to share their experiences with learning analytics. Chapter 8 deals with the context-related features of the participants that were relevant for making sense of the affordances they perceived, which are then presented in chapter 9. In particular, these chapters explore learner goal orientation, and the ways in which learning can be recognised to develop a picture of the different indicators that are used. Affordances are presented in terms of the utility of certain types of data to illustrate the indicators that educators and learners use.

Finally, chapter 10 summarises and presents the main conclusions that can be drawn from the findings. Starting from what the study was able to highlight about how learners develop, the chapter guides the reader through how learners appear to shift their thought processes and strategies to accommodate any number of factors including their personal goals, circumstances and desires. Each section includes a set of recommendations for learning analytics research and development, summarised in terms of the data which should be collected, the necessary analytic procedures and communication strategies around learning analytics or learning analytics outputs. The chapter also presents the findings as sets of software requirements and associated metrics that the findings suggest are important to educators and learners. In addition, it includes some informal evidence collected from colleagues who are involved in the development of learning analytics tools and platforms about the feasibility of these requirements or the implications made about what this information could communicate about learning processes. Finally, the chapter closes with an evaluation of Mediated Learning as a framework, the limitations of the study and some suggestions for future research on the basis of these.

Chapter 11 offers a review of each chapter along with an outlook on learning analytics research and development.

Chapter 2

Learning Analytics in Higher Education: A Critical Review

The real problem is not whether machines think but whether men do. - B. F. Skinner

As mentioned in chapter 1, "Learning Analytics" describes the tools, technologies, methods and outputs involved in the "collection, measurement, analysis and reporting of data" to "understand and optimise learning" [3]. The expected feedback loop that should exist between understanding how learning occurs and developing appropriate interventions is the major contribution of the field [4]. Thus, it is a complex socio-technological domain, with strong roots in distance education and educational data mining, as this chapter will demonstrate. It differentiates itself through attention to the human lever as an agent of change. The subject of learning analytics is not neutral, in that there are pedagogical, instructional, and social values implicit in how learning analytics are developed and implemented. It is important to consider the effects of the origins of a field on its further development and application.

This chapter explores the developmental background of learning analytics and some common applications. 2.1 describes the emergence of learning analytics with a particular focus on higher education, the context of this thesis. 2.2 describes several learning analytics approaches and themes that are particularly relevant to that context. Illustrating what learning analytics can achieve is necessary for preparing the foundation for the next chapter, which addresses what might be missing in learning analytics research and development.

2.1 Background

This section describes how learning analytics emerged as a "decision relevant science" [28], differentiating itself from other types of academic analytics or data mining techniques. 2.1.1 discusses how data has driven development of technology for the classroom. 2.1.2 describes the main differences between learning analytics and one of its closest companions, Educational Data Mining (EDM). The section demonstrates how differentiating the two fields is important in considering how to evaluate and measure their impact on learning.

2.1.1 Learning Analytics in the Digital Age

The field of learning analytics has been bolstered by the large volumes of data produced by students in higher education [29] [30]. It is not surprising that providers of distance education have been particularly instrumental in driving current theory and practice in learning analytics. As interaction is now predominantly "computer mediated", providers of distance education can aggregate large amounts of student and institutional data [31]. Educators and learners involved in contemporary distance education are examples of what Williamson described as "prosumers", stakeholder groups that both produce and consume benefits from data analysis, including learning analytics [32].

Over the past ten years, the impact of learning analytics on higher education, even in traditional brick-and-mortar Universities, has been growing [29]. Research indicates that this is influenced by extensive research in the field of "Technology-enhanced Learning" (TeL) [33], and motivated by both economic and pedagogical factors [34] [35].

To be successful in the contemporary educational contexts, **learners in higher education must be more self-directed and independent in their learning** [36]. These characteristics have always been valued by providers of distance education. TeL is "the study of how we learn and teach with interactive technologies, and how to design and evaluate effective technologies for learning" [33]. Learning theories in TeL, because of their strong connection to distance education and computer-mediated learning, emphasise learner autonomy and mobilisation of existing resources (including other people and technology) [37][33]. TeL also tends to focus on transferring learning from theory to practice [36] [38].

For example, Self-regulated Learning (SRL), a learning theory commonly coupled with TeL, is about developing awareness for one's own learning strategies, so that they can be self-monitored and controlled [39]. Self-regulation, while an individual process, can also be socially influenced and guided [40]. Strong self-regulated learners are able to optimise their own potential in a knowledge economy. Higher Education Institutions (HEIs) are thus motivated to help learners gain skills in self-regulation, for both pedagogical and pragmatic reasons. TeL has contributed toward developing tools that can assist learners in recognising and changing behaviour [41], notifying students when their strategies are not working [42], even helping them organise and monitor their behaviour online [43].

Steiner *et al* argued that **the focus on learner autonomy can have the consequence that some learners are left behind, lacking the skills necessary for recognising, understanding and regulating their learning strategies [44]**. Research has indicated that students often have limited or faulty mental models of how they process information, which affects their strategies in learning [45]. The issue of how to correct those models and support students' understanding of their own learning processes has become a central issue for contemporary education [39].

TeL aims to contribute to this through the development of tools and technologies for independent, problem-based, inquiry-based and social learning. Problem-based and inquiry-based learning are about mobilising relationships with others to learn *in situ*, rather than a potentially inauthentic classroom setting [46]. TeL tools for collaborating in problem-based and inquiry-based learning online have complemented existing strategies, especially through computer simulation of problems, use of multimedia resources and virtual learning environments [47]. There has also been a natural connection to game-based learning in the Digital Age [48]. Learning analytics, as a part of TeL, appears to share these motivations.

2.1.2 The Emergence of Learning Analytics from Educational Data Mining

Learning Analytics emerged from a branch of computer science that concerns itself with processing "big data" in educational contexts. This field, referred to as Educational Data Mining (EDM), is focused primarily on automating certain processes with limited human support [3] [1]. The contributions EDM has made to educational science are therefore largely about"discovery with models", in which a model is "developed and applied to data, and then used as a component in other analyses, typically to discover aspects of the construct in the model" [49]. This has illuminated some of the unknown-unknowns that shroud contemporary educational contexts [3]. Ferguson, Baker and Siemens have argued that while there has always been an understanding of human agency in EDM research, learning analytics research adopts a more holistic approach to understanding the complex system of education [3] [1]. From Figure 2.1, one can see that Siemens and Baker summarised the primary differences between learning analytics as it is understood

	LAK	EDM
Discovery	Leveraging human judgement is key; automated discovery is a tool to accomplish this goal	Automated discovery is key; leveraging human judgment is a tool to accomplish this goal
Reduction & Holism	Stronger emphasis on understanding systems as wholes, in their full complexity	Stronger emphasis on reducing to components and analyzing individual components and relationships between them
Origins	LAK has stronger origins in semantic web, "intelligent curriculum," outcome prediction, and systemic interventions	EDM has strong origins in educational software and student modeling, with a siginficiant community in predicting course outcomes
Adapation & Personalization	Greater focus on informing and empowering instructors and learners	Greater focus on automated adaption (e.g. by the computer with no human in the loop)
Techniques & Methods	Social network analysis, sentiment analysis, influence analytics, discourse analysis, learner success prediction, concept analysis, sensemaking models	Classification, clustering, Bayesian modeling, relationship mining, discovery with models, visualization

FIGURE 2.1: Learning Analytics and EDM (from Siemens and Baker, 2012 [1])

by the Learning Analytics and Knowledge (LAK) community[1] and EDM as having to do with the rationale, origins and techniques that characterise the two fields. In particular, **the lever of human judgement is applied at different moments in the process of analysis, and for different reasons**. In learning analytics, the goal is to empower students and educators to intervene. In EDM, the goal is to perfect classification and clustering processes to improve models and consequently, automated adaptation in the system [1].

[1]LAK stands for Learning Analytics and Knowledge, the annual learning analytics conference held in cooperation between the Society for Learning Analytics Research (SoLAR) and the Association for Computing Machinery (ACM).

Papamitsiou and Economides noted that this relationship between EDM and learning analytics can be viewed as *complementary*, with *particular* attention to the role of human agents, responding to and interacting with technologies to support their efforts [50]. As the two are particularly close in structures and processes, **it is important to focus on the human actors involved in learning analytics, to truly ensure a differential analysis**.

2.2 Learning Analytics and the Human Lever

The subsections below outline some of the specific contributions that learning analytics have made to higher education, focusing particularly on how those contributions directly involve the human agency which specifically defines learning analytics in the literature. More specifically, each subsection addresses an important theme in learning analytics, along with an evaluation through the literature of its impact on education and educational policy.

2.2.1 Predictive Learning Analytics

Perhaps one of the most widely reported uses of learning analytics in formal education is for predicting learner attainment and retention [30]. There are several examples of institutional, large-scale prediction and intervention analytics initiatives to identify at-risk students and provide them with the necessary support to improve learner retention and progress [42][51]. Predictive analytics was originally a field of business intelligence, meant to help organisations make customer-relevant decisions about future business operations based on predictive models of customer activity in relation to key performance indicators. In education, predictive learning analytics involve **uncovering actionable information through large data sets of student and organisational information and activity, so that it can inform institutional response to student needs** [52]. Case studies from the past 5-8 years have provided evidence that learning analytics have been successful in **validating predictive models, carrying out effective interventions with students and illustrating the benefits of a "data-driven approach to higher education provision"** [30].

However, there are also institutional risks associated with predictive analytics. First, the premises of the prediction must be very well understood. **Asking the wrong questions or having the wrong data to answer the question can significantly impact the accuracy and utility of a prediction** [30]. Predictive analytics are most useful when they can answer a rather direct query, such as whether or not a specific intervention resulted in any behavioural change or cognitive improvement for the student. In higher education, predictions are typically calibrated toward retention and performance (as determined by grade) [30]. Such a narrow line of inquiry can make it difficult to understand more complex relationships within the data.

The appeal of predictive algorithms to provide actionable insights is already impacting educational structures. This is an area of concern, both in considering how to interpret data currently and in *shaping how educational settings are designed in the future*. For example, Williamson has argued that predictive analytics have contributed to the emergence of digital education governance:

> “digital technologies, software packages and their underlying standards, code and algorithmic procedures are increasingly being inserted into the administrative infrastructure of education systems” [32, p 2]

The “datafication” of education, according to Williamson, is driving educational technology toward a real-time, “future-tense” analysis of educational settings, in which **the necessity for counting certain events or behaviours leads to a necessity for monitoring an ever widening selection of data** [32]. Selwyn has cautioned that this creates a reciprocal relationship between technology and educational settings that ought to be seriously questioned [53]. He argues that educational technology is not simply a tool that can be applied with a clear outcome. **Technology has a wider social context that is continuously exerting influence over how the technology is understood and applied, which also shapes the context itself** [53, p 9]. Williamson references the National Pupil Database (NPD) and the Education DataLab in the UK to illustrate how data-driven approaches have become critical policy instruments, primarily through providing evidence that can be presented, audited and actioned [32, p 129]. Williamson argues that this has shifted power toward individuals involved in these processes:

> “the new managers of the virtual world of educational data are the technical, statistical, methodological and graphical experts” [32, p 138]

In fact, data management and a standardised data collection rationale are now two key areas of educational policy [29].

Predictive analytics can also shape course design itself. With regard to the Course Signals initiative at Purdue University[42], for example, the need for collecting data from the Virtual Learning Environment (VLE) was determined to be of such importance that many humanities courses were required to be redesigned “to have more frequent assignment points and more use of VLEs in order to generate more learning activity data" [30]. In this way, **even just the *context* of learning analytics' research has shaped the pedagogy and didactic approach of those courses**.

Predictive analytics has developed from a very different theoretical foundation (Information Systems) than the field that it is intending to support (Education). Information Systems Theory could be viewed as behaviourist, in that it seeks to explain behaviour through a stimulus-response line of inquiry, which is more observable and measurable [54] [55]. For example, the "Course Signals" initiative at Purdue University [42] and "OU Analyse" at the Open University UK (OU) [51] both track a combination of learner characteristics, effort (which is measured by behaviour in the Virtual Learning Environment, or VLE), performance and academic history to predict learning success and identify learners who are "at-risk". The impact of such initiatives is typically measured using the bottom line of performance and retention with the following question: *did intervention result in at-risk learners staying enrolled and performing better?*

Clow's description of the "closed loop" suggests that it is the action after prediction that makes an impact [4]. What was done to intervene and how did the intervention work? Kuzilek *et al* do not describe a strong evaluation of interventions based on recommendations from the system. For example, some of the of OU Analyse predictions involved using the k-Nearest Neighbour (k-NN) model to compare at-risk students with their "nearest neighbours", or students whose characteristics and overall behaviours most resemble that of the at-risk student in question. By examining k-NN in more granularity, the authors assert that it is possible to identify and suggest some behaviour changes or resources that might assist the at-risk student moving forward. However, Kuzilek *et al* did not provide information on whether or not this information was actioned by the educator or whether the information was able to change learner behaviour or attitudes toward learning. The authors also note that the dynamic changes involved in course preparation from presentation to presentation remain a persistent challenge for making certain types of predictions and understanding the wider impact [51].

Temporal and social factors around prediction, as well as the consequences for educational policy and development are worth considering. Selwyn claimed that the parsimonious idea of making learning observable and measurable has led to an overly optimistic view of learning analytics, and in particular prediction. He argued that **it is necessary to explore institutional responses to learning analytics more deeply, to understand the social factors involved** [56].

2.2.2 Social Learning Analytics

Social Learning Analytics are an interesting counterweight to predictive learning analytics, particularly in the early literature from 2011-2013. In prediction analytics, educational data is ordered by the passage of time and stabilisation across several variables. This strengthens the power of the predictions. Ferguson and Buckingham Shum noted in 2012 that inside of this approach, there is “little mention of pedagogy, theory, learning or teaching” [15, p 5]. Because of its roots in business analytics and data mining, which tend to be outcome-based, **predictive learning analytics may ignore important interaction processes that are relevant to learning** [3]. The authors proposed social learning analytics as a “distinctive subset” of learning analytics that deals with the process of learning, which is not simply an individual endeavour. Rather, learning is a contextualised experience, shared with others and influenced by their presence [15].

Learning analytics based on the analysis of social networks, social content, discourse and learner disposition have been identified as sources of key knowledge for educators on the context and process of learning [15][3]. As such, research on social analytics draws on data extracted from a variety of sources, some of which are institutional (such as the learner’s activity on the VLE or their demographic data) and some of which may be more informal (such as a learner’s profile on social media) [57].

For example, SNAPP (Social Networks Adapting Pedagogical Practice) has been used in learning analytics research to analyse and visualise forum contributions as a network diagram so that educators and learners can learn more about **social dynamics, the flow of information, the gate keepers and isolated students** [57] [58]. Other tools focus on leveraging this data to **help students understand their own “learning power”** [59]. Learning power can be described as the aggregate of certain factors and characteristics that make a “good learner”. The ELLI (Effective Lifelong Learning Inventory) is a self-report questionnaire that explores individual learning power across several dimensions. Researchers have used the ELLI to develop a tool that gathers and aggregates data related to each dimension of the inventory and presents it as disposition, in the form of a spider graph. The analytics allow for exploring dispositions on the individual and cohort level. This tool has been successful in **promoting “self-growth”, “personal experience” and “self-awareness” in education** [59].

However, **social learning analytics have not particularly materialised as a serious pedagogical tool within higher education**. It is **difficult to integrate data between different learning platforms and social media sources**, and tools that are built-in to the learning management system often have very **limited functionality** [60].

Commercial learning analytics platforms such as Knewton [2], do have the capability of drawing in extensive data from a large variety of sources (including social media), but the size and scale of its approach drives its services more in the direction of prediction through comparison, once again. Williamson writes

> "Learning analytics transforms comparison by enabling the individual student to be compared with global data-sets in a recursive fashion. As the individuals performance on a particular task is monitored, it is continually compared with norms algorithmically inferred from a global database, and then used for customizing future instruction. The big data logics of social media are firmly articulated into the governing practices of education through such instruments. Learning analytics functions through the same principles of recommender systems such as those found in consumer/prosumer spaces such as Facebook and Trip Advisor. In this way, the governing logic of global comparison becomes a real-time event concentrated to the scale of the individual among the global masses." [32]

Tufekci has called attention to some of the methodological and conceptual issues around using social media behaviour to infer anything about society. She warns that **structural biases of platforms and general ignorance of social "field effects"** (large-group shared experiences) can risk oversimplifying or misunderstanding certain behaviours. She also notes that **"human reflexivity," that humans will change their behaviour based on metrics, must be assumed and "built into the analysis"** [61].

2.2.3 Multimodal Learning Analytics

One of the more recent areas of learning analytics research is in using sensors and wearable technology to understand more about the classroom experience [62]. Multimodal analytics **diversify data sources by aggregating and integrating information from the both the physical and digital learning environment**. This includes "logs of computer activities, wearable cameras, wearable sensors, biosensors (e.g., skin conductivity sensors, heartbeat, and EEG), gesture sensing, infrared imaging, and eye tracking" [62]. One of the applications of this type of data, for example, has been in **understanding classroom orchestration**. Orchestration is the flow of classroom instruction, from individual to group work, and any other actions that the teacher provides to support these processes [63][64]. Orchestration has been studied using eye-tracking, EEG, accelerometer, audio and video recordings to study teacher interaction

[2] https://www.knewton.com/

with students. Using a machine-learning approach, one study showed that the "plane of interaction" (whether the teacher is engaging with one student, a small group of students or the whole class) can be detected with high accuracy using sensors [64]. The vision is that multimodal analytics of this kind will **help illustrate what types of activities seem to drive student learning from a pedagogical standpoint** [65], a closer application of learning analytics to constructivist learning theory .

However, **"concrete teaching activities" are more challenging to detect** [64]. In addition, Blikstein and Worsley note that many Universities are not in the position to pursue experimental pilot studies with multimodal analytics.

> " The direct instruction approach is inherently easier to test and quantify using currently available tools that include mass-production of content and decades of research concerning psychometrics and standardized testing strategies. Meanwhile, the constructivist side counts on laborious interventions, and complex mixed-mode research methods. The result of this asymmetry is that public systems, more dependent on high-profile research results, are left, by inertia, to the designs of the proponents of traditional approaches, while only affluent schools, private or public, who can experiment more, can afford to implement modern, constructivist approaches to learning" [66].

One of the concerns, as with any technological advancement, is **the length of time it will take for the benefits of learning analytics to reach the most disadvantaged stakeholder**. In education, this can become an ethical concern if it means that only private, wealthy institutions will be the primary beneficiaries of advancements in educational theory, while less fortunate schools will be continuously asked to do more with less, in terms of both money and data.

2.2.4 Process Learning Analytics

As mentioned previously, what distinguishes learning analytics from other types of educational analytics is the attention to human agency and interactive processes. This suggests that **impact in learning analytics is based on their ability to influence human decision-making**. *Preparation and delivery of learning experiences* are two areas of education where decision-making is most readily apparent. It also provides a useful backdrop for connecting learning analytics with clear impact [11]. Lockyer, Heathcote and Dawson have suggested that aligning learning analytics with "pedagogical intent" would provide a strong context for understanding learning analytics' impact on teaching and the environments in which learning occurs [10].

The term **"instructional design" was a post-war, behaviourist educational concept**. Behaviourism was the dominant psychological approach from the end of the 19th century to the beginning of the 20th century [54] in which learning was viewed as a system that could be analysed and interpreted. Structured approaches to learning, based on what was known about that system, were viewed as the most effective foundations for teaching [67]. **Learning design**, in the sense that it has been defined since the early 2000s, can be viewed as **a cognitivist and constructivist equivalent**, in which the system itself is part of the overall evidence considered. Cognitivism and constructivism are differentiated from behaviourism in that the complexity of human psychology began to be more clearly understood [68]. Educators are responsible for properly interpreting that context in the process of designing learning experiences within it [69] [10]. In particular, this field has developed alongside the permeation of technology into education and the use of Learning Management Systems (LMS), to track the activities of educators and learners and make them machine readable [69].

Learning analytics can apply the marriage of technology and pedagogy to interrogate the efficacy of different instructional approaches. This is particularly useful when scaling learning analytics approaches [70]. For example, Toetenel *et al* applied a learning analytics approach to understand which types of learning activities tend to have the greatest impact on learner performance and satisfaction. Their taxonomy describes assimilative activities, information handling, communication, production, experience, interaction, and assessment. Their results indicate that learning designs that include many assimilative activities appear to be negatively correlated with learner outcomes. While the authors concede that more research is necessary before it would be possible to generalise, it could be a significant discovery to have concrete, *measurable* evidence of the impact of certain learning designs on students [71].

Lockyer *et al* describe learning design as **an expression of "pedagogical intent"**, which is possible to operationalise and assess using technology. They argue that analytics that are aligned with the instructional context can enable educators to **measure progress toward certain *specific*, pre-defined goals and milestones**. They refer to this as **"process and checkpoint analytics",** which describe the learning journey in terms of the relationships between resources, tasks and support mechanisms. [10]. Lockyer *et al* provide the example of using social network analysis to understand whether the educator's intended aim of increased learner interaction could be detected in the communication patterns, or to illustrate student engagement [10, p 1448]. As mentioned previously, there are also many smaller learning analytics applications that can guide educators in looking at specific issues around social networks to identify and assess learner isolation [58], or provide more meaningful comparisons with peers [72]. However, much like social analytics, **process and checkpoint analytics have not**

been meaningfully implemented, as of the preparation of this thesis, in the higher education context.

2.2.5 Learning Analytics Dashboards

Learning analytics involves not only collecting and analysing data, but also **interpreting information and presenting it to potential stakeholders**. This typically occurs through an interface (or dashboard) that **allows a user to explore and interact with the data**. Learning analytics dashboards can be targeted at educators, administrators or learners [73]. As tools for exploring learning and teaching, learning analytics dashboards are one of the most significant contributions of learning analytics to higher education.

As mentioned above, the Purdue University Course Signals initiative had a student-facing dashboard to **communicate analytic insights to students, allowing them to compare themselves against standards and their peers** [42]. In HEIs, however, learning analytics initiatives with **student-facing dashboards are not particularly common**. As Schwendimann *et al* discovered, most learning analytics dashboards are targeted toward educators in higher education settings for predicting student performance. The primary named purpose for student-facing dashboards is typically to **promote awareness and reflection** [74]. One example of a student-facing dashboard that explores these affective areas is the Automated Wellness Engine (AWE) piloted at the University of New England. The AWE dashboard allows learners to track their emotional states through a series of self-reports using emoticons, which then form the basis for learner interventions. The project appeared to have cut attrition from 18-12% [72] [30].

Comparison with classmates is another interesting feature that has been debated in the literature on student-facing dashboards. **Continued concerns about the impact of comparisons on student motivation, as well as the difficulty in determining who and what to compare** [73] represent two moderating effects in why student-facing dashboards have not seen the same level of development as educator-facing or administrative dashboards. It is worth noting that the Course Signals study did not find strong evidence of the signals having a demotivating effect on students. Only 2 students of 1500 that participated in the Course Signals evaluation mentioned any negative effects of the intervention [42]. Still, **the paucity of evidence in the area of student-facing dashboards, especially in authentic settings, indicates a need for more research in this area.**

Bodily and Verbert also found that they could distinguish between two general types of systems, those that provided recommendations to the student based on data-mining techniques, and those that provided visualisations based on descriptive statistics. Very little is known about how these two different types of systems affect different classes of learners engaging with the system. The authors recommend that **future research "should ask students what effect they believe the reporting system had on them and what feature of the reporting system led to that effect"** [73] to help understand more about how learners understand the information that is being presented to them.

2.2.6 Learning analytics for Personalised Learning

As mentioned in 1, the current trends, *both in education and technology*, are toward **mobilising the social to improve the individual**. In formal education, and particularly in computer-mediated learning of any kind, learning analytics tools can be incorporated into Personal Learning Environments (PLEs) to support individual learning strategies [37][75]. **PLEs attempt to recreate the "socio-academic context" of learning, which is made up not only of institutionally provided materials, but also of information sourced elsewhere, from other colleagues and incidental experiences** [37, p 897]. Analytics can increase the power of that socio-academic context. For example, the software nStudy that was developed at Simon Frasier University is a kind of note-taking, research and reference plug-in that is able to track and support student learning activities. It collects a large volume of trace data, both from within the VLE and the personal web environment as a learner is researching and annotating resources [43]. Tools like nStudy aggregate data from many sources, some of which are within the domain of the educational institution (like the VLE) and some, such as a social media profile, which are typically more a part of a student's private life. They aim to **identify more concrete student behaviours and outcomes. This is done by improving the granularity of what technology can currently identify using more limited data** [6] [76].

2.3 Learning Analytics and The Open Learner Model

With the trust that is required in such a transaction, researchers anticipate that learners will expect a lot in return. Chatti *et al* argue that learning analytics tools of this type are contextualised within discussions about ethics, data privacy, "real time" feedback and "mobile learning analytics" as the smartphone learning analytics dashboard equivalent [76]. Chatti *et al* found that **"effective analytics tools are thus those, which minimize the time frame between analysis and action"** [77].

Learning analytics dashboards themselves are interesting objects for the subject of personalisation [78], much in the way that Lockyer *et al* described with the concept of process and checkpoint analytics [10]. The vision is that individual stakeholders will be able to set and monitor a particular pathway toward a chosen outcome and, using the dashboard features, mobilise relevant data toward that end. The direction of the discourse is toward an evermore flexible conceptualisation of learning, referred to as the "open learner model" [79][77] [76]. The open learner model was described by Bull and McKay as "a model of the knowledge, difficulties and misconceptions of the individual" that are continuously monitored through technology and "updated to reflect their current beliefs" [23]. In contrast with Williamson's comments, Bull and McKay view the idea of global comparison as providing an ever more personalised and authentic experience, rather than a homogenising one. **As learning gain becomes more personal and concrete, needs around educational assessment would also move in this direction** [76]. As Chatti *et al* have noted, however, **learning analytics systems tend to be "data rich but information poor"**, without more pedagogically driven indicators, predictions and recommendations to help parse potentially useful information [77][76].

The convergence of educational philosophy and technological advancement in using learning analytics for self-regulation and personalised learning represents the most significant *constructivist* contribution of learning analytics research toward understanding and optimising learning. For example, the Open Learner Model and the concept of Open Assessment do not replace the role of teaching with technology. Rather, they **allow for a *softening* of the lines between who is a teacher and who is a learner**. Open learner models also **emphasise how the *social environment* around the individual can be captured to understand how resources, tasks and support systems within that environment are perceived**. Through technology, the learner will be guided through awareness toward relevant action, similar to what Harasim envisioned with Online Collaborative Learning [38] and what Siemens described as "Connectivism" [80].

2.4 Chapter Summary

The improved mediation of learning through technology is the red thread that is interwoven through learning analytics research and its envisioned future.

This chapter described the field of learning analytics through the lens of its developmental background and applications in higher education. The chapter began with an examination of the connection between learning analytics and other advancements in digital tools for education. 2.1 described how technology is shifting the focus toward learner autonomy, why it is necessary to support learners in building those skills, and how learning analytics fits broadly into that goal. 2.1.2 delved more deeply into the conceptual history of learning analytics and its differentiation from educational data mining, highlighting the role of the human being as a facilitator.

The second section, 2.2, explored some of the more commonly described applications of learning analytics, as well as those that are emerging. 2.2.1 discussed the appeal and concerns around predictive analytics, which are already shaping educational practice. It concluded that the dynamic nature of the classroom and a lack of orientation around institutional or educational response can threaten the value of predictive analytics. 2.2.2 discussed the emergence of social analytics as a tool for both educators and students, supporting educators in understanding the social dynamics of their classrooms, and providing learners with opportunities for reflection and awareness. However, it argued that social analytics are not as useful if they have limited functionality and fall short of delivering what they promise. In addition, they require more support in terms of how they should impact decision making. 2.2.3 described more recent developments in using sensor technology to record and present information as multimodal analytics. While multimodal analytics were determined to be useful in understanding some aspects of the classroom experience, granularity is difficult to achieve and the technology may be financially prohibitive to acquire for some institutions. The impact of learning analytics on learning design was discussed in 2.2.4. In particular, it explored how learning analytics and learning design emerged as complementary concepts from their more behaviourist counterparts. It focused on pedagogical intent and how the educator could best communicate those intentions, using learning analytics as a guide. In 2.2.5, learning analytics dashboards were presented as the intermediary between learning analytics and the stakeholder. It argued that while student-facing dashboards could help contemporary students to make meaningful comparisons with their peers, they are not particularly common in higher education. The subsection concluded that consultation with students could most efficiently quell worries about impacts on student motivation, and improve knowledge about which types of comparisons are most useful and why. Finally, 2.2.6 examined how personal learning environments have the potential to transform digital education in ways that reflect the best of face-to-face and digital interaction. In particular, it discusses how learning analytics are contributing to the development of the Open Learner Model and Open Assessment, and determines that this development coincides with contemporary educational theory.

While several concerns and potential gaps in the literature have already been explored in this chapter, chapter 3 drills down into some of the underlying assumptions that are made about education and educational processes in learning analytics research. It also examines some of the factors that frustrate evaluations of impact. Understanding the current limitations of learning analytics is important in understanding how to make improvements, which is the primary aim of this study.

Chapter 3

Motivation: Learning Analytics, what's missing?

> *"Relevance is a search engine's holy grail. People want results that are closely connected to their queries."* - Marc Ostrofsky

The future direction of learning analytics, based on the previous chapter, is one in which a) more and more data will be captured in order to increase granularity of findings, b) filters, automation and recommender systems will be so finely tuned that a stakeholder will not be overwhelmed by the data and c) the decision-making processes on the basis of that information will provide specific evidence of impact. From a machine-learning perspective, that vision is coherent. More data, plus the ability to know which data matters to whom, will equal better outcomes for students. However, it is important to ask - *how will we get there?* How are decisions actually made with regard to learning analytics? What are the steps between awareness and action?

The constructivist psychological approach, which currently dominates the field of education, is distinguished from its cognitivist and behaviourist relatives in one very important way; rather than viewing humans as acquiring meaning from the world around us, constructivism purports that we create it [68]. In a sense, learning analytics is a field with a past and a future that looks constructivist in nature, but no present. The motivation for the body of work described in this thesis is based on the following four concerns around learning analytics research: Firstly, the development and primary applications of learning analytics within higher education **do not appear to fully represent contemporary development in learning or educational theory**. This makes it difficult to contextualise any decision-making on the basis of learning analytics findings. Second, learning analytics are **already influencing educational research and policy,**

as well as attitudes about educational theory, without fully understanding the real impact of learning analytics on practice. Third, evaluations of learning analytics, because they are computer-mediated, are **difficult to separate from the tools created to collect and communicate information**. In addition, the activities associated with learning analytics pilots and eventual adoption are **not aligned necessarily with the typical daily actions of the educator**. Finally, all of the above is impacting acceptance of learning analytics for large-scale, wide adoption. Without addressing these concerns first, it will be very **difficult to obtain stakeholder buy-in at the institutional level**, in particular for some of the more innovative and important contributions of learning analytics research.

The following sections address each of these concerns briefly, by reviewing and expanding on the critical review of learning analytics presented in the previous chapter. Once again, the purpose of examining these issues in more detail is to create a more accurate picture of when, how and why learning analytics are likely to impact practice.

3.1 Learning Analytics and Contemporary Education

Contemporary learning theory is increasingly focused on the learner and on the social context of learning experiences [81] [35]. Building upon the behaviourist, cognitivist and constructivist traditions, learning theory is now articulated within the context of what is called the Knowledge Age,"a time in which knowledge has key social and economic value" [38, p 2] and the Digital Age, a time when digital literacy is not only about tools but about metacognitive awareness and good judgement [48].

This reality calls into question the purpose(s) of education in the Digital Age. Peters asserted that distance education was "industrialised education", focusing on the form of mass production and making comparisons with the auto-motive industry [82]. Rumble, conversely, argued that distance education can resemble whatever theory upon which it is based [82]. Providers of distance education can and should decide **to which end are students meant to be educated at University? What is the most efficient way to get there? How do we get there without compromising learning?** Learning analytics are presented as a solution for answering all three of those questions. This section addresses some of the ways in which learning analytics are currently helping to define the answers to those questions and some of the concerns involved.

3.1.1 Efficiency and Optimisation

Though learning and technology have always been connected, Harasim argues that our relationship to technology has become more consistent in the Digital Age. She claims that in education, this relationship has been leveraged primarily to make learning more efficient, rather than to gain deeper insights about teaching or learning [38]. Research implicates the technology in part, which is new and requires a familiarisation phase, especially for those with less experience in digital technologies [24]. **It is worth considering whether or not the two are connected and if different attitudes toward learning analytics would change if the technology itself (the software) and its application (efficiency or optimisation) were not a factor**.

3.1.2 Skilled and Unskilled Users

Learning analytics are also shaping the requirements institutions have of educators and educational researchers. The vision of open learning analytics includes a caveat that tools must have a complex range of capabilities without requiring the end users have "extensive knowledge of the techniques underlying these tools" [77]. However, the transition toward this has not been fully realised and, as Williamson argued, **many influential actors in education are now data managers, analysts and visualisers** [32]. This has an impact on learners. The focus on learner autonomy that characterises contemporary education, and the tools created to support it, are leaving some learners behind. Many learners lack the skills necessary for recognising, understanding and regulating their learning strategies. They need educators and support staff that can help them do that [44].

3.1.3 Socio-Technological Factors

Perotta and Williamson cautioned that contemporary education requires "educational researchers to develop new methodological repertoires that can both (a) critically account for the social power of technical devices and artefacts, and (b) provide detailed analyses of the technical and mathematical mechanisms of such devices." [83].

For MacFadyen and Dawson, context is the one factor often absent in analysis and interpretation of educational data [24].The authors argued that researchers must

> "delve into the socio-technical sphere to ensure that learning analytics data are presented to those involved in strategic institutional planning in ways that have the power to motivate organizational adoption and cultural change" [24]

In this one statement, MacFadyen and Dawson name **institutional power, organisational culture, change and strategy as moving social-targets of learning analytics research**. They place the onus on the learning analytics community to develop analytics that "surprise and compel, and thus motivate behavioural change" [24].

However, as Schwendimann *et al* found, many learning analytics studies did not appear to have any particular pedagogical approach [74]. Bodily *et al* recommended that "more systems should consider bridging the gap between these fields by including both what has happened as well as what to do because of what has happened." [73]. Having to think about and prepare for the actions that could result from having a piece of information requires the system to create the necessary connection between the idea of pedagogical intent and a given behaviour. Gašević argues that this includes **developing learning analytics themselves from more "theoretically established instructional strategies, especially those related to provision of student feedback."** [11].

3.1.4 What and Why Questions

Even the most holistic learning analytics initiatives, with both educator and learner dashboards and intervention strategies, such as Course Signals, have not been able to produce much concrete data around the timing, frequency, or content of student feedback and its impact on student performance [30]. The JISC evaluation of Course Signals indicated that certain strategies seemed to be more effective, such as instructional rather than motivational feedback and comparison to peers rather than standards [30]. However, this thesis argues that such evidence is not sufficient for shaping educational policy or instructional design, because it is not framed within learning theory. *Understanding how and in which ways such feedback enhances student learning is important to meet the expectations of learning analytics' contribution to theory.*

3.2 Learning Analytics and Impact on Practice

Learning Analytics can provide a powerful lens through which to interpret learner behaviour, or, at the very least, contribute to the partial picture that educators and institutions have currently [3]. Yet, as the previous section argued, a considerable amount of learning analytics research is not pedagogically contextualised or evaluated in authentic environments. The majority of papers surveyed by Schwendimann *et al* on learning analytics and data mining research had "no evaluation whatsoever" [74, p 2]. Chatti *et al* claim that "researchers need to find pedagogically useful indicators, predictions and recommendations by evaluating the quality of analytics results in practice." [77]. This section looks at some of the current ways of measuring impact and the problems that arise with regard to evaluation and relevance.

3.2.1 Collecting and Cataloguing Evidence

Researchers have recognised that impact is studied within specific learning contexts in which many other variables may be involved. To address this issue, at least in part, the Learning Analytics Community Exchange (LACE) project http://www.laceproject.eu/ offers a richer description of outcomes in the contexts in which they occurred. The LACE Evidence Hub encourages researchers and practitioners to share their authentic experiences of applying learning analytics in the classroom, so that others can appropriate and adapt useful approaches. This evidence is delineated with regard to the LACE projects four major propositions that learning analytics a) improve learning outcomes, b) improve learning support and teaching, c) are taken up and used widely and d) are used in an ethical way [1]. The LACE project represents a significant contribution to learning analytics research and development in investigating impact.

In addition to promoting what works, the learning analytics community is open to discussing what did not work. In consecutive years of the Learning Analytics and Knowledge conference, researchers have hosted a workshop on learning analytics failures and what could be learned from those experiences. The "Fail-a-thon" as it was titled, was intended to mitigate the biases of the literature toward positive results [84][25].

However, as Schwendimann *et al* discovered in investigating learner dashboards, the field still "lacks comparative studies" that help to differentiate exactly what did or did not work in different settings [74, p 2].

3.2.2 Measuring Impact

The education research community has always had difficulty in assessing the impact of interventions on learner outcome and this difficulty has been projected onto the study of learning analytics:

- How do we define and measure success?
- How do we get this information to educators?
- How do we get it to learners?

[1] `http://evidence.laceproject.eu/`

- How do we know if it has worked?

The Joint Information Systems Committee (JISC) has published two overviews of available evidence on supporting student learning through learning analytics [30] [85]. These publications cite evidence that learning analytics have been effective at improving graduation rates, course completion rates, drop-out rates and overall retention, as well as increasing attendance, final marks and grade point average (GPA) [85]. In addition, their research indicates that learners feel generally positive toward learning analytics and respond well to learning analytics initiatives [30]. However, it should be noted that many of the studies involve the use of predictive analytics, and generic proxies for learning, such as retention, course completion and GPA. **Without understanding exactly which processes of learning are in play, it is difficult to move past prediction toward diagnosing and prescribing certain interventions in higher education**. The fact that predictions are successful, however, may build an expectation that *understanding* is "just around the corner". This optimism can create a bias [86] around how learning analytics techniques and tools are evaluated.

For example, Caulfield reviewed several anomalies he had discovered in the Course Signals data and found that "the experiment may suffer from a 'reverse-causality' problem" [87]. He found that claims about participation in Course Signals classes influencing retention could also be explained by a reduction in the over all number of classes being taken as other students drop out over time. He also cautioned against being too optimistic about the overall effect of Course Signals on student grades. He points out that students also have limited time and that better grades associated with Course Signals classes could also be at the expense of their performance in other classes. While he recognises that some explanations are more plausible than others, Caulfield was concerned that the Course Signals study had never been properly peer reviewed, despite the study's inclusion as a key citation in many learning analytics papers. Caulfield's argument illustrates the importance of researchers properly contextualising their results, as intervention is not a simple cause and effect relationship.

Ferguson had already noted in 2012 that work on cognition, metacognition and pedagogy was under-represented in learning analytics research [3]. The more recent findings of Schwendimann *et al* and Bodily *et al* suggest that *a deficiency in understanding how to close the loop between awareness and action still exists as of writing this thesis*[73]. The silver lining is that qualitative evidence demonstrates that educators still feel generally positive about learning analytics, if they can have more input in research and development [88].

3.2.3 The Problem with Relevance

Part of the problem in understanding learning with learning analytics is in parsing and interpreting vast amounts of data. Researchers have acknowledged the abundance of data with which institutions and educators are currently burdened [89]. In education, technology can be used to gather trace data about learners' activities almost anywhere online: on the Web more generally [43], or within a VLE [42][51]. Multimodal analytics can use sensors to collect data about a number of physiological responses that learners have to certain stimuli during learning experiences [62]. Social Learning Analytics can use forum data and peer interaction to gather information about the kinds of relationships that learners have with one another and with certain types of content [15]. Such advancements in technology offer many potential opportunities for educators and learners to understand more about teaching and learning. This is especially true in the context of distance education, where contact with learners is limited. However, these few examples already highlight the breadth and complexity of the types of data that are possibly available, which can be overwhelming for educators. It can also make it difficult for institutions to decide on holistic tactics for collecting, measuring, analysing and reporting on analytic data for their stakeholders. **Deciding what is important to whom is a complexity that requires unravelling**.

For example, in the development of their support tool eLAT for understanding and visualising analytic data for educators, Dyckhoff *et al* discovered that teachers were most interested in using analytic data to interrogate the efficacy of *specific interventions* that they implement in their classrooms. However, most of the tools teachers were given were too complex and tended to overshoot their requirements [9]. These results indicate a necessity for deeper investigation into what kinds of data matter, to whom they matter and why they matter to support the search for relevance in the broad landscape of information.

With regard to what learners require, this thesis has already discussed some of the potential for learning analytics to support learner strategies and provide an early warning system for quick intervention [42] [85]. In addition, some recent qualitative studies have explored learner perspectives on what they hope to gain from learning analytics [90] [91]. Schumacher and Ifenthaler conducted a mixed methods study into the requirements of students and found that the majority of learners saw learning analytics as an opportunity to help them plan their studies and perform self-assessment. Students disagreed on several features about comparing their progress with others, leading the authors to conclude that a highly customisable interface would be required [91, p 70]. However, Khan concluded that learners (and educators) may still lack foundational knowledge about learning analytics and their significance, and that more research was needed to promote a shared understanding at the institutional level, across stakeholder groups [90]. Both studies indicate that **there are differences in the way that individual learners may approach the topic of learning analytics and that there is something deeper to be understood about those differences**.

3.2.4 The Problem with Evaluation

Challenges of relevance are also manifested in problematic attempts to investigate how real impacts on practice are evaluated. **When data is overwhelming, evaluations are likely to be either too broad or too narrow** to get an accurate picture of an educators' real intentions to use a given tool, their understanding of its utility and their actual use of the tool in an authentic environment.

For example, Judith Schoonenboom's research on disparities in how Learning Management System (LMS) tools are used, support the findings expressed by Dyckhoff *et al* that educators can have difficulty finding relevance in learning analytics tools [92]. Applying an extended Technology Acceptance Model (TAM), Schoonenboom analyzed educators' use of LMS tools to perform 18 different instructional tasks, such as preparing for an exam, moderating discussion, or providing learners with feedback. Schoonenboom found that the TAM factors of usefulness and ease of use did, indeed, correlate with *intention* to use a given tool. However, most reasons provided by educators for using or not using a specific LMS tool, were related to *specific* tool, task and interface combinations. As a result of these findings, Schoonenboom posited that it is inappropriate to apply a Technology Acceptance Model at the level of the LMS system *as a whole*, because this is not how educators' engage with them [92].

At the other end of the spectrum, many **evaluations of learning analytics approaches and methods are too "tool-specific"**, rather than a more general evaluation of educators' ideas and motivations related to using analytic data for their practice. For example, in a 2013 survey of 15 learning analytics dashboard applications for educators and learners, Verbert *et al* [93] found that evaluations of tools were primarily organised around usability studies and efficacy in controlled environments. This connects the potential impact of analytic data on learning outcomes with usability and satisfaction.

Usability studies are a very useful (and necessary) mechanism for understanding whether or not the user is able to perform the activities intended by a specific tool to reach a specific outcome. However, Greenberg and Buxton have argued that usability studies on new and radically innovative ideas can limit their creative development, as well as put the validity of the evaluation at risk [94]. The authors suggest that the focus on usability shapes the research question to the method and not the other way around [94, p 113]. The knock-on effect of this tendency is that **the research community knows much more about how tools could and should work, than how they *do* work**. This finding is supported by a 2016 review of available research literature on the impact of big data and learning analytics within blended learning environments, which present unique challenges to gathering and utilising data. In their attempt to study the impacts of learning analytics on learning strategy and reflection, the authors discovered **tendencies in the literature toward exposing organisational aspects of learning analytics adoption or technological capability, rather than impacts on learner behaviour and cognition** [95].

3.3 Learning Analytics Acceptance

Wide-scale adoption of Learning Analytics tools remains a problem for institutions [96]. The technology itself, as well as the "presage aspects" of the technology (preconceived notions and experience) will influence stakeholder perceptions and eventual use of a system [97]. In addition, individual goals and priorities will influence intentions and actual use of learning analytics tools and technologies.

This section describes each of these challenges in more detail and presents some reflection questions that helped to guide the methodological choices that are presented in the following two chapters.

3.3.1 Presage Factors

Recognising that there was limited empirical research on factors that influence the adoption of learning analytics tools, Ali *et al* developed and validated the Learning Analytics Acceptance Model (LAAM), to examine more fully how perceived ease of use and perceived usefulness correlates with behavioural intention to use a learning analytics tool (see Figure 3.1).

The authors found that pedagogical knowledge also influenced beliefs about learning analytics and the perceived usefulness and ease of use, relative to specific tools. Pedagogical factors were gathered through looking at the role of the individual and the years of experience that individual had in their role [2].

However, one could argue that this is not sufficient to understand the role of pedagogy in influencing beliefs about learning analytics. As Ferguson and others have noted, studies on cognition, metacognition and pedagogical intent are missing to explain exactly

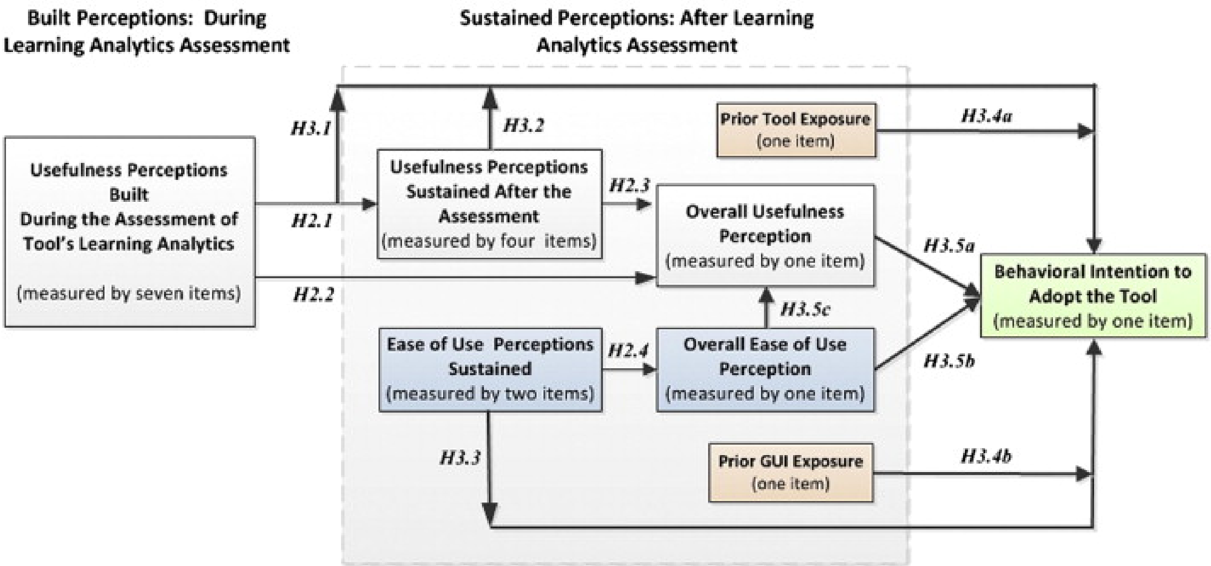

FIGURE 3.1: The Learning Analytics Acceptance Model[2]

how such factors impact perceptions of learning analytics and learning analytics acceptance. *What is the relationship between learning analytics and pedagogy? How can it be managed?*

3.3.2 Intention to Use

To gain stakeholder support within institutions, researchers have been motivated to clearly demonstrate useful solutions that address both real educational problems and institutional concerns. For example, one research group developed a "Rapid Outcome Mapping Approach" to uncover the most important barriers to adoption and to develop a policy around learning analytics adoption that addresses those concerns [98]. Others have attempted to convince their stakeholders through concrete frameworks for testing and evaluating interventions that are proposed through learning analytics [99]. The results of such inventories generally lead toward the assessment that it is necessary to obtain more accurate, specific information about learner and educator goals [100]. *How can learning analytics help to detect and optimise those goals?*

3.3.3 Actual Use

Once those two hurdles have been surmounted, there is the issue of actual use in an authentic environment. Herodotou *et al* gathered insights from educators using learning analytics in the context of an institutional pilot study at the Open University UK. Their research concluded that **teachers tended to use learning analytics tools in**

very diverse ways that *complement* their existing strategies [101]. For example, if a teacher was already interested in identifying at-risk students and improving their achievement, use of the system either "systematised" their existing approaches or prompted them to be more "proactive". The actual impact of teacher interventions, however, remained unclear in their analysis.

This is troubling because teachers represent a large part of student experience. Multi-level models of classroom dynamics indicate that teacher behaviours can explain much of the variance in classroom outcomes, "mediated by the perceptions of the learners themselves." [102]. Learning analytics has confirmed this as well in studies of the impact of different learning designs on learner outcomes [10] [11] [70]. In fact, it is not just a teacher's behaviours, but also their attitudes, which impact what different stakeholders agree is a "good" teacher. A recent study on perceptions of physics teachers showed that learners view teachers' enthusiasm and excitement for a subject as being one of the primary influencing factors on their achievement over time [103]. *How can learning analytics capture these kinds of detailed relationship features?*

Muijs makes two recommendations that are relevant for this thesis. Firstly, instruments or methods to establish efficacy should be related to the specific goal involved and should not be chosen on the basis of "convenience or familiarity". Secondly, he discusses briefly the "expanding role" of teachers and how researchers must consider how to describe and measure these roles, as well as their impact on "differential teacher effectiveness" relative to the subject or domain [102].

3.3.4 Developing Learning Analytics Literacy

Learning analytics literacy among educators is relatively low [104].This presents practical and ethical questions. For example, *how does learning analytics literacy impact an educators' ability to perform their function and deliver the outcomes expected by the institution?*

A recent paper by Ochoa *et al* proposed that the above issues be dealt with by seeking common ground, methodologically, ideologically and practically [105]. The authors suggested that convergence in the field can be gained through the development of a collective body of knowledge, sub-working groups and communities that assist one another in exploring the development of learning analytics as a field [105, p 3]. They also caution developers and researchers to remain diverse in their working teams and to challenge the field, expanding more firmly in the socio-technological character of learning analytics [105, p 4]. **How can educators and learners help to bootstrap the development**

of effective learning analytics by contributing the data that researchers really need?

3.4 Chapter Summary

This chapter addressed challenges outlined by the research community in understanding exactly what kinds of impacts learning analytics can and does have. Section 3.1.4 addressed inconsistencies involving learning theory and how best to achieve a high quality education. In particular, it discussed efficiency and optimisation as subtly different concepts, and how the technology itself creates skilled and unskilled users. It also supported the argument that learning analytics require more attachment to "theoretically established educational strategies" [11]. More specifically, it proposed that educational theory is necessary to get beyond asking *what* learners and educators need from learning analytics, to *why* they need it. 3.2 supported this assessment, in describing challenges around collecting and analysing data, knowing what to measure and how, as well as what will be important to whom. Finally, 3.3 addressed the issue of wide-scale, ethical adoption of learning analytics and the ways in which the research community is currently prompting this trajectory.

The chapter concluded with some questions that the literature review helped to highlight.

- What is the relationship between learning analytics and pedagogy? How can it be managed?
- How can learning analytics help to detect and optimise goals?
- How can learning analytics help capture and optimise the learner-educator relationship?
- How important is learning analytics literacy in the every day performance of the educator?

These questions remain unclarified or open in the literature. As such, they helped to guide theoretical and methodological choices involved in the study design. In the following chapters, those choices will be described in more detail. Building up to what the study actually illuminated about learning analytics, it is important to clarify what is being discussed and at which level the conversation is happening. The next chapter on Mediated Learning is intended to provide that framework.

Chapter 4

Mediated Learning as a Theoretical Framework

"Through others we become ourselves." - Lev Vygotsy

This thesis is motivated, as described by the previous chapter, by certain open questions in learning analytics research. A framework that is appropriate for addressing these deficits must be a) attentive to education and learning theory in learning analytics research, b) aware of the optimism that is influencing policy before impact has been adequately vetted and c) sceptical of conflating technology acceptance and learning analytics acceptance.

This chapter proposes "Mediated Learning" as the framework for the study presented in this thesis. "Mediated Learning" provides not only a comprehensive picture of the various actors and relationships that are theoretically involved in learning experiences, but also a way to categorise them through a set of demanding criteria. These criteria form the basis of assessing whether or not a successful learning experience can *potentially* take place. "Mediated Learning" was a revolutionary perspective on learning, that learning is social, psychological and technological in nature. Amongst those levels, there are multiple relationships perpetually in motion, between humans and tools, or humans and their belief structures, mediating the experience of learning. Understanding those relationships and how they work provides a lever for the human agent to impact teaching and learning [17].

Learning analytics, *as a field of educational science*, has the potential to contribute to the process of mediating learning by providing evidence of those relationships and their impacts on the learning experience. The research presented in chapter 2 illustrated this potential. However, learning analytics, *as a concept*, may have a more reciprocal relationship with mediating learning. The challenges in learning analytics research are accurately measuring impact, ensuring relevance, avoiding unnecessary complexity and gaining stakeholder acceptance. These are all issues of human interpretation and compliance, signalling that **learning analytics are *educational propositions* that are not uniformly perceived in the same way**. The framework of "Mediated Learning" makes it possible to distil what those propositions are and how they are perceived by those who interact with them.

The sections below describe first the components of "Mediated Learning", as described by Vygotsky and the universal criteria of a "Mediated Learning Experience" proposed by Feuerstein. The final sections explore "Technology Mediated Learning" and its relationship to the "Mediated Learning Experience". They also introduce learning analytics as a mediatory agent with psychological, social, and technological aspects. This chapter will lay the foundation for explaining the expected theoretical and methodological contributions of this thesis in the following chapters. It will also briefly explain what this theoretical framework offers that others cannot.

4.1 Vygotsky's Mediated Learning

Vygotsky viewed psychological function as an integrated output of both natural and social processes, which were moderated by culture in a process he called "Mediated Learning". While human beings, as organisms, have a natural progression of psychological function that is developed with age, Vygotsky believed that human development is also heavily influenced by those around us, as well as the material and symbolic tools we use to interact and construct meaning. Vygotsky referred to such signs and symbols as "psychological tools", and proposed them as one of **three classes of mediatory agents: material tools, psychological tools and other human beings**. According to Vygotsky, **activity mediated through these agents can produce "higher mental processes", which can facilitate the individual's transition from one set of tools to another**. [17] [18].

This section describes Vygotsky's theoretical contributions to understanding the interactions between learners, tools and belief structures. The final subsection deals with Vygotsky's particular contribution to this research study and how his work contributes to the framework.

4.1.1 Self-awareness through contact with the other

Perhaps the most basic principle of Vygotsky's "Mediated Learning" is the idea that self-awareness arises through contact with the "other". This idea hearkens back to the Hegelian concept of "mediation" ("Vermittlung"). Hegel wrote:

> "The philosophical notion of mediation already suggests a whole range of possible mediating agents. First, work presupposes material tools interposed between the human individual and the natural object. These tools, though directed at natural objects, also have a reciprocal influence on the individual, changing his/her type of activity and cognition. Secondly, since work is nearly always work for somebody else, then social and psychological characteristics of the other person also enter the equation. Finally, since work is impossible without symbolic representations, they and the means of their transmission become two additional mediatory agents." [16, p 8]

From the previous passage, one can distil three "mediating agents" of learning: *material tools, people and the symbolic representations they negotiate (psychological tools).*

A human mediatory agent has one of two courses of influence: direct or indirect. The human agent will either a) help an individual to internalise inter-psychological interactions with others, or b) directly mediate through example or guidance [16]. Vygotsky suggested that each person has a "Zone of Proximal Development" (ZPD), which describes a learners *potential* for learning "where that learning is culturally shaped by the social environment in which it takes place" [106, p 193]. Kozulin has further argued that the **Zone of Proximal Development delivers an opportunity to focus on emerging skills and "assisted performance"**, to describe the difference between actual ability and learning potential [26]. Smagorinsky argues that Vygotsky's work on ZPD is often misinterpreted as simply a person's learning potential with or without assistance from a more knowledgeable person. A "more knowledgeable person" could include people who are more knowledgeable, but who are situated inside of a value system that is harmful to development. He gives the hyperbolic, but effective, example of a child raised in the pornography industry, who might be surrounded by "more knowledgeable others", but in an environment that is unlikely to lead to development of learning potential [106]. In Smagorinsky's view, the idea of proximity includes proximity to values, structures and experiences that promote psychological development. This adds a qualifying feature to the process of *self-awareness through contact with the "others"*, namely that **learning potential is more likely to be *positively* impacted by contact with the "other" when the *environment* is conducive to development**.

4.1.2 Psychological Tools

A part of that environment is the system of psychological tools that are available to a person, to make sense of the world around them. Vygotsky's concept of psychological tools represents a significant contribution to the new paradigm. Inside of that term he packaged many abstractions, "those symbolic artifacts signs, symbols, texts, formulae, graphic organizers that when internalized help individuals master their own natural psychological functions of perception, memory, attention" [26, pp 15-16]. Essentially, what Vygotsky is referring to is the cognitive structure of the human mind, the epistemological assumptions and knowledge that propel (and limit) thought.

4.1.3 Vygotsky's Contribution to this Thesis

Vygotsky argued that both material and psychological tools are developed and negotiated through cultural systems of belief and interaction [17] [18], such that, when these different systems collide, the sociocultural facet becomes emphasised and must be recognised. The reciprocal relationships between tools, symbols and people, which shape an individual's understanding of the world, became the cornerstone of Vygotsky's theory of *"Mediated Learning"*. For the purposes of this study, Vygotsky's theories will **help to frame how learning analytics impact learning, by unpacking the psychology of users relative to learning analytics technologies**.

4.2 Feuerstein's Mediated Learning Experiences

Vygotsky's theories went on to form the basis for Activity Theory, which [107] which explored psycho-social relationships from a systemic perspective. Activity Theory however, looks at authentic action in authentic settings to describe those relationships and also does not appear to suggest a clear pathway forward, to mobilise the theory into a practice that can be implemented. Feuerstein fills this gap with a more socio-cultural perspective on mediated learning, which includes **a range of criteria he proposes as essential for producing an impactful Mediated Learning Experience (MLE)** [16] [20].

The contribution of Feuerstein's criteria is that their successful application should **facilitate the transition to new systems of psychological tools**. As Smagorinsky suggested, an environment conducive to development has to be achieved in order to positively impact the potential for reaching other levels and systems of psychological tools

[106]. **The criteria provide a mechanism for evaluating the learning environment in this regard.**

The following section describes Feuerstein's universal criteria for a "Mediated Learning Experience" and how these criteria can be used to examine learning analytics as a mediatory agent.

4.2.1 Cognitive Modifiability

Like Vygotsky, Feuerstein argued that interactions between human beings within their social and cultural contexts illustrated our "cognitive modifiability" and that understanding these interactions was key to improving learning skills [20]. More specifically, Feuerstein studied the interactions that effect a child's *"propensity to learn,"* in particular with respect to "differential cognitive development" [16].

Feuerstein argued that differences among individuals could be attributed to deficits in one or more of three key areas: "cognitive structure, knowledge base, and operational functioning" [16]. To understand the source of these deficits, Feuerstein examined mediating **factors that are able to positively modify a learner's "propensity to learn"**. He developed 12 criteria to operationalise this concept of a Mediated Learning Experience [16].

4.2.2 Universal Criteria

Feuerstein proposed three universal criteria that all Mediated Learning Experiences (MLEs) will share. The first criterion of an MLE is "Mediation of Intentionality and Reciprocity," by which Feuerstein refers to the point at which the learner is aware that something is being transmitted and that their response to that object is the "primary target of mediation," not the object itself [16, p 13]. The mediation of "Intentionality and Reciprocity" is the "deliberate attempt to influence [a person's] performance and [a person's] willingness to accept influence" [108]. This might involve activities such as integrating a learner's perspective directly into the organisation of the classroom routines or negotiating rules of communication. What is important is that **the learner understands that learning is a mutual process and that the *way* they learn is as important as *what* they learn**.

The second criterion is "Mediation of Transcendence", which refers to information that is made available to the learner with broader context than their actual query [16]. For example, a language learner might ask a teacher to define a given verb. The teacher could simply provide a definition, but this would not mediate transcendence. Transcendence is mediated when **the learner is guided in the process of categorising information and incorporating it into known models**. For example, the language teacher might also offer the student a way to classify the verb on the basis of its ending or remind the student if it is a regular or irregular verb. This is an important factor in ensuring that learners can transfer what they have learned onto different contexts, which is an important skill that many learners find difficult to master [109].

The final criterion that is universal to all MLEs is "Mediation of Meaning". Presseisen and Kozulin summarised meaning as "the questions of why, what for, and other reasons for which something is to happen or be done" [16, p 15]. In any given learning experience, the mediation of meaning involves ensuring that **the agent of learning, the student for example, is capable of grasping why a given object should be learned and for what it may be useful**. The philosophy of Italian educator and philosopher Maria Montessori was based on the founding principle that all subjects may be introduced meaningfully to children at any developmental age. A Montessori approach, for example, leverages the learner's attention in order to prime them for input, so that whatever object of learning may make a more lasting "impression". Montessori believed that the stronger this initial impression is, the better it may be used to anchor subsequent learning objects. As such, Montessori advocated that children have the liberty to "freely choose activities in the service of their education." [110, p 79]. If the child was responsible for assigning value to the task, this could be mobilised to support the child's cognitive development.

Other areas of mediation that impact "propensity to learn", according to Feuerstein, are the following: a feeling of competence (a sense of self-efficacy), regulation and control of behaviour, sharing behaviour (between and among peers), individualism and psychological differentiation, all goal-related activity (including goal-seeking, planning, achieving, etc.), a desire for challenge, an appreciation for novelty and complexity, optimistic alternatives, a feeling of belonging and a sense of the human being as a "changing entity" [16]. While this list is not exhaustive, it provides a picture of a positive, mediated learning experience.

4.2.3 Feuerstein's Contribution to this Thesis

Vygotsky and Piaget believed that the presence of information that contradicts or questions existing ideas will lead to insight [111][112]. Critiques of Vygotsky's early theories questioned this assumption and expanded on it. Activity Theory, for example, asserted that contradictions must be *made conscious* through studying organised activity within a given system, which highlights stress points and makes them relevant for the learner [113].

Presseisen and Kozulin sought to investigate this assumption as well and found that **without "mediation of meaning", the mere presence of a contradiction is not enough to improve cognitive development**. Presseisen and Kozulin argue that Feuerstein's universal criterion of mediation of meaning is critical for **helping learners and educators understand *how* to understand and modify their approaches** [16]. In the context of this thesis, Feuerstein offers a way of **diagnosing whether a given learning analytics approach is more likely to be productive in mediating learning or not**. The universal criteria provide an heuristic mechanism to test ideas and assumptions.

4.3 Technology Mediated Learning

In the context of contemporary education, technology has become an important mediatory agent; a tool, with both material and psychological implications. However, as Marshall and Cox argued, competing epistemological approaches have frustrated attempts to study the impact of technology on education [114]. A lack of standards in research and "underpinning theory", as well as inattentiveness to the reciprocal relationships between the technology and how it is applied, contribute to the complexity [114, p 997-998]. Ochoa *et al* highlighted this same challenge for learning analytics specifically, in expressing the need for minimal common ground [105].

This section explores some of the ways in which technology is examined as a mediatory agent and some of the challenges associated with this. In particular, it explores technology acceptance and acceptance modelling, as well as their limitations in exposing layers of social influence.

4.3.1 Technology Acceptance

At the material level of the tool, technology acceptance modelling is one way to investigate the most salient aspects of technology integration. Modelling technology acceptance helps to describe influencing factors and predict certain behaviours in a reciprocal fashion. It is one of the most developed fields of Information Systems research [115]. The Technology Acceptance Model (TAM) described by Davis in 1989 is still one of the most widely referenced and refers primarily to two constructs: perceived ease of use and perceived usefulness [116], which still form the basis of current models. Subsequent revisions of the model further refined and described these constructs in terms of more specific "cognitive instrumental processes" (perceptions such as job relevance, output quality, result demonstrability) and social influence.

4.3.2 Expanding Technology Acceptance

Venkatesh and Davis have suggested that **harnessing the social influence factors in technology acceptance** is more effective than compliance-based approaches that institutions (of higher education, for example) might propose. In addition, they argued that organisations should do more to demonstrate comparatively how the innovations a technology provides stand up to existing solutions. **Understanding how a user is able to match their own goals to the consequences of a system is a particular challenge and would present a significant contribution to the state of the research** [116]. Finally, the authors suggest that the factors influencing how perceptions are formed, which they refer to as **"determinants of perceived usefulness" and "determinants of perceived ease of use"**, are important to identify for technology acceptance, but are overlooked in traditional models [116, p 199].

To address these concerns, Venkatesh *et al* put forth a Unified Theory of Acceptance and Use of Technology (UTAUT), which emphasises four major constructs: performance expectancy, effort expectancy, social influence and facilitating conditions [115]. Despite its improved success in predicting behaviour and intent to use, the authors concede that the **theory is lacking in "meso-level formulations" of the model, by which they refer to investigations of technology acceptance on the *organisational* level**, examining the layers of technology acceptance within an institution. The authors propose a "paradigm shift" as a necessary instrument of innovation in the field of technology acceptance, particularly in the direction of theorising about the context of technology acceptance as a contribution to knowledge [115, p 338]. The work presented in this thesis will address this gap.

4.4 Learning Analytics as Mediatory Agents

As Harasim noted, the contemporary educational climate is moving toward increasingly collaborative problem-solving, facilitated by technology including the Web [38]. This is a reciprocal relationship, mobilising the social for the enrichment of the individual, who will then enrich society. In this reciprocal relationship, it is necessary and recommended [105] to develop a common language, or at least a way to decode what is meant by learning inside of learning analytics research. This is particularly important for entities with a mediatory role that is supposed to facilitate the acquisition of knowledge.

This section outlines how learning analytics can be viewed as mediatory agents. The first subsection maps the field of learning analytics to the theories of Mediated Learning presented earlier in this chapter. The second subsection proposes the identification of metacognition in learners as a parsimonious signal of higher mental processes resulting from a given stimulus (a new idea, piece of information, etc.). The final subsection describes how to evaluate the potential of learning analytics as a mediatory agent.

4.4.1 Locating Learning Analytics in the Theory

Learning analytics include symbolic representations, socially-interpretative and technological dimensions. They involve material tools of software and hardware. They evoke psychological tools, such as belief systems and values. They are also shaping and shifting psychological tools. As such, **an examination of learning analytics as a mediatory agent lies between the concepts of technology-mediated learning and the more human-centred, philosophical construct of mediated learning described by Vygotsky and Feuerstein**.

Educational philosophers Vygotsky, Dewey and Piaget, argued that learning is an active process in which we build knowledge through engaging with our environment and manipulating it, the tangible and intangible [111] [117] [112]. Unlike the *tabula rasa*, or "blank slate" conceptualisation of human learning that characterised the behaviourist school of educational theory, social constructivists position learners as contextualised beings, an embodiment of social and cultural norms, psychological and physical structures that require consideration [17] [112]. For the individual learner, new knowledge is formed when preconceptions and new observations clash or are thrown off balance, an event most likely to occur in a social context with many different agents acting according to their own set of beliefs and motivations [118, p 68].

Learning analytics are perceived as a way of bringing awareness to potential moments like these and to facilitate the "clash". However, *how do learners make sense of the "clash" and what do they do with it?* The previous chapter highlighted that the inner-workings of decision-making remain largely unearthed by the most common applications of learning analytics in higher education. *How can learning analytics support learners in knowing what to do? How can we recognise conscious decision making?*

4.4.2 Metacognitive activity as a higher mental process

Capturing metacognitive activity is key to understanding how learning analytics mediate learning by *driving awareness toward action.* The term "metacognition" is often accredited to American Psychologist John Flavell, who used the term from the mid-1970s to describe "cognition about cognition" and awareness of cognitive phenomena in young children [119]. Flavell wrote:

> "Metacognitive experiences are any conscious cognitive or affective experiences that accompany and pertain to any intellectual enterprise. An example would be the sudden feeling that you do not understand something another person just said." [119, p 906]

Flavell's description of metacognition is quite open and intuitive. It involves cognitive, behavioural and affective components of awareness, which should result in an evaluation of the self. In the context of social constructivist learning theory, **metacognition is now understood as a building block in monitoring and controlling thinking, a *gateway to learning* through exposure to new ideas and influences** [120]. Attention to metacognition, and the **external and internal forces that drive metacognitive activity**, is a hallmark of many social constructivist educational theories, if not the centrepiece. Metacognition plays a key role in developing constructs such as self-efficacy [121] and motivation in social environments [39]. Learners compare themselves against their own expectations, external standards and other learners. Vygotsky described this in terms of knowing ourselves through knowing others [17].

4.4.3 Evaluating Learning Analytics as Mediatory Agents

Learning analytics should be examined in relation to their **mediating effects on all aspects of the learning experience, from the tools and technologies, to the attitudes, beliefs and structures around learning analytics acceptance and their role in educational policy**. This includes psycho-social and technological factors, which can be captured through analysis of metacognitive activity. **Meaningful interactions that produce metacognitive activity about learning, those that positively impact "propensity to learn"** [16], will meet the criteria described by Feuerstein [16][20]. In addition, analysis of metacognitive statements will provide evidence for "determinants of perceived usefulness" [116, p 199].

4.5 Chapter Summary

A theoretical framework provides a lens through which to examine and structure data. This chapter outlined how the framework of Mediated Learning could be applied to the field of learning analytics. In particular, it examined the mediatory potential of learning analytics technologies on the learning and teaching process. The philosophies of Vygotsky and Feuerstein provided two avenues for investigating mediated learning. Section 4.1 discussed Vygotsky's perspective on learning from the "other" and the impact of psychological tools on learning. In addition, it addressed Vygotsky's concept of the Zone of

Proximal Development, which models learning potential with assistance. For the study presented in this thesis, Vygotsky's theories were determined to be useful in examining the psycho-social experiences of the potential learning analytics user. Section 4.2 presented Feuerstein's elaborations to the theory with a description of cognitive modifiability and the universal criteria for Mediated Learning Experiences. More specifically, the section outlined how the criteria provide a mechanism for exploring "what counts" as a mediated learning experience. This thesis applied these criteria as a checklist to evaluate the mediatory potential of learning analytics tools and technologies. Section 4.3 explored the unique landscape of Technology Mediated Learning. It discussed how various technology acceptance models attempt to identify what really drives behaviour, discovering that social influence is very significant to this process. Finally, section 4.4.1 focused the theory onto learning analytics as mediatory agents. The first subsection described how learning analytics fits into the concept of psychological tools and mediation more generally. Subsection 4.4.2 addressed difficulties in capturing awareness and intention. It proposed identifying metacognitive activity as a way of demonstrating learning and action potential. Section 4.4.3 described how learning analytics as mediatory agents should be evaluated, and how the different viewpoints presented in the chapter should be regarded in the analysis.

The subject of Mediated Learning will be revisited in the discussion chapter, following the findings presented in chapters 7, 8 and 9. The next chapter describes the approach that was determined to be most appropriate for addressing the questions evoked by the research literature presented in chapter 2.

Chapter 5

Research Approach

The scope of this research is to examine in more detail the different perspectives of educators and learners toward learning analytics and to understand more about how they would or do actually use learning analytics to support everyday aspects of their practice. As the study concerns itself with individual perspectives and everyday experiences, a qualitative investigation [122] [123] is an appropriate choice of research design. This chapter describes the theoretical assumptions involved in that choice in more detail.

5.1 Research Question and Objectives

This research was originally motivated by a rather simple, but timely, question that was evident in the research literature: **What impact is learning analytics having on practice and how can it be improved?** [4][89][96]. However, as has been discussed previously in this thesis, impact is a *complex* measurement with many moving parts within the *dynamic* context of learning and teaching. Important gaps in our understanding of the *individuals* involved in education and their metacognitive *processes* limit what we can know about their *decisions* around teaching or learning [96]. Therefore, the question was further refined to reflect this gap:

> **What impact is learning analytics having on practice and how can it be improved for educators and learners?**

Chapter 2 described how impact is currently understood and measured within learning analytics research. It presented the challenges associated with recognising and evaluating impact, as well as issues of data overload and interpretation. Chapter 3 explored this more deeply in terms of what is missing in learning analytics research and how that compares with expectations. The purpose of this study is to uncover and investigate ways of enhancing and increasing positive impacts. The following sections of this chapter describe how the research questions should be answered and the different considerations that were involved.

5.2 Epistemological and Ontological Considerations

The qualitative research paradigm, as described by Flick, makes explicit its epistemological and ontological assumptions:

> *"...qualitative research uses text as empirical material (instead of numbers), starts from the notion of the social construction of realities under study, is interested in the perspectives of participants, in everyday practices and everyday knowledge referring to the issue under study."* [124]

The following sections describe how those assumptions fit with the context of the study presented in this thesis. More specifically, they illustrate how the literature on learning analytics circumscribes a gap in understanding around what educators and learners are trying to achieve. This chapter lays the foundation for later methodological choices presented in the following chapter.

5.2.1 Learning Analytics as a Subject for Qualitative Research

Though often grounded in constructivist educational philosophy, learning analytics research still applies many methodologies that are positivist or behaviourist in nature. This has led to some epistemological and ontological tension in the field [125].

As was discussed in earlier chapters of this work, the insecurity around proof of impact on practice can be traced back to a surfeit of conceptual rather than empirical studies [89], as well as a lack of available contexts in which to evaluate learning analytics approaches in an authentic environment [9]. MacFadyen and Dawson have cautioned that

> *"Interpretation and meaning-making, however, are contingent upon a sound understanding of the specific institutional context. As the field of learning analytics continues to evolve we must be cognizant of the necessity for ensuring that any data analysis is overlaid with informed and contextualized interpretations."* [24].

To move forward, researchers acknowledge that educator and learner perspectives have been neglected or underutilised, and are important to help define, frame and test our assumptions about learning and learning analytics [96].

In addition, learning analytics are often coupled with a specific tool, making it difficult to separate the tool itself from the kind of information it is able to provide when evaluating impact on decision making [9]. If the educator cannot connect with the tool itself or the design decisions involved in creating it, for example, it is difficult to know whether the information the tool provided was unimportant or irrelevant, or if it was just the technology to deliver that information that was insufficient [9][92].

Finally, the lack of evidence of impact has meant that learning analytics have not yet been able to inform institutional planning meaningfully [24]. Researchers have begun to collect evidence of impact from disparate studies around the globe [96][65]. However, institutional planning is not only about evidence of impact. It is also about people and culture, and attitudes toward learning analytics remain mixed [126] [127].

5.2.2 Justifications for Qualitative Work

The conditions above appeal to a qualitative approach. First, qualitative research is exploratory and interpretative, and intended to help generate *new* theory rather than test it or generalise [128] [129] [130]. Flick described qualitative research as stemming from the “pluralization of life worlds,” a disintegration of current categories into a “new diversity” [123]. When the existing categories stop explaining reality, Flick described that a “disenchantment with objectivity” [123] arises, carving a path for qualitative research. The failure to inform institutional planning, the established need to discover new patterns and relationships, and the difficulty in proving impact are all evidence of a “disenchantment with objectivity” in learning analytics research, which appeal to a need for qualitative investigation.

Second, qualitative researchers are “naturalists” [128]. They do not conduct controlled lab experiments. Rather, they attempt to study phenomena in the environments in which they occur [129]. This allows a qualitative researcher to register emotional, behavioural and cognitive responses around the real phenomenon. Within the context of the research question relevant to this thesis, the phenomenon is essentially the lack of knowledge about educator and learner perspectives on learning analytics in their own practice. To explore this, a qualitative researcher must investigate learning analytics in the real context of educators’ and learners’ everyday practice. This means that **the research design must allow for a close examination of the challenges educators and**

learners face, and an analysis of the ways in which they currently deal with those real challenges.

It is important to note that qualitative research is not intended to prove valid or invalid the assumptions of learning analytics research. Rather, it creates an "interpretative portrayal" of practitioner perspectives on learning analytics [131] meant to expand our assumptions and test some of their boundaries. In terms of understanding mediatory effects of learning analytics, qualitative evidence can be used to inform future investigations [128] that operationalise, for example, some of Feuerstein's more elusive criteria of mediated learning experiences, such as mediation of intentionality and reciprocity, mediation of transcendence and mediation of meaning [16]. This is discussed further in chapter 10.

5.3 Qualitative Research Design

Within the qualitative research paradigm[1] research designs have subtle differences that are meant to harmonise with the type of knowledge or evidence the researcher is looking to collect. Creswell *et al* [122] provide a rather simple reference for each of the five most commonly applied designs: Narrative approaches, for example, are applied typically for questions about life experience or chronology of events. Phenomenology addresses questions of essence and the nature of human experiences. Participatory Action Research is typically applied to community-based questions to drive future action. Grounded Theory, the design that was chosen to investigate the research questions presented in this thesis, is a systematic procedure for analysing textual data using an inductive logic. In Grounded Theory, data is collected and analysed simultaneously following two procedures called "coding" and "constant comparison" (described further in chapter 6), whereby new conceptual categories that appear to be relevant for the research participants can emerge [130]. Finally, Case-Study allows for a deep-dive into a given issue through the lens of different perspectives on the same phenomenon [132].

This section explains in more detail why Grounded Theory has been chosen as the best way to explore educator and learner perspectives on learning analytics, and how Case Study was applied to provide an organisational, contextual investigation of learning analytics use and acceptance.

[1] It should be noted that the research designs presented in this chapter are not exclusively qualitative. For example, Grounded Theory and Case Study are general methods.

5.3.1 Grounded Theory and Learning Analytics

Suthers *et al* described learning analytics as occupying a "middle space" between learning and computer science. They argued that learning analytics needed "boundary objects", flexible yet meaningful concepts that can be interoperable between different disciplines and communities [133]. The "middle space" describes the socio-technological aspects of the research context, which includes multiple individuals with agency, as well as ontological and epistemological tensions within learning analytics research. At the time of writing, no theories of perception with regard to learning analytics were available to explain how these tensions within research might be felt within practice as well. Grounded Theory has the flexibility to co-occupy that "middle space" by not imposing predefined categories on the data. Rather, the researcher documents what emerges and identifies places of agreement and disagreement among the participants and their statements through constant comparison of the data and analyses [131]. What separates Grounded Theory from other types of content analysis is that Grounded Theory recognises human agency as an important aspect of knowledge production. Its purpose is to develop substantive, multidimensional, conceptual theory about the data rather than categorise it [134].

In Grounded Theory, the researcher must make some epistemological decisions about the data. *What does knowledge look like? How does it evolve?* When Grounded Theory was first developed by Glaser and Strauss, they intended it to "bridge the gap between the theoretically 'uninformed' empirical research and empirically 'uninformed' theory" [135]. The tendency toward both theoretically uninformed empiricism and empirically uninformed theory in learning analytics research was presented in chapter 2. Gašević *et al* reminded the learning analytics research community that "the computational aspects of learning analytics must be well integrated within the existing educational research" [11].

Glaser and Strauss, however, disagreed on a few key aspects of what it means to do Grounded Theory. Glaser believed it could actually describe reality through a multidimensional approach. Strauss, on the other hand, viewed reality as extremely contextualised. For Strauss, that context must be a part of any analysis of the data it produces [136]. Charmaz's approach to Grounded Theory offers a suitable balance between the more open-ended approach of Glaser and the more systematic approach of Strauss and Corbin (who later joined Strauss) [130] [131]. While Glaser was never able to fully reconcile how the researcher's preconceived notions impact the evidence, Charmaz felt that exposing these realities improves rigour and validity. Like Strauss and Corbin, she asserts that a robust methodology can absorb at least some of the risk of misinterpretation. However, instead of attempting to erase the researcher from the process, Charmaz incorporates them through constant comparison and reflection on the interpretation of evidence [131].

Charmaz wrote of Grounded Theory "An emergent method begins with the empirical world and builds an inductive understanding of it as events unfold and knowledge accrues." [27, pg 155]. Like Strauss and Corbin, Charmaz has a set of rules that should guide Grounded Theory, but the most important is that the rules should be seen as flexible, so long as the following conditions of analysis are met: "(1) the systematic, active scrutiny of data and (2) the successive development and checking of categories"[27, pg 161]. This becomes key during the process of Qualitative Analysis described in the chapter on Methodology.

5.3.2 Case Study as a Structure for Qualitative Evidence

According to Creswell *et al*, Case Study and Grounded Theory are two of the most popular qualitative research designs and they are often used in concert [132], perhaps because they compliment one another in terms of the questions they can help answer. Grounded Theory examines processes and Case Study provides structure to define the context of the phenomenon one is examining.The research literature indicates some disagreement about whether a Case Study is actually a design, a method or a methodology, as it does not provide a "prescriptive guide for how to proceed with the business of collecting, analysing and interpreting data" [137, pg 83]. However, in conjunction with Grounded Theory, it can also be viewed as a strategy for inquiry, a decision on "what is to be studied" [138]. In the context of this research project, the Case Study is an extension of the research process in Grounded Theory, to help "explain a phenomenon in a specific context and suited to its supposed use" [134].

5.4 Affordance Theory

Charmaz asserted that researchers using Grounded Theory should investigate qualitative data for "action and analytic possibility", what participants are doing, feeling or thinking about a given phenomenon [27, pg 163]. The research questions that guided this study imply that "data collection" consists of gathering "perceptions" from educators and learners about learning analytics and to identify metacognitive activity around those perceptions. To understand how this process contributes to answering the research question, it is important to consider what counts as "perception" and how it will be recognised within the data. Charmaz would argue that looking for actions provides the best evidence for making a meaningful interpretation of the data [130]. Affordance Theory provides a framework for connecting action with perception.

Affordance Theory has become a popular lens through which to interpret human understanding of information systems [139]. Affordances are the "actionable properties" that an individual perceives of a given object [21]. To provide a simple example, one might see a handle and, through its properties, perceive that it affords grasping, lifting, pulling, etc. with limited guidance from anyone else. Affordance Theory has gained considerable attention in the field of Human-Computer-Interaction (HCI), because it offers a different perspective on object utility. Affordance Theory uncovers the "actionable properties" that a potential user can perceive in a given object to perform certain functions [21].

Affordance Theory has several advantages over the usability study approach described earlier in chapter 2. Instead of analysing the usability of a specific tool for some specific tasks, this study focuses on analytics as a general object and the affordances that educators perceive in using analytic data in general to support their practice. At the time of writing, we were unable to identify any qualitative studies that approach the subject of learning analytics in this more general sense, unattached to a particular tool or project that has been developed to perform a certain function or reach specific objectives. Asking educators to reflect more generally on the properties of analytic data and its uses allows for them to vocalise their specific or individual interests, rather than prompting them into an evaluative role.

In addition, asking participants to provide affordances of learning analytics prompts them to consider what a particular tool, methodology or idea is offering to their existing strategy, a future strategy, or even an imagined strategy. Metacognitive activity will be identified within the data as any statement that reflects "cognition about cognition" as Flavell described [119], which includes cognition about thoughts, feelings, behaviours, and the context of learning as well [16].

5.5 Chapter Summary

This chapter provided a solid orientation for the methodological and epistemological choices that were made in the development of the study presented in this thesis. Section 5.1 reviewed the research question that guided the present study and the motivation to improve or enhance the impact of learning analytics on practice. Section 5.2 described the qualitative research paradigm and the reasons why this approach was chosen as the most appropriate for the type of research question presented in this thesis. Section 5.2.1 presented an argument for why qualitative research is particularly necessary at this point in the development of learning analytics as a research field, to understand the culture, attitudes and barriers to learning analytics acceptance. It also presented Grounded Theory as the underlying research framework that influenced methodological choices presented in the next chapter. Finally, section 5.4 connected the process of qualitative research with the decision to use Affordance Theory, to understand what educators and learners can actually perceive and how this might drive their decision making. In the following chapter, the research approach is translated into the concrete methodology used to gather, analyse and validate evidence.

Chapter 6

Methodology

In conducting a study based on Grounded Theory, the methodology is structured such that data collection and analysis are concurrent [131].

Grounded theorists explore theoretical categories in the data and look for relationships between them. The categories and processes are then refined during iterative cycles of analysis and further data collection [131]. Because of the impact on interpretation, this process needs to be made transparent so that it can be coherently followed. Grounded Theory includes intermediary reflections on the data and the process of analysis to serve this purpose [27] [131].

However, in order to improve readability and to structure this section, the methods for data collection are presented first, followed by the methods for analysis.

6.1 Qualitative Interviews

To gather information on educator and learner perceptions of learning analytics, intensive interviewing was chosen as the primary method of data collection. Intensive interviewing is a common method that grounded theorists rely upon. An in-depth, discursive interview is a rich source of qualitative data [27][131]. To assist with the interviewing process, an interview guide with a set of open-ended, intermediate and closing questions, was developed before the interviews took place [131].

6.1.1 Sampling

A convenience sampling strategy was used at the beginning stages of this research to gain access to educators and learners from various types of institutions (formal and non-formal), who have different roles within the institution (staff tutors, associate lecturers, facilitators, module chairs, tutors, etc.). A convenience sample is simply those research participants to whom one has the best access [140]. As mentioned previously, the term "educator" is defined broadly as any individual involved directly in the process of working with learners or developing their curriculum. "Learner", refers to anyone currently enrolled at a learning institution. This wide sampling strategy made it possible to avoid determinations about categories of interest before the data was collected [131]. This strategy was narrowed and focused toward purposive sampling, as theoretical categories emerged and the study progressed. A purposive sample involves finding research participants that represent potential perspectives that should be drawn into the research, based on what is emerging in the data [131][141]. As "constant comparison" (see 6.3.1) among the transcripts and the emergent theoretical categories no longer produces new insights, saturation is determined to have been achieved [130].

6.1.2 Procedure

Before each interview, participants signed a consent form stating clearly that the interview would be recorded, transcribed and used for research purposes. Participants were also made aware of data protection measures. Interviews were conducted both by Skype, Web-Ex and face-to-face at the convenience of the participant. Though scheduling online interviews can result in absenteeism and a loss of rapport, it is a useful tool when face-to-face interviewing is otherwise impossible [142]. An informal, conversational interview style was adopted to collect rich data while allowing the participant to enter and exit the interview easily [131] [140]. Each interview was expected to take approximately 60 minutes with educators and 15-25 minutes with students (due to the fact that learners do not tend to have much exposure to learning analytics [89]). Extensive field notes were taken both during and after the interview.

6.2 Focus Groups

Focus Groups were chosen as a method to collect social information on learning analytics by studying verbal and non-verbal interactions among participants with different backgrounds. Focus Groups provide insight that cannot be gathered through a survey or even an in-depth interview [143]. According to Charmaz, conducting Focus Groups is also an understandable choice when "researchers face limited resources for qualitative work" [140, pg 354]. As a PhD student, with limited time and resources, Focus Groups were both an effective and efficient methodological choice.

Charmaz recommends that researchers should still follow an inductive, iterative, comparative and interactive data collection, as well as analysis. Researchers should expose and analyse how their questioning changes across focus groups and what impacts their choices have on subsequent decision-making in research [140]. This information is provided through the thesis in the reflections sections that accompany each findings chapter.

6.2.1 Sampling

Designing the Focus Groups also involved a multi-stage, convenience sampling strategy followed by purposive sampling across subsequent Focus Groups [140] [141]. Participants were either emailed about participating in the study, or they were informed through other means, for example, another key participant. To strengthen the analysis through comparison, learners who were active in the same modules/courses as the educators who had taken part were particularly a focus of recruitment. Educators were asked to voluntarily share the details of the project with their students.

While the profile of participants remained mostly the same as with the qualitative interviews, the Focus Groups were intended to concentrate on the Case Study of the Open University UK. Therefore, recruitment for the Focus Groups was limited to educators at the OU UK and learners currently enrolled in a module at the OU UK. The target was to recruit the recommended 6-10 individuals for each Focus Group [143].

Focus groups were not designed to mix educators and learners. This decision was made because it was an important aspect of the research question to see how these two different groups approach the topic of learning analytics without interference from the other. However, within focus groups of educators or learners, the study aimed to host both homogenous and heterogenous groups in terms of domain, background and level of experience, to test the strength of emerging categories [140]. This is intended to highlight the most salient and thought-provoking issues [143].

Saturation was achieved through constant comparison among the transcripts and the emergent theoretical categories [130].

6.2.2 Procedure

Focus groups were scheduled for both face-to-face and online, according to participant convenience. Online Focus Groups are subject to the same considerations as online interviews concerning potential loss of rapport and the risk that technology alienates the participants [144]. Still, suitable alternatives to a Focus Group could not be identified at the time of writing, which would provide data rich enough for a grounded analysis.

The same interview guide used in the interviews was re-purposed for the first part of the Focus Group, the assumptions and theoretical categories from previous interviews and focus groups could be tested. In the second part of the Focus Group, participants were given a basic description of some of the more common types of information collected in learning analytics research. The affordances they perceived in using that information were documented.

Focus Groups were planned for 1.5-2 hours, to ensure enough time to get through both parts of the Focus Group procedure. Extensive field notes were taken before, during and after the Focus Group.

6.3 Qualitative Analysis

In qualitative analysis “evaluative criteria...should be commensurable with the aims, objectives, and epistemological assumptions of the research project” [145]. The paragraphs below describe methods of qualitative analysis that are used in research conducted using Grounded Theory.

6.3.1 Coding and Constant Comparison

Charmaz described initial coding as “attaching labels to segments of data that depict what each segment is about” [131, pg 4]. In Grounded Theory, the unit of analysis is initially as granular as partial sentences or utterances, as one reviews the transcript. This becomes more organised as the research progresses and segments are more broadly delineated, to include the theoretical categories that the initial codes might represent [27]. As the categories emerge, the transcripts are continuously examined using constant comparison. This may include comparisons within a single transcript or across transcripts, to look for signs of coherence in the theoretical categories. A lack of coherence indicates a need for additional sampling and data collection, or a revision of the theoretical codes [27]. Coherence between evidence, analysis and collection is the hallmark of validity in Grounded Theory to which Charmaz subscribes [27][130] and which is discussed in more detail below.

6.4 Validity

The concept of validity in qualitative research, and especially in Grounded Theory, is a point of contention within the discipline [27][146]. Barbour has cautioned that mixing concepts of validity from qualitative and quantitative research threatens validity and attempts to remove the subjectivity from critical review [146]. However, there are guidelines that researchers can establish to help lend weight to their interpretations of the evidence they collect. The following sections discuss the ways in which validity is addressed this study based on Grounded Theory.

6.4.1 Triangulation

Denzin originally proposed triangulation as a way to establish validity, where *triangulation* referred to gathering data from multiple sources, at different times and places, from the perspective of more than one individual, and through the lens of multiple theories and hypotheses [147]. However, responding to criticisms that this approach would lead more to "extreme eclecticism" [148] and less toward validity, Denzin refined his approach toward triangulation. As a tool for analysis, triangulation in the means previously described does more to establish the deeper context of the issue, rather than affirm hypotheses along the way [147]. Still, there are valid arguments for asserting that cohesion within that deeper context and with the interpretation of the evidence, is a kind of internal validity in itself. Triangulation is incorporated into the research presented in this thesis as a way of checking the boundaries of emerging arguments and refining arguments, rather than black and white "confirmation or refutation of internal validity [146].

6.4.2 Constant Comparison

The concept of *constant comparison*, proposed by Charmaz [130], contributes to establishing validity by seeing patterns within the evidence that fit together with what has already been observed and recorded, and with the body of evidence and the wider context itself. Constant comparison is incorporated in the analysis presented in this thesis as contributing to validity by comparing the evidence with itself, with previous evidence and with expectations of the evidence. Barbour suggested that constant comparison is only useful with a closer examination of how the themes were established and built up over the course of the analysis [146]. These comparisons are reflected, for example, in the frequency distributions presented in chapter 7 and the reflections presented at the end of each of the findings chapters.

6.4.3 Participant Checking

Participant checking is another feature of Grounded Theory that is relevant for rigour and validity. An initial analysis was returned to the participants for their comments and additions, a important aspect of data collection in Grounded Theory, as well as analysis and validity [27]. Participant checking is referred to at two stages in the study presented in this thesis: after the exploratory interviews and after the focus groups. A random selection of participants received a short summary of insights and were asked to further elaborate or correct any assumptions. Rather than take these corrections "at face value", as Barbour cautioned [146], they were used to help refine the different themes that emerged within the findings.

6.4.4 Inter-rater agreement

Initially, the research design included multiple coding to establish inter-rater reliability. Inter-rater reliability is the level of agreement that can be achieved among multiple coders working with the same data using kappa statistics [146]. However, it is uncertain what this process contributes to improving the quality and validity of qualitative research. Inter-rater agreement is most useful when the "rates of misclassification" informing kappa values are already established in the literature [149]. This presented a problem, as the level of kappa appropriate for qualitative educational research was difficult to define. Additionally, Barbour has proposed that inter-rater reliability may be an inefficient and ineffective way of establishing validity in certain contexts, as it is not the agreement that is important, but the discussions that emerge from the *disagreement*, which are relevant for establishing validity [146]. For this reason, rather than employing a strategy of multiple coding, the findings presented in this thesis were discussed with different experts in the field of learning analytics and learning theory. Those discussions are presented in the final reflection section of each findings chapter, and once again in the discussion.

6.5 Chapter Summary

This chapter described the methodological choices that were made in the preparation of this study. It introduced the sampling procedures for both interviews and focus groups and provided a basic description of the procedures, which will be discussed in more detail in the findings chapters. In addition, the chapter presented choices made with regard to the analysis of data and validation of findings. In particular, the chapter promoted constant comparison among the different transcripts, triangulation with other data collected in the course of the study and participant checking as contributing to the "comprehensiveness" of the study, which Barbour believed to be a more "realistic goal for qualitative research" [146].

Chapter 7

Findings: Exploratory Interviews

> *I don't know anybody who said, 'I love that teacher, he or she gave a really good homework set,' or 'Boy, that was the best class I ever took because those exams were awesome.' That's not what people want to talk about. It's not what influences people in one profession or another. - Neil de Grasse Tyson*

As the previous chapters have outlined, the aim of the study presented in this thesis was to understand how the positive impacts of learning analytics may be understood and amplified in higher education. As a new technology that is touching upon many ideological and practical assumptions, learning analytics is a socio-technological field of study, with the potential to impact the psychological, social and educational lives of learners. Due to the complexity of the topic of education in general, and the dynamic development of learning analytics tools and technologies, it was necessary to identify the most salient issues that may impact how learning analytics are perceived and utilised.

The exploratory interviews conducted early on in the study were intended to guide the research toward areas of focus that are relevant to educators and learners. During in-depth, semi-structured interviews, participants with different roles and from different institutions discussed the particular challenges of delivering online education. They described their perceptions of learning analytics and their experiences of using any learning analytics tools and technologies in their practice.

The research findings that are presented in this chapter are based on the analysis of those interviews, as well as publicly available documents about the participants' universities or educational institutions, as well as the modules with which they were involved. The chapter includes a background section, describing the context of the interviews, the actual participants and the procedure as it was finally implemented. The following section discusses the context of the participants, their various goals and intentions. The remaining sections address specific affordances that participants mentioned during the interviews. The chapter concludes with observations made during the data collection process, which provide a context for the focus groups discussed in chapters 8 and 9. It should be noted that some of the work presented in this chapter was published in [150] as part of a conference paper for the European Conference on Technology Enhanced Learning (ECTEL).

7.1 Background

7.1.1 Participants

The initial interviews attracted participants from fully online and blended-learning programs in Germany, the Netherlands and the UK. Email correspondence and telephone calls to potential research participants were successful in recruiting enough candidates for the exploratory interviews. 10 research participants were recruited from 3 European universities that are involved in online education, either fully online (n=7) or as part of blended learning programs (n=3). The class sizes of the entire group of participants ranged from 15 to 2000+ students. 2 of the participants were female and 8 of the participants were male. 1 of the female participants was a chair of her department as well as an instructor and 3 of the male participants were either module chairs or senior academics. The rest of the participants were associate lecturers and tutors, or facilitators in non-degree awarding institutions. All of the participants who were senior members of staff had more than 5 years of experience. Tutors and Associate Lecturers generally had less than 3 years of experience in teaching, with the exception of one participant who had been a teacher, before retraining in a different field.

The participants were all interested in learning analytics, as such, though with various degrees of interests and motivations.

7.1.2 The Procedure

To prompt educators in articulating affordances, interviews required them to reflect on their current experience and efforts in the online or blended classroom. Educators were asked to express their perceptions of challenges they believed were unique or particular to their practice, their ideas of a successful learning experience and the steps they take to achieve that. In describing this process, learning analytics could be directly referenced by participants, in terms of affordances, as a resource for understanding or improving specific aspects of their teaching practice, as well as student learning. The questions guiding this portion of the investigation were as follows:

1. *To which extent are educators able to perceive specific affordances of learning analytics without prompting?*
2. *Will affordances be uniform across participants?*

5 of the interviews took place in a face-to-face setting and 5 interviews took place over Skype.

7.2 The Participants' Contexts

In the first part of the interviews, all participants made explicit reference, unprompted, to the goal of education as they perceived it. Though participants expressed many goals, there were some to which they returned again and again, to underline the importance of calibrating practice toward that goal. These discussions help to frame the context in which the different participants are working and reflecting on learning analytics. This section outlines that context, to which the following sections refer in reporting on the affordances that participants could perceive in using learning analytics for their practice.

In the contextual analysis, these goals were classified as having 1 of 3 *main* priorities: Learner Satisfaction, Developing Strong Minds, or Preparing Learners for Practice. A goal statement was coded as "Developing Strong Minds" when the educator focused on the general skills in thinking and productivity that education should provide. Consider the quotes below from Andreas[1] and Ingrid:

> "The whole point of education is to make you a self-reflecting person." - Andreas

> "They should be able to think critically, speak intelligently and according to scientific principles, contribute to the discourse." - Ingrid

These statements can be contrasted with those that were coded as "Preparing Learners for Practice" in which the end-goal of future work was explicitly mentioned.

> "They've got to make it work. Ultimately, that's what we're trying to do, prepare them for working." - Gary

[1] All participants' names have been changed to protect their anonymity

Goals of "Preparing Learners for Practice" were more often closely associated with the statements about students as independent agent, who "choose to absorb" (Gary, Preparing for Practice). Educators typically viewed themselves as a resource that a learner is responsible for exploiting.

> "I have a certain expertise. I am here to offer that to the students and they have the responsibility to learn how to talk about it, how to contribute, how to find meaning inside of it. That is education." - Harry

Not surprisingly, a goal statement was coded as "Learner Satisfaction" when the primary focus was on whether or not students would appreciate the educational experience. In both cases that were noted in the evidence, the participant is able to differentiate stakeholder perspectives.

> "It depends on which side of this you're on. I mean, if I am the University, I am thinking 'I want the students to stay, I want them to give us their money.' If I am a lecturer, I am thinking, 'I want the students to learn and have fun." - Richard

7.2.1 Connections Between Goals and Disciplines

In the analysis of the transcripts and the background of each educator, **perceptions of the goal of education appear to be related to the type of course or module with which an educator is involved.** Figure 7.1 shows the percentage of participants' statements, from each major faculty group, expressing sentiments that were coded as one of three main goals identified through in the transcript. Domain differences were particularly noted for goals associated with developing strong minds and preparing learners for practice. One can see from the bar chart that **preparing learners for practice was a common goal of educators in the STEM faculty. The goal of developing strong minds was more likely to be expressed by educators in the Arts and Humanities or Social Sciences**.

For the code "Learner Satisfaction", it is worthwhile to note that all educators with this goal had class sizes of 1000+ students. The analysis of the type of platform of delivery [2] and educational goal did not yield any specific insights, nor did the domain of instruction.

[2] such as futurelearn.com, coursera.com, or udemy.com

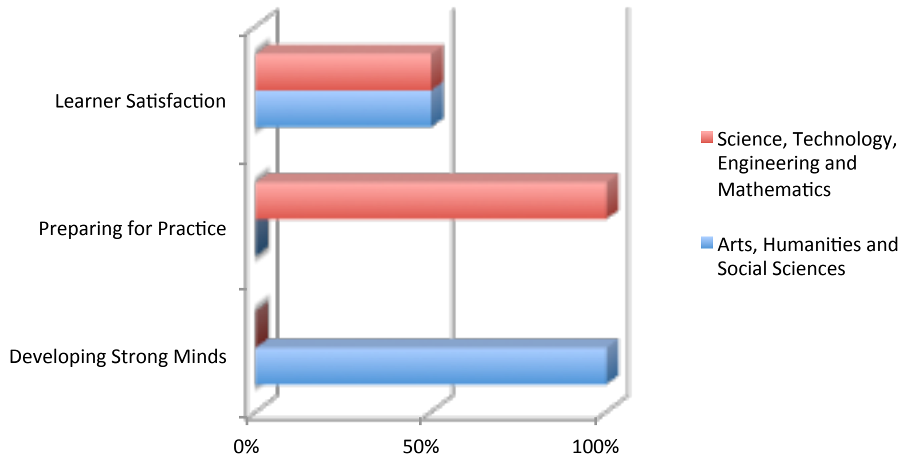

Figure 7.1: Goal of Education by Professional Domain

7.2.2 Consistency in Goals and Learning Designs

From an analysis of the participants' course and module designs, teaching goals appeared to be consistent with the type of classroom orchestration and learning design activities chosen by the educator. Orchestration describes an educator's awareness, forethought, planning and regulation of the classroom experience for learners, including the educator's perception of their own role and the structure of learning [63]. Learning design is the pedagogical companion to orchestration and expresses an educator's intentions for learner success [70]. Information on module designs and orchestration was drawn from how educators described the classroom experience in the interview evidence, as well as available institutional data, (including activity reports for VLE data, as well as assessment and learner performance data). Each module was manually assessed according to the learning design taxonomy provided by the Open University Learning Design Initiative [70]. This taxonomy describes assimilative activities, information handling, communication, production, experience, interaction, and assessment. Goals to develop strong minds generally accompanied more assimilative, communication and productive activities, with opportunities for learners to work alone and with others to engage in sense-making.

Figure 7.2 illustrates that having a goal of Learner Satisfaction was connected most often to assimilative activities, which supports recent research that identified the same positive correlation that learners appear to appreciate assimilative activities in the classroom [70]. Developing strong minds was a goal heavily associated with communication and

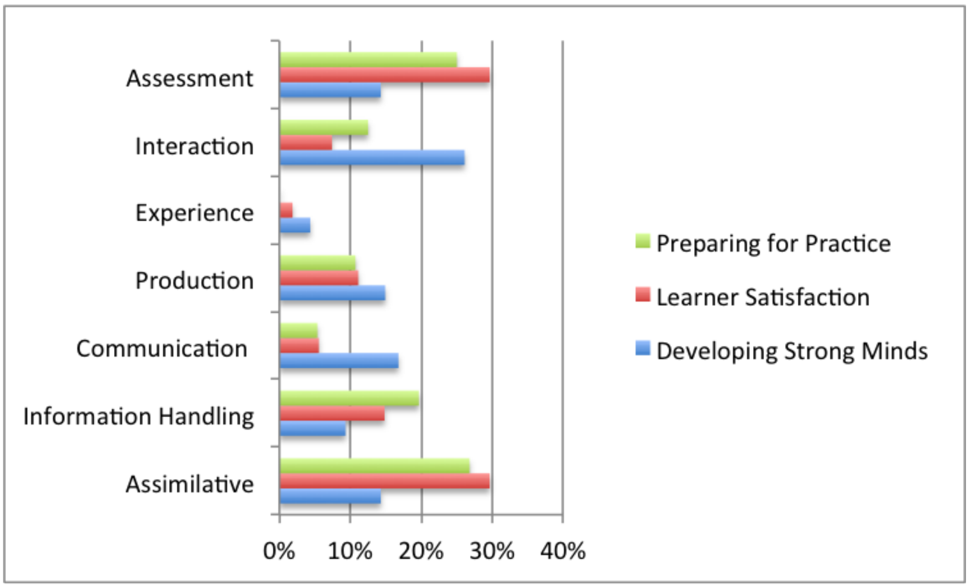

FIGURE 7.2: Learning Design by Goal

interaction activities, with much fewer assessment activities in comparison to learning designs aiming at other goals.

7.2.3 Current Challenges

A first pass of the transcripts using open coding [130] resulted in the emergence of 26 distinct types of challenges, which could be classified into 9 larger themes. The table in appendix A shows the thematic categories and some examples of subcategories related to the question of challenges in online teaching.

The 3 main educational goals in the data (see Figure 7.1) provided a lens through which to interpret the evidence referenced in Appendix C. Interview data suggested that educators with different goals had significantly different priorities and viewpoints on challenges.

For example, educators who were coded as developing strong minds tended to focus on challenges related to the lack of visual referencing, decentralised discussion, and difficulty creating a sense of community among participants, more than other instructors.

> "In a real classroom, you would see people looking at you or even raising their hands, but in the virtual classroom, there is this awkward silence all the time. Even thought you have the option of raising your hand in [name of software], nobody ever does that" - Uwe, Developing Strong Minds

Educators coded as "Preparing for Practice" tended to focus on the importance of understanding learner prior knowledge and educational background, as well as how to encourage self-direction and self-regulation among students.

> "You just don't know anything about them and it's very frustrating. I suppose you have to hope that they've managed to gain some ability to manage their own learning." - Harry, Preparing for Practice

To triangulate these findings, a frequency analysis of the open codes related to challenges from each transcript was conducted and and is presented as a radar graph in Figure 7.3. Instances in which the educator initiated the discussion about the challenge or referred to it after the conversation had moved on were included in the frequency analysis. The purpose of this is to better illustrate what was important to the educator, rather than the researcher. The frequency analysis supports and expands the interpretation of the data.

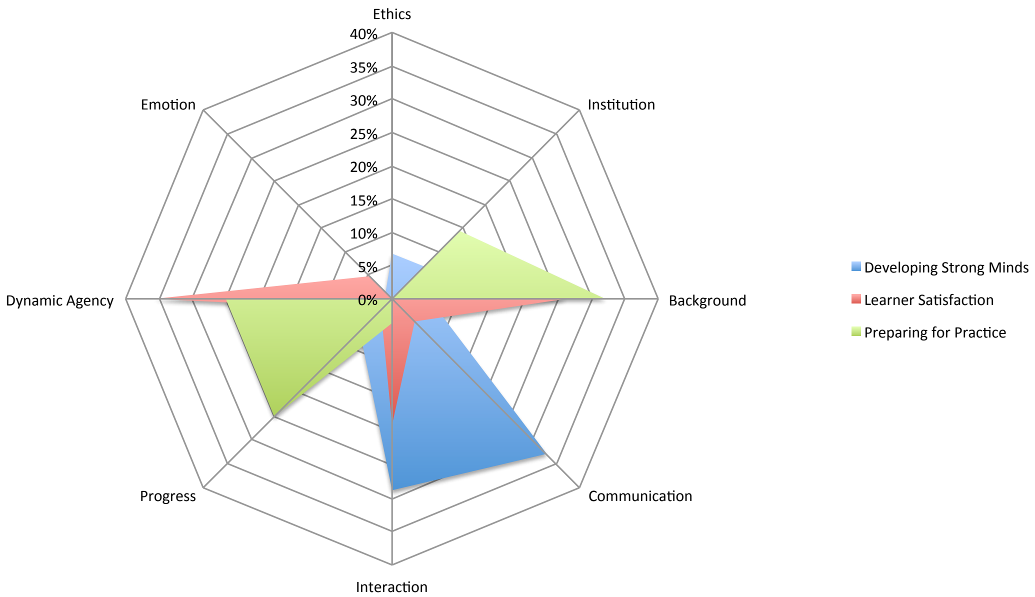

Figure 7.3: Perceived Challenges by Educational Goal

From the graph, challenges related to the code of "Developing Strong Minds" were most closely associated with problems in communication and interaction, which is consistent with that goal and its accompanying tendencies in learning design. Likewise, challenges associated with "Preparing Learners for Practice" had to do with understanding more about how to gain more information on learner background and how to accurately measure progress toward real goals. "Learner Satisfaction", as an educational goal, shares some of the same challenges as educators with both types of other goals. More specifically, in matters of the dynamic agency of learners and in understanding learner background, educators with this goal share some of the same challenges with educators "Preparing Learners for Practice. With regard to creating community and student support networks, they share a common perspective with educators developing strong minds.

7.2.4 Desired States and Indicators

After being asked to describe the challenges they experienced as online educators, the participants were asked what they hope to achieve in their classrooms and how they determine whether or not they are "doing a good job". To assist with comparison to participants' stated challenges, desired states were first organised under the same thematic categories as challenges (see 7.4).

Interaction	Progress	Dynamic Agency	Communication	Emotion
The learner has regular contact with other learners in the cohort (also privately)	The learner performs well on assessments	The learner is active in class and online	Positive feedback from learners	Educator intuition
Longevity of social cohesion (learners remain in touch, for example)	The learner has made progress in comparison with previous performance	The learner is present in class	Learners express a level of certainty in questions	Positive emotional response from the educator (pride, confidence, pleasure)
Learners ask follow up questions and provide answers to others' questions.		Positive changes in learner behaviour		
Learner provision of external sources and ideas				
Positive changes in learner engagement with other learners				

FIGURE 7.4: Codes for Desired States

With regard to what educators hoped to achieve, or the "desired state" of the classroom, analysis indicated that educators who are coded as "Preparing for Practice" focus significantly more on the notion of progress than other educators. They tended to connect performance with having a strong motivation for learning and identification with the future career objective.

> "You see their assignments being handed in, you can see good work. You can see progress. You can see, even if somebody started at 90% and slowly squeaked up to 94%. That's doing really well. You see the person who started off at 40 and managed to make it to 60...and it's just relative to them, you spot that." - Gary, Preparing for Practice

Educators who felt they were responsible for developing strong minds tended to determine their success through energy and euphoria, particularly in the presence of lively, rich discussion.

> "I can sense the energy. Someone will write something and I will think, 'Whoa, that's going to get some commentary' and the next thing, 10 students have responded within an hour. They're writing these little mini-essays to one another about it, arguing back and forth. That's how it should look. That speed. That exchange. I can see it anyway, but if you could measure that, it would be helpful" - Richard, Developing Strong Minds

> "When they ask follow-up questions, when they show that they understand how a technique works and then ask when it wouldn't work, or what the alternatives are or why it works in a particular way...for me, that's an indication that they know at least roughly how it works" - Ingrid, Developing Strong Minds

These two quotes illustrate how educators with this goal operationalise complex concepts like "energy" and self-regulation. Richard describes energy in terms of the speed of response, and the length and quality of those contributions, as arguments and counter arguments. Ingrid mentions inquiry as a sign of learning, including help-seeking behaviour, and a demonstration of wider transfer of the concept. "Learner Satisfaction" as both a primary goal and an explicit secondary goal of 8 of the 10 participants was verified through self-report from learners, the educator's own emotional responses and learner interaction.

> "Of course you get to see what they've written on their evaluations. However, it rarely comes as a surprise. I find I like the students who like me and it's a sign of a reciprocal relationship that's working." - Michael, Learner Satisfaction

Educators focused on learner satisfaction, as mentioned previously, tended to have 1000+ students, regardless of whether or not this was a University or continuing education platform. They often expressed doubts or worries about creating coursework that would appeal to the greatest number of students.

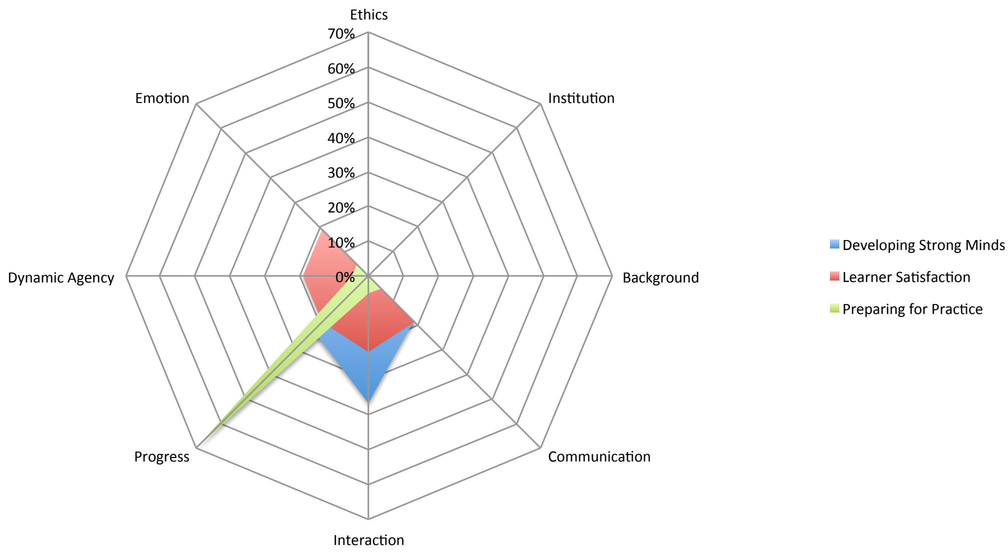

FIGURE 7.5: Desired States by Educational Goal

Figure 7.5 illustrates the frequency distribution of how and how much participants spoke about their desired state. From the graph, the connection between the concept of "Progress" and "Preparing for Practice" is apparent. The code "Developing Strong Minds" is most often connected with the desired state of euphoria and interaction. "Learner Satisfaction", once again, shares characteristics with both other code groups.

When asked to further operationalise some of their success markers, participants provided 22 unique indicators for how they know they are doing a good job, which were organised under the thematic categories of *learner willingness, retention, cohesion of learner work, social presence, demonstration of skill, positive learner feedback, positive institutional environment, positive personal emotional response, excitement or energy in the group, and emergence of discourse.* Figure 7.6 illustrates this operationalisation process.

One can see from Figure 7.6 that educators can have some clear and precise ways of operationalising complex concepts, such as euphoria or emerging discourse in the classroom. Interaction appears to be measured by educators in terms of the regularity, intensity and longevity of contact, as well as reciprocity in the classroom (in terms of providing additional resources or asking questions). This is contrasted with the code for "Demonstration of Skill" in which assessment over time provides a more concrete metric of learning.

"Communication," as a code, was distinguished from interaction codes in the presence of a concrete message that is intended to be delivered. For example, in delivering feedback

Willingness	Positive Learner Feedback	Emergence of Discourse	Excitement/ Energy	Cohesion	Social Presence	Demonstra-tion of Skill	Retention	Positive Personal Emotional Response	Positive Institutional Environ-ment
the learner responds to feedback	learners provide positive evaluations	learners introduce new ideas or information	learners participate in long message threads	learners show ability to engage with a subject personally	learners support other learners	learners achieve high marks	learners complete their module	educator has a positive intuition	attitudes are learner-centred
the learner changes behaviour after feedback	learners are in touch by email or informally	learners effectively transfer knowledge	more learners participate than usual	learners work is well-rounded	learners are active in their participation	learners perform well on practical assignments	learners complete their study program	educator feels joy	support for learners is more than adequate
	learners offer gifts or other tokens of gratitude		response times are quicker on forums and in emails						

FIGURE 7.6: Indicators for Recognising the Desired State

or asking concrete questions and help-seeking. Educators that participated in the study *universally* had confidence in their own emotions and intuitions as a measurement of the “desired state”. Reflecting on their own thoughts and feelings about their students helped to confirm and adjust their strategies.

While many participants mentioned elements from each category, the frequency analysis of participants’ statements allowed for a more detailed examination of which measurements might be more or less important to educators with shared educational goals.

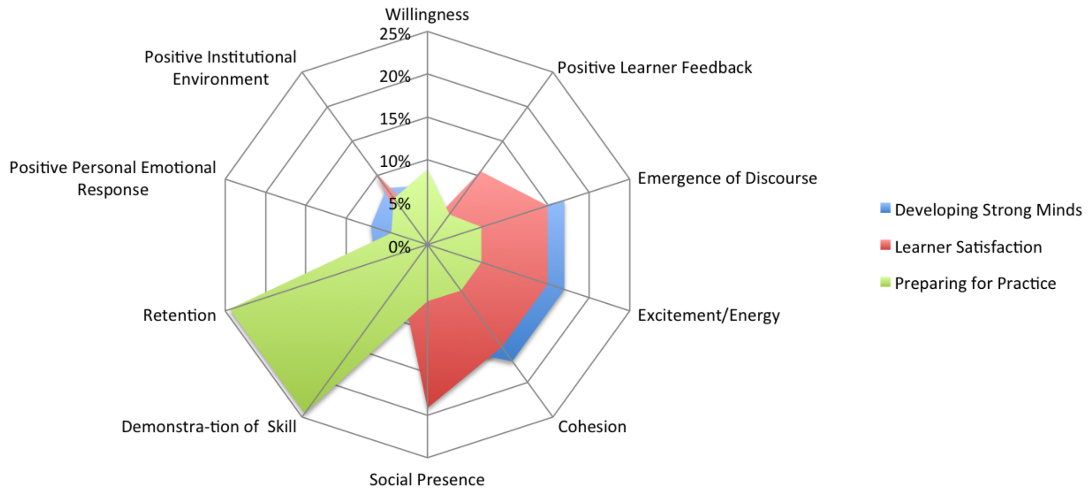

FIGURE 7.7: Indicators of Learning by Educational Goal

Figure 7.7 illustrates the percentage of each group’s statements, which corresponded to each indicator. The graph shows that each goal has one overarching indicator of success that differentiates itself from the other in terms of priorities. Educators "Preparing for Practice" measure their success predominantly in terms of demonstrated learner progress, typically in the form of performance in class and learner marks. This is identical to the desired state that educators with this goal described and therefore, is not a proxy. Educators "Preparing for Practice" had more concrete ideas about successful learning and more pragmatic ways of determining success.

Learner Satisfaction was unsurprisingly strongly linked to communicated statements of learners about their level of satisfaction, but also in terms of the level of interaction that the educator could perceive in the classroom among learners. In fact, interaction appears to be even stronger as an indicator of learner satisfaction for educators than retention.

> "Of course you don't always hear back from the students and even when they're a bit grumpy, sometimes the feeling of satisfaction is more than a feeling of happiness. It's a feeling of having purpose or some other broader idea of fulfilment." - Michael, Learner Satisfaction

Michael's statement recognises that learners may not always enjoy what they are doing, even if they might view it as useful or necessary for their learning. He also recognises that without an actual feedback from the learner, having a proxy, such as interaction, may provide a good sense of how the student is feeling about their experience.

The emergence of emotions and intuition as indicators was a surprising finding in the data. However, given the difficulties in assessment that were voiced by participants with the goal of "Developing Strong Minds," it is consistent with a lack of other appropriate measurements. However, it is also consistent with the goal itself. Educators with this goal, as mentioned previously, viewed success in the classroom as resulting in a euphoric, dynamic energy in the classroom, of which the educator is a part. The educator's ability to sense this (as a participant in the classroom) is therefore a credible, if only partial measurement of whether or not learning is taking place. It also makes sense that challenges associated with isolation from the learner and a lack of visual referencing are so serious for educators that rely on their "intuitions". Those intuitions are based on their participation in the learning experience, alongside learners.

7.2.5 Current Information Needs and Sources

Finally, participants were asked about their information needs and how they gather data to help them understand if the "desired state" has been achieved. For example, if learner interaction was a success factor for a participant, how did they gather information about interaction and from where? Referring back to the guiding questions mentioned at the beginning of this chapter, the study intended to capture specific affordances of learning analytics as a tool for understanding or improving practice. If learning analytics were a source of information for participants, this was noted during this portion of the interview.

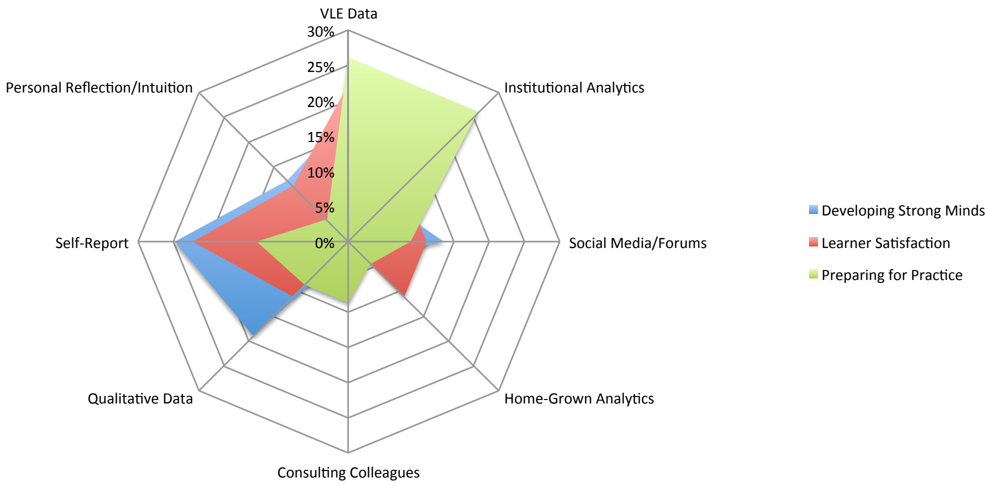

Figure 7.8: Sources of Information by Educational Goal

Figure 7.8 shows how educators' data needs map to their perceived goals of education. "Preparing for Practice" involved focusing more on hard evidence that the educator can see, e.g. if the learner is able to demonstrate skill, or if the learner is active in the VLE and looking at the appropriate resources. While they showed interest in the personal lives of their learners, it was typically to the extent that it could impact stress and time management. They did not see many opportunities for gathering data about learner emotions, unless the learner provided it directly through self-report. However, supporting learners through the course or module, so that they can progress toward their future employment, was a part of their responsibility as educators. Thus, educators coded as "Preparing for Practice" more often relied on institutionally provided descriptive and predictive analytics, for example, those that inform them of learners who might be at risk. Educators that expressed the goal "Developing Strong Minds" focused much more on their intuitions about learners, what the learner has communicated to them and what they can observe in the class (referred to as "Qualitative Data" in the coding). Educators in this goal category tended to have more sincere reservations about how their learners are assessed and whether or not it is a meaningful measure of what they have learned. Educators reported that as class sizes have grown, their concerns about appropriate assessment have been amplified.

> "I have relied so unconsciously on my own judgement, which I only realised once I was working with hundreds of students at once. I used to have a

> sense of all of my students and now I find that more difficult. How are you supposed to teach hundreds of students about how to interact meaningfully with other human beings on a subject, when the environment is so clearly not about that." - Richard, Developing Strong Minds

Educators with the goal to "Develop Strong Minds" tended to express doubts about whether or not institutional analytics could collect enough relevant data. However, this was not necessarily an aversion to analytics as such. One educator described how he keeps his own records, tracking a combination of indicators alongside personal notes.

> "I have a list where I have different categories like participation. Logging into a system and being logged in and watching a movie, just being logged in to me is no sign of active participation. Active participation is if you ask questions, if you propose answers to some questions, if you engage with other students. I take that down. I can tell at some point if people are on a constant level of participation or are getting more or less active. I try to track that. I don't use some kind of sophisticated tracking machine. I just make my notes in a simple spreadsheet and that's it." - Andreas, Developing Strong Minds

This statement represents an important reminder that the idea of tracking and analysing behaviour and the actual tools that are used to accomplish this are two different aspects of learning analytics that need to be explored. Andreas has clear metrics for how he will observe and recognise participation, most of which could potentially be enhanced through technology, but he may not have the experience with technology to understand how it could better support his existing strategies. These kinds of individual methodologies were referred to as "Homegrown Analytics" in the coding procedure.

Finally, educators focused on "Learner Satisfaction" shared data needs with both other groups, relying almost equally on self-report and VLE data.

Learning Analytics appeared as a resource for information seeking and processing in four of the categories described above, gathering VLE data, utilising analysis from institutional tools, homegrown analytics and self-report. The following sections relate to specific statements about learning analytics, in terms of general attitudes, actual use, intended use and imagined use of learning analytics for understanding and optimising learning.

7.3 Attitudes and Experience

The first category in describing participant statements about affordances of learning analytics relates to triggers and attitudes, those ways in which educators came to be involved with or interested in learning analytics and how they feel about them. Through asking the participants about their background and their interest in participating in the study, it was possible to examine valuable information about motivations to use learning analytics (or not to use learning analytics). This is an important middle space, in which attitudes are mediating what educators are doing with analytics, and are also mediated by interaction with analytics.

This section reports findings from the interviews related to attitudes and triggers around learning analytics, and the factors that appear to influence acceptance. The section also addresses some observed connections with the "Context" described in the previous section.

7.3.1 Computing Experience

For half of the participating educators, their background or interest in computers is what led them to online teaching and to take part in the study. **For those who were familiar with learning analytics, computing experience was also cited as being the *primary reason* for their early adoption of learning analytics as a tool to help them understand and improve their practice**. Of these educators, half are module chairs or directors of their course of study and learning analytics has become a part of their job.

Figure 7.9 shows a breakdown of positive and negative statements about learning analytics according to whether or not the participant has experience with computing. "Experience with Computing" was determined through either an expressed personal interest in computing, a professional title or job description involving computing, or a past course of study in computing. **Regardless of educational goal, experience with computing seemed to be the single most important determinant of someone's interest in learning analytics.** One can also perceive the depth of an educator's arguments in favour of or against learning analytics, by reviewing the diversity and balance of comments. Educators with little to no experience in computing voiced many more negative, surface-level opinions of learning analytics than positive sentiments.

Conversely, educators with experience in computing have more nuanced perspectives on learning analytics. Their sentiments were widely varied in terms of positive and negative sentiment. They tended to be more concrete as well.

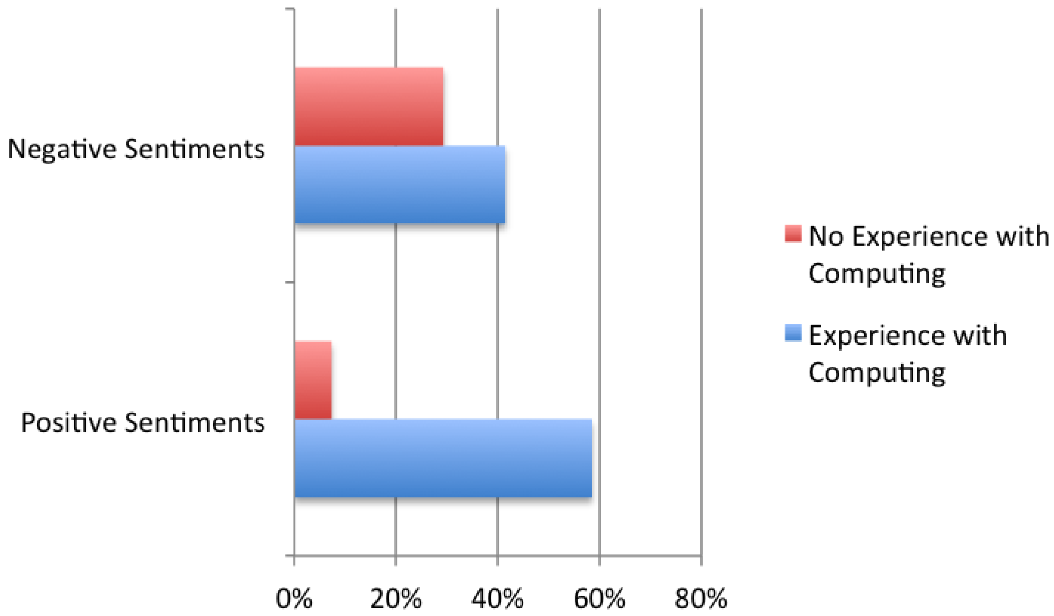

Figure 7.9: Sentiments Toward Learning Analytics

7.3.2 Fear and Ignorance

For participants with no background in computing whatsoever, learning analytics were often described purely in terms of Big Data and prediction. This is an indication that the finer points of learning analytics research, and the potential for other types of output than predictions have not yet trickled down to those who are not working or interacting in a context of computing. All participants that expressed fear and ignorance around learning analytics mentioned worries that online education and analytics are a push in the direction of replacing educators' work.

> "What if lecturers lose their own ability to assess the health of their students? I mean, who can remember anymore how to, I don't know, use a map to find out where they are going? We have always had a difficult relationship with technology, but we must admit that there is always a loss of skill when we allow it to take over a job that involved us using our intellect." - Ingrid, Developing Strong Minds

Two participants felt that collecting analytic data on the activities of learners was an ethical concern and worrying in general.

> "As a student, I wouldn't want my instructor to really see all of my performance data, like one of those Champion League football players." - Uwe, Developing Strong Minds

> "The very first thing that comes into my mind is the data. This just wouldn't be possible in some contexts. The students would protest" - Ingrid, Developing Strong Minds

The comments above illustrate a **general fear among educators of losing agency and privacy**. However, the arguments provided above show that **many educators still do not understand the basic premises of learning analytics enough to understand what the actual state-of-research shows**, in particular about student reactions to analytics [30], the purpose of predictive analytics [51][42] or what learning analytics actually aims to achieve in terms of empowering human agents [1].

Ethical concerns are shared by those with experience in computing as well. However, findings indicate that **those with experience in computing are more comfortable with what they view as a partial solution and one that can be improved upon and developed in the future**.

> "[VLE] data is only partially helpful. We can't quite figure how they respond to the teaching materials from the videos, the TMAs, the occasionally online activity and forum activity. I haven't dug into that in a lot of depth, partly because it has a low-priority because we can't reconfigure the module. We haven't got the resource, basically, to do that. The big VLE stuff is going to be very important for on-going module design." - Michael, Learner Satisfaction

> "That's good information [predictive analytics], but it doesn't mean that - let's say it gives a profile of a weak student. It doesn't mean they're going to be a weak with me, because lucky them, they might have found the right subject at last." Gary, Preparing for Practice

Michael's statement mirrors the pragmatism found in other participant statements about promising conceptual work and the backlog of efforts that could be made in the future to implement some of what is already known or predicted to be helpful. Gary's statement illustrates that he is aware of what kinds of information are missing from predictive algorithms, but he is still able to view it as "good information."

7.4 Actual Use

Half of the participant group had direct experience with applying learning analytics to understand or optimise learning. Three of the participants were involved at the time of their interview in an institutional pilot for learning analytics that was focused on predicting at-risk learners. Two additional participants had gained experience in using analytics data provided through educational platforms like Blackboard[3] and Coursera. Of the five participants who were familiar with using any kind of learning analytics, two participants taught class sizes of over 1000 students and shared the goal of "Learner Satisfaction", two were teaching some kind of a STEM course and one was teaching a course in Social Science.

Each educator was asked to describe the ways in which they were currently using learning analytics. As affordances were more personal and unique, a frequency analysis was not appropriate. The participants' statements resulted in the development of 11 codes that organised into 2 major categories, affordances for course creation and development, and affordances for understanding more about learner context and disposition. This section describes these two major categories in more detail, describing participants' contributions not only in terms of the affordance, but its expected impact as well.

7.4.1 Affordances for Course Creation and Development

A significant number of the individual affordances offered by educators were in the area of course creation and development. Six thematic categories emerged as specific affordances of learning analytics in this area with two other codes as related concerns or ongoing debates ("dumbing down" and "cohort influences").

Scope	Critical Path	Checking Interventions	Classification of Learners	Triangulation	Use of Resources	Dumbing Down	Cohort Influences
What is the learner's cognitive load?	What are the threshold concepts to be learned?	Where should one intervene?	What is the learner's goal?	Are the assumptions of the department correct?	What do the students look at/use?	How can we make coursework more straightforward without compromising quality?	When are interventions not effective?
How much can be accomplished in the given amount of time?	What is the shortest or most efficient path for the learner?	How should one intervene?	What types of learning activities help a learner?	Are the interventions being implemented useful?	When do they look at it/use it?		What are the influences of the other learners on the learning?
	What is the learner's goal?		What motivates learners?		How often do they look at it/use it?		

FIGURE 7.10: Categories and Subcategories of Affordances for Course Development

Figure 7.10 illustrates these thematic categories and describes the questions that educators were using learning analytics to answer, relative to each aspect of course development. Their experiences showed that **learning analytics were helpful in revealing**

[3]Blackboard is an educational technology company that provides many types of institutional solutions for learning management systems. http://www.blackboard.com

weaknesses in the educators' learning designs, identifying problems with scope and key concepts, understanding which parts of content were most important to understand in order to be successful (coded as "critical path"), interrogating cognitive load more generally, **and investigating successful patterns in learning**. Some participants felt that learning analytics helped them to **triangulate data** and they combined analytic data in different ways to **look at clusters of skills or behaviours that influence learning**.

Course development affordances were typically perceived by participants who were module chairs or high-level academics in their department. All participants described the context of course creation as one of high pressure – pressure to engage students, to fix broken modules, to roll out new modules. Learning analytics were described as tools that help sift through the data and identify the most salient aspects of the very complex issue of retention.

> The impetus for wanting to fix [the module]...the educational premises were exactly right. It was a really correct and very clear, skills strategy connected to assessment, with a clearly scaffolded assessment strategy that built up these abilities gradually. But it was overloaded. For years people tried to address it. They would play the marginal game. They would make little tweaks and see if they made a difference. Nothing shifted it." - Michael, Learner Satisfaction

Michael describes how learning analytics allowed the department to see when students were dropping out of the course, and to identify the pinch points in the module where students are struggling. This information allowed them to make some marginal but effective changes to the module.

> "We cut it down to 10 hours per week. We gave people a lot of furlough time in between...we tried to wind down the usage complexity quite a bit. Effectively, we redesigned the module so that the students came in and had an access-level experience in the first half of the module." - Michael, Learner Satisfaction

Module chairs and tutors appeared occasionally to have different points of view on course development, especially with regard to the accessibility and difficulty of content. The subject of "dumbing down" courses was brought up in 7 of the 10 interviews, by participants who instruct in fully or mostly online classrooms, whether they had actually used learning analytics or not. Module chairs and academics with high-standing tended to view the simplification and restructuring of modules as an "ethical issue" of inclusion, making content more straightforward for their students to increase their chances of success. Conversely, tutors tended to express worries that the variety of students might lead to diluting course content to an extent that learning is compromised.

Interestingly, more than half of participants referred to an achievement in the past in creating or modifying a module successfully, using learning analytics as a tool. Two participants referred to the resulting module as a "work of art". This indicates that **the effects of prior (and perhaps early) success or failure with learning analytics could be an important factor requiring further investigation**.

In terms of the success or failure of specific learning interventions, participants all seemed to agree that the efficacy of interventions is inconsistent. What worked in a previous year, might not work in a subsequent year, which 6 participants said was related to populations of students and different needs/relationships that emerge within them.

> "I am interested as a teacher, not necessarily because I think I would know how to parse all of that, but I can see the appeal, the crystal ball, letting you peer into things that you wouldn't normally. I would be most interested in seeing how the numbers are affected by different things. But, as I've said before, it's probably just going to shift around, that satisfaction. One presentation you will make this group of students happy, the next presentation you make others happy. There are so many variables." - Richard, Developing Strong Minds

Three participants felt that this tends to stabilise over time, indicating that at some point, there is some type of "sweet spot" in which the majority of learners' needs are met and the tutor has a handle on their pedagogical practices.

However, despite what educators can see about the improvements to their courses, findings indicated that **the impact of learning analytics on improving learning, more directly or in shifting retention, had not yet materialised**. One explanation that educators provided for this phenomenon was that tutors lacked guidance on what to do with the information they were receiving.

> "The tutors were preoccupied with the data, not with the intervention strategies. The outcomes were, they said 'we didn't save anyone. We had more contact with people and we combined the predictive data with other stuff we knew and it didn't work'" - Michael

On two separate occasions, Michael mentions worries that tutors will not know how to appropriately intervene. However, Michael goes on to say that he feels that successful interventions are actually very simple and the tutors were reading much more into the data than was necessary.

> "I suppose the thing I've learned about intervention is how unremarkable it is. It really is like when you say 'Hi'. It was very much relationship-based. Sometimes, students just want to be heard." - Michael, Learner Satisfaction

Findings indicated that **participants had the most concerns around the *variability* of data and how this could impact the decisions being made as a result of learning analytics insights**.

7.4.2 Affordances for Understanding Learner Context and Disposition

All of the participants agreed that gathering information on what learners need and want, with or without the help of learning analytics, improves the quality of education. Half of the participants expressed the desire to be able to "tweak" course materials for individual students, depending on what they could learn (possibly from analytics) about their learning needs and habits. Educators with this affordance are aware that those needs and habits change, but they still believe it is possible to offer more personalised instruction. Figure 7.11 shows the categories and subcategories that emerged with regard to exploring learner context and disposition as an affordance category of learning analytics. The first two codes, "Learner Background" and "Goal of the Learner" have to do with specific affordances of learning analytics. The subcategories underneath represent the information educators need to make their judgements about dispositions more effective. For example, learning analytics could analyse data related to a learner's background, including any previous studies (to understand competency), barriers to learning (to understand needs), or previous professional experience (to understand exposure and expertise). With regard to the category "Goal of the Learner", participants seemed to agree that they need more information on what a learner wants to get out of the educational experience, what they need to get out of it and what they appear to be prepared to do to get it. The last category, "Change", was noted as a major factor for all participants; Learners' goals are not stable. Thus, they need tools for recognising and documenting subtle changes in learner behaviours, attitudes and performance to better understand learning processes. This is an interesting conceptual companion to what Shum *et al* discussed in using the ELLI tool to evaluate learning dispositions, based on students' self-report statements about their learning process [59]. In their statements, the educators participating in the study are offering a type of "road map" for how they detect, and even prepare for, certain attitudes about learning.

Learner Background	Goal of the Learner	Change
previous course of study	learner desire	recognising change
barriers to learning	learner needs	documenting change
previous professional background	classification of learners by goals	

Figure 7.11: Categories and Subcategories for Learner Context and Disposition

Educators who discussed the importance of learner context and disposition were typically motivated by having to prepare coursework for "everyone and their mother", which was a term used on three separate occasions by three different participants. This indicates an overall pressure to fulfil too many needs. Rather than succumb to that pressure, educators are using learning analytics to make it easier for learners with different goals to take what they need from the learning experience.

> "We're actually using the data to see if we can classify learners. One of the things for this analytics, but I think also for the teaching that's really important is - what's the goal of the student? That's really important to know, because I think that's what really determines how you should guide them and what you should offer them." - Hendrick, Learner Satisfaction

As mentioned previously, one tutor was using analytic data to classify his online learners in terms of what he perceived as their learning goals. He described the main classes of students as voyeurs (those who are just there to have a look), dabblers (those who want a more brief or introductory experience with a topic), refreshers (those who once knew the topic, but who have had a significant break), deep divers (those who really just want to get into a topic completely) and completists (those who want to finish their program of study). He felt that learning analytics could provide indications of learner goals by collecting key information about the educational and personal background of learners, and through proxies such as when a learner pays their tuition fees, how often and when the learner is returning to online resources (watching lectures, reading papers, etc.), and whether or not the learner is studying sequentially. Figure 7.12 illustrates this participant's statements as a description of how he might classify learners according to their style of engagement with the materials, the system and other learners. His modifiers, such as “little”, “moderate”, or “significant” were suggested as being subjective and dependent on both the context and the educator’s own personal judgement. “Saturation” refers to how much of the University provided content has been viewed and reviewed by the learner. A learner with high saturation would engage with most or with all of the provided resources, at least marginally. While there are definite gaps in his operationalisation process (coded as “not given”), he provides some insight into how educators perceive their students and how they make use of information that they find personally relevant.

	Voyeurs	Dabblers	Refreshers	Deep Divers	Completists
Contact with the Educator	Little to no engagement with the tutor	Little to no engagement with the tutor	Moderate engagement with the tutor	not given	Significant engagement with the tutor
Contact with other learners	Little to no engagement with other learners	Sporadic engagement with other learners	Sporadic engagement with other learners	not given	Significant engagement with other learners
Submission Style	Unpredictable	Sporadic and unreliable	not given	Reliable	Sequential and Reliable
Performance	Unpredictable	Variable	Average-High	High	not given
Tuition payments	Close to start date	not given	not given	not given	In Advance
Use of Resources	Sporadic use of resources and low saturation	Sporadic use of resources and low saturation	Returns to certain resources and has low saturation	Returns to resources and has high saturation	Returns to resources and has high saturation
Retention	Unlikely	Unpredictable	Unpredictable	Likely	Likely

Figure 7.12: Classification by Engagement Style

Another participant described how he uses information that learners disclose to reveal certain aspects of the learner’s context, such as their mental and physical health, background etc. so that he can try to accommodate that learner. A different participant with no background in analytic data also felt that application data, for example, could be integrated into what is known about the learner, to provide tutors with a richer picture of student experiences before they reach the classroom. He felt this would allow him to target his material more neatly toward their needs. Two participants (one with experience in computer science, one without), spoke about using analytics to explore statistics on interaction and engagement, looking at log-in data and activity on the fora, etc. One of these participants felt that log-in data can be a proxy for student engagement, telling him when the best time to capture students might be and how to tell when he has lost their attention.

When asked what they know about their students, instructors described some of the proxies they use to understand learner lives and contexts. For example, some **proxies that were relevant for all educators included assignment style (content and form, quality), submission habits (late or early submitters), choice of communication (email, social media, telephone), time of communication, extent of communication, style of questions, sense of humour, quality of work and changes in their work (indicating troubles at home or other distractions).**

Findings indicated that, for educators, **classifying learners is about understanding and accommodating learners' goals**, which are continuously in flux. Educators were aware that their classifications of learners can change and that **classification needs to be dynamic**.

7.5 Intended or Imagined Use

As the subject of actual affordances (for course development and classification of learners) was limited to half of the participants, part of the interview involved brainstorming with participants about possible applications of learning analytics tools and technologies. This occurred throughout the interview, if a participant mentioned a proxy that they knew could be digitally captured. Some participant affordances have already been discussed in previous sections, for example, in the quote from Richard referring to measuring euphoria in the classroom. Others were prompted by conversations about the state-of-the-art in learning analytics research and what might be possible to capture about the learning experience.

The following section summarises these intended or imagined affordances, and organises them according to a general thematic category. Figure 7.13 provides a visual summary of these categories and the affordances that educators mentioned.

7.5.1 Affordances for the "Academic Fitbit"

Participants that did not have a background in computing still found it possible to imagine what learning analytics can offer, through applying previous knowledge and conceptions about Big Data or Personal Analytics, such as health and fitness trackers.

The Academic "Fit-Bit"	The "Crystal Ball"	Cohort Analysis	Interaction/ Communication	Recognising Complex Skills	Other Measurements of Learning
student-facing	unknown-unknowns	exploring and improving group constellation	alerting students to key conversations	looking at how students find and use resources	identifying euphoria and excitement among learners and educators
real-time activity feedback		exploring and leveraging group dynamics	identifying duplicate queries	tracking how learners pose questions and which questions they ask	tracking other signs of student appreciation such as sustained contact over time
		conducting cohort-level emotional analysis	helping students to prioritise conversations	making argumentation visible	looking at how students seek or generate alternatives to given resources
		creating collabora-tions	playing with emoticons and other forms of digital expression		analysing forum dynamics
			incorporating sensory data that conveys emotion		

FIGURE 7.13: Categories and Subcategories for Imagined Affordances

> "Just imagine if they could do a time-planning pro-forma, with an indication of what they hoped to achieve? I would like that. I don't know if other students work like that...an academic 'Fitbit'". - Michael, Learner Satisfaction

Similar ideas were voiced in several of the participant interviews. This is the only affordance perceived for a student-facing applications of learning analytics, until the end of the interview after the interview schedule had been exhausted (see section 7.7).

7.5.2 Affordances for the "Crystal Ball"

Another commonly mentioned imagined use of learning analytics had to do with the possibility of uncovering "unknown-unknowns", the things that educators might not have any idea are happening, but which learning analytics data could highlight.

> "I am interested as a teacher, not necessarily because I think I would know how to parse all of that, but I can see the appeal, the crystal ball, letting you peer into things that you wouldn't normally. I would be most interested in seeing how the numbers are affected by different things. But, as I've said before, it's probably just going to shift around, that satisfaction. One presentation you will make this group of students happy, the next presentation you make others happy. There are so many variables." - Richard, Developing Strong Minds

7.5.3 Affordances for Cohort Analysis

The quote from Richard, in the previous subsection, demonstrates one of the biggest concerns for educators in using learning analytics to form the basis of their educational strategies, cohort dynamics. Even more important than the individual, educators tended to feel that the cohort makes a significant difference to learning experiences. The cohort can be mobilised to support learner success.

> "I was very fortunate to have two very useful players within the group; there were two people who were 1) technically skilled and 2) very enthusiastic, and they fed off each other. And they were like that snowball going down the mountain; they were picking everyone up as it was going". - Will, Developing Strong Minds

The cohort can also be curated to improve the chances of success. In one interview, a participant spoke about a particular course that attracted students from 2 different disciplines. The module team realised that discussion seemed to flow more smoothly when equal numbers of students from both disciplines were represented.

One participant who is working on MOOCs talked about the opportunity to use learning analytics to create learning groups that can mimic those ideal conditions.

> "Coursera data is doing some experiments with learning groups, you create vertical small study groups and let the people study together, so they explain among themselves how to interpret certain things." - Hendrick, Learner Satisfaction

Educators felt that the cohort, in addition to affecting classroom dynamics, can also provide some useful insights about individual students. Richard proposed that using individual students' ratings of the overall cohort's emotional well-being might be a more valuable proxy than asking each individual student to gauge their own emotional state. He argued that the collective assessment of emotion allows learners to distance themselves from the emotion, which would lead to them being more honest. Learners can detect undercurrents of dissatisfaction in the group that the educator would miss.

Participants with an interest in cohort dynamics viewed learning analytics as being a starting point for understanding the social aspects of learning. For example, learning analytics could uncover some of the effects not only of the number, but the combination and constellation of students on a variety of psychological, social, and experience levels.

7.5.4 Affordances for Interaction and Communication

In discussing the challenges they faced in online education, educators with the goal of developing strong minds had often referred to problems of “decentralised discussion”.

> “On these forums, people can help each other better because all questions are visible to everyone, at the same time, you cannot centralise things that easy because it’s all public anyway. If someone asks a question for the third time, you can point them to the thread where it is discussed but you can’t really centralise discussions that easily” - Hendrick, Learner Satisfaction

Hendrick spoke about how he wished there were more tools to help students understand how to identify key conversations that could be important for them. He described how, in a typical classroom, a student can passively overhear much of what is going on in the classroom and “tune in” on discussions as they become personally or socially relevant. Some students are more attentive to these shifts in information sharing than others, but the educator can answer learner queries more efficiently. In a digital classroom, Hendrick felt that information is often presented sequentially, which is not always effective in working with the attention of the student. Hendrick’s understanding of learning analytics was that it would be possible to **look at the conversations in which successful students are participating, to help learners prioritise their engagement**.

Another challenge that was important to many of the educators was the “lack of visual referencing” in online classrooms.

> “All online teaching is a problem. If you fall back on the pedagogy, you will find out that 65% of communication is not spoken. And online, you have severed that. The body language. Well, silence is silence. You can’t see if unless you have got sort of videos on.” - Will, Developing Strong Minds

In discussing possible interventions to improve communication in this way, one proposal was to establish other digital visual cues for expressing emotions that one might be able to interpret face to face.

> “But what I encourage people to do is if they don’t want to speak, play with emoticons”. - Will, Developing Strong Minds

Emoticons, as an expression of learner emotion, might be no more or less likely to be correctly interpreted than a student’s actual facial expression. Still it can provide some useful information. Will discussed an online collaboration and meeting tool called "Flashmeeting"[4] with the researcher, in terms of its capabilities to track and represent when a meeting participant was smiling. Will noted that it would be easy to tell "the highlights" of a meeting, by looking at the moments when all of the participants are determined to be smiling. He then acknowledged that such a tool could also be used to help educators understand learner emotion in relation to specific issues or topics of discussion, by annotating lectures or live presentations.

7.5.5 Affordances for Recognising Complex Skills

For many educators with the goal of developing strong minds, metrics of success were often a combination of several indicators that are complex and difficult to capture. On occasion however, an educator was able to articulate exactly what they were considering to weight their interpretations of the data.

> "Of course, there is always the performance of skill [in Critical Thinking]. The question is, which skills? I want to see that they not only know where to find an answer to a question, I want to see that they can form an own opinion. I want to see them try to convince others". - Angela, Developing Strong Minds

.

The combination of information seeking and argumentation skills is necessary for becoming a critical thinker for Angela. Speaking about argumentation software, Angela felt that **learning analytics could be mobilising tools that can detect "cohesion" and "critical thinking" in learner assignments and forum contributions**.

As learning is something that is difficult to detect, instructors have developed proxies for learning that touch upon student expression of emotion, demonstration of skills and sustainability. For example the following proxies were provided across the group of 10 interview participants: feelings of success among the learners (euphoria and engagement), feelings of success by the teacher, demonstration of a learned skill, signs of student appreciation (such as gifts and letters), student feedback (written and verbal), the student being logged-in and consistently active on the VLE as well as with other students, learners posing questions, seeking or generating alternatives, contributing "second-order questions" about the topic, bringing in new aspects of the topic, lively classroom discussion, feelings of surprise, assessment results, student progress (measured over time) and

[4] http://flashmeeting.com

general quality of work in comparison to other students and to previous work. Learner satisfaction was also deemed a reasonable proxy, although most instructors felt that learner satisfaction was dependent on marks. 2 instructors described how they determine whether or not learner satisfaction is a good indicator of learning, in that it results in a feeling of pride or identity expressed by the student, or it is sustained over time. 3 participants mentioned sustainability of learner satisfaction as being visible through the extent to which they stay involved with one another, with the instructor and with communities of practice.

7.6 Goals and Roles in Learning Analytics Affordances

Affordances were often shared across educational goals, which made them difficult to categorise definitively. However, there were some general tendencies, which are illustrated in figure 7.14. For example, for educators focused on Learner Satisfaction, having information about what the student did before entering the current educational environment would be perceived as very helpful.

As mentioned previously, these educators are often also teaching very large class sizes and expressed the most worry about having to prepare for a very diverse student cohort. Conversely, educators that were hoping to prepare learners for practice seemed to be most interested in understanding how to predict student behaviour, with the hopes of intervening early and sufficiently to prevent poor educational choices. Educators developing strong minds appeared to fall somewhere in the middle, sharing some of the concern for the past and some of the concern for the future with educators from both other groups. However, this group tended to be most interested in understanding what was happening in the present moment. Words like “emergence”, “energy”, “euphoria”, which educators in this category tended to use, denote ephemeral experiences that they find difficult (but useful) to document. From the left to the right of the graphic, the affordances named closest to the left tended to address the past and preparing with the past in mind. Toward the right side of the figure, the affordances become more about prediction, evaluating interventions and developing good recommendations for the future. From top to bottom, affordances are more longitudinal, analyses based on data collected over a significant period of time. Toward the bottom of the graphic, affordances become more immediate, such as understanding a learner’s goal at any given moment, or what immediate recommendation can be made.

The colours in figure 7.14 represent which types of participants tended to discuss each affordance more often, with tutors and associate lecturers focusing the most on what they could know about their learners and their goals, and module chairs and senior academics paying most attention to course design and delivery. The affordances named in the purple box were shared across all types of roles and responsibilities within the institution.

FIGURE 7.14: Affordances, Goals and Roles within the Institution

7.7 Reflections on the Exploratory Interviews

To contextualise some of the statements in the section above, it is important to describe how some of the conversations were triggered within the course of the interview and how experiences of the exploratory interviews shaped the direction of the study that follows. This section explains the impetus behind conducting focus groups with learners and educators in the context of a case study about perceptions of learning analytics at the Open University UK. The section begins with educator perspectives on student facing analytics and whether or not students are up to the task of using analytics data to support their learning. The section then ends with some final reflections on the exploratory interviews and some of the feedback received after the interview was completed.

7.7.1 Educator Perspectives on Student-facing Analytics

Before ending the interview, all participants were asked if there was anything they would like to ask about the research project. Most participants asked about my initial interest in the subject of learning analytics. Because of my background in social science, I admitted that my initial interest in learning analytics was to explore how learning analytics could assist the learner in interpreting contextual elements of classroom experiences to highlight issues such as social exclusion, racism and sexism. I viewed learning analytics as providing evidence for philosophical debate [151]. During this time, participants expressed some additional ideas, that were potentially triggered by this conversation. At this point, educator perspectives on learners having access to analytic data became a more concrete aspect of the study.

Several participants felt that learning analytics could help learners identify their own goal.

> “I guess if students could just have access to their own data, if no one else ever saw it. If it was just to give them some insight. Maybe this would be acceptable.” - Angela, Developing Strong Minds
>
> “I can definitely see the value in seeing some of that data, for some students. And essentially, all of the tools we develop for students will only ever be useful for some of them. That’s simply the way it goes, as they say. If I imagine that someone were to follow me around for several days, noting this and that about me and what I did, and then gave me a report on that, that would be really interesting. This is kind of the same thing, is it not? It’s going to ‘notice’ some things and not others. The student will have to decide what’s relevant. That’s true for us as well. We’re seeking relevance. We want to see that this data has relevance for our vision.” - Richard, Developing Strong Minds

The imagined affordances that some educators had previously mentioned were also recognised as such by additional participants during this post-interview discussion. For example, 2 additional participants described the concept that Michael referred to as the “academic Fitbit,” a way for learners to monitor their own progress and activity through various indicators.

Educators were divided as to whether or not such data would be interesting for students. Unsurprisingly, this sentiment pairs with an educator’s level of “Experience with Computing”. **Educators who were interested in analytics themselves tended**

to feel more optimistic about students' ability to cope with analytic data as a source of information about their practice as learners.

7.7.2 The Impact of the Findings on the Study

At the beginning of this chapter, the questions guiding this portion of the investigation were listed as follows:

1. *To which extent are educators able to perceive specific affordances of learning analytics without prompting?*
2. *Will affordances be uniform across participants?*

The initial, exploratory interviews illustrated, relative to these questions, that **there are definite, notable differences in how participants from certain departments and faculties viewed learning analytics and learning analytics tools or technologies**. The types of affordances that participants mentioned indicated that **some educators are better equipped than others to make use of learning analytics to support their practice**. It appeared that these differences were not only influenced by the current domain of the educator, but also by their background and interest in computing.

Exposing educators to some alternative perspectives on learning analytics, at the end of the interview, changed the way that participants spoke about learning analytics and the opportunities they were able to perceive. This indicated **that perceptions of learning analytics are also socio-cultural**.

With the subsequent case study, it was important accomplish 3 things: First, it was necessary to explore whether the epistemic and departmental divisions in the exploratory interviews can be detected even within a single institution. Second, it was important to evaluate how differences affect educators' abilities to deliver their educational plans. Third, it was important to investigate if educators and learners could highlight any blind spots for learning analytics research that could be easily resolved.

As a case study provides the frame for developing an organisational perspective on learning analytics within one institution and a theory of context about departmental or epistemological impacts on how learning analytics are perceived.

7.8 Chapter Summary

This chapter presented the findings of exploratory interviews conducted with educators involved in online and blended learning from different Universities in Europe. The purpose of the interviews was to create a clearer picture of the most salient issues around learning analytics now, at this point of the field's development.

The first section of the chapter described the background of this part of the research process, including the participants and procedures involved. The second section introduced participant context and the apparent connection between the research participants' goals and disciplines. The section also explored how learning design and classroom implementation appear to support participants' statements about their goals, and how goals shape what the participant views as a challenge or opportunity in learning. The findings indicated that participants who aim to develop strong minds measure learning through the interaction and participation in the module, along with their own intuitions and reflections. Participants who were focused on learner satisfaction, tended to focus on the learner feedback, while those who were preparing students for practising their disciplines were more interested in learner performance.

The third section addressed attitudes and experiences of participants around learning analytics and the factors that appeared to influence participants' statements most, namely, computing experience fear or ignorance around the subject of big data in general and learning analytics in particular. Section 6.4 discusses experiences of actual use of learning analytics tools and technologies to support practice. Findings indicated that course creation and development and learner classification were the dominant themes in actual use. Section 6.5 explored intended or proposed uses for learning analytics data, which centred mostly around improving current actual uses, to gather enough big data about individual learners or groups of learners to understand their behaviours and highlight "unknown unknowns". Participants also perceived affordances in looking at cohort composition for creating supportive learning communities, and in analysing social interaction and communication to understand more about learners' emotional well-being and motivation for learning. Finally, participants described affordances for measuring and recognising complex skills, such as critical thinking and argumentation.

The chapter ended with a section on reflections from the exploratory interviews, which introduced information gathered after the end of the participant interviews and impact of the findings on the subsequent case study. The exploratory interviews suggested that context may play a greater role in learning analytics acceptance, adoption and impact than is currently recognised in the literature. The next chapter presents the findings from focus groups that were related to the participants' context, to frame the discussion of affordances in the following chapters.

Chapter 8

The OU Case Study: What Matters to Educators and Learners at the Open University

> *Our goals can only be reached through a vehicle of a plan, in which we must fervently believe, and upon which we must vigorously act. There is no other route to success. - Pablo Picasso*

The exploratory interviews described in the previous chapter suggested that pedagogical intention, background and experience may influence what kind of information an educator requires and for what purposes that information is used. The purpose of the Open University case study was to examine these relationships further from an institutional perspective. By understanding what influences perceptions and behaviour, it is possible to theorise how learning analytics' positive mediatory effects may be amplified to improve practice.

In particular, the case study aimed to expose organisational aspects of learning analytics adoption and acceptance, by choosing participants from different departments within the same institution as part of a case study. The motivation for conducting focus groups, as previously stated, was to collect social information about different perceptions of learning, teaching and learning analytics in homogeneous and heterogeneous groups. By studying interactions between the participants, it was possible to see which aspects of a given topic are most significant, the negotiation of meaning and approaches to conflict or differences of opinion.

This chapter summarises the findings from the focus groups which refer to the context of participants and their current ways of teaching and learning. The chapter opens with

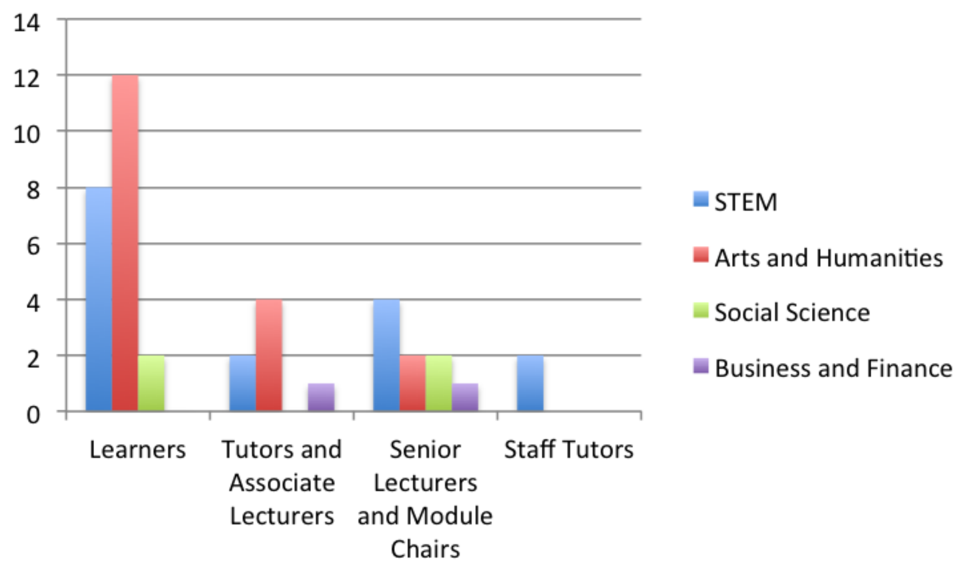

FIGURE 8.1: Participant Breakdown

a background section providing a description of the case, the Open University UK. The section introduces the individuals who actually participated in the study and discusses some experiences in recruitment, implementation and analysis of the study. The next section delves deeper into the context of the participants. This includes information on their background, educational experiences, personal and professional goals. Section 8.3 describes how participants perceived their own learning and some of the factors that appear to influence these perceptions, such as transitioning from one type of discipline to another. The section also explores some of the comparisons and metrics that learners and educators use to understand that learning is taking place. In section 8.4.1, learning strategies are addressed, with educator and learner perspectives on how learning should be monitored and controlled. The social aspects of learning are the subject of the fourth section in the chapter, with regard to working with peers, gaining access to new strategies and using student forums. It also briefly addresses the issue of "abusing" social aspects of learning to support laziness and to plagiarise. The contextual information in this chapter will provide a lens through which to consider the affordances that participants contributed in the following chapter.

Wherever the box around a quotation is square, the quotation comes from a learner focus group or focused interview. When the box has rounded corners, the quotation is taken from an educator focus group. The purple colour indicates that an educator is speaking. The light-orange colour indicates that a student is speaking. Quotes that are contained within the same box represent a dialogue within a focus group. Quotes contained in separate boxes indicate that a speaker's comment stands alone.

8.1 Description of the Case

The Open University UK (OU) case study was conducted from 2016-2017 and includes evidence collected from educators and students through a series of focus groups. The OU was determined to be a strong case study for an organisational investigation of learning analytics and learning analytics acceptance because of its unique position of access to student data, the express interest in learner experiences, and the skill and expertise the institution has in learning analytics.

As a long-time provider of distance and online education, the OU has considerable access to learner data [3]. The OU also maintains a strong institutional identity of technology-enhanced, inclusive learning [152]. This overarching goal has attracted educators who feel strongly about inclusion. In addition, the reality of accepting students from a wide variety of backgrounds and abilities means that the OU is faced *daily* with challenges related to learner diversity. Learning analytics is, therefore, of considerable interest at the OU [96], to identify learners at risk of dropping out [51], to evaluate learning design [153] and assessment [154], to categorise learners and learning dispositions [59][155] and to understand more about the social aspects of learning [3]. As an institution, the Open University stands to gain considerably from a strong data-driven approach to managing the institutional challenges of providing a high quality, accessible education to a large number of students, *and* put "students first" [1]. With the opportunity and expertise that exist at the OU, the institution is in strong position to advance toward the goal of wide-scale, ethical adoption of learning analytics tools and technologies that impact the learning experience [96].

The OU is already making a strong case that learning analytics can impact many key areas of teaching and learning, including learner satisfaction and retention [156]. However, it is not just the technology or even the reality of positive impact that effect the wide-scale, ethical adoption of learning analytics. Organisational culture, resistance to change and issues of ownership also impact how learning analytics will be successful at a large-scale [24]. The case study was designed to give space to these types of influencing factors and to understand how they link up with other theories or approaches.

8.1.1 Structure of Open University Courses

The Open University is a provider of distance education. However, this does not mean that students never meet face-to-face. The University provides tutorial groups, day schools and other types of activities for students to meet one another and engage in

[1] http://www.open.ac.uk/about/main/mission

their work. However, the majority of the student's studies will be self-organised, which the OU refers to as "open, supported learning"[2].

Assignments vary from course to course, but most courses will involve several Tutor-Marked Assignments (TMAs), followed by an End-of-Module Exam or Assignment (EMA). In addition, the student may have project work with classmates, or other types of written assignments and oral exams as is appropriate for the course of study[3].

8.1.2 The Participants

Participants were recruited through direct appeal to the faculties at the Open University. Once an educator participated in one of the focus groups, they were asked for their assistance in recruiting student participants from their modules. This was entirely voluntary and 7 of the participating educators agreed to do so.

The invitation to take part in the case study focused on perceptions of learning and how educators and learners understand learning strategies. The invitation for educators read:

> *"This study aims to collect information about how online instructors understand their students' learning processes (in particular, how learners exercise control over their own learning) and their beliefs about how learning analytics can support this process."*

The recruitment letter was sent out to individual faculties. Educator participants were relatively easy to identify. The Open University is conducting several pilot studies in learning analytics that participants said had increased their awareness of the field and their interest in learning more. Within the first 4 months of the case study, the educator participant quota (n=20) had been reached. However, due to a scheduling conflict with one focus group, 2 participants had to decline and only 18 educators took part in the study.

Learner recruitment was more difficult that originally anticipated. Initially, students were recruited using a similar approach and language as was used with educators, making explicit mention of learning analytics and student data. After a period of limited response, even with assistance from the different faculties, the research ethics committee at the Open University was contacted for approval to revise the invitation. The

[2] http://www.openuniversity.edu/study/how-study-works
[3] http://www.openuniversity.edu/study/how-it-works/exams-assessment

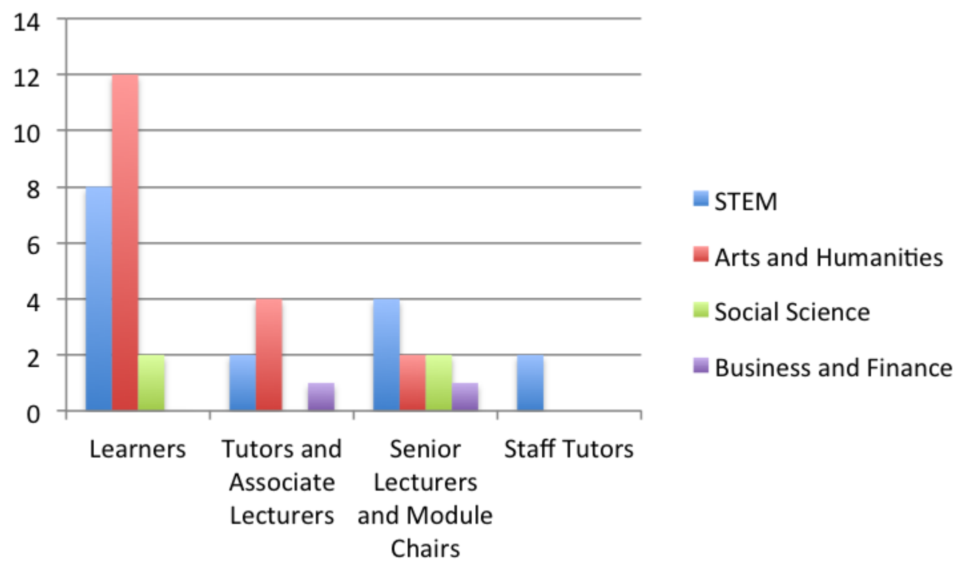

Figure 8.2: Participant Breakdown

more informal and conversational invitation focused on learner experiences, rather than analytics, and was more successful:

> *"My research is about supporting student learning and it depends heavily on being able to speak to some of you about your experiences. So I would like to invite you to participate in my research. You will get 15 for one hour of your time (in the form of a voucher) and you can participate at a time and place convenient for you. The procedure is pretty straightforward - I will just be asking you some questions about your learning and you will provide some thoughts on those questions. You don't need any special skills or insights - just your own experience."*

This alteration in the invitation text resulted in reaching the maximum participation quota for learners (n = 20) within only a few days.[4] An additional 2 students participated spontaneously on the day, having been recruited by other students in the focus group.

Figure 8.2 shows the breakdown of total participants according to position, role and discipline (n = 40). Students were mostly undergraduate, with the exception of 2 graduate students.

Figure 8.3 shows the years of experience participants had working or learning at the Open University. Educators in senior roles typically had 10 years of experience or more in education. More than half of those educators had been teaching online or at a distance

[4]The maximum number was determined to be 20 students and 20 educators, to ensure enough time for transcription and data analysis. This was discussed with the supervision team.

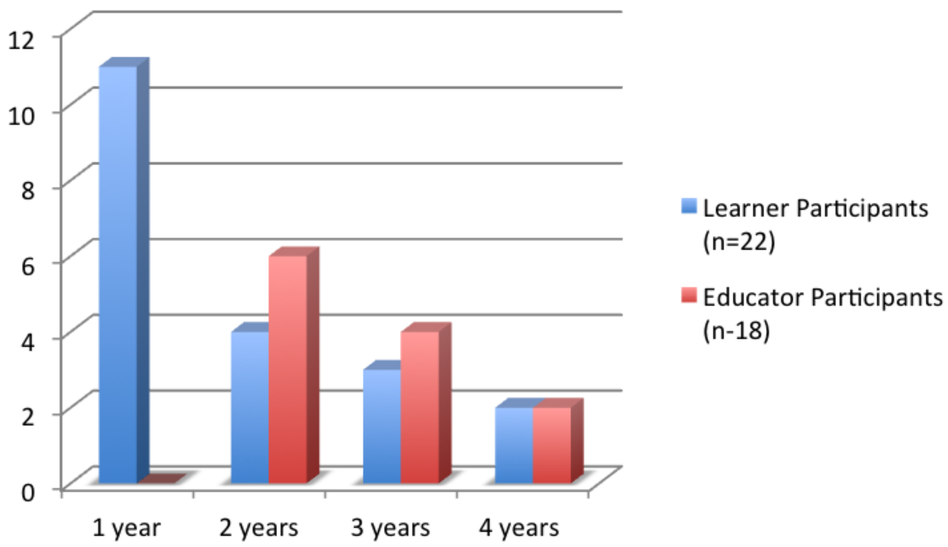

FIGURE 8.3: Years of Experience at the OU

for nearly the entire period. All had been at the Open University for more than two years. Half of all learners who participated were mostly at the end of their first year of studies. However, all but two learner participants had already completed a previous degree, or worked for a significant period of time in some other capacity. This includes being a home-maker. Five learner participants were currently retired. In addition, four learner participants reported disabilities that they believed impacted their studies.

8.1.3 The Procedure

The focus groups were conducted separately with educators and learners, but occasionally mixed in terms of the discipline and level of experience or role within the institution. This was intended to highlight the most salient and thought-provoking issues. 10 focus groups were conducted, 5 with educators (n=18) and 5 with learners (n=13). In addition, 9 in-depth interviews were conducted with learners who were unable or unwilling to participate in a focus group. Each focus group had 2-5 participants. While two individuals would be generally small for a focus group, these sessions still provided space for important social dynamics. Focus Groups took place in person at the Open University (n=3), online using Skype (n=4) and online using WebEx (n=3). The reason for these changes, relative to the research design, had mostly to do with scheduling conflicts and a preference for 1-to-1 interviews among learners. OU students are used to working independently, many have second jobs. It was difficult to schedule and keep appointments. In addition, some OU students expressed anxieties about speaking up in a focus group and referenced their decision to study at a distance as proof of this concern. The decision was made to accommodate these students with a 1-to-1 interview. In the text below, these are referred to as "focused interviews", as they followed the same format as the focus groups and occasionally involved sharing perspectives from other focus groups with interviewees, in order to stimulate ideas.

In the first part of the focus group or interview, participants were asked to describe how they know they are being successful at learning or teaching and to give an example of how that can be measured. For example, if an educator said that they know they are a successful teacher when their students are learning, they were asked to explain how they define student learning. They were also asked if they could think of any information that they have already noticed is missing for them. As the issue of intentions and goals was of particular interest after conducting the exploratory interviews, the decision was made to explicitly seek this information in the focus groups/focused interviews. Participants were asked to verbalise a goal or at least a description of what they were trying to achieve.

In the second part of the focus group, participants were asked to consider different forms of information and analytic technologies that are available, and describe any affordances they see in using that information to impact their current practice of teaching or learning. During this exercise, participants were given a brief introduction to 4 main sources of information: 1) click data and other activity information from within the Virtual Learning Environment (VLE) or Learning Management System (LMS), 2) demographic and social data, 3) multimodal data, and 4) data from the Web environment (outside of the VLE). During the focus groups, the attempt was made to avoid discussing *specific* tools with the participants. The reason for this was to divorce a specific implementation from the concept behind it, so that participants could consider the potential utility of the information, and not just of the tool. However, on occasion, when the participant did not understand a certain type of information or technique, an example was provided. In some cases, this example came from another focus group participant.

Every attempt was made to accommodate participant schedules. Snacks and beverages were provided where possible.

8.1.4 Context and Practice Analysis

After transcription, as described in the Methodology section of this thesis (see chapter 6), the focus groups and focused interviews were reviewed and open coded. The codes were then organised as categories and subcategories of wider thematic regions through constant comparison, as will be described throughout the chapter. A full description of each of these codes can be found in the appendices of this thesis.

Educational Background	Professional Background	Triggers (Students Only)	Goals	The Tutor	The Institution	The Discipline	Pedagogy (Educators Only)
having previous educational training	having experience with computing	returning after retirement	the learner's aims	tutor feedback	offering distance learning	knowing what is expected from students	the educator's aims
having knowledge of advanced numeracy	having experience with numbers	returning after having a family	the presence of module specific goals	tutor responsibility	caring about social inclusion	having access to expert knowledge	the educator's own belief structures
expressing faith in numbers	having experience with strategy	having a disability	the presence of module agnostic goals	tutor character	deploying innovative technology		the educator's perspectives on the purpose of education
having experience in discourse		being a new student			showing flexibility toward students		

FIGURE 8.4: Categories and Subcategories about Participant Context

Context and current practice are two major subjects of the present chapter, as it formed a significant portion of each focus group and focused interview. Figure 8.4 provides the major categories under the thematic category of context for reference. From the figure, one can see that educators made reference to their own background and experience, the discipline and department in which they are working, their other colleagues and the institution, as well as their own learning design and pedagogy. Learners referred to their own background and previous educational experiences, their triggers for learning at the Open University and their current goal(s), other learners, the institution, their tutor and the discipline. A full description of these codes can be found in Appendix A.

8.2 Goal Orientation and Aims

As with the exploratory interviews, the focus groups revealed several aspects of learner and educator contexts that provided a frame of reference for understanding participants' statements. The ways in which both educators and learners orient themselves on a goal and the ways in which they verbalise their intentions and aims appear to be significant in understanding how they define and measure their success.

This section illustrates the interplay that participants described between who they are, what they want to achieve and the mechanisms they deploy to do so.

8.2.1 Goals and Triggers

With regard to their pedagogical intentions, educators participating in the focus groups generated many of the same codes and thematic categories related to goals as those introduced in the exploratory interviews. Once again, educators expressed disagreement about the purpose of education and the ways in which a quality education should be delivered. The goals of "Learner Satisfaction", "Preparing for Practice", and "Developing Strong Minds", discovered in the exploratory interviews, were also recognised within the focus group data. The focus groups additionally included educators working in interdisciplinary areas, such as business and finance. Figure 8.5 shows how participant goals mapped to the different faculties represented in the focus groups. Once again, the pattern of STEM educators prioritising practice and Arts and Humanities educators prioritising more general learning is visible in this data. The one educator in business described a primary goal of satisfying learners and meeting learner needs, whereas the one educator in finance appeared to support more pragmatic approaches to teaching that prioritise practice and skill building in specific areas.

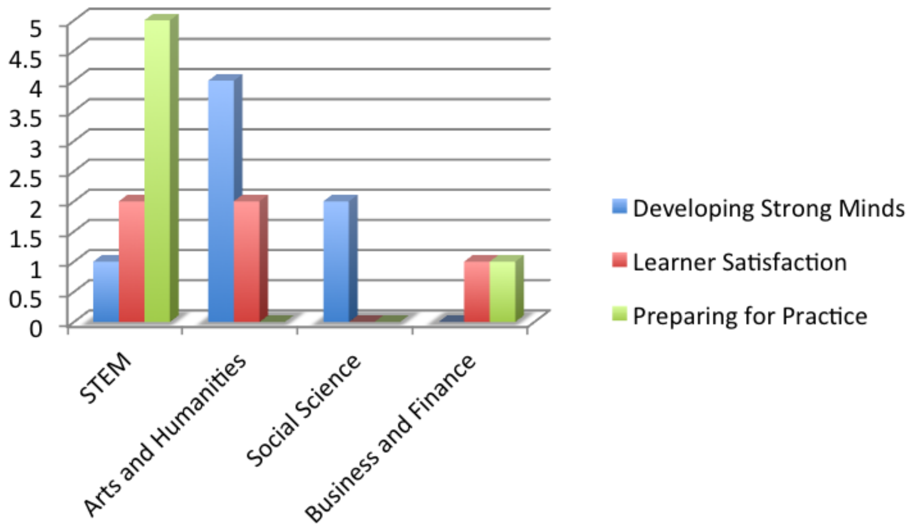

Figure 8.5: Educator Goal by Faculty

The transcripts showed that **motivations that educators explicitly voiced for working at the Open University were the flexibility of the institution, inclusive and accessible higher education and innovative instruction using technology**.

Learners expressed two categories of educational goals, those which relate to an over-arching sense of the purpose of their education (coded as "Aims") and those which related to goals they would like to achieve within the module (coded as"Module Specific Goals"). With regard to the over-arching educational goal, learner participants could be broken down broadly into three groups: those that are studying for their own "Personal Development", those that are seeking "Qualifications" for a specific job or profession, and those that are studying for the "Joy of Learning". Figure 8.6 illustrates how these divisions appear in the coding.

"Personal Development" applied to goals that were particularly related to wanting to challenge oneself, do the best one can do.

Personal Development	Qualifications	Joy of Learning
wanting to learn to better oneself	wanting to learn to get a specific job	wanting to learn because of sheer enjoyment
wanting to be the best one can be	wanting to be good enough	wanting to enjoy learning
having module agnostic goals	having module specific goals	having module agnostic goals

Figure 8.6: Learner Aims and Associated Codes

"I don't want to spend my life behind a supermarket till. So I thought I'd just study something. And I went for the course that I did years ago, it was actually 1979, to see if I could finish it. Well, I did finish it, but I decided I wasn't going to stay in English Literature and I didn't fancy History. I did, but I couldn't think of anything to do with it. But then, I always had an interest in environment, because of the environmental group in my neighbourhood. So, I thought I'd try this then. And if it doesn't work out well, I could try something else." - Laurie

"I want to keep learning and I want to keep using it, maybe do more because I'm not going to let all that I'm learning go. So, for me, I think the main thing is, I just want to see what I can do. It's seeing how far I can push myself in a sense of my ability." - Harriett

When a learner did not seem to have this added pressure of personal best, but still had a significant sense of self-motivation and interest in study, the learner was coded as having the goal "Joy of Learning". This included learners who were engaged in studies to "keep an active mind", or to follow an interest or curiosity.

> "I'm 71, I'm hardly going to go through getting a career out of this. I'm doing it for the pure love of it." - Chris

Learners who are learning for the joy of learning, as well as those who are trying for their personal best, *did* often wish to achieve a certain qualification or expertise in a given field. However, when the focus of the learner's statements was on gaining qualifications for a *specific* job or profession, that learner was coded as having a goal of "Qualifications".

> "I really thought it would make me better at my job, give me an advantage over other people." - Jonah

> "I started with the OU because the head teacher at the school I work at, wanted me to get a degree." - Allan

These two quotes illustrate that the motivation or push to study can be both internal or external in the case of wanting qualifications.

There were no learners participating in the study that had absolutely no particular aims or goals. However several learner and educator participants claimed that such students exist. It is not surprising that such students, if they indeed exist, would not have been motivated to participate in this study.

8.2.2 The Influence of Background on Learner Aims

Figure 8.7 shows learners' aims, by the faculty in which they are currently studying. A pattern such as was seen among the educators was not visible in learner groups.

However, **when discussing with learner participants their various *backgrounds*, how they came to the Open University and what they were trying to achieve, some tendencies were apparent**. Figure 8.8 shows learner aims broken down by their background. Women who had been homemakers previously and were returning to higher education consistently reported aims associated with challenging themselves, doing their best and working very hard on their studies. This was true across age groups, faculties and number of years spent at the Open University. Harriett, who had not studied

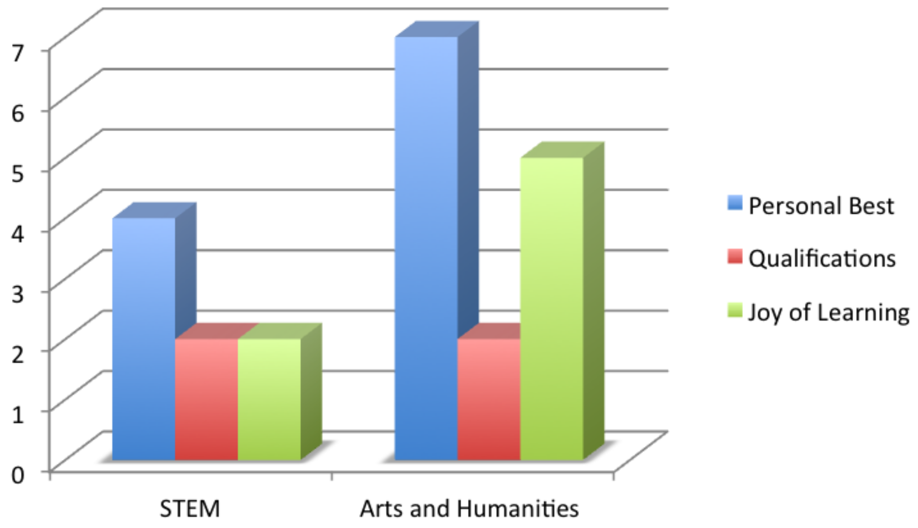

FIGURE 8.7: Learner Aims by Faculty

previously and who was raising a son with dyslexia, was originally drawn to her studies by wanting to help her son with his own learning. She described how she moved from one level to the next challenging herself to go one step further. Grace, who still had young children, described how she expected her family to adjust to her study schedule, now that her family did not require as much of her attention.

> “I thought, if I don’t do this, I’m really going to regret this, so I, that’s when I jumped and started doing it, and it is really good.” - Harriett

> ”After I stayed up until 4am in the morning writing an essay, I thought, I just can’t do this again. I need to be strict with my husband and children and say ’look, I need to do this, you need to sort yourselves out.” - Grace

Learners with disabilities also expressed a strong interest in personal best and challenging themselves appropriately. As will be discussed later in this chapter, learners with disabilities also tended to express much more confidence in their knowledge of their own learning habits and preferences.

Learners who were retired, especially those from the STEM sciences, Medicine, Finance and Business, expressed the desire to enjoy what they are doing. Often, their current experience was compared to very hectic professional lives in the past, and an interest in trying something new.

> "They suggested I drop English Literature and concentrate on accounting. Turned out, I was reasonably good at it and had a 50-year living from it. But the dream had always been to be a writer. So I had the opportunity now to return to the dream." - Chris

> "I've got a Master's of Science and I've got a number of medical qualifications. But I really want to do something more artsy. I mean, I find it difficult to find the time, my daughter has been in very poor health, both before and during pregnancy, we spent a lot of time in the hospital. I've got this elderly father who needs me. I'm married. I've got all sorts of responsibilities. But I feel this is the thing I'm now doing for me." - Louise

Louise points out that her current life is stressful too, for a number of reasons. However, her motivation and aim make her clearly prioritise her studies. Learners like Louise tended to express frustration and confusion toward learners that find it difficult to self-motivate, particularly when future career perspectives are at stake.

> "You would think that a qualification they need for their job, that would be motivation enough." - Laura

> "Obviously, if this was going to be used some way in your career, for your future, you always want to do your best, right? And so I think a normal student, a younger student, who is wanting to make use of his degree, would be more concerned than I was." - Ralf

First-time students tended to express more generic goals, either associated with a job qualification or with the flexibility that the OU specifically offers.

> “I chose it because I’ve got two children and I just can’t travel.” - Grace

> “I am out of work just a little over a year now. I need this degree to improve my prospects of getting a job.” - Frank

However, there were some tendencies for such students, especially in the presence of other students from their faculty, to express firmer ideas about goals and expectations.

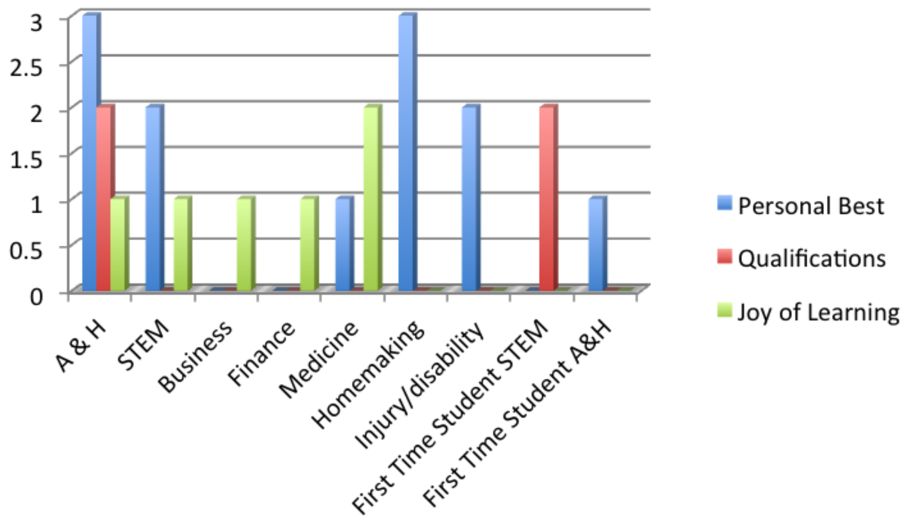

FIGURE 8.8: Learner Goals by Background

Learner participants stated many different reasons for choosing the Open University, none of which were academic related. Rather, **participants stated that they had chosen the Open University because of a *career or life change*, because of *disabilities that made distance learning attractive*, or because of the *flexibility* that the Open University can offer.**

It should be noted that learners who were funded in some way to complete their studies at the OU were identified in each of the three aim categories. This was an interesting finding, given that many educators in the exploratory interviews seemed to believe that free online education was damaging learner motivation and overwhelming learners with content. Whether or not this is a true statement, it did not appear to affect the learner’s goal or motivation *from the learner’s perspective* in the context of this study.

8.2.3 Module Specific Goals

Some learners had goals that were specific to a given module, for example, obtaining a pass or gaining a prerequisite. Some learners had goals that were relatively consistent, regardless of which module or activity the learner was speaking about. Learners coded as having the goals “Joy of Learning” and “Personal Best” often expressed module specific goals that were quite similar to their over-arching aim. For example, a participant striving for her personal best in her degree program, was also likely to be striving for her personal best in the module. Learners whose module goals were consistent were coded as having “Module Agnostic” goals.

Learners that expressed the goal of obtaining specific job qualifications more often described module-specific goals that were different from the overall aim. In particular, these goals appeared to be influenced by whether or not the module was perceived by the learner as a real prerequisite for the job. For example, two participants, who had an overall aim to have a particular “Qualification”, described treating modules they did not perceive as being directly useful for that aim strategically, calculating the lowest necessary mark or effort.

> “I just need to pass this module. I’m not even sure why I need it when I know I don’t need it to do what I want to do.” -Boris

> “I know if I manage a pass in this [module], I can move on to the next, which is, well, that’s the one I really signed up, or registered to do.” - Jonah

The findings indicate that **learners with module specific goals, while they often described themselves as being able to learn more efficiently in some cases, also expressed having some difficulties in new strategy adoption**.

8.3 Recognising Learning

The findings thus far support observations from exploratory interviews that **goal orientation and adoption relate to one’s own idea of the purpose of education**. This section describes how those differences extend, as they did in the exploratory interviews, to the ways in which the participants in the focus groups and focused interviews

Comparison with the Self	Comparison with Others	Coherence	Comparison with the Discipline	Marks	Recall	Feedback
against previous performance	trends between cohort vs. cohort	expressing appreciation for the domain	against expectations of learners	general marks	remembering key concepts	receiving direct feedback from the tutor
against health and well-being	trends between learner vs. cohort	sense-making in arguments	against other examples	general percentage in relation to the class	retaining written information	receiving indirect feedback from other learners
against overall progress toward goals	comparison with the average	having access to discourse				
against previous social interaction	comparison with a selection (top 10%) or self-defined					

FIGURE 8.9: Learner Categories and Subcategories for Recognising Learning

recognise learning. To illustrate the active component of recognising learning, the codes associated with this category were based on actions, for example "comparing", "reflecting", and "tracking", etc., as well as the objects that are being acted upon, such as "performance", "participation" and "cohesion".

The subsections discuss the categories of recognition that learners described and how learners transitioning from one domain to another adjust their strategies. Subsection discusses the categories of recognition that educators described, comparing these responses to information obtained in the exploratory interviews. The next subsections discuss the various comparisons that can be made using only the individual's present and past performance or background, or a body of other students (in terms of past and previous cohorts, or within the same cohort). Following comparisons, the next subsections address the role of educators and other human facilitators in helping learners to identify their learning. More specifically, the subsection deals with how individuals offer direct feedback or an indirect opportunity for reflection. Finally, the last three subsections deal with recall, coherence and marks, common heuristic mechanisms that learners and educators describe as parsimonious ways of identifying learning.

8.3.1 Transitioning Learners and Recognising Learning

Student descriptions of how they recognise learning fell into one of seven categories: "Comparison with the individual and past performance", "Comparison with Other Students", "Coherence", "Comparison with the Discipline", "Marks", "Feedback" and (for students only) "Recall". Figure 8.9 shows the codes as they were organised as categories and subcategories for recognising learning.

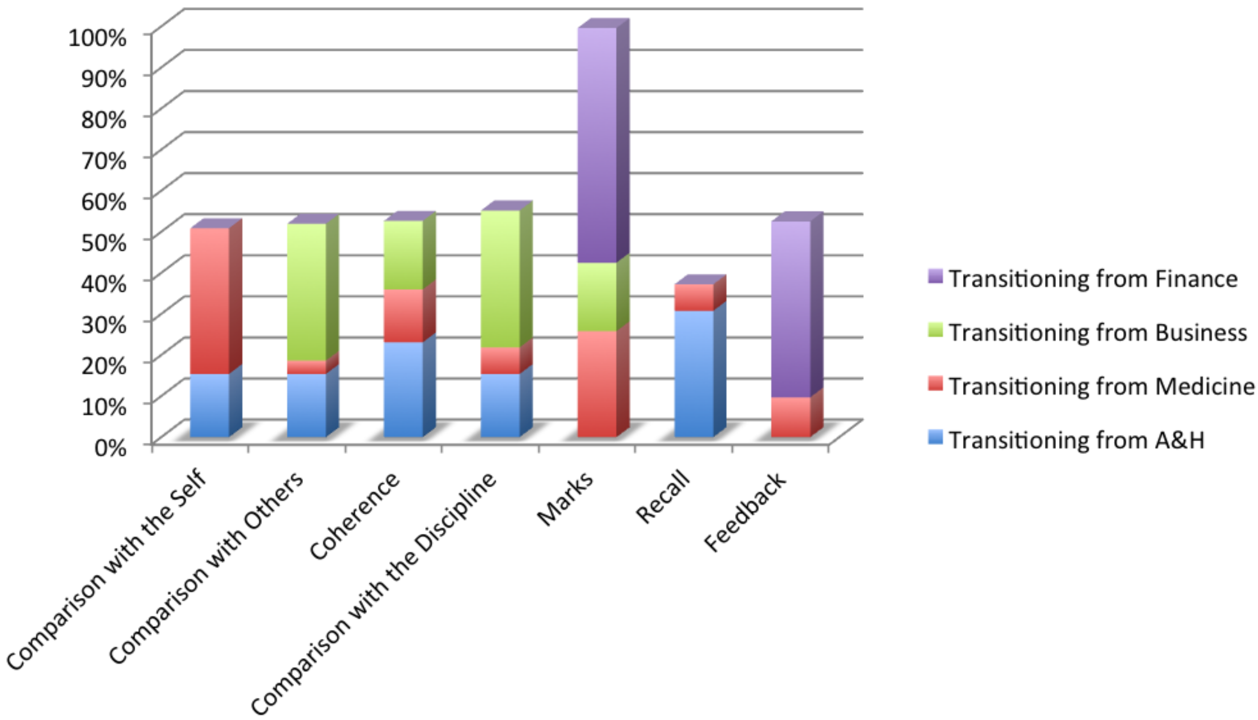

FIGURE 8.10: Transitioning Learners' Measurements

The findings indicate that to a certain extent, the **learners adopted measurements of their own learning from their background**. Figure 8.10 shows a breakdown of how students who are transitioning from one domain to another measure their learning. The percentages refer to the number of conversational turns related to that particular way of recognising learning and the percentage of those turns that was devoted to a particular measure. All of the students represented by this chart who are transitioning from Finance, Business and Medicine, are transitioning into the Arts and Humanities.

In contrast, Figure 8.11 shows how students who are not transitioning to another discipline recognise their learning. Definite trends among those active in the Arts and Humanities are visible, for example, in terms of the importance of coherence. For participants learning a STEM science, recognition of learning appeared to be much more related to performance and, more specifically, marks. **Those transitioning tended to show more flexibility in conversations and individuals increased the amount of time they spent talking about measurements of learning that are not necessarily typical of their previous domain.** *This was particularly true when students were in mixed focus groups (of different domains and backgrounds).*

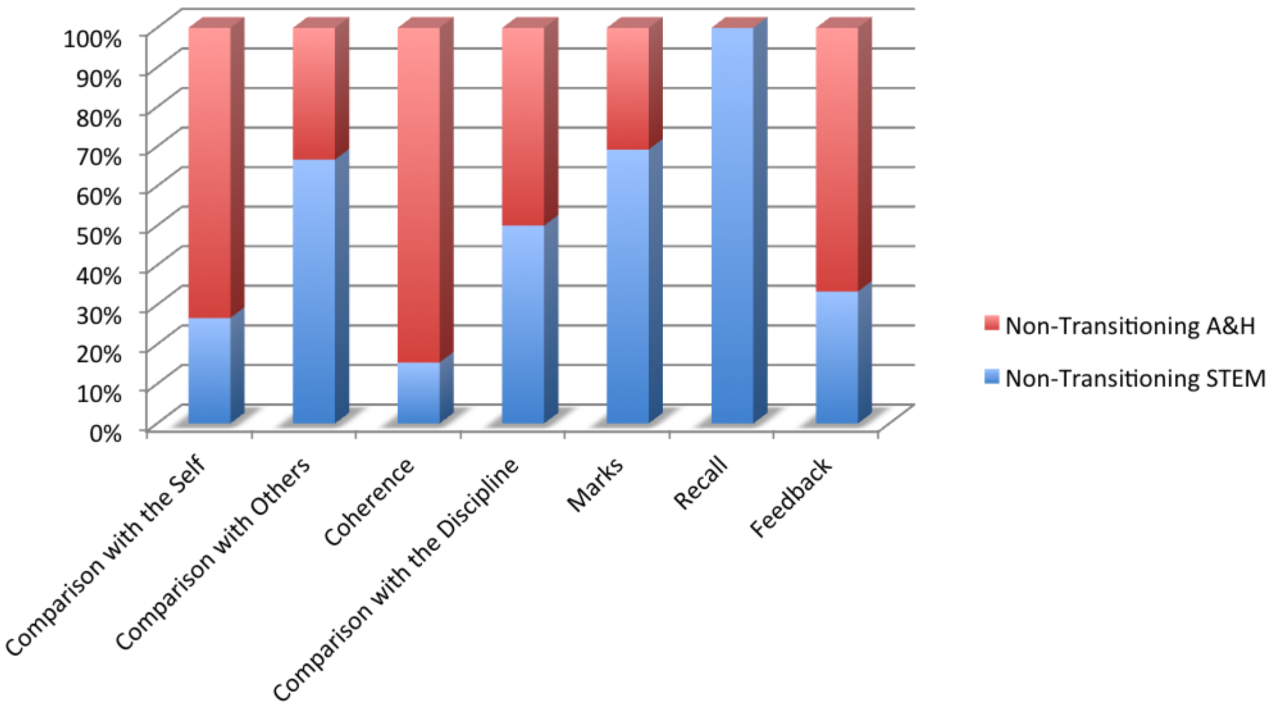

FIGURE 8.11: Non-Transitioning Learners' Measurements

8.3.2 Educator Indicators

Educator indicators of learning are slightly different from those of students, which was apparent in the exploratory interviews. However, in mapping educator comments on learning to learner recognition of learning codes shows some interesting trends. Marks and comparisons with the average student, for example, were more commonly discussed by educators who had the goal of preparing learners for practice, while feedback from learners about their learning appeared to be more important to educators trying to satisfy learners and develop strong minds. Figure 8.12 shows the percentage of overall comments about recognising learning that related to each type of measurement and educational goal.

Educators developing strong minds, who were typically identified among educators in the Arts and Humanities or Social Sciences, discussed how they rely on coherence to understand whether or not a learner has really absorbed the content of the module.

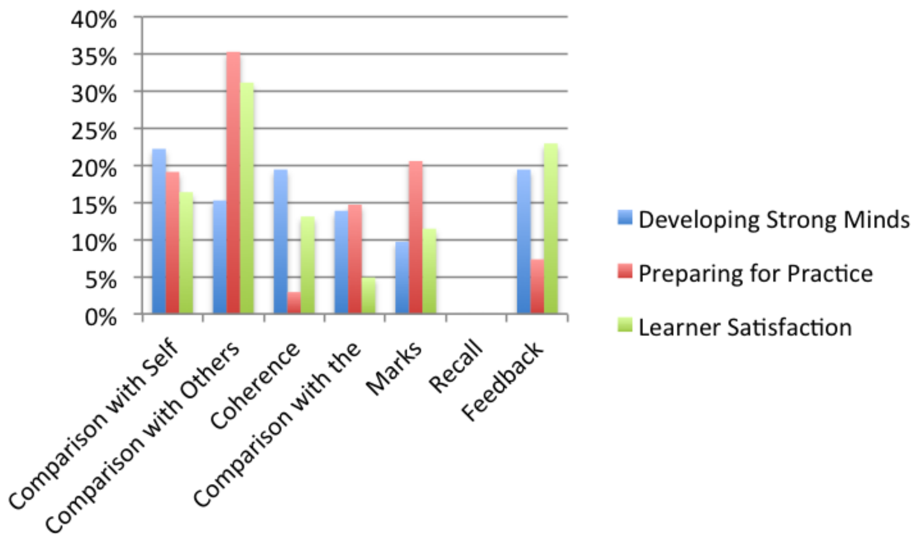

Figure 8.12: Educator Recognition of Learning

> "It's in those little details. Does the person know how to transition from one idea to the next? Is there a flow? Does it 'hang together'? You get a sense for that. A student who is not just repeating back what you say, but knows how to, I suppose, navigate around the topic." - Nora

Recognising learning more generally was not as large a part of the educator focus groups as it was for learners. This was, in part, by design, as the exploratory interviews had already looked quite deeply into this from educator perspectives. It was also possible that, due to the fact that educators came to the focus group with an express interest in learning analytics, the discussion was moved swiftly in that direction. However, in comparing educator perspectives from the exploratory interviews, one can see some consistencies in the data. Educators developing strong minds, who described measuring learning through euphoria and excitement in the classroom, do so by observing learner activity and comparing it with previous states of activity. In addition, they recognise learning through seeking coherence in learners' work and being receptive to their feedback. Once again, educators preparing for practice expressed more interest in using marks and comparisons against averages or other groups of learners as tools for recognising learning.

8.3.3 Comparison with the Self

Comparisons between past and previous behaviours and emotions of the individual student were a common measurement for both educators and learners. Self-comparisons were identified among learners through the ways in which they described tracking and monitoring their own performance.

> "I go back to those first tutorials and think, oh my God, seriously, look how far I've come. I know I've learned a vast amount this year, a serious amount. I think it's from looking back and realising that actually, that was really difficult at the time and now that's okay."
> - Vicky

Recognition that something is easier or makes more sense over time was the most common type of self-comparison after comparing one's previous and present marks. Learners also made self-comparisons with regard to **states of emotional well-being, social well-being and over-all progress toward their goals**. For both first-time and return students in the Arts and Humanities, self-comparison was often described in terms of the **affective aspects of learning, feelings of excitement and engagement**.

> "I don't feel guilty anymore. I know I'm working because I feel proud of myself." - Frank

> "I know if I'm learning effectively when I have to keep switching to my laptop to Google stuff or want to research something a bit more. That's how I know that my brain's active and I'm really doing something." - Allan

Improvements appeared to be more difficult for learners to concretely measure, because the individual was typically comparing this affective state with ill-defined parameters, such as "better than before" or "more than before", where "before" was not defined explicitly, even for the learner. This is another example of how the interpretation of certain metrics is subjective.

For first time and return STEM students, past performance was more about assessment and performance, in terms of marks. Generally, these students described easily recognisable data points to make general decisions about effort.

> "I got low 70s for my first TMAs this year, which surprised me, because I was a 80s kind of student the previous year. It got me thinking about whether or not I was taking it in." - Mascha

This type of comparison relies on the learner's self-image and how this image compares to reality. Other students have more difficulty understanding how to leverage marks as information relevant to the practice of learning.

> "I wouldn't really be able to say, simply based on my marks if I was doing well or not. I mean, compared to what? Each assignment is so different, each module, each tutor. I can get 1sts for 4 modules and 3rds for the rest. My performance has very little to say about what I've actually learnt." - Moritz

In this exchange, Moritz's statement shows that he struggles to understand how he can contextualise a mark in any meaningful way. His interest in marks is more "procedural" in terms of how they contribute to his overall aim of doing his best (for example, getting a distinction).

> "Obviously, I can see that if I am able to perform well on these exams, I get rewarded for that. I am interested in the reward, the distinction. It's not just a pat on the head." - Moritz

Educators also compared an individual against their previous performance, behaviour and attitude.

> "You will see improvement in the students, from whatever level they came in with. Sometimes with a group of students, you don't get such a steep curve. You get a shallow incline because they're already up there. They don't have far to go. I guess for me it was always a question of looking at where the students started. I hate to use the word 'baseline assessment' but that's what it is. You make a mental note of where they're at and you're looking for them to move upwards. Formative and summative assessment. If a student takes a sudden dive, you've got to look at that because something's wrong. I wouldn't expect any student to be on a downward curve ever. If it was level, I would say, okay, there's an issue there." - Elizabeth

This simple measurement, of whether the student is doing better than before, is one that many educators used to help them gauge learning. Elizabeth's expectation that no student should be "on a downward curve" indicates that she views this as a general measurement, one that can also be used in diagnosing a learning challenge, potentially even for learners who are already average.

8.3.4 Comparison with Others

Comparisons with others included comparisons between cohorts, between individual students and cohorts, past and present students in the same module, and with students that meet certain criteria (for example the top 10% of the class). They include not only comparisons of performance, but also of activity and retention (across modules, study programmes and the University as a whole).

Learners were less interested in cohort comparisons, unless they were small groups in the same module. However, learners disagreed on how much could truly be compared between two different groups of individual students.

> Asha: "We did this exercise once, a group presentation. The quality between the groups was enormous. You could see that. The presentations looked rushed in some cases, spelling and grammar mistakes, no cohesion in the fonts, no structure. You could just tell that what we'd done was much more...much more professional than that."
>
> Betty: "That's not learning, that's something, that's something else."
>
> Asha: "It says something about the time spent, though, doesn't it?"
>
> Betty: "If I'm in this class and I've done such a presentation, what have I learned, then?"
>
> Asha: "You've learned how to be diligent and detailed about something, how to put together an argument that makes sense. That's learning."
>
> Betty: "That's form. I can deliver something polished that is not very insightful. You can't judge group work based on that."

Betty and Asha's discussion was typical of learners with open strategies (such as Betty) and learners with pragmatic strategies (like Asha). For Asha, the proxy for learning should be the cleanest, most easily recognisable factor. Betty has difficulty in seeing such a proxy as useful, without it giving her a sense of the larger picture.

As learners debated how they apply comparisons with others, it became clear that **students have different expectations around what a useful comparison might be. Ultimately, the participants agreed that the learner decides.**

> "I would like to know where my mark sits in the overall marks...It would make me work harder." - Ralf
>
> "I suppose you could get something from that. I don't know if I need to see all of that. Maybe just the top 10%?" - Asha
>
> "Top 10%, top 20%, whatever target you have." - Ralf

For educators, **comparisons against others appeared to be particularly important for educators looking to prepare learners for practice and for those**

looking to satisfy learners. Educators seeking to satisfy learners made comparisons between cohorts to assess the overall "health" of the module, rather than the individual learning of students. Educators preparing for practice, were more likely to compare students against other students in their same cohort, particularly in terms of marks and participation.

> Georgia: "I am somewhat of a, kind of, stick in the mud. I have some high marks, which I am willing to award to students who work very, very hard. You can see they are leading the discussions, they are putting in the effort. You can't really compare them to anything else but each other."
>
> Dana: "There are normal fluctuations in the module, you know, one year everyone is really active and taking it in, and the next year it feels like you have to push them. There are also these kinds of, I suppose, effects that you can see, looking at how the students have responded to certain information. That might not be something I see this year or the next, but I do feel that we, I don't know, have a sense of it, of what is happening."
>
> Mark: "This year, we had one TMA and they all struggled, which was a surprise because we thought..."
>
> Dana: (interrupting)"We just need access to that information."
>
> Mark: "We hadn't had a single difficulty in the previous year and there is some truth to what [Dana] is saying. I've not seen the numbers on all of my modules, but this information is out there."
>
> Georgia: "It's not perfect, but I think you have to look at retention."

Dana and Mark, who both have the goal to satisfy learners expressed worries over a lack of access to information and orientation around their cohorts. **Comparisons between cohorts was a simple measure used to gauge the overall success of the module**. Georgia, who is preparing learners for practice, expresses more belief that longitudinal comparisons will highlight learning effects that are as of yet unknown to her.

Retention was an interesting and very common comparison for educators, relative to the University, the departments, the course of study and specific modules. **Most educators agreed that retention was an important figure and that it is difficult to**

interpret. This finding was in keeping with findings from the exploratory interviews about the topic of retention.

> "I think it is institutionally important, that if we take a student on, we expect them to finish...I think retention is only one measure. And it's the measure we've got." - Jeremy

However, this information was occasionally interpreted and applied in different ways. Educators focused on learner satisfaction tended to also see retention from a learner's perspective.

> "If I were a student and I saw all of these people dropping out within the first two weeks, I might think I ought to have a look into that and find out why." - Dana

> "I think it would be good to know how many of the students do finish in my area. How many go on to become [names his profession]." - Jeremy

Educators preparing learners for practice were more concerned about retaining students through to the end of their course of study.

> "The problem is that we are obsessed with retention in modules. And that's not our problem. Our problem is retention across programs. " - Ivan

> "I'm not entirely sure if the Open University can even look at retention in the same way. We have a lot of non-traditional students, who come to us for many different reasons and a good many of them are not seeking degrees." - Georgia

The perceptions of educators around retention illustrate that, for a simple measure, the implications are very complex. It is worth noting that these interviews were taking place within the context of the Teaching Excellence Framework [5], in which (nationally) retention was an important figure for measuring university performance in teaching. There appeared to be much concern within the OU that the nature of the University's mission and the type of students we attract with flexible, distance education would impact our ratings. Retention is viewed as a problematic metric, in particular, with regard to degree-level retention [6]. No doubt, this will have been influencing the statements that educators made about retention.

8.3.5 Feedback

Feedback was coded very generally, in terms of any information that a learner "gained" from human interaction, with the intention of applying it or learning to apply it. This included direct and indirect interactions.

Most learners spoke about **tutor feedback, in particular, as being an important tool for recognising, monitoring and controlling learning.**

> "I think most of my learning comes from feedback with assignments and tutor comments, as well as assessment scores." - Chris

> "In some of your assignments, you write an essay, you receive your feedback and then you adjust accordingly, which I've done. But he [a tutor] hasn't given me anything to go on." - Grace

At the end of Grace's statement, she is discussing a new tutor. This tutor has not met her expectations, which were set by her first tutor, that she would receive *concrete, applicable feedback*. In discussing conflicts that learners had with tutors, this was one subject that nearly every interview touched upon, diversity among tutors. This was particularly true of learners with pragmatic strategies, who relied on their tutors for much of their expert knowledge and feedback.

[5] https://www.officeforstudents.org.uk/advice-and-guidance/teaching/what-is-the-tef/
[6] https://www.timeshighereducation.com/blog/why-my-university-not-entering-tef

"If someone tells me, 'you've got to work on your argument here', but I am not entirely sure what an argument is, consists of, that's significant. I am going to need some help. That's why I am here." - Ora

"You have to put it right in front of my face kind of thing, exactly, what is it that's wrong." Jonah

"Tell me why I need to do this in this way." - Boris

"It's almost as if some of them really don't know what to say, but they have to say something, so they just say whatever and then you find yourself with all of these vague comments wondering what or how, what you can do with it." - Ida

Other students, in particular those with open strategies, expected some emotional and social support from their tutor.

"It totally depends on your tutor whether you feel as if you're getting support or not. The tutor we've had this year has been fantastic, really, very proactive with us, actually and very motivating. Last year, they just sort of marked your TMAs and that was it, kind of thing." - Joan

Students, more than educators, considered the role of other human beings in their learning experience. In a feedback email, one student participant reflected on her experience of participating in the research study and how it triggered a reflection on reflection.

> "Perhaps just talking to someone who you know is really listening is the vital key to increase motivation, enable effective reflection and to support students to progress through understanding themselves. I not sure that it matters whether it is in person (though that is nice) or on a computer, as we did. It is the fact that if someone asks a question and is really listening, then we are more likely to consider and provide a more honest and in depth answer, and when the questions are about yourself, then the answers are surely going to lead to more effective reflection and resulting progress." - Ora

Similar to the findings of the exploratory interviews, **educator participants in the focus groups also relied heavily on learner feedback to understand and make sense of learning**. Once again, this information appeared to be most important for educators developing strong minds and satisfying learners, as illustrated by Figure 8.12.

8.3.6 Recall

The ability to recall was mentioned by several students, in particular students that return to education after retirement, as an important measure of learning. In particular, forgetting was viewed as a sign that learning had not taken place. Laurie recounted a story in which a fellow classmate was able to participate in the classroom discussion, because he was able to remember the name of a certain theory that they had learned in a previous class.

> "I knew when he said the word, I knew what he meant. But I couldn't have answered the question because I didn't remember it." - Laurie

Statements about memory were unclear in whether they were about recognising learning, or recognising a skill that is helpful for learning. Most of the participants that discussed memory issues were older students. However, some claimed that they had always had memory problems. It is therefore unclear whether these perceptions are related to age, or to a conceptualisation of education that was formed much earlier when rote learning was a more popular method of study.

8.3.7 Coherence

Coherence was described by learners as a sense of meaning and logic within the whole, almost as thought the pieces of the puzzle were coming together as the student learned. **Participants described recognising coherence through moments in which their participation in the discourse was facilitated by what they had learned**.

Grace described how her architecture class has helped to her to gain an appreciation for things that had previously escaped her.

> "When I go past a church, things spring to mind and I can tell I look a lot more into it than I initially did...So, after you've read the chapter, if you're looking around at paintings, at buildings, and things are springing to mind, you realise you've picked up the thing." - Grace

Learner participants also described **seeking coherence in terms of holism, examining their arguments and their work from multiple perspectives**.

> "When you answer a question, you actually have to sit back and look at it from as many different ways...it's almost like an interrogation. You interrogate your answer to make sure that you've got all the sides in." - Laurie

Coherence was an important issue, in particular for educators developing strong minds and those pursuing learner satisfaction. Often, these educators described difficulties with assessment, which forced them to seek information about student learning from other composite variables.

> George: "The difference between a 1st and 2nd year student is the bridges between paragraphs."
>
> Sam: (laughs) "That's what they say, but no, yes, it actually does have some, potency, this statement. An advanced student knows how to massage the topic, play with it, cast it in an alternative light. A 1st year student struggles to use the terms correctly."
>
> George: "I am still struggling with our terms!"

George and Sam are able to provide a few measurements in this statement, but they are difficult to capture. When asked how they get a sense for those measurements, Sam said:

> "It's something you acquire with time, I think. I couldn't really say. Or maybe I could? I would really have to sit and think about it."

George agreed that it might be possible to describe what is meant by coherence in concrete terms, but that it would have to be an individual exercise by the educator who wanted to use such a measurement.

> "What makes sense for me is not going to make sense for someone else. Could I tell a tutor helping me mark my assignments, 'could you please make sure that all of these things are covered?' Wouldn't that be just immense?" - George

George's perception of the impossibility of such types of assessment was shared among many educators, those for whom the measure was deeply important as well as those for which it was not. The understanding that there are certain things that cannot be measured appears to be a necessary scepticism toward recognising learning, which is shared among educators at the Open University.

8.3.8 Marks

Of course, marks were also generally perceived as an important measure of learning, particularly in combination with comparison. However, when a learner did not use a comparison, but rather a more generic standard, they were coded as using "Marks" to determine learning. For example, Chris said in a focus group that he knew he was learning when his grades were "high". After one of the participants in the focus group asked him "what is high?", Chris says"Over 80". On what it is about this score that helps Chris to understand his learning, he said:

> "I am appreciative of the feedback he gives, as well as the actual, simple score, I mean, aren't grades ultimately the final arbiter? You either pass, or you get a distinction, or not." - Chris

Chris was not the only student who had such a generic standard. Occasionally, the standard would start much lower, a pass, for example. Over time, that benchmark occasionally had changed for the learner. For example, Allan also finds grades important, though this is a new experience for him:

> "I coasted through school and I coasted through college, and it wasn't until about 21 that I realised that. So part of my thing, especially this year, was to ensure that I put as much effort as I could in order to see my grades go higher. I suppose a grade is a kind of measurement of the effort I'm putting in. I could probably coast it at 70 out of 100 in assessments, but like [Chris], I am thinking anything about 80 and that's when I know that I'm putting in the work for me." - Allan

Allan does not describe the grade itself as the actual measurement, like Chris does. For Allan, the grade is a proxy for effort, so long as it is above what he knows he is capable of achieving without much effort. This is something that only Allan can know. If Allan did not particularly mind coasting, his behaviour would not likely trigger any red flags, as he is able to perform fairly well without trying. As he describes it, however, he would clearly not be acquiring much new information or learning from the experience.

The findings indicate that **it is necessary to understand something about the strategy of the student, who recognises their learning through marks**.

8.3.9 Comparison with the Discipline

Comparisons that learners made between themselves and the discipline were typically dependent on how far along they were in their studies and the discipline in which they were currently studying. Interestingly, the less experience a student had and the newer they were to the discipline (without any previous training in the subject), the more they sought criteria within the discipline as a measure of their learning, even when this criteria was very vague. A first year student in environmental science, with a background in activism, rather than science, expressed doubts and insecurities about how much she was able to understand and learn in her class.

> "This course is a scientific base for people who are going to be going forward, maybe to measure things in the environment. I wasn't taking it that far. I'm interested in waste and the amount of stuff we throw away. I don't think I'll be measuring things in the same way. You don't think that there are all of these other things involved, all of these measurements, all of these massive numbers that you can't get your head around. It's a bit like saying 'I've got a trillion pounds in the bank.' What does that mean?" - Laurie

A first year student in English Literature, with a background in accounting, was looking for signs of passion and creativity inside of himself. He spoke about needing to "fall in love" with his tutor, and be inspired by her. Whatever the student thought was expected of them by their perceptions of the domain, they judged their capabilities against that. Findings indicated that **a sense of insecurity in their new field led transitioning students to seek comparisons between themselves and what they perceive to be the expectations of their current field**. They may need assistance early on in orienting themselves in a new system.

Educators, even those that had quite heated discussions about other issues in online and distance education or pedagogy, all seemed to share one very common but vague metric in determining learner success, **their own sense of shame and pride when they intellectually compared the learner to the expectations of the discipline**.

Lucy: "In terms of content, I like to think about it in terms of whether or not it can stand up to scrutiny from the outside."

Ivan: "The student should be able to pursue a PhD degree in Manchester and not look like [an idiot] when they show up for the interview because whatever they've been taught is not what is accepted within the community."

Lucy: (Interrupting)"That when they go out, that they can fit within the community."

Jeremy: "You have lots of different types of students, the floggers, the sackers... and for me, it's heartbreaking when you see someone on the borders, when you have someone who has clearly done, you know 'almost enough'. I could pass this person, fail this person, whatever. My only criteria is, finally, when we argue this is if someone came up to me on the street and said 'you passed this person' if I think I would feel ashamed. Then I would fail them."

This measurement is *intuitive, and relies on the educator consulting their own affective state with regard to the learner*. The only group of educators for whom this seemed to be less important, were educators pursuing learner satisfaction. However, both of these educators were from Business or Finance faculties, which introduces another variable and makes interpretation of this phenomenon difficult.

8.4 Learning Strategy Orientation

Thus far, the previous sections have constructed a picture of the participants' context and background, their learning goals and the ways in which they recognise progress toward those goals. The importance of dynamic strategies in driving those efforts became apparent in discussing how students approach learning in general and, in particular, how they gained access to the strategies they are using. This section explores learner and educator perspectives on learner strategies and relates this information to the findings discussed in the seconds above. Subsections 8.4.1 and 8.4.2 provide an explanation of the strategy codes "open", "pragmatic" and "applied", and the apparent influence of background features on strategy orientation adoption. Subsections 8.4.3 and 8.4.4 deal with strategies that learners believed were carried over from their previous educational or professional backgrounds. Subsection 8.4.5 discusses learners with disabilities and the special awareness that some of these learners expressed around their learning competencies and strategies. The final subsection includes educator perspectives on learner strategies that were distilled from the focus groups.

8.4.1 Open, Pragmatic and Applied Strategies

Learner participants described their current strategies for achieving their aims and their module specific goals. While strategies themselves were rather mixed, 3 types of strategic "approaches" emerged from their statements: "Open Strategies", "Pragmatic Strategies" and "Applied Strategies". It is important to note that these strategies only represent a snapshot into the current experience of the learner and do not represent a static, or fixed trait or quality. Rather, they represent the whole of what was visible at the moment of the interview, with regard to where the learner had come from (in a professional sense), what stage of life they were currently experiencing, any confounding life circumstances and the usual qualifiers having to do with personal character, desires and needs.

Learners coded as having an "Open Strategy" a) were currently open to questioning their current strategies and b) actively seeking inspiration from outside of themselves. These learners tended to have more general than specific strategies. They also tended to struggle with the isolation of online learning.

> "I do like to discuss what I'm thinking and the opportunity really isn't there. I think, maybe, if I was discussing it more in a group, I might hear things, bounce ideas around and then come away and maybe just do one draft and then change it a little bit...I don't get to talk about what I'm keen on sometimes, and learn, just enthusiastic, and I really want to talk about it and there's no one to talk to. Sometimes, if I just get feedback, I find that I might take it differently to what is meant. And so, I'm like it would be good to discuss that, I think." - Harriett

Learners like Harriett find it difficult to cope when their social needs in learning are not met. Access to a community of learners would help Harriett, as she describes, particularly at the beginning, where she needs orientation.

Learners with "Pragmatic Strategies" a) already had specific strategies for *optimising* performance, b) were typically seeking the *easiest* path to achieve the aim, and c) generally looked only for *specific* advice from other people around them. Pragmatic learners tended to express more confidence around their learning and were, surprisingly, most eager to share their strategies with others. In gaining strategies from others, pragmatic learners described their behaviour more like information gathering, seeking out specific answers to specific questions from classmates and tutors.

> "I've found I learn well when I have very concrete examples of things, of how to play out key concepts. I've also realised that I am not terrible good at focusing on key concepts and I love going my own way, exploring my own literature and my own roots. But that's not what's expected here. I have to buckle down and be disciplined about what exactly I am being told to read." - Jaisha

Jaisha's comment is an example of how pragmatic strategies seemed to be organising around delivering what is expected.

In contrast, Learners with "Applied Strategies" appear to organise their learning around personal mastery. Such learners a) already had strategies for *maximising* performance, b) were typically seeking the *best* path to achieve the aim, and c) looked for both general and specific advice from other people around them. For example, Ralf spoke about utilising students who have previously studied the module to gain important information on key concepts. But he understands the difference in applying that strategy to his assignments, in comparison with what is necessary for the project work he is about to undertake.

> "Luckily, one of my colleagues I keep referring to did the module last year, so she gave me a head's up on what I needed to be doing and when. I think the biggest piece of advice that I got [from the forum] was to choose a subject you're interested in, to do the project on. And that's what I've followed and plus, it interests me...on the project module, you have to be very self-motivating. Whereas with a normal module, you have to have certain things done by certain times and read certain chapters by this. The diary for the project module is just a blank sheet, really." - Ralf

Learners with applied strategies demonstrated that they were choosing strategies to suit the task.

8.4.2 The Influence of Background on Strategy

Figure 8.13 shows a breakdown of participants according to background and strategic approach. The findings indicate that **the learner's background appeared to influence strategy, especially in combination with the overall aim.**

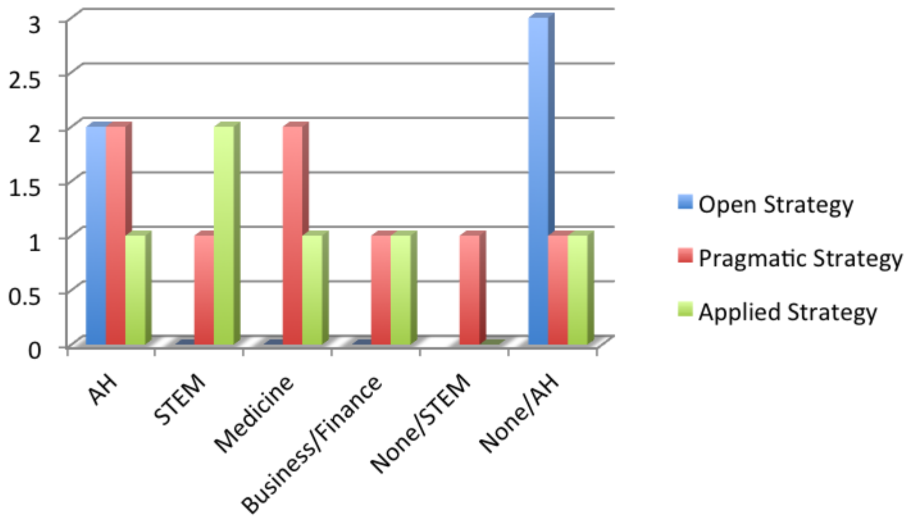

FIGURE 8.13: Learner Strategies by Educational Background

It is, perhaps, not surprising that learners who have the goal of personal development tend to do everything they know how to do in order to prepare themselves for the learning experience. They described activities such as looking at the full course materials, logging on to the VLE early, and completing school preparation on holiday. Learners who have the goal of qualification did not uniformly exhibit this behaviour. It depended on the learner's secondary goal, regarding the module itself, and whether or not the learner perceived the module as highly necessary for their future success.

However, many new students and those who had raised children or worked in a non-academic field before studying also found it difficult to formulate a strategy.

> "Especially those that have a job already working as a manager or someone in charge. They already have experience of having to be in charge, of having to be self-directed. I found that difficult." - Harriett

Findings suggested that **learners without previous academic experience relied on other learners to help demonstrate strategies that work**.

8.4.3 Strategies Carried over from STEM, Medicine and Finance

Learners with a background in STEM sciences, medicine and finance exhibited more pragmatic and applied strategies. Some learners even described very clearly how this background affects their current learning experience. Louise, who worked as a doctor for many years, described "list making" as a practice she adopted from her professional career.

> "I'm afraid it's a very medical thing. You know, when I started as a doctor 30 years ago, you had a bit of paper with lists of things you had to do and you just struck through them as you did them. I'm always a list maker." - Louise

Findings suggest that **the idea of a right and a wrong answer and the importance of grades also appeared to be a part of STEM strategy that learners occasionally questioned, when they found themselves in another domain**. Chris and Louise, who both worked with numbers and performance indicators in their professions, seem to be aware that these strategies might not be the only or the best that they could apply in their new domain.

> "I can only say that I am a product of 50 years of being results orientated." - Chris

> "Writing a humanities essay, it's a different skill. And my first essay, probably, objectively, went very well. But when my tutor advised me how to make it more suited to the humanities, I could see that there was a change. I used to write in a very sort of, staccato way. In science, often, you know, you state the facts and there's no waffling. Although it's not exactly waffling, I think, in the humanities you often bridge the paragraphs in a slightly different way." - Louise

In this example, Louise's quote is particularly interesting because her use of the word "waffling" supports her overall statement that she has left-over negative connotations with what she now claims are a positive strategies. This demonstrates how certain strategies are under-appreciated in some disciplines, and even *actively rooted out as poor practice.*

8.4.4 Strategies Carried over from the Arts and Humanities

Learners with a background in the Arts and Humanities, or who had no background and were currently studying in an Arts and Humanities module, were the only learner participants to report having open strategies. Participants with open strategies saw interaction with others as a large part of their own learning.

Participants with open strategies also tended to be more likely to see the increase of coherence in their work as a recognition of learning. In particular, coherence appeared to be related to the student's perception of their understanding of and contribution to the discourse. Coherence was described as a signal of learning, which was applied to non-formal or incidental learning moments as well.

8.4.5 Lessons from Learners with Disabilities

One student group that expressed a strong sense of self-awareness regarding their general study habits and strategies were learners with *recognised and accommodated* special needs and disabilities. All of the participants in this category (n=5) were receiving some type of institutional support that required reflection on needs and solutions for successful studies.

> "It was only at postgraduate level that I sought and obtained an educational needs assessment. Since studying with the OU, I have been meeting with a specialist mentor who is funded by the Disabled Students Allowance...Obviously my own interest in improving my self-awareness and experience has been an important part of this process, which is ongoing. Paying attention to what is difficult/-painful and what flows more easily, I have been able to see more clearly what I have always experienced." -Lane

Upon being asked how the mind-mapping tool her specialist mentor offered is impacting her learning, Lane said:

> "being able to target my time and energy on the most relevant material, because mind-mapping allows me to think about how things are related and what is relevant (I find this much more difficult with linear text). And I have limited effective study time/energy so it is important for me to be able to work smartly rather than trying to put in lots of hours. As a result I am not always struggling with burn-out in the way I was before. The mind-map software allows me to categorise the notes I am making, so I can put markers for incomplete notes, reference required, important point etc so I don't lose sight of those things because I can't remember them by myself. So I lose less material and therefore work more efficiently. The mind maps help me reconnect much more quickly with my work when I have periods of not being able to work and memory gaps. I don't have to re-read everything again like I used to have to before using the mind-mapping software. As a result I don't tend to need extensions to assignment deadlines. Before I frequently needed extensions which I found stressful asking for and felt a bit of a failure because of." - Lane

Lane also reported that her marks were more consistent, now that she was able to make better use of her time, and that the tools she was using helped to assist her memory in devising a clear path to success, with more manageable milestones. The emotional effects for her are also considerable.

"This helps me to manage anxiety and feel less anxious; which then helps with my concentration. I am more able to enjoy studying in a formal academic setting than I was before - this is a really big gain for me and comes out of being able to relax more plus not burn-out as often. Before, I loved learning but found negotiating the difficulties of formal academic study so challenging that there wasn't much enjoyment despite achievement. The mind-mapping software and knowing more about my learning process do not take away the challenges I have as a student, but they make them more manageable so that I can make the most of my analytic ability. I got a distinction for the last MA module (but not for the first module when I was learning how to use the software and had not yet found out so much about how to work more effectively) so I guess that is another measure of the success of the changes."

The purpose in sharing this entire portion of the focused interview with Lane is that it provides a very clear picture of how she could have recognised her problem in the first place (through inconsistent performance, anxiety, difficulty with linear learning, having to read essential materials several times, need for extensions, etc.). This maps to some of the educators' descriptions of their own indicators of trouble, which were described in the previous chapter. For example, students needing extensions and inconsistent performance was a general sign of instability in the learning process.

8.4.6 Educator Perspectives on Learner Strategies

Educators participating in the study were aware that some students make judgements about whether or not to devote time and attention to certain topics, on the basis of whether or not that topic will be represented on an assessment. Some educators choose to support students in making pragmatic decisions about their studies, while others choose to test the learner's own ability to parse large amounts of information. This particular aspect of pedagogy did not seem to be related to the educator's actual goal, but rather the educator's self-image.

Figure 8.14 describes the categories and subcategories that emerged from the data regarding educator self-image. For example, **Educators that described themselves as "innovators" or "frontiersmen" tended to place more responsibility on the**

Facilitator/Guide	Innovator/ Frontiersman
easing the path of learning	training cognitive skills
viewing learning motivation as reciprocal	viewing learning motivation as self-driven
focused on inclusive learning	focused on innovative learning

FIGURE 8.14: Categories and Subcategories for Educator Self-Image

shoulders of students to distil the most salient points of the lesson or module. Educators that viewed themselves as "facilitators" or "guides" tended to describe their own responsibility to ease the path of learning for a diverse group of students. When asked if he would facilitate a student in doing the bare minimum for a course they were moderating, one tutor said:

> "That's up to them. If a student is sitting in my office telling me that they are working full time and trying to raise several children or whatever, I am really inclined to advise that student on how to get where they want to go in the most expeditious way possible."

This included, for those who felt it was appropriate, advising students to drop a module because the student has determined that the workload is too significant to manage. One educator, talking about peer support networks, voiced concerns that students might advise each other toward unrealistic expectations and that it was necessary as an educator to inform a student when they see that the student has taken on too much work.

> "What you've got to remember is that choosing to drop a module is also a valid decision. There is no point in keeping a student here who cannot do the work. The better strategy is to understand why they cannot do the work and address that." - George

The learner's ability to "self-regulate" and control their learning process is often described as a secondary goal that is vitally important. However, it appears that it is mostly *implicitly* trained and tested.

> "One of the things you should come out with after completing any kind of degree is how to manage your own learning, I believe. So as the student progresses along their learning journey, I believe we should be less and less hands on in terms of how the student engages with the information, and leave that more and more up to the student...And on the forums, you'll have some students who are happy with the amount of work that they've got and you'll have other students who are not. And I am trying to tell these students you've got this knock on exam at the end and you should be selecting the most important information and engaging with it in a way that you feel is appropriate. At which point you get comments back from some of the students saying 'well, actually, this is not how I like to work. I like to sort of make sure I've understood everything and move on.' And I say 'well, I can always give you more stuff. Does that mean that you are going to try and do everything?' Part of the skills you should be developing is how to manage large collections of information and documents." - Ivan

Ivan's statement indicates that he finds fault with this type of learning strategy, as he feels it is ineffective in building a skill he feels is critical. However, not all educators agree with this approach. The following exchange between Ivan and Jeremy is an example of a disagreement that was commonly recorded during the focus groups, especially those with heterogeneous participants (in terms of goals).

> Ivan: "I do not see University as an educational provider of an educational service...My job is to create something that is going to support the development [of a] discipline."
>
> Jeremy: "In contrast to what you've said, my concern when I am teaching is 'is the student having a good time?' Is it fun? Do they like what I'm doing? I agree with what you've said about their motivation and their educational aspiration, but we can still do a very bad job of..."
>
> Ivan: "...I'm not saying we couldn't deliver a very bad module...My point was that it is reasonable for me to have an expectation that they want to study this, at which point it becomes my job to make it as interesting as possible. However, it is not my job to make it more interesting for people who have no intrinsic interest in that subject".

Ivan's statement exemplifies concerns raised in earlier chapters of this thesis that a market-style approach to University education is counter to its traditional purpose, when compared with other forms of higher education, including trade schools and Universities of applied sciences. This corresponded typically to a belief that the learner arrives at the institution with the motivation to learn whatever it is that they have chosen to learn. However, **educators that view themselves as facilitators and guides, see learner motivation more as a reciprocal event, which educators and should influence**. The focus group was a vehicle to explore these differences.

Educators like Ivan, who perceived themselves as pioneers or innovators in education and who are preparing learners to enter a specific discipline, tended to place more responsibility on the shoulders of the learner to self-motivate. **The only exception to this trend found in the data was when the educator reported a large class size. In the exploratory interviews, the class size where this tipping point occurred was 1000+ learners**. In the focus groups, this number was determined to be smaller, from 250+ learners.[7]

Educators like Jeremy, who describe themselves as facilitators, tended to more easily recognise student agency as being influenced by the educational context and his own behaviour.

[7]The exploratory interviews did not include any participants with a class size range of 150+-1000+ learners, so this effect was not previously identified in that first set of interviews.

Innovators and frontiers-people, as well as facilitators and guides, can be found in different faculties across the University. **When conflicts in focus groups arose, educators who viewed themselves as facilitators and guides tended to invoke the mission of the University as an arbiter**.

> "Then we have to remember that the mission of the OU is inclusive learning, and that means that we'll have lots of students from different backgrounds. And I do get your point, I hear from some students things like 'Oh, this is not at the Master's level' but I am more inclined to help those who...so the way we are designed we try to provide some challenges for those who are at that level, but we are designing the course so that those who are not yet at that level can access it. I agree with you, we should do something to ensure the high level of teaching and coursework, but we need to have balance". - Dave

Some educators viewed this type of accommodation as being unfair toward other types of students.

> "You have to think about the high performers too, and actually, the mid-range students. Where are they? How can they be supported? I would really love to understand that middle-of-the-road type of student. Where is the support for that student?" - Nora

> "My point is, we're often told we need to focus on the weaker students and I disagree with that. Actually strong students pay the same fees as weak students. They should have the same chance to explore their strengths as the weaker students have to have their weaknesses accommodated." -Ivan

These findings indicate that **some educators perceive a trend in supporting weak-learners at the University, which they feel has resulted (in part) from analytic data that has been used to reform or re-calibrate modules**. This activity of streamlining modules, which some educators perceive as "dumbing down" was also seen in the exploratory interviews.

8.5 Reflections on the Case Study Context

Context was such a significant part of students' lives that it consumed most of the conversation with students studying at the OU. Each story was uniquely challenging, making it difficult to understand how to pin-point real factors in recognising learning. One ever-present factor was change; in accepting new definitions of learning, in developing expertise, in choosing an individual target. This section describes some reflections on these changes, in keeping with the procedure of constant comparison [130]. These reflections led to shifts in theorising about educator and learner experiences with learning analytics, and how they can be improved. In particular, the importance of agency and having tools for improving visibility of that agency, became more apparent in the data.

8.5.1 Indicators of Learning

Reflecting on what educators described in the exploratory interviews as "learning" (see Figure 7.6) and how this mapped to learners' ways of recognising learning (see Figures 8.9 and 8.12) brought up several interesting themes in the data. First, educators and learners have to be receptive to information for it to inform their judgements about learning. If they trust their intuition, this is perceived as a good tool for recognising learning and it is used. If they trust data, this is perceived as a good tool and it is used. **Learning analytics researchers and developers will need to build trust for their tools to be perceived as *good* tools for learning.** Second, educators have more sophisticated ways of describing what they view as learning. For example, educators delineate between different categories of social relationships and their importance in recognising learning. **Learners did not describe their *relationship* to other learners and what that indicates about their learning.** Only in comparison with others, did learners see how others frame their learning journey. Educators saw many more indicators of learning by looking at the success of communication and interaction in the classroom. This birds-eye view may also be interesting for learners, based on what they feel is important about issues such as coherence and accessing discourse.

8.5.2 Transition and Change in Recognising Learning

In the data, stakeholders agree that goals and strategies change. In addition, some indicators for learning have qualifiers that are known only to the individual and which are also changeable, such as "better than..." and "more than...", or "good enough". For example, having a specific grade target or class percentile is a threshold set by the individual. After the first focus group, I realised that I had not noticed these qualifiers and inquired after them. On reflection, I realise that this is because I was simultaneously interpreting them for myself or assuming that some objective value could be given. At this point, more attention was given to qualifiers in the focus groups and focused interviews, and when they were mentioned, I asked the participant to tell me exactly what that meant for them.

8.6 Chapter Summary

This chapter described the context of the Open University as a case study. The Open University invests in analytics, has significant expertise in the field and could benefit considerably from its insights. As such, the OU provides a suitable environment for examining the impact learning analytics is having, and seeking ways to leverage and improve those effects. The first section of the chapter described the Open University's interests in learning analytics, and provided a description of the participants, procedure and processes of analysis involved in the study.

The second section discussed findings related to goals and goal orientation. Findings support indications from the exploratory interviews that educators' goals are associated with the practicalities and ideologies of their departments, as well as the Open University. Learners tended to express two types of goals, one higher aim for their educational trajectory, and one for the module. Findings indicate that the learners' backgrounds were important in orienting them on a goal. In particular, the findings suggest that learners seeking qualifications as their primary aim express more module specific goals that may not be the same as their aim. The third and fourth sections address how participants recognise and evidence learning, and the strategies they use to influence the learning process. Findings indicated that transitioning learners, moving from one domain to another at the Open University, were able to describe and discuss more strategies than other learners, but may not know how to incorporate them all into their studies. Findings also indicated that ways of recognising and controlling learning are shared more commonly among students with a certain educational background, which supports educators' perspectives from the exploratory interviews. The findings of this chapter are important for interpreting why a certain affordance might be particularly apparent and attractive to learners or educators with a specific background, goals or strategies. Participants' statements indicate that their motivation to achieve, the recognition of their achievements and the ways in which they control their learning processes are connected. Certain information will be valuable or not, depending on its position in the "hierarchy" of priorities that students have. The next chapter will discuss how learners and educators perceived affordances in using certain types of learning analytics' data or technologies to support their practice.

Chapter 9

The OU Case Study: Affordances of Learning Analytics for Improving Practice

He who loves practice without theory is like the sailor who boards ship without a rudder and compass and never knows where he may cast. - Leonardo da Vinci

Context-related findings presented in the previous chapter suggested that learners at the Open University have considerable knowledge and skills from other professional, personal and educational undertakings. Learners and educators at the OU believed that this background shaped their learning strategy and its influences are also apparent in their strategy choices. Learners participating in the study were able to describe how this process occurred, particularly when they are were experiencing a change in their domain of engagement (from one type of faculty to another, or one profession to a very different course of study). Participants also discussed the role and importance of different figures in education, such as other students, tutors and the Open University as an entity, and the impact of those agents on their practice. Findings indicated that **educators and learners can perceive, even if they do not exactly name, a problem of competing student goals "in the classroom" at the Open University**, which is difficult for students and educators. Each participant had an understanding of what that diversity means for them, in interpreting means and averages, learner progress, participation and engagement of learners.

The focus of the current chapter is to present the affordances that learners and educators described in using learning analytics to support their practice. Affordance Theory asserts that objects can be perceived in terms of their actionable properties, how an object can be manipulated or used. During the focus groups, educators and learners discussed the potential of learning analytics (the object) to perform certain functions (affordances) [21]. Affordances were examined in terms of the metacognitive activity that the participant expressed in discussing the given affordance. Particular attention was paid to how having that information would impact a particular strategy or approach to education, teaching or learning. Understanding the role that particular needs and interests play in using learning analytics, it is easier to understand their mediating potential, and thus the ways in which that potential can be nurtured.

A statement was coded as an Affordance when the following subcategories were present: a direct reference to a type of digital data that the participant believed would be possible to capture using the technologies discussed (coded as "Measurements"), along with an *application* for that information that would be *useful* (coded as "Intentions"). When the participant made an *explicit connection with their own practice*, this was coded as "Metacognitive Activity". These codes were not mutually exclusive and include subcategories that will be discussed in subsequent sections. Rather, combinations of codes revealed the findings within the transcripts, which are presented in this chapter. The perceptions and influences that participants described about their context will be interwoven throughout, to help illustrate how different types of information and technology trigger metacognitive responses in learners. Examining the weight of certain affordances over others, as was done with the frequency analysis in the previous chapter, would potentially lead to a false impression of perceived utility. As was previously discussed, "familiarisation phases" with new technologies sometimes limit what participants can imagine is possible [24]. Instead, the chapter compares and contrasts the perspectives of learners and educators, along with their various departmental, pedagogical and strategy positions.

The sections are organised by *sources of data and measurements* that participants discussed, with an exploration of their *intentions* and any related *metacognitive activity* triggered by the discussion about the participants' own practice included in the body of the section. This reason for this choice is that participants discussed the subject of learning analytics by category of data in their focus groups and this division illuminates the more subtle differences in their perceptions of how to use the same type of data. In addition, it should be noted that affordances often link together to to support a specific intention. This intention is highlighted within the text in boldface. *Evaluating learning* *design*, while an important affordance of learning analytics, is a large composite of affordances of learning analytics. Thus, the connection of learning analytics to learning design features in several sections and subsections below.

The first section addresses affordances related to demographic, background and legacy data for understanding learners' prior experiences, and performing analyses on different groups and cohorts of students. Section 9.2 describes the many affordances that educators and learners perceived involving data from the VLE. This included general affordances, such as "Testing Assumptions" (see 9.2.1) and "Predicting At-Risk Learners", as well as specific affordances for tracking individual student behaviour (see 9.2.3). Section 9.3 outlines the affordances that educators and learners identified in using social network data and social analytics, primarily for exploring the impact of others on learning. Subsections 9.4 and 9.5 address learning analytics based on non-traditional sources of data in higher education, sensory data and web data external to the VLE. The final sections offer some additional insights about the way that participants spoke about learning analytics and their impressions of what is possible.

9.1 Affordances of Demographic, Background and Legacy Data

According to educator participants, the Open University has a considerable wealth of information about students. Participants reported that in some faculties and at some student levels, it is possible to obtain information about students' backgrounds and previous experience from applications to particular courses of study or registration forms. From student feedback forms, participants said that they had access to some limited information on learners' reasons for withdrawing, as well as written evaluations of their modules. Years of collecting valuable student data means that the Open University has legacy data about previous presentations of modules [96]. While it is not within the scope of this thesis to describe in full the data sources that are available to staff at the OU, it is important to discuss *perceptions* on how this information can be used to support student learning. In nearly every case, this data is combined with other data to produce meaningful insights. The affordances listed in this section, are those which rely *primarily* on the type of data that is named in the section title, in order to be effective in fulfilling the *intentions* of the participant.

This section is divided into two parts. The first part examines direct and indirect affordances of learning analytics for supporting complex sociological studies. The second part explores cohort-level comparisons, on the basis of demographic, legacy and other types of background data.

9.1.1 Complex Sociological Studies

In combination with performance data and other information, in particular, from the VLE (see 9.2), educators saw opportunities to use learning analytics to **understand more about how the experience of education is different for different groups of people.** Social effects of problems commonly noted in society, such as racism, sexism, poverty and other forms of discrimination or exclusion are believed by some educators to seriously influence the educational experience [157]. Educators participating in the study, in particular those in the Arts and Humanities and Social Sciences, were more likely to *report awareness for these effects in their classrooms and viewed learning analytics as an opportunity to explore them.* However, these educators were frustrated at the lack of *integration* of data.

> Elizabeth: "It does seem like there is information coming from one direction, but it doesn't join up with data coming from a different direction...you can't look at a particular package of students. So, for example, if you're concerned about students from a lower economic background or of a certain gender or ethnicity, you can't break that data down in any way. They said, 'Oh well, you need to go back to the faculty data crunchers for that kind of data'. No, it should come from the same place. We should be able to dig into the data and see more detail about particular groups. So if we're concerned that the module is not attracting women, for example, just for the sake of argument. Can we somehow track the behaviour of female students through the data? And the answer to that is 'No you can't, because unless you get it down to the student level, you can't do that.' If we're going to be designing courses that have a broad appeal across gender and ethnicity, disability, etc., we need to be able to extract that information and we can't."
>
> Researcher: "And if you had that information, what would you do with it?"
>
> Elizabeth: "That's a good question too. In some ways, we need to be able to tease out what it is that enables success for that type of student."

Recognising that some learners may be at a disadvantage, Elizabeth and several other educators felt that it would be possible to better **understand and accommodate**

students with special needs using learning analytics to understand their experiences. One common complaint with regard to this point, however, which was particularly voiced by educators in the Arts and Humanities, Social Sciences and Business, was a *lack of qualitative data.*

> "I can get access to data, but what is missing for me is the qualitative data, in the sense that my module is an introductory module, so the students don't necessarily know if they want to go higher. I might have 100 students and in the first week, there will be a big drop off. And I don't understand why they are leaving. I get the data, But I don't get the qualitative reason why they are leaving. Are they leaving because of a personal reason, because the course is not good, because they didn't see a way into the materials, it's three different things...In terms of numbers, I can get everything I want. In terms of intentions, I don't have that information." - Dave

For Dave, some key questions that could be critical for his practice remain unanswered due to what he perceives as a gap in the institution's knowledge about its learners. Implicitly in Dave's statement is a desire to **act on student intentions**, which is a common feature of educators who have the educational goal of satisfying learners. Getting information on intentions is problematic, either because it is not being collected, or it is not being integrated.

While frustrations with the lack of integration and access is understandable, given the *proximity* these educators have to answers they feel they need, there are real concerns behind integrating data from multiple sources. As one participant explained:

> "The problem is not that we don't have the data. The problem is integrating that data. There's a real privacy concern there that integration makes it possible to recreate the data set." - Viola

Viola's statement refers to how integration of multiple sources could provide enough vectors for someone to effectively identify individuals in a large anonymous data set.

Findings indicate that **data privacy concerns are a major set-back in providing meaningful insights on demographic data for educators**. This is a concern that has been noted in other big data projects involving sensitive information, such as in the field of health care or banking, in which the benefits and risks are significant. Interestingly, students did not perceive any particular benefit in sociological studies. Rather, they tended to view their differences as being goal and motivation dependent, rather than cultural.

9.1.2 Cohort Comparisons

Using legacy data from previous presentations of modules and academic years, Staff Tutors and Module Chairs, in particular, spoke about using cohort-level comparisons to **help make important decisions about learning design and pedagogy.** Cohort comparisons represent only one part of this complex application. Other factors that educators use to evaluate learning design are included in affordances addressed in subsequent sections.

One affordance of legacy data, that was described as useful in its own right, is to **understand which skills the participants should have developed before they reach their current module.**

> "I teach at level 3 and I can see exactly where they dropped off...What I can't do is to see how the student did and what their marks were for the prerequisites." - Ivan

Ivan was not the only educator in his focus group that would have appreciated understanding the *knowledge* background of the learners. Dave, Lucy and Jeremy all agreed that **having more information about the skills with which a student comes to the module, leads to better interpretations of the performance of those students.**

Another common affordance for cohort-level comparisons, with regard to legacy data, was to **gain orientation in the faculty.** Ken, a relatively new associate lecturer, and Elizabeth, a former associate lecturer, shared their experiences of being without orientation early on in one's career:

> Ken: "You're kind of in the dark. And you can see who's passed the TMAs and the EMA and you can sit down and analyse that, but not much else."
>
> Elizabeth: "I know what you mean, I was an AL for 15 years before I was central staff. And yeah, as an AL you're kind of in a different position because you only get the data that sort of relates immediately to your group. Trying to see the bigger picture is often quite difficult."
>
> Ken: "Exactly."
>
> Elizabeth: "And sometimes that matters and sometimes it doesn't. It's one of those things where if you're in contact with other tutors and you can say 'Well, how's your group doing?' you can kind of get a picture of where the cohort sits. But if you aren't in contact with anybody else, you are, as you say, totally in the dark. Sometimes it would be nice, even if it it was just beginning, middle and end, to get a picture of okay, 'You have x amount of people in the cohort, the average mark for the TMA was that, just even basic information so you could see how you group sits within that. How that would impact teaching, I don't know. As a lecturer you are dealing with the individual students and as a central academic, you're dealing with cohorts. I think it's a slightly different dynamic."

Rather than being part of a *specific* teaching strategy, seeking cohort-level comparisons appears to be more of a *general* teaching strategy, similar to learners who compared their own marks with those of other students. The overall health of the cohort could be quickly examined by referencing a few measurements, such as the percentage of withdrawals from the module, overall performance and number of students, for example.

However, Ken and Elizabeth agreed that most educators at this level lack orientation on how to make complete sense of cohort-level studies.

> "It should be longitudinal, it should have reliable data over time. And it should be presented in a way that makes sense to module teams to work with. That it's something that someone without a degree in maths can understand." - Elizabeth

Across the findings, this appears to be a *generic* critique of learning analytics tools and technologies, particularly arising from participants without a background in advanced numeracy or computing. This particular finding will be discussed in more detail in 9.7.7.

9.2 Affordances of VLE Click-Stream Data

For providers of online or blended education, one of the most readily available sources of information is from interactions and activity within the Virtual Learning Environment. Students must engage on the platform to perform certain functions, such as accessing resources and submitting assignments. Though no one participating in the study suggested that click-stream data can create a *complete* story of learner experiences, it appeared to be a common perception at the Open University that this information is useful, at the very least *to the Open University and, in select cases, individuals within it.*

Not surprisingly, many of the ideas that educators, in particular, were able to generate for using learning analytics in their practice were related to **predicting and classifying learning behaviour**, through analysing their VLE behaviours (and in some cases, demographic profiles). For educators, the majority of affordances fall into this category. This section explores the main affordances that educators and learners perceived in using VLE data to support their practice.

9.2.1 Testing Assumptions

The most commonly mentioned, if rather general, affordance for having access to click-stream data and other information from the VLE was to **test the educator's own assumptions.** Inside of these types of affordances, the measurement, intention and metacognitive activity appeared to be self-contained: the meaning was assigned by the educator, as was the intention, and the technology had more of a *facilitating* than enlightening role. Jeremy, who had experience in MOOCs, as well as in other types of digital pedagogy, described a theoretical tool that could serve this function:

> "I imagine having my screen with all of the students and maybe one student is blue and another is green, indicating a certain type of student pattern, for example. So, I can see the structure of the cohort and the dynamics of the cohort, and within that there is still the individual student. I want to improve education and I think that's the best way to do it. I think analytics can support that."

As Jeremy was describing his tool, the other participants in his focus group, regardless of their goals, were interested in such a prospect. Later on in the focus group, when asked "who knows best", when it comes to interpreting learning analytics, the participants had the following exchange.

> Jeremy: "I don't think anyone knows best."
>
> Ivan: "I agree."
>
> Jeremy: "I think we all have different perspectives, we all have different opinions and it can all get very dynamic. If I had the choice, I would not have some top down, 'this is the best'...I would make it sort of automatic so people can access it and play with it and do creative things with it."
>
> Ivan: "But that's why I think your vision with the screen and all of the little dots on it, that's very appealing. Because as well as the screen with all of the little dots on it, you could have a column down the side that says these are the features that have been incorporated in this model."

Ivan's statement describes a potentially useful "top-down" aspect of learning analytics, as a framework or model that could have "standardised" measurements. The combination and interpretation of those measurements would be manipulated by the educator. Ideas similar to those Ivan and Jeremy discussed appealed to most of the educators, even those without advanced numeracy. Findings indicate that, for testing assumptions, educators would appreciate semi-structured "shell tool" of different indicators that could be bundled together using the educators' own systems of recognising learning. By the description of "shell tool" it appears to be described as **a tool that would incorporate**

some different models of learning that educators can "play" with to learn more about learning analytics.

Jeremy further indicated that he had a practical interest in analytics because he believed that, through learning analytics, it would be possible to **create different "streams of educational content that will allow a greater number of students to manage it on their own."** As a believer in the philosophy that the OU communicates, Jeremy, who focused on learner satisfaction, believed this would resolve an ideological issue for him around accessibility and personalisation in learning.

However, it is clear that Jeremy views technology as enhancing his role, rather than replacing it. Participants in the focus groups that described themselves as "innovators" and "frontiersmen" tended to speak more about the risks of "top-down" analytics, in which the measurements and intentions are not self-contained, when speaking about wanting to test their own assumptions. However, the reason for this could be that they perceive their assumptions as necessarily *challenging* commonly held beliefs in education that *required* a new perspective.

> "I imagine it as something really dynamic, so patterns, the dynamic patterns are interesting too, to me. There is an example from France. They have about half a million students who are learning maths and they use this kind of analysis of the different pathways they can take based on personality and some kids will want to go this way and some will want to do whatever first and this that and the other. And that is incredibly interesting. And they've done that for some years now. And so, with our students, the analytics could show that even though they can manage this sort of linear progression, maybe they would like to learn differently." - Jeremy

Jeremy's sense of optimism and enjoyment around having access to data is one that was shared by participants who regularly interacted with analytic data, or who had large class sizes that made testing assumptions more practical. The findings indicate that **testing assumptions is a type of exploration, described as play, that educators believe would assist in their acceptance of learning analytics** as a tool for improving their practice.

9.2.2 Predicting Weak or At-Risk Learners

Educator participants, in particular those who were familiar with learning analytics initiatives at the Open University (through proximity of departments, personal contacts in other departments, etc.), all discussed the affordance of learning analytics to help **predict weak learners.** Feelings were generally positive that having more information about learners is good, even when it is partial information. As retention was described as one of the simplest metrics for the University, **improving retention** was perceived as a measurable impact of this affordance, which is *concise and easy to communicate*. In particular for educators with large class sizes, retention was the most reasonable measurement currently available. There was some difficulty, however, coding retention as a measurement or an intention, with regard to this particular affordance, because many educators described it as both. Findings suggested that, **as a proxy for learning, retention was an important measurement, one that became an intention as participants described how they would use learning analytics tools and technologies.** Once again, it should be noted that the Open University was beginning to become fully aware of its poor financial situation [1]. Staff will have had some strong opinions about this when speaking about retention, in particular.

When discussing how these predictions would and do impact *practice*, only educator participants with class sizes of 250+ students identified a *personal* use for that information and how it could be incorporated into their own existing strategies. Predicting weak learners was viewed as an efficient way of **helping educators to distribute their resources and keep students involved.** Jeremy noted a simple reality that makes this kind of affordance particularly valuable.

> "No one educator can engage with that many students at one time."

To help them cope with a large number of students, educators with larger class sizes felt that this was a positive tool to help them ***quickly*** **intervene with at-risk learners**. This is consistent with the literature on educator perspectives on predictive analytics [96]. Findings indicate that **the *speed* at which learning analytics can help educators perform a strategy they are already using is its greatest added value.**

Among educators who had more negative or neutral feelings toward predictive analytics, there was a general fear that focusing on "weak learners" could lead to "educational triage" that would be damaging to the educational experience.

[1] https://www.timeshighereducation.com/news/open-universitys-second-chance-model-may-already-be-gone

"I think there's a danger of...there's actually been some good papers on this...I think someone called it 'educational triage', where you're saying 'Well, these ones aren't worth saving, these ones are, so we'll intervene here, but not there' and I think there is a very cynical financial, almost sinister financial aspect to it, where you intervene because there's money to be saved. And its not about the student anymore, its about the financial picture behind it and I think that is totally and utterly wrong. There's a very fine line to be drawn at what point you are doing it for the student's benefit and not for the financial benefit and I don't think the two necessarily coincide." - Elizabeth

Elizabeth may be referencing research on the *No Child Left Behind* program in the United States of America, which assessed whether or not high standards testing was increasing learning gaps in the lowest performing schools [158]. One suggestion of where that "fine line" might be was in whether or not the University's interventions would also support students at all levels.

George: "I can see that it's useful to, I don't know. There is something in that red, underlined thing of 'at-risk' that would be really compelling to any educator and my fear would be, what about that student that is just lacking in confidence, or needs a push to do even better?"

Sam: "Those students in the middle."

George: "I was that student!" (both laugh)

Sam: "I was that student too, and maybe this is why I feel, responsible for those students, the average, mediocre... (both laugh). Quite honestly, I do care about that student and I am rooting for him."

Discussions about "weak learners" often merged with shared concern for **identifying the lost, "mid-range" student**, an affordance shared among many educators *and learners* with regard to predicting weak learners. Educators felt that if it were possible to model and predict learners who were under-performing or at-risk, it would also be possible to **identify learners who were performing erratically or who seemed**

to be on a downward trend. Drilling down on predicting weak learners, Lucy, who already had experience with learning analytics initiatives, was able to describe an affordance for **early warning signs of trouble.**

> "One of the first things we did was look at students who hadn't accessed the course before it started, because it's totally online if you don't get on at the beginning, you'll fall behind. We then had the tutors look at this data, which was unfortunate because the tutors weren't actually being paid at this point, they didn't tell me this, they agreed to do it. And then they would phone up the individual students and find out, was it because they didn't realise it was online, or did they change their mind, or..." - Lucy

Lucy also felt it would be possible to look at the number of *additional credits* a learner was taking, and learners' *banked assessments.*

Educators with the role of module chair or senior lecturer tended to perceive the biggest beneficiaries of *predictive analytics* as the tutors, who would ultimately be responsible for intervening. Tutors also felt that they would have the greatest gains from predictive analytics, but typically, this was described in terms of *imagined* needs rather than current needs or strategies.

> "If I had a lot of students I was managing and I was worried something might slip through the cracks, I could imagine it." - Georgia

> "If you were insecure, it might provide you with a potential way to test your, test your assumptions." - Sam

Lucy's previous statement offers a potential explanation for this: that tutors involved in her pilot were not being compensated for some of the additional work they were doing to help validate learning analytics tools and approaches. Tutors reported finding predictive analytics useful to do their jobs better or more efficiently, but only under certain circumstances such as class size, or level of experience. It is possible that tutors were initially alienated from wanting to support an initiative that they perceived as potentially increasing their work-load with no immediate benefit.

Predicting weak learners was such a common topic of conversation in the educator focus groups that the decision was made to ask students explicitly about it as well, to determine how they perceive this particular affordance. Students who were prompted to discuss the value of predictive data in the focus groups had mixed feelings about whether tools notifying them of their "status" would specifically help them. This data was more viewed as being "nice to have". Only a small number of participants, however, feared that students could be potentially *demotivated* by knowing whether or not they fell into an at-risk category. Additionally, this was typically described as a *potential* concern someone could have and not an *actual* concern of the participant.

Educators also considered the potential demotivating effects of tools that would issue students with any kind of "at-risk" label. One educator described herself as the type of learner who "never read, always asked for extensions and only ever worked for the assessments". She felt that if she had received information that said that she was going to fail, *too early on before her own strategy had a chance to take effect*, it might have tipped her toward dropping out. This, combined with other student perceptions of predicting weak learners, indicates that the **timing of interventions based on predictions, if they are student facing, matters.**

9.2.3 Study Tracking

Affordances for tracking study behaviours were related to either tracking one's own activities (self-tracking) for purposes of **self-discovery and monitoring, or modelling learner behaviour.** As modelling learner behaviour has several purposes that are ultimately affordances in their own right, this subsection deals entirely with self-tracking. Most educators that participated in the study did not consider using VLE data to understand learner behaviour at an individual level. The two reasons proposed were that it would be too intrusive or lacking in meaning.

> "I don't want to identify particular students, I think that's the wrong direction to go. I think we need to be able to identify groups of concern and to be able to track patterns through those groups."
> - Elizabeth

> "I would see that somewhat as prying, particularly when someone is dropping out. However, at the cohort level, if many students are dropping out, then you know it has to do with the module" - Drew

> ”You don’t want to get into counting data, which is identifying names. It’s not a matter of names. The danger with that is that students start to feel like they’re kind of spied on and all the rest of it. Over time, because it’s the old story of you need to be looking at trends over a period of time, not only over one group, then I think it’s really helpful to start to see patterns. That’s in terms of both your group, but also quite obviously, how your group compares with the overall.” - Ken

Educators also expressed some concerns over whether or not students would be able to make sense of that data for themselves.

> “I think students who already have developed habits in their learning may learn something from looking at all of that. Would it be really useful? Would it be a distraction? I tend to think the latter, simply because I am not quite sure what could be done about it.” - Dana

> “If I’m kind of pushing myself to do this, like I know a lot of my students are, and I am kind of, breaking through, however difficult that is for me, might it push me beyond the limits of my capacity? I am seeing this example and maybe that person has more time than me, more money or support or whatever.” - George

In the last part of George’s statement, he referred to whether or not the student would then be able to compare their study plan with that of a “successful” student. Participants debated this idea in the context of the affordance described above, using learning analytics for “predicting weak learners” (see 9.2.2).

Some learners, however, felt that having a long-term record of VLE data may help them to **understand their own patterns of activities toward their goals**.

> "One idea I have had that I dont think we touch on is it would be good if the OU developed some sort of study planning tool where buy you can have it as an app on a windows phone apple phone or iphone and you can plot your study of each topic based on the recommended hours and extra activity and it sends a notification to your phone and emails you to remind you of your study plans each day this would enable student to better plan their studies." - Jonah

In a completely separate focused interview, Harriett proposed a similar tool and elaborated on it.

> "I think that could be a good reminder of where you should be. And then, it could even have a few questions. So that, when you get to that point and it says 'try and access this now', or 'you should have accessed this', that would be helpful I think." - Harriett

Harriett emphasised several times a particular standard that could be communicated to the student using learning analytics, to help keep the student on track by ensuring they are moving through the material in an effective way. She mentions that her module included a pre-assessment, which she enjoyed. Her only comment was that it was basic and that "something a bit more in-depth" would be interesting, like reflection questions.

Jonah's statement implied that each student would develop their own study plan and that the learning analytics tool he would find helpful would utilise his VLE data to help him understand his progress within that plan. It appeared important to many learners in the study, regardless of their goals or strategies, that those **goals and strategies are personal and unique**.

However, other participants argued that personal conditions are also unique and sometimes immovable. While a person may not always have the perfect conditions for working, it is possible to learn to adapt.

> "I guess the whole point is, you're studying when you're succeeding. And even if that means, you know, you've got your kid screaming down the monitor and you're exhausted or whatever. It's about yourself, and the direction you understand this is going in." - Grace

Overall, the findings suggest that **affordances for study tracking are most useful for learners with a concrete goal, who are able to create time and space to consciously monitor those goals and who feel prepared to act on that knowledge.** The only students participating in the study with that profile were students with a disability, for which they were receiving support, and graduate students who experienced skills audits. These students all believed their general study habits had improved as a result of that support and they were interested in having access to additional information.

9.2.4 Recognising Patterns in Behaviour

Most dialogue about learning analytics and learning design had to do with **recognising patterns in behaviour within the VLE.** Patterns were typically related to performance across TMAs, behaviours accessing resources and participating online with classmates, similar to what educators discussed in the exploratory interviews.

> "For example, I would be very interested to know which students did the first TMA, which did the second TMA..you know, all of the analytic stuff you can do, just to figure out some patterns of behaviour." - Jeremy

Once patterns were recognised, educators felt that they would have the possibility of intervening and then testing the impact of their interventions on those patterns.

> "I did a project with my level 2 module last year where I was looking at one particular intervention we created at a point in the module that we know is an issue to see can we actually intervene at that point and try to ease students through that difficulty." - Elizabeth

Identifying pinch points and providing extra support during those phases was considered to be valuable for the purpose of **improving student retention**.

Some educators felt that **VLE data could also tell you something about the mindset and intention of learners**. Lucy, who was the participant most familiar with learning analytics initiatives, shared some of her early experiences using learning analytics to adjust a module.

> Lucy: "We had a questionnaire and we picked up, for example, that they hadn't been taught how to annotate online, or we picked up something else where we can put something in [an intervention] immediately...they still dropped out. We were also part of this program OU Analyse, so we looked at clicks. And we saw, they seem to be dropping off after this block, so we gave that block more time. And even more dropped out (everyone laughs). The loss of these people, they weren't being retained, the retention was about 10%."
>
> Researcher: "So how are you interpreting that? What do you think is happening there?"
>
> Lucy: "They get to a particular TMA which is, which actually accounts for 25% of the exam component, they obviously have been taken ill or they decide that they can't do themselves justice. So they bank the previous ones and come back next year to do it properly."

Despite her early failures in using learning analytics to improve retention, Lucy and two of the other focus group participants felt that **seeking new types of patterns in the data could help to more correctly calibrate and test predictions**. Seeking patterns as an affordance was mentioned both generally as part of an intention to improve learning design, and as a vehicle through which to fulfil other more specific intentions, described in the subsections below.

9.2.5 Identifying Potential Anxiety

One pattern that educators had already perceived as being important had to do with the feeling that some students were overwhelmed and that this was visible in their behaviour on the VLE platform. Educators felt that this information could be captured by learning analytics tools and techniques to **identify potential areas where learners might behave erratically or counter-productively.**

> "A student who is doing really well on some assignments, and then terrible on others... I would see that as a sign that something has gone wrong. Clearly, something has changed in the learner's life circumstances or goals. I have to find out what that is." - George

> "Some of my students have been very late to access the materials. They only ever go onto the VLE during work hours or on weekends. Sometimes, I can just tell by their level of experience with technology. They don't have as much computer access as they need." - Nora

> "I was the type of person who worked late at night, early in the morning, whenever it suited me, really. So, I wouldn't necessarily think that, has any kind of, knowledge that you can gain from seeing that. Maybe though, you could at least suggest that the student try to bring some structure to their study habits. They might listen to you, they might not, if you tell them enough times how helpful it can be, perhaps they will listen." - Justin

Changes in learner habits, certain types of erratic behaviour and signs of disadvantage were all captured by educators in an anecdotal fashion, a task which they also believed could be much better facilitated through learning analytics approaches. Rather than relying solely on the educator's own observational and interpretive skills, learning analytics could **support the educator in recognising more subtle changes over time and earlier than the power of human reflection might afford.**

Educators spoke about students taking too many courses and overestimating their capacities as additional stressors that can produce anxiety. While the University offers flexible pathways to avoid losing credits through banked assignments, for example, educators worried that extensions and banked assignments might be simply forwarding the problem to a later time and place.

Ivan: "Our experience has tended to be on that, is that students don't tend to improve. So it is very difficult to tell if life has just gotten in the way or if they actually thought they could do better and actually they couldn't."

Researcher: "So, the ones that are coming back are coming back with the same level of competence that they left with."

Lucy and Ivan (in unison): "Right."

Jeremy: "I think you'll find the same poor decision making. I had a number of courses that I was into that were very popular and what we found was that we had some students who were getting it for free, an entire course of stuff. And they were getting all kinds of other courses for free as well and all at the same time. So they would have 60 points worth of stuff."

Jeremy, Lucy, Ivan and Dave, all of whom have different over-arching educational goals, were able to agree that students need to be supported in how they can *improve* their study habits, as well as how they can *continue* their studies. When asked if students who bank assignments often return to their studies, each educator felt confident that they do. This means that students who may have withdrawn, but who have banked assignments, are excellent targets for intervention. Findings suggest educators felt that learning analytics could **help learners to identify habits that put their studies at risk, and provide them with a support framework to change them,** so that their next learning experience can be more successful.

9.2.6 Understanding Withdrawal

One of the most important aspects of retention for educators was understanding *why* learners leave an educational experience. Using learning analytics to **recognise disengagement** was, therefore, another common affordance related to improving learning design. While most educators and learners agreed that the decision to withdraw is often personal, recognising when the student is *starting* to disengage could **provide educators with more time and resources to help the student in time.**

> "Often times, you'll find that the problems, students let them get out of hand, or are afraid to say something. I think it would help us to find those students more quickly." - Dana

Staff tutors, in particular, saw many opportunities for applying learning analytics to recognise disengagement and other early warning signs. For example, studying student extensions, much like Lucy's statement about banked assignments, was believed to provide information about a learner's time management skills. Looking at the pace and timing of extensions, in comparison with that student's typical behaviour, staff tutors felt that one could gain a feeling about the student's workload and how they are coping.

Findings illustrated that being *overwhelmed in general*, was viewed as the easiest explanation for why students withdraw. While the University may not be able to help the student cope with every situation they might encounter, most participants felt that the University could do more with learning analytics to help learners manage their studies more efficiently.

Learners, perhaps unsurprisingly, did not perceive any use for learning analytics to help them understand their own reasons for withdrawing. In considering whether this information could be useful to the *University*, most learners felt that there would not be much that the University would be able to do, short of *resolving some of the foundational problems that prevent the development of good habits from the beginning.* The major classes of problems include funding, both tutor and learner familiarity with technology, and more contact with other students.

> "If I got funding for my daughter to go to nursery... my tutor being a better teacher, that's the kind of thing that would make the biggest difference to my education."

> "I've had issues where one [tutor] was insisting he had the paper TMA's submitted by post. So she [a classmate] posted it and she didn't receive her results"

> "I think maybe actual facilitated discussions would be really good. You know, getting people together once a week for an hour to talk online. With a focus, a simple, clear focus to talk about something. I think that would be really helpful. You just learn so much by talking to other people."

Findings suggest that **withdrawing from a module is a personal decision that learners typically perceive as resulting from a lack of resources, rather than a lack of study skills.** Educators have the benefit of being able to reengage with students after they have returned, conceivably when life conditions have become more favourable to studying. **Educators' perceptions are that a lack of study skills contributes to the overall feeling of being overwhelmed, which then results in the student withdrawing.** They note this in that learners returning from having taken a break, rarely exhibit improved learning skills, even when life conditions have changed. The shifting responsibility that was noted in the evidence, between the impact of skill and strategy development *versus* the impact of life conditions indicates that the reality is most likely somewhere in the middle.

9.2.7 Classifying Learners

As was noted in both the exploratory interviews and the focus groups, educators classify learners to **help understand learner trajectories, to target the right materials at them, at the right time, and to identify learners with special needs or concerns.**

> "So, [Jeremy] describes his screen and you have a point for each student and so and so... so according to this, there is lots of data that is being collected. Has any of this been put through a classifier?" - Ivan

Ivan's statement is representative of those educators who had extremely high confidence and experience in advanced numeracy, either due to their domain or their interest in computing. The experimental nature of his suggestion suggests that classifying learners can **expose "unknown unknowns"** that educators also referenced in the exploratory interviews described in chapter 7.

Educators preparing learners for practice and those looking to promote learner satisfaction spoke mostly about classifying learners for the purposes of **creating different**

pathways for success. Justin and Nora, who are both Arts and Humanities educators looking to develop strong minds, had a discussion with Georgia, a STEM tutor preparing for practice, about different "types" of students.

> Georgia: "Not everyone arrives at this moment with the same intentions. If we really ought to save time and money, that is where we will do it."
>
> Justin: "While I accept that the University has to care about money, I don't see necessarily why I should. My job is to care about what the students are learning, not the University..."
>
> Georgia: "I'm not suggesting you do it for the University, but for yourself. When you have a class of 300 students, and you have to diagnose and deal with all of their various issues, you need some ways of identifying clusters. That's all I'm saying."
>
> Justin: "Oh, in that case, absolutely...absolutely. I'm just not sure if we should be educating people at that scale..."
>
> Nora: "Though if you are, certainly what [Georgia] is suggesting is the way to do it. What will be the criteria?"
>
> Georgia: "Well I think there are already some clear winners...the people who will always want everything you've got to show them, the ones who just want to pass, the ones who are sporadic in their involvement. We could figure out a way to support those types of goals and behaviours if we only understood what exactly is and perhaps how to automatically identify it."

What Georgia is suggesting in her statement is, once again, the idea that learning analytics can **help learners to identify what their goal might be, on the basis of their behaviour** and to **identify and develop strategies that assist with the learner's goal.** Participants viewed this relationship as being two directional with regard to learning analytics. Classifying learners according to their goal could be the product of a machine-learning approach to **identify best practices**. This would then inform the development of an algorithm that can **spot certain classes of students and support real-time analyses of learners' behaviour on the VLE platform.** Educators with large class sizes or who were module chairs were particularly interested in performing such analyses to help them **target their own effort.**

When asked how this knowledge would influence their practice, educators described how they would deal with students having different goals:

> Georgia: "Well you don't flood the people who don't engage that often with even more information. You really have to streamline and reduce content. In the same way, you have to feed those students who want more and a lot of what they want is other students' time. I don't know how to offer that unless I pair students who really want to benefit from this with other, similar students."
>
> Nora: "What about the students who aren't aware that it's important to them? I just feel like it's, like it's part of my role to encourage growth, study growth."
>
> Georgia: "And that is always the difficulty, isn't it?"

Allowing learners to choose their own path was not always an avenue that educators found appropriate, in particular when they were coded as having the goal of developing strong minds.

> "A fitbit is a personal choice and you cannot address a whole cohort, if you're giving choice to individuals. What would you expect to gain from it? I can't see if they are going to initiate a choice and student X chooses to use analytics and student Y chooses not to, how are you going to teach them together as a cohort?" - Elizabeth

Elizabeth voices some legitimate worries about the asymmetries that could develop between students who make use of learning analytics and those who do not. This is particularly relevant in the context of this study, which suggests that it is not the lack of interest on the part of the student, but perhaps a missing skill-set in terms of how to interpret and apply analytic data, that influences understanding and use of learning analytics.

9.2.8 Setting Expectations

As the exploratory interviews and focus groups illustrated, educators do not always have confidence in students' abilities to set realistic expectations. Educators proposed that this results in students overextending themselves or incorrectly assessing their capacities, as was discussed previously. Some educators felt that learning analytics could be utilised to help learners to set expectations, and to inform themselves about the course of study and its demands in advance.

> "At least if you can have a realistic idea of what will be expected of you, you can then look at your situation and ask yourself 'okay, how is this going to be possible?' Without that, you have nothing, so I think that would be a good thing." - Georgia

> "If you could tell prospective students about which modules the University recommends in preparation for starting a new module or qualification, this could help students to have realistic expectations" - Regina

Once this had been proposed in the educator interviews and focus groups several times, it was decided that all of the remaining *learner* focus groups would be asked directly about this type of affordance.

Learners were divided as to whether this information would be useful to certain types of people, but all agreed that it would not likely have changed their *personal* decision to take a course.

> "If you're looking into starting a course, knowing how well people have done might help you to choose whether you would do that course. But for me, I think, how other students have done, yeah, it might make a bit of difference but not too much, I don't think. - Harriett

> "I need to be a [names profession] to do what I want to do and have anyone take me seriously. End of story. If I had known how much math would be involved, I think it would have just worried me, rather than changed me." - Laurie

Interestingly, educator Regina reported that after a pre-course call that was intended to let students know what would be expected of them, 50 enrolled students dropped the course. At the time, Regina understood this as a positive, self-regulatory behaviour. She considered this type of affordance as belonging to an "early warning system" that does not detect students who are struggling, but predicts learners who might be likely to struggle, given the expectations of the course (in terms of prerequisites, for example).

In general, however, the findings indicate that **motivations for studying can be stronger than "being realistic", sometimes resulting from fixed decisions based on interests and needs.** Students entered into their study programmes because they really wanted to explore something different, or make up for lost time, or to get a higher paying job. Those motivations were perceived as extremely influential for Open University students in driving their behaviour.

In contrast to learners' feelings about setting expectations as an affordance of learning analytics, many learners and educators agreed that learning analytics should be used to **deliver targeted content**. Findings indicate that pragmatic learners envisioned learning analytics as being able to **determine what the learner should focus on, given their academic goals**. For learners with open strategies, "targeted content" tended to be described as that which would **appeal to the personal interests of the learner or the interests of those around them.** Learners with applied strategies perceived "targeted content" as the **delivery of self-defined categories of useful content**.

For educators, delivering targeted content was an affordance that arose in connection with classifying learners (see 9.2.7). Educators with both large and small class sizes perceived somewhat predictable divisions in their classrooms as Jeremy discussed in subsection 9.2.1. Educators with small class sizes and more teacher-student interaction felt that it would be more difficult to assess learners, if multiple pathways were possible (see 9.2.9). However, nearly all of the educators agreed that offering more learning pathways would be beneficial for students.

9.2.9 Evaluating Assessment

In discussing the issue of distributed marking across large class sizes, participants agreed that learning analytics could contribute to a workable solution to the serious problem of somewhat arbitrary systems of marking student assignments.

> Jeremy: "To my mind, that is systemic. That will happen. What can we do? If what they say is true, it should be mandatory that every course is double marked, if not triple marked."
>
> Ivan: "We wound up triple marking 50% of the assignments. The marking was being done by a smaller group, the module team, so that when there were disparities in marks we could sit together and say 'okay, what do we think is really going on here.' It had that sense that the students had been properly done by. I now feel confident going to students and say 'okay right, we did this and I am happy with the mark that we gave'."
>
> Jeremy: "I must say, I think this is an area where analytics could really help. The institute has to accept that this is really a problem, for the past 40- 50 years."

Lucy interrupted this exchange to share a story about several students who noticed a disparity in the marking, which they dealt with promptly, but it left her with a feeling of dissatisfaction.

> Lucy: "Supposing some of these other people are deserving of a second mark? For some of the other smaller courses, you could have someone marking the whole class."
>
> Jeremy: "Even with that there is an issue that this might be a very generous person or a very difficult person."

Knowing that many students judge their learning through their marks, even those that also have other types of strategy monitoring in place, educators felt learning analytics could **help expose some of the arbitrary aspects of assessment and provide more complex tools to examine learner competencies**.

For educators in the Arts and Humanities, assessment was already a sticking point that was difficult to surmount in the focus groups.

Elizabeth: "I think the interesting thing is that there's a difference in the Arts and Humanities. We deal very much in the grey areas. We're dealing with developing thought processes, self-reflection, things that are very difficult to measure. You can't push a quantitative measure on that as a student develops. In the same way as you can't quantify a creative process."

Ken: "I fully accept that idea that in the arts, qualitative measures are...your measurement of students is harder to quantify. The only part of that I doubt is that I think that you can measure student progress on any course, both quantitatively and qualitatively. You may well make a case for saying that things like creativity cannot be measured by analytic data and I can accept that. But, that's rather missing the point that some of the nitty gritty of... what am I trying to say. I don't think that what you've said means that quantitative analysis doesn't have a place. There are lots of things that you could measure."

Elizabeth: There are, but you can't measure a students individual development as a creative entity. You can only measure the outcomes and the creative process is about more than the outcomes.

Researcher: So that's an assessment issue.

Elizabeth: "Yes! We measure creative outcomes. We ask students to contribute a commentary on what they've done, but that doesn't tell us how they've got there. They are telling us what they want us to know."

However, participants did occasionally try to break down the complexities of those "grey areas" and found that there were several points at which analytics could eventually provide some support, as Ken proposed. Initial suggestions that educators proposed were typically related to **analysing the structure of effective discourse or written assignments such as essays.**

> Researcher: "What is a good essay?"
>
> George: "That's tricky. It really is."
>
> Sam: "Is it? A good essay has structure. It has an introduction and a conclusion. Depending on what type of essay it is, it provides evidence or arguments. You could identify all of that, couldn't you? These days?"
>
> George: "Even if you could do all that, what about the content that fills it? That could never be automatic. Well, not at first."
>
> Sam: "Okay. It helps you whittle their assignments down, into a couple of different...I don't know, piles. For me, that might be useful. You could at least standardise the scores for the structure."
>
> George: "That's the easiest part! Deciphering a good argument and a great argument, that's more difficult."
>
> Sam: "There is always going to be an element of magic in marking." (both laugh)

Sam and George, both of whom have very little computing experience and knowledge of learning analytics, are able to work out the boundaries of their own ideas within the given technology and pedagogical structure of the social sciences. They both recognise some aspects of their work as being algorithmic and predictable, to a certain extent. Sam sees the value in **improving standardisation across non-dynamic variables**, such as the structure of an essay.

Learners also saw some potential uses for learning analytics to support the evaluation of assessment, but this was typically framed in relation to evaluating a tutor's competencies more generally, which is discussed later in section 9.6.

9.2.10 Comparison with a Selection

While comparing oneself with others was a major category of affordances, the category itself could be broken down into **"comparison with the average" and "comparison with a selection" of students.** This corroborated what students and educators reported about recognising learning, as described in the previous chapter.

When students considered having access to the VLE data of themselves and their classmates, several student participants mentioned that they would only concern themselves with whether or not they were performing somewhere in the average of other students. These students tended to have the goal of gaining a qualification, and were more often likely to have a pragmatic view of their specific modules.

> "As long as I am somewhere in the middle, I guess that's okay. I just need to not do poorly." - Boris

Occasionally, students had a more general selection, such as comparison with the top 10 or 20%, or with other students from their same background. Students with applied strategies exhibited the most metacognitive activity around discussing this affordance of learning analytics, in terms of applying this information to their own practice. Some students felt that if learning analytics would be able to show them **how students with similar skills or experiences become successful**, they would have a better chance of being able to absorb those strategies into their current practice. Other students described how they could use the modifier of the top 10% to **ring-fence the students whose strategies were most likely to be useful.**

> "If I have limited time, it's just about reducing the noise. I have to focus on something." - Ora

This affordance was very closely connected to the ways in which students described using others to recognise their learning. Earlier in the focus group, when asked what she gains from sharing physical space with classmates, Betty described how she benchmarks her own progress through comparison with a select group of students.

> Betty: "I know who in the class I trust to know what they're talking about and I orientate myself on those people."
>
> Researcher: "How do you recognise them?"
>
> Betty: "It's a combination of their attitude in class, how they speak and argue. It's - a lot of it is non-verbal. I know who I can trust."

Betty's choice of words indicate that her criteria are personal and complex. Without regular access to her fellow classmates, Betty is less able to get a sense of her colleagues, enough to know which will be part of her snap self-evaluations. Betty went on to describe this feeling as being at the "back of the classroom", observing and listening to others.

> "I can see why that is useful to the University. It really is remarkable that...I'm sure it helps them. I'd have to comb through that for days, though, to make sense of it for me. I can sit at the back of the classroom and get much more valuable information chatting about it all over a cup of tea." - Betty

Findings indicate that **comparison with a selection may be a digital manifestation of the "back of the classroom"**, one that some students need in order to **calibrate their existing strategies and gain access to new, relevant strategies.** Participants have confidence that learning analytics could meet aspects of that need.

9.3 Affordances of Social Network Data and Social Analytics

Social Network Analysis is something with which most educators and learners were already familiar. In the age of social media and social marketing intelligence, the value of understanding human interconnections was easily understandable and relatable through familiarisation with other tools. In terms of how this information could inform strategies for learning, affordances were more *conceptual* than actual for learners and educators. None of the participants in the study felt that this type of technology had been adequately utilised in education. This section explores some of the ideas that educators and learners had for harnessing Social Analytics for improving practice.

9.3.1 Exploring the Staff-Student Relationship

Similar to testing assumptions and classification, social analytics were perceived as **external observational tools for understanding the impact that others have on our learning.** In particular, educators with large class sizes, or who had the goal of developing strong minds, perceived social analytics as a tool for exploring certain undercurrents and relationships that influence classroom dynamics in subtle ways.

> "I used to provide a weekly message on the tutor group forum. I received a lot of positive feedback, so they just implemented it across some other modules. I just had a vague feeling for it and it would be interesting to confirm it. Is that relationship actually successful or not?" - Regina

Most educator participants described a general impression that the students who contact them the most perform better, but they still could not explain why. What exactly is happening inside of that contact that learners are responding to? **Deciphering the relationship between teachers and students** was something that participants felt may be an affordance of social learning analytics.

One participant described a small experiment, in which she was concerned that the students were not reading the TMA thoroughly, so she left a little note at the end for the students to email her that they had read it. She correlated this information with the assignment marks they received. She found that the students that emailed her did get higher scores. However, she admitted that this could be for a lot of different reasons. She did not know for certain if it was the materials, their accountability to her as their teacher or the fact that they were just "better students" that made the difference.

> "It would be interesting to see use social analytics to just see if certain interventions helped. How many people are reading the comments? Inside of that group, what other behaviours might explain this? Even contact with other students." - Regina

Findings indicate that educators perceive social learning analytics as a complementary tool for **interpreting impact more precisely.**

Learners also spoke about social analytics for exploring the teacher-student relationship, though primarily this was expressed as a tool for evaluating teacher efficacy, rather than learner response. These findings are aggregated in a separate section on affordances for exploring teacher activity (see 9.6). Students viewed the teacher-student relationship as being very important to their success and having the *right* tutor, even more so. Findings indicate that students would welcome analytics that could **provide orientation on different ways of grouping individual students and teachers together, to have the greatest impact on learning.**

9.3.2 Identifying Key Conversations

The decentralisation of discussion on student forums was a challenge that learners in the focus groups described, similarly to educators in the exploratory interviews.

> "It's very...messy. That feeling you get when you open your inbox and it tells you how many unread messages you've got. That's what I feel like when I look at those endless threads of seemingly irrelevant discussion. I just want to be able to know...here...this is what we're talking about." - Frank

> "If we could be alerted as to where conversations are happening, that would be great. If you were struggling, you could look there." - Harriett

Learners envisioned social analytics as a tool for following the flow and density of certain conversations, to be able to **extract major topics of discourse.** The ways in which they recognised this themselves had to do with how many of their fellow classmates were participating in the discussion, and occasionally, how intensive the discussion was or how many different subtopics it produced.

Educators with large class sizes, or who described having a particularly active forum, tended to agree that being able to **structure and represent student discourse** would allow them to more efficiently utilise already diminished resources.

> "Every year, we're doing more for less. We want to give the students the best experience and we need to think of ways to do that in a more economically sustainable way." - Dave

Findings indicate that **affordances of social analytics for topic detection are based on perceptions that important topics are those with which many students are engaging**. However, both educator and learner participants believe that this can be explored more deeply with learning analytics. In particular, learners with open strategies and educators looking to develop strong minds perceived other, more specific measurements that could be captured by learning analytics to **determine the *quality and trajectory* of conversations, as well as the quantity**.

> George: “What’s interesting is to see which conversations students tend to congregate around. Sometimes I feel it is for my benefit, sometimes it’s the conflicting or controversial issues. It’s always something. Perhaps learning analytics could help me to define what that is.”
>
> Sam: “You can also do all sorts of things these days, looking at influence in discourse and how ideas sort of spread around from one person to another. If you were looking at trends and all that, you might be able to see how habits are formed.”

Educators were cautious of reading too much into social analytics conducted on formal, university-managed, student networking tools.

> Ken: “The reality is there are an enormous number of Facebook groups that students set up independently of the Open University.”
>
> Elizabeth: “It’s probably because they know they aren’t being tracked there.”
>
> Ken: “You could make a case for, why are we not looking at that? Why are we not working at Facebook?”
>
> Elizabeth: ‘I think the question we can ask is why are they going on Facebook and not on the forums we provide for them and I think the answer to that is because they know they’re not being tracked on that.”
>
> Ken: “Okay. So we need to be providing better forums that they are not going to shy away from.”
>
> Elizabeth: “They know that the OU Forums are tracked.”
>
> Ken: “My point is that if the OU wanted to track Facebook they could.”
>
> Elizabeth: “Reading it is one thing, but analysing it is different. To have that statistically analysed is a very different issue.”

Elizabeth’s point was corroborated by learners.

> Joan: "If you go online and do an online forum, it's much more stilted and you're much more polite, you're phrasing things, not academically, but in a much more formal way. However you try to be informal, you're still always going to be slightly formal I think."
>
> Researcher: "Why do you think that is? Why are the forums so formal?"
>
> Joan: "Because they're run by the University. So you're always aware, I think, of the fact that there's somebody watching."

As has been mentioned previously, students also expressed fear in contributing to student forums, primarily because they feared that their contributions would be read as plagiarism if they included thoughts from the student discussion on the forum into their final assignments. However, if one was not allowed to actually discuss the content of the assignment and how to understand the question, some of these students did not understand the purpose of contributing on the forum. Findings suggest that **educators and learners find social analytics to be most useful in cases where contributions are voluntary and uninhibited, and where students are the primary beneficiaries of any insights.**

9.3.3 Assessing Participation

As was already mentioned in the previous subsection, participants viewed social analytics as a way of also looking at how the students in the course communicate with one another. Sam and George discussed the issue of influence and using learning analytics to **explore how conversations are shaped**. The lowest hanging fruit from this type of analysis would be to **track student participation more generally.**

> "When a student is doing their first and second modules, it's really helpful to know how well engaged they are and that's not to...I think one purpose of looking at social analytics would be to monitor if, if they're not engaging, if they're not participating into student communication over the VLE, why not? Because one would hope that they would because it is a helpful way of learning and developing. If they're not doing it, you would be curious to know why. At the cohort level, not the individual level." - Ken

Once again, educators proposed learning analytics for **exploring cohort-level dynamics of attention, interest and communication** to get an overall sense of the classroom experience.

9.3.4 Forming Successful Peer Groups

Educators that valued class participation highly generally agreed that group constellation was important for successful peer work. Good student teams are described as those in which *each student has skills and expertise to offer*, and where the *students feel satisfied with their performance as a team.* Yet students and educators described the formation of peer teams as being rather arbitrary in practice. For some students, especially those who had negative experiences in co-working with peers or who reported general social anxiety, peer working and peer assessment, in particular, was a source of aggravation.

> "I would think I'd have to actually experience group working and reflect on what happens. Whether I was able to think analytically and creatively about joint work would be one indicator. And how I experienced things inter-personally within the group would be another. Plus feedback from others in the group would probably be part of it too." - Lane

The success or failure of peer work, as Lane described it, depends on *multiple, complex measurements*, that are derived from both internal and external evaluations. Lane's ability to name them, however, suggests that she understands how to *monitor* the experience of group work and how it would impact her learning experience.

Students, in particular those with open and applied strategies, had hopes for social analytics that could help pair them with other students who shared their motivations and goals, something which they perceived as impacting the *quality and enjoyment* of group work.

> Mascha: "I don't need everyone to agree with me or do it my way. I do want some push-back, some argument, some skillful argumentation."
>
> Researcher: "And you didn't have that?"
>
> Mascha: "I think the rule of thumb is that you might have one other reasonable person in any group assignment."
>
> Moritz: "You do see some people not doing their share and you wish that there were some way to kind of extract that person's effort, also for their own benefit. 'You've not actually done it, so we can't quite assess, whatever it is..."
>
> Researcher: "What do you think the purpose of a group assignment is?"
>
> Mascha: "To aggravate us (both laugh). No, honestly, I think it can be really a good thing, character building, presumably readying us for a life of working in inefficient teams."

For some students, the purpose of forming a type of "home group" with learners that share your way of working is not a way to avoid frustration, but a way to **accommodate different needs.**

> "I suppose to be able to highlight those students and put, you know, like-minded students together, because there are students that don't want to get involved. And I appreciate that there's people who just kind of want to get their head down, do their own work. But I'm not like that. I'm quite interactive and want to get involved. It seems a shame that you get a region of people and just class them all together and there's no, you know, maybe they're selected at random and given to a tutor at random and maybe there's be a better tutor that could meet their needs better by being, a more proactive tutor." - Vicky

However, the necessary tracking and interpretation to be *able* to use social analytics in this way, was viewed by some educators, as potentially tricky.

> "We have assessed group work on [module] and there is a very strong feeling from students that they do not want to be tracked on their engagement with other learners. We know that this can be a powerful tool, but the students don't know that yet. I would be concerned about what tools, and how we use them. It's a very grey area. For students to interact with each other is very important, but I don't think we should be controlling it down to that level, analysing it down to that level. I think there is an element there that needs to be self-reflected, self-regulated. It could so easily be misused, so easily backfire and be used as something against us." - Elizabeth

Another educator raised the concern that mapping such relationships might be viewed by students as an invasion of their privacy, or as exacerbating existing anxieties over class participation. Particularly in conjunction with *forced* participation (where participation forms a percentage of the learner's final grade), the educator feared that students would not be open to having their every movement and social exchange documented through the data collection process.

9.3.5 Additional Comments on Affordances of Social Data

The comments summarised in this subsection relate to expectations that participants appeared to have toward social data and analytics. While these expectations may extend to other types of analytics and tools, they were primarily expressed in speaking about social analytics.

First, the visual element of social analytics was something that was important to both learners and educators.

> "What would it look like? Would I be receiving an enormous graph in my inbox each week? Would there be some text highlighted, or bold, or something to draw my attention? I need for things to be readable, to a certain extent, immediately." - Dana
>
> "If it looks too techy, I just won't use it. These tiny fonts and endless streams of information. It wears me out." - George

Expectations of social learning analytics tools match models of technology acceptance described earlier in this thesis, in that familiarity and experience with "similar tools" is perceived a major factor in acceptance. Findings suggested that **participants expect what they have come to expect from commercial analytics software: clean, accessible, easy-to-use with customisable interfaces.** This was particularly (but not exclusively) true for educators with less experience with computing and advanced numeracy.

Another common theme that emerged from several educator perspectives, is the perception that students cannot fully grasp what they really want or need within a learning experience.

> "You can ask students what they want and what they say they want is not reflected in their subsequent behaviour. It would be interesting to see how analytics could help students reflect on that."
> -Violet

Statements like Violet's were common in both the exploratory interviews and in the focus groups, discussing everyday challenges that all educators experience around learner motivation and behaviour. Findings indicated that **learning analytics were perceived as an extra-observational tool to test the difference between *sentiment* (using social analytics, for example) and *behaviour* (through click-stream analysis, for example).**

9.4 Affordances of Multimodal Data and Multimodal Analytics

Discussing multimodal data required more examples and explanations within the focus groups and focused interviews. Participants were familiar with some technologies, such as eye-tracking and the use of sensors, but there was some difficulty in imagining how multimodal analytics could support learning and in particular their individual practice.

> "The problem with this type of analytics is that it's all so theoretical. I'd have to see the data first. See what you can get from it."
> - Drew

Still, the technologies were generally perceived to be novel enough to be interesting and several participants tried to consider how such new techniques could be incorporated into their daily experience.

Eye-tracking and noise detection were perceived as predominantly useful for establishing the learner's attention and focus. Some students felt that it would aid educators in **understanding how students review the resources available to them.**

> "If you could see how slowly people were turning the pages, where they stopped and put their attention on, any part of the module that they lingered over and why, have they got bored? or is it difficult?" - Harriett

Educators could also see possibilities in using multimodal analytics as a way of **evaluating human-computer interaction.**

> "Eye-tracking could be interesting in a course that is hosted on a different platform, to look at the differences between that platform and on the VLE, for example." - Drew

The difficulty for most participants, lies in interpreting the data accurately.

> "The problem with social or multimodal analytics, is that interpretation is open to a lot of presumptions and assumptions that could be problematic." - Regina

Participants from both educator and learner groups, independent of strategies or goals, expressed *less confidence* that this type of data could be viewed as objective, regardless of the empirical methods involved in data collection. In addition, when asked if this data would actually change their behaviour, most students felt that it wouldn't, at least not directly.

> "I'd find that a bit intrusive. I'd probably just break the rules anyway." - Harriett

> "Maybe, if I hadn't already decided." - Boris

> "It doesn't really matter, so no. I feel I was always going to do this eventually, so it was kind of inevitable." - Ora

Regardless of the type of strategy that the student described, findings suggested that learners perceive the effects of multimodal analytics on learning as most likely to be indirect or deferred, used as a **tool for orientation.** When Harriett was asked why she would like a tool that wouldn't change her behaviour, she said:

> "Just to know. Maybe later it matters and I come back to it."

This was an interesting finding of the study, that **some students gather (or would gather) information to assess their own performance that does not have an immediate application or potential impact on the learning experience.** This was most true for students with open strategies.

9.5 Affordances of Web Data External to the VLE

As previously mentioned, one of the four types of learning analytics technologies presented to participants during the focus group were different types of software to track learner behaviour in the web environment, external to the VLE [43]. Such software is able to track learners' movements through the web environment and keep track of what pages they searched. They also offer tools for organising key terms or annotating web pages and specific resources. Having this data was a tempting idea to many of the educators that participated in the study, because it provided the most insight into learner strategies and process.

Participants discussed how knowing which websites a student visited, in which order, could tell them a lot about how the student approaches preparing for an assignment and completing their work.

> Lucy: "It would be interesting to see what websites they were opening. To see if they are really working on one thing, or looking at train times."
>
> Jeremy: "What interests me is when they can combine different streams of data, structure the data. It can be very informative. For example, if you can see that the content that a person is engaging with is exactly the same as what you are offering, but they are looking at it on YouTube or whatever, it might tell you that the way you are explaining it is insufficient."
>
> Iva: "Or that they want to go to the source."
>
> Jeremy: "Indeed, it can also be that."
>
> Lucy: "What is the usability like?"

The affordances educators perceived in the excerpt above were quite differently applied. Jeremy would utilise such a tool for **evaluating the suitability of resources and educational approaches**. Lucy would be interested in **knowing more about how learners spend their time.** Interestingly, Jeremy is the only educator to mention an affordance of learning analytics that focus on educator behaviour (see 9.6).

Students with open strategies were most interested in web data external to the VLE. In particular, these students were interested in how such a tool could expose them to the strategies and information of their fellow classmates.

> "I think that would be helpful because a couple of times, somebody said something about a program that's on TV, or something like that, or that's on the forum and you don't always look at them. But also, if you could have alerts or like link you with your email so that if something comes up that you were looking for, that would be good." - Harriett

> "If there are things people are looking at that I'm not looking at, I'd find that really interesting to see, in case there is something I find useful. It's a bit like peering into someone else's mind." - Moritz

Something as simple as having the web histories of classmates was viewed as being something that could be potentially very useful, if there were a way to sift through and categorise the information meaningfully. Other types of web activity external to the VLE that educators found enticing, though for no particular reason than to test a hunch, included examining assignments in Google Docs to see how many versions a student creates, how often they check social media and how long they appear to stay engaged in the study process. However, all agreed that such intrusions would constitute an invasion of privacy and all recommended that the student be responsible for sharing or agreeing to share any part of their web history as part of such an analytics initiative.

9.6 Affordances for Tracking Educator Activity

While many participants spoke about the possibilities of evaluating and adapting their learning design as a result of learning analytics data, or of recognising some "discriminating factors" in educational experiences, only one educator independently mentioned tracking his own activity as a source of information. At the end of the focus group, the participants had not come back around to this topic, so they were asked about it explicitly.

This section describes some of the characteristics and activities of educators that educators and learners felt were significant in the learning process. 9.6.1 talks about collecting information on groups of educators and their characteristics and 9.6.2 discusses how to interpret information about the educator and learner relationship. 9.6.3 provides some examples of learner indicators of a positive learner and educator relationship.

9.6.1 Looking at Educator Sub-Groups

Findings indicate that students and teachers agree that the most important influence on the student's learning is the tutor/educator. Tutors and educators view their own intuitions, their pedagogical intentions, their learning designs and their character as important to learner success.

Lucy, who was currently participating in several learning analytics initiatives, had wondered about the effects of certain characteristics, such as an educator's gender, on the learning process.

> "I've been looking at data recently and wondering,'maybe that's the reason', and one of the things I have been looking at is that women, especially chairs, tend to spend a lot of time on the forum supporting students, raising the replies, very friendly and replying promptly. Does this actually prove this." - Lucy

Jeremy and Dave responded that they had noticed other tendencies, from anecdotal evidence shared by colleagues, that might be interesting to explore using analytics. For example, Jeremy suggested that experienced and novice educators could be identified looking at the amount of time they spend achieving an excellent result. Dave also felt that understanding how learners feel about the tutors they work with could reveal a lot about the learning experience. Ivan, however, expressed concern.

> Ivan: "The whole University is set up so that you have the central academics who should not ever have to directly support the students. Now we do, we choose to, but the whole idea is we're here, we do our thing and there's a couple of layers in between so that essentially, the student shouldn't have to deal with anyone except their own associate lecturer."
>
> Jeremy: "Maybe this just goes to show how bold we are, but I wasn't trying to be facetious when I said that perhaps we could learn that we're not doing a very good job sometimes. It never really occurred to me that you could mine that data and essentially find out some very useful things."

Ivan's concern points to a fear that the data will not tell the whole story and that less-experienced data wranglers or other colleagues would not understand how to read it. Jeremy's argument, however, is that it is simply too valuable of a data resource to be ignored.

9.6.2 Interpretation of Educator and Learner Relationships

While Dave, Lucy and Jeremy agreed that tracking their own behaviour could be a key piece of the puzzle in understanding learners' experiences, Ivan was clear about how that data should be qualified.

"So earlier I said, I'm not a teacher, I'm an academic and teaching is just part of what I do, it's just one part of what I do. That applies to many of us...You say it could show our arrogance and possibly our failings, but you know, we're trying to innovate here and the analytics could, or should be the things that tell us if our innovations are working."

Ivan went on to describe his evaluation of the current applications of learning analytics.

Ivan: "If you look at all of these packages of tools that are being developed at the institutional level, these are not being developed by the people trying to innovate teaching."

Jeremy: "We all see things differently. I'm just saying that maybe I find out my TMAs aren't very nice, or the students aren't really understanding them. It could be very interesting to get those insights."

Ivan: "I'm totally agreeing with you. What I'm saying is that we're the ones who are making the changes."

Ivan and Jeremy appear to be arguing on two different sides of the same coin. Ivan's point is that the final say in interpreting educator activity should be in the hands of those who are implementing changes in the classroom. Jeremy's argument is that there are insights that learning analytics could provide that he would not have anticipated.

Findings suggest that **educators and learners agree that it is important that they be involved both in the interpretation of data and any resulting interventions.** They cite two justifications for this. First, participants believed that data will be vulnerable to misinterpretation, particularly at the module level, where sample and effect sizes will be smaller and potentially less reliable. All of the research participants wanted *some* power to *use their experience and insight to decide the extent to which information collected about them is relevant.* Second, participants statements indicate that they believe that data could eventually be used to undermine or harm them.

This second justification is related to the first, in that participants believed misinterpretation of data could be used to justify unfair attitudes or actions against an individual or group.This finding supports what was learned in both the JISC [30] and EDUCAUSE [159] publications on learning analytics in higher education.

Educator participants that were experienced both in computing and working with large class sizes, tended to feel the least comfortable with what some described as "top-down" analytics. They also had the most scepticism about what actions would be taken as a result of learning analytics insights.

> Jeremy: "I would like to have the data. I don't want any analytics on top of that, I have my own. I don't want to use anyone else's analytics (Ivan nods in agreement). I am not convinced that the top down stuff is very good. However, there are a lot of people who would like to have standard tools. That's fine. I would like to get my hands on this data, if I knew where to find it."
>
> Ivan: "There is also the question of what we have the freedom to do. Let's suppose, for arguments' sake, I found out that students who did poorly on the prerequisite module, dropped out after the third electronic assessment. Well, there's actually not a lot I can do about that."

These statements from Ivan and Jeremy illustrate what was proposed in the previous chapter about the tendencies for potential experts to have the most misgivings about learning analytics' adoption. However, when speaking directly about actual affordances, even non-experts can perceive some of the complex issues around the wide-scale ethical adoption of learning analytics. George and Sam also spoke about feeling a lack of agency in making changes:

George: "We've had countless discussions on assessment already and have been able to do nothing about it."

Researcher: "Why is that do you think?"

George: "It's too much change, I suppose. It's too different. It makes people... uncomfortable."

Sam: "That's a very strange thing, indeed, that. It's about choices, priorities and, to a degree, investment. The OU is quite a progressive environment. I'm not entirely sure what the Uni would have against rethinking how students are assessed. Nothing very significant has changed in that regard in so many years."

George: "Too much interpretation. That's what I think. It's easy to say 1+1=2 and all of your statements and hypotenuses and hypotheses, and all of those wonderful Greek mathematical terms (both laugh), but if you ask two maths teachers to grade the same paper, you're going to get the same mark. It's all about reducing chance, isn't it?"

9.6.3 Learner Evaluations of Educator Activity

Learners had more ideas for evaluating educator activity using learning analytics. Specifically, learners look at tutor reactions to their questions, involvement on the forums, leadership in the classroom, communication style, and the ability to inspire and motivate, as primary influences on their ability to succeed.

Mascha: "You know when you ask a question and the tutor sends you a link and that link doesn't work or if it does, it directs you to something that does not answer your question at all. It would be good to have one of those little questions pop up that asks you, 'was this information helpful?' You could provide quite direct feedback but it might be useful over the long-term."

Moritz: "I think people would go crazy with that. If they didn't like the answer they would say it wasn't helpful."

Mascha: "Okay, maybe 'Did I answer your question?' then."

While interaction and response from the tutor are easier indicators to measure, the ability to inspire and lead in a classroom may be more difficult to immediately identify. Rather, longitudinal, rich data may provide some insights into these qualities and their effects on a classroom.

9.7 Evidence Summary and Remarks on Affordances

Some general comments can be made about how participants engaged with the subject of learning analytics, which are important to summarise and elaborate before moving on to the discussion in Chapter 10. This section will distil some of the most salient insights from the focus groups on affordances of learning analytics for improving practice.

The first three subsections, 9.7.1 and 9.7.2 examine relationships between Influences, Affordances and Intentions, with regard to metacognitive statements about learning analytics. These subsections explore different groupings of these elements that emerged from the data. 9.7.4 describes the dimension of "distance from the learner" to the discussion of affordances and how this influenced perceptions of impact. 9.7.5 reflects on the concept of "time well spent" and how different educators and learners appeared to prioritise their time. 9.7.6 returns to the subject of "unknown unknowns" and the consensus that analytics can illuminate important and currently invisible aspects of the educational experience. 9.7.7 addresses some specific concerns around accessibility of data and 9.7.8 discusses issues around training.

9.7.1 Metacognitive Activity

As mentioned in the introduction to this chapter, statements that related directly to the participant's *own* practice were coded as "Metacognitive Activity". When discussions triggered metacognitive activity in participants, this was noted as a positive signal of perceived usefulness. 179 metacognitive events were captured in the focus groups and focused interviews that could be reduced (through removal of repetitions) to 46 metacognitive events in which a participant described intentions for using learning analytics for a specific purpose related to their practice (see B.7).

The 46 metacognitive events were then grouped into categories based on the focus of the intention, or the most important general outcome as given by the participant. This process produced 9 categories that were titled: "Focused Intentions". Focused Intentions were general uses for learning analytics that participants felt were particularly important: Orientation, Intervention, Retention, Agency, Reciprocity, Reflection, Accommodation,

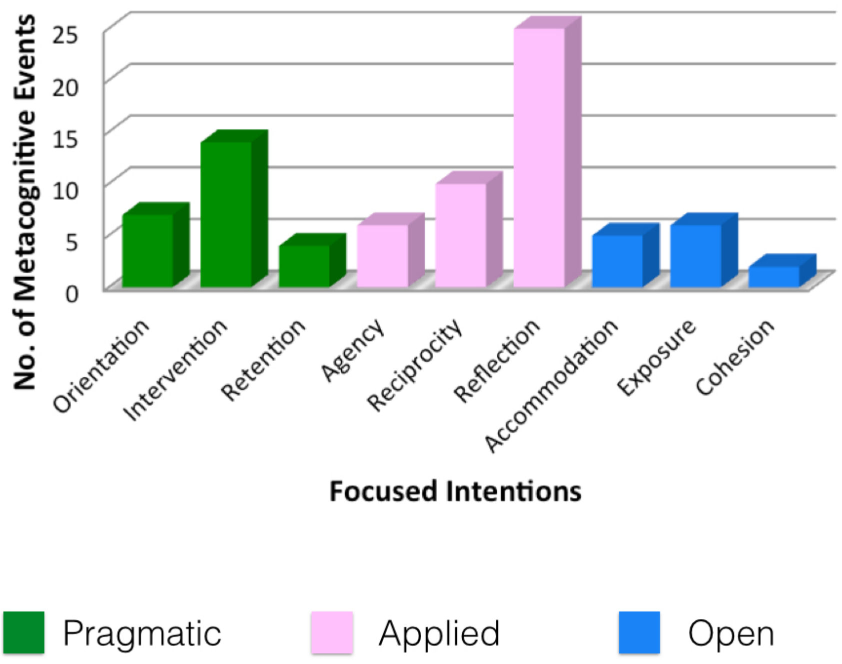

Figure 9.1: Metacognitive Activity and Intentions

Exposure and Cohesion. Orientation intentions were those that were about preparing the learner for the educational environment and helping them to set expectations, or helping new educators to gain orientation in the field. Intervention intentions were those that involved looking at learner behaviour to help develop, implement and evaluate specific interventions for preventing problems. Retention was simply the code given for any intentions that were expressly about keeping students enrolled and completing their studies. Agency, Reciprocity and Reflection respectively refer to intentions that empower the individual, encourage the individual to share their thoughts and ideas, as well as reflect on the thoughts and ideas of others. Accommodation intentions were those applications of learning analytics that identified special needs and recommended ways of dealing with those needs. Finally, Exposure and Cohesion intentions were about bringing learners into contact with new people and ideas, and then supporting their sense-making activities (see B.5 for a full description).

Figure 9.1 presents the number of metacognitive events that were identified for each of the focused intentions. The colour scheme for groupings is the same as in figure 9.2 in the following subsection. Findings indicate that **most metacognitive activity was located around affordances for reflection and reciprocity, such as recognising patterns in the data and testing pedagogical assumptions, activities that *required participants consider what it is that they are trying to accomplish and how it can be measured*.** When connecting affordances with real practice, educators

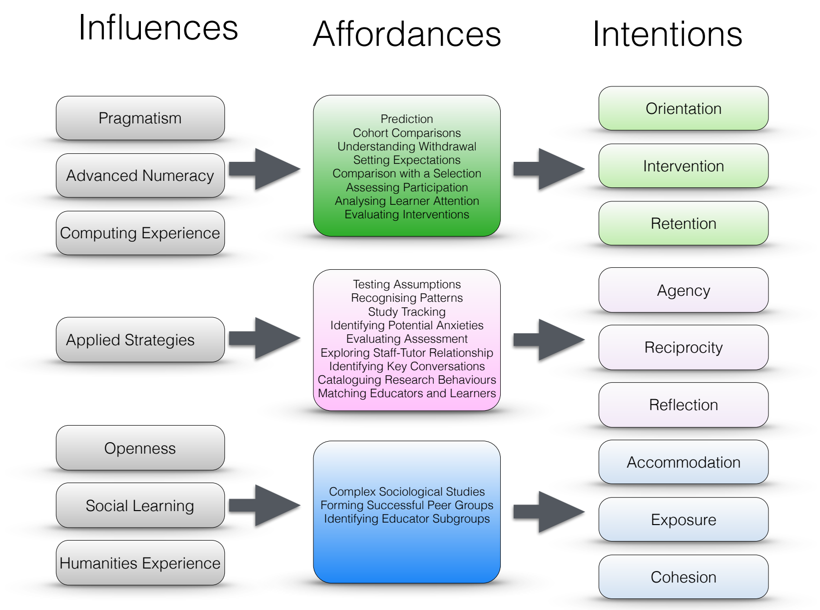

Figure 9.2: Influences, Affordances and Intentions

and learners were looking to **resolve real challenges, such as exploring their own assumptions, seeking patterns in the data, finding novel ways of identifying learner emotion and of gaining access to different strategies and choices**.

9.7.2 Affordance Groupings

Focused intentions could be grouped into three systems. Figure 9.2 summarises how influences and experience appeared to influence the types of affordances and intentions that participants were able to perceive in supporting their own individual practice.

Individuals with a **pragmatic strategy**, in particular when they have an understanding of advanced numeracy and computing, tended to perceive more affordances for **helping learners to understand what is expected of them, to understand when they are struggling as quickly as possible, and to do whatever possible to retain the student**. Individuals with a very **open strategy**, in particular if they highly valued interaction in learning, were more likely to perceive affordances that could help to **identify and accommodate special needs**. In addition, they were more likely to promote affordances that **bring people together in the process of creating meaning**.

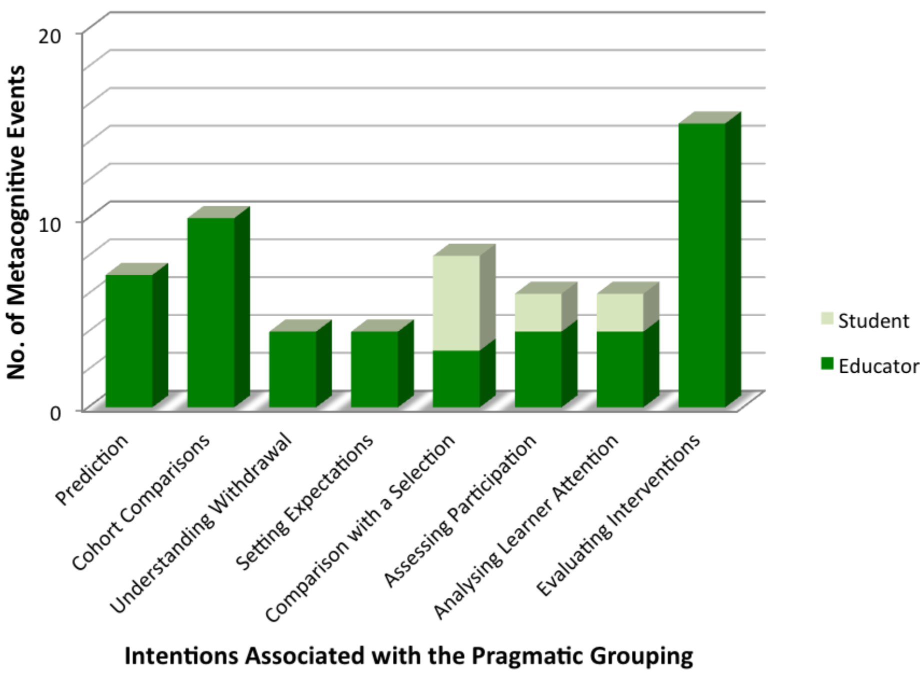

FIGURE 9.3: Educator and Learner Breakdown of Pragmatic Intentions

Individuals who were **transitioning** between domains, and those who had extremely well developed, **applied strategies**, seemed to circumscribe a **middle-space between those two territories of open, social learning and optimised, effective strategies**. In this space, the intentions appear to be focused on creating buy-in by **involving different stakeholders more in the process of data collection and interpretation**. In addition, affordances tend to **invite learners to consider the process of learning as important as the outcomes of learning**. Finally, there is a sense that learning analytics can **aid in the process of reflection on a much deeper level, still using all of the same tools and technologies**. For example, participants who occupied this middle space tended to describe using learning analytics to really understand more about how to **optimise the teacher-student relationship**, and to **recognise *different* types of patterns in behaviour, also at the strategy level**, to make those inner-workings of individual study more transparent for learners.

Groups were named by the strategy approach most commonly represented within the grouping: **a Pragmatic Group, Applied Group and Open Group**.

9.7.3 Educator and Learner Differences

Returning to figure 9.1, these categories can be reconstituted into their original 46 intentions to examine how educators and learners differed in their intentions.

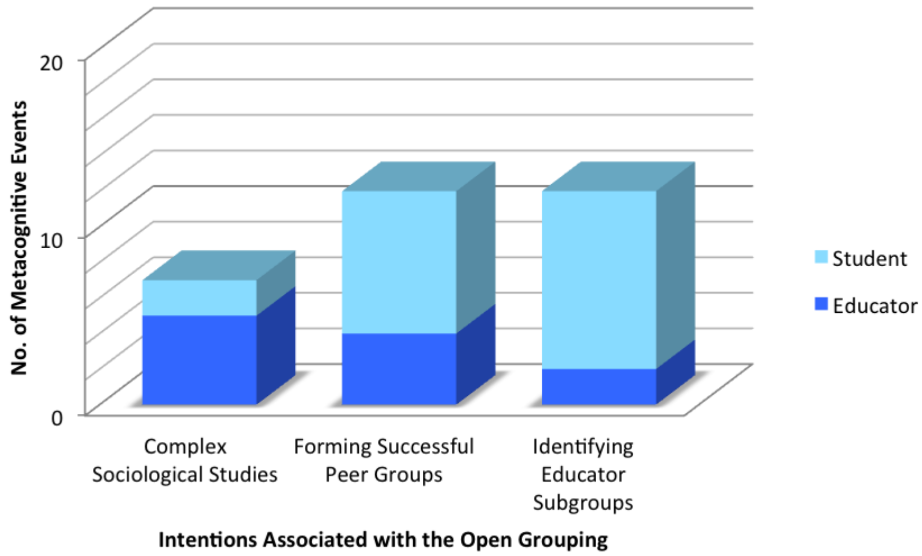

Figure 9.4: Educator and Learner Breakdown of Open Intentions

Figure 9.3 shows the breakdown of metacognitive activity within the pragmatic grouping, according to whether the metacognitive event was experienced by an educator or by a student. Nearly a third of all metacognitive activity identified in the study was experienced by educators who saw pragmatic applications of learning analytics to evaluate their interventions and improve retention through prediction and cohort level comparisons. As mentioned previously, most of the educators who expressed these types of affordances had advanced numeracy and computing in their background. **Educators and learners in the pragmatic grouping typically perceived the utility of learning analytics in providing insights about a few, key metrics**.

Figure 9.4 illustrates the mirror effect for educators who expressed affordances associated with the open grouping. As mentioned previously, educators that fall into this category were typically from the Arts and Humanities, as well as Social Sciences disciplines. Especially educator participants from these domains had difficulties in seeing how to apply learning analytics to their practice. However, findings indicate that the **affordances critical for the open grouping are concentrated in examining social aspects of learning in great detail**. In addition, it is interesting to note that more students than educators in this grouping experienced metacognitive activity relative to thinking and speaking about learning analytics. This suggests, perhaps, a resistance among educators in the open grouping (typically from the Arts and Humanities, and Social Sciences) that will have to be dealt with as learning analytics research progresses at the Open University. Educators in the open grouping run the risk of falling behind in understanding and working with learning analytics.

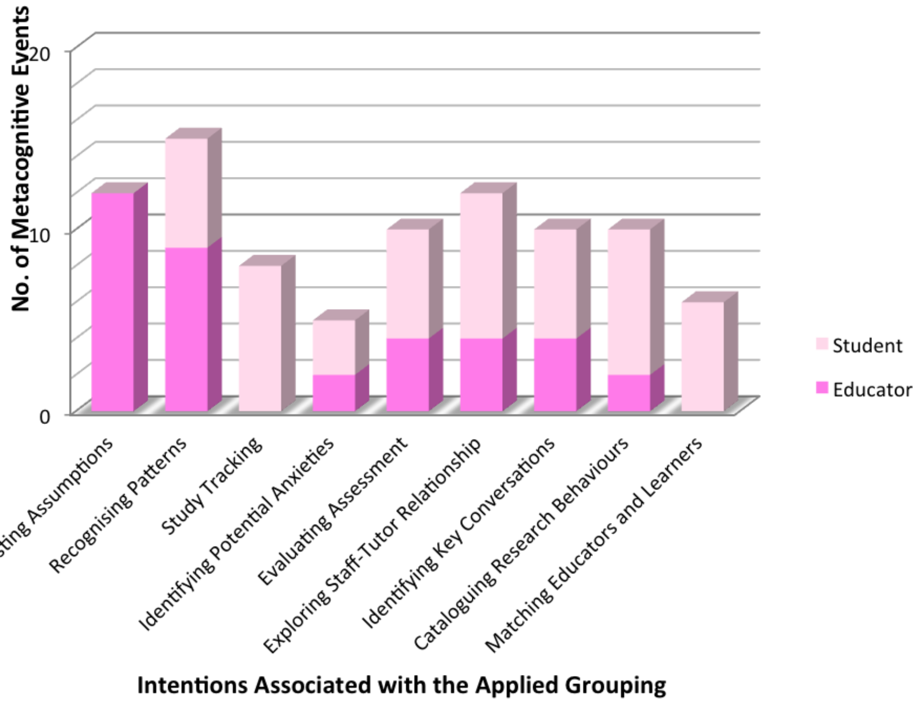

FIGURE 9.5: Educator and Learner Breakdown of Applied Intentions

Finally, Figure 9.5 presents the educator and student breakdown for intentions associated with the applied grouping. Educator and learner affordances were much more well balanced in this grouping, which is not surprising, because this grouping was generally composed of equally competent educators and learners with shared goals and cross-disciplinary or transitioning experience. Learners in the applied grouping identified as many affordances for learning analytics as educators in the pragmatic grouping. They had a very strong sense of their own study habits and needs, or at the very least a wide array of study habits and strategies from which they could choose. **The affordances they suggest provide a picture of the kinds of activities they engage in that support them along the way**. Findings indicate that affordances in the applied grouping appear most linked toward, as mentioned previously, **supporting the agency of individuals within the institution and consciously exposing them to strategies through contact with others (whether a tutor, a peer group or some other entity)**. In addition, affordances appear to involve a bit more **investment for some of the "high-hanging fruit" of learning analytics research**, in pairing learners and educators, testing assumptions and developing new forms of assessment.

The open grouping produced the least number of metacognitive events. The reasons for this implied by the individuals in that group are that pedagogical and assessment choices are already a struggle for these individuals within the institution, which make it difficult to perceive a useful application for learning analytics based on the current (presumably inadequate) system of assessment.

9.7.4 Direct and Indirect Benefits

One dimension of affordances that became increasingly relevant in the evidence was **the distance of the affordance from the learner.**

Direct affordances were those that were closer to the student, who is actually responsible for learning. These affordances would be those that could inform a student-facing application. For example, a study tracker that would make recommendations to the learner (see 9.2.3), or a tool for helping the learner to compare their progress against a select group of students (see 9.2.10 would offer a **direct pathway to influencing student learning**. Direct affordances tended to be perceived as **helping learners to identify and monitor their goals and strategies.**

Indirect affordances were more removed from the learner. Educators and learners described indirect affordances as potentially **influencing educators' pedagogical choices**, such as identifying pinch points in the module where students struggle. Indirect affordances helped educators to identify best practices and interpret learner behaviour so that they could modify their own approaches.

The existence of direct and indirect benefits warrants attention in considering how such approaches could work together. **Indirect benefits appeared to have more support among educators because they were perceived as impacting a greater number of people. However, tools for making a direct impact were far more interesting for learners.**

9.7.5 Time Well-Spent

Most educators in the study, particularly the more senior members of academic staff, hoped that learning analytics could **identify "time well-spent"**, the sense that what one was doing was "worth it", for the institution and for oneself personally. Time well spent was defined differently depending on the educational goals of the participant.

For educators that were preparing learners for practice, time well spent tended to be defined as **saving time on irrelevant or non-critical activities.**

> "If I know I don't need to be cropping those five images, or whatever because no one is actually looking at them, that's what I need to know." - Dana

If the educator had the goal to to develop strong minds, time well spent was defined as **saving time on certain activities through reducing their complexity or automating aspects of the activity.** Returning to the discussion between Sam and George about the qualities of an essay, the two agreed that the exercise of thinking about learning analytics helped them to see how they could describe more concretely what skills they were hoping to develop.

> George: "It's interesting how we've been talking about this now for more than 45 minutes and I've got ideas in my mind that I did not expect to have about this subject. I didn't even know what it was, really, 30 minutes ago."
>
> Sam: "I am thinking. I am thinking and I find it a bit shocking that I couldn't answer that question right away, the point of my module. I want students to be better informed. I suppose that means, using more of their own resources in the right way, making stronger arguments."

Learners who viewed the learning process as very pragmatic, perceived more affordances for **saving time in everyday tasks such as information gathering and identifying key concepts.** Students with more open or applied strategies viewed time well spent as more personal and subjective. Findings indicate that for these students, **useful learning analytics tools were those that afforded the individual as much agency as possible in both deciding which information is relevant and how it should be interpreted.** This finding is significant in considering what it means for learning analytics to *optimise* learning.

9.7.6 The Unknown Unknowns

One of the more complex affordances that nearly all participants discussed, was to illuminate "unknown unknowns". In this case, participant statements weave in and out of the discussion of learning analytics to discussions about big data and the promise of understanding what one does *not* know. The measurements typically included everything that is possible to measure, a composite of all of the various types of analytics that had been discussed already. The purpose was to help the participant to **uncover the discriminatory features that set one person's experience apart from others.**

The significance of this expressed interest in "unknown unknowns" (that was nearly universal across focus groups and focused interviews) is that it signals a sense of trust, however small, that there is something about the educational experience that is possible to illuminate with learning analytics.

9.7.7 Perceptions of Accessibility and Awareness

Some educators were aware of a selection of the information they required was available to them through the Statistical Analysis System (SAS) at the OU. No one had considerable experience with the SAS tools, but the experiences they did report were positive. Still, **educators agreed that it was not always clear what information was available to them.** Dave, who had expressed interest in such tools, but did not know how to access them, met up for a separate interview after the focus group, to be introduced to the system. He had difficulty knowing how to interpret what was there, and wished it were possible to set his own parameters and interrogate the system on his own. He was informed that he could make an *ad hoc* data request if there was something specific he wanted to know. He agreed to submit and inquiry about the retention rates between modules that have a final written exam vs. modules that have an EMA report. A data insight manager responded within a 2-week period with useful information for the participant. The analyst cautioned that the data Dave requested was not sufficient to answer his question. For Dave, however, the data did satisfy his goal of having a **small piece of information** about his module.

Dave explained that he was considering whether to change the way he assessed his students, toward providing an essay-based exam, rather than a classical exam. Dave had observed that the students in his module appeared to grasp concepts more when they wrote about them. They also seemed to enjoy it. He was concerned about the drop-off of students and he wondered if the form of exam might be an avenue worth pursuing. The results of his query, though they were not *proof* of any phenomenon, did tell Dave something about his initial query that was relevant for his next steps. Dave's response to this information was similar to how other educators with a more open pedagogy viewed learning analytics. Findings suggested that educators who wanted primarily to promote learner satisfaction or the development of strong minds were interested in **quick partial measurements that provide an indication, rather than proof, of a phenomenon.**

9.7.8 Responsibility and Training

Educators were ardent in their feelings about training. For example, staff tutor with experience in the SAS tools described how it took someone sitting with her for approximately one hour to explain the basics of what she could interpret from the data available there. Findings suggested that **participants found ample training to be absolutely necessary to the success of any learning analytics initiative.**

Most educators were aware of the advanced skills necessary to interpret learning analytics. They spoke about the necessity of spreadsheet skills, knowledge of statistics, but also robust techniques of analysing qualitative data. **Educators with advanced numeracy were better able to see both the possibilities and limitations of learning analytics. Educators with less experience in advanced numeracy were both less able to perceive subtle benefits and less likely to distinguish more nuanced concerns from general problems.** Paradoxically, this effectively raises the level of evidence required to topple assumptions that learning analytics are overly complex. The implications of this are discussed in the following chapters.

Educators pondered whether or not the development of *"new skills"* in data collection and analysis were simply becoming a part of digital pedagogy.

> "When I first started, IET[a] had much more information. They had an IET member on every team. They were supposed to teach you, what they learned about teaching." - Lucy
>
> [a]Institute of Educational Technology: https://iet.open.ac.uk/

It appeared that while the University did, at some point, recognise the need for training and support, the mechanisms for empowering the right people seemed to deteriorate.

When educators were asked who is responsible for interpreting the evidence produced by learning analytics tools, they often referred back to the issue of **who is asking the question and why**. Most educators felt that no single person or entity could be the sole interpreter, because the motivations for collecting and using data are very different.

> "I think you would find that students, educators, module teams and the VC would have very different opinions. It may be that what the module team needs and what the student needs are different." - Regina

When asked what those different needs might be, educators and students tended to perceive the University's first priority as saving money. This was interpreted in different ways. Many participants expected that the University would prioritise its finances like any other institution. Some participants even found the cost-saving structures worthwhile, if they are ridding the University of any unnecessary burdens. However, findings suggested that **participants perceive a lack of transparency around University goals**, which threaten not only the financial stability of the institution, but also the pedagogical stability.

> "If they are teaching to retention, we're going to have a big problem later on when we don't even know anymore what we're producing or measuring. We can't tell students we're providing cost-effective education. That's not enough. Education starts with a plan." - George

The one area where participants were prepared to give up a bit of their autonomy was in uncovering "unknown unknowns". This was true of participants both with and without advanced numeracy or computing experience.

> "I wouldn't trust only myself to look at the data. I was amazed at what professional statisticians could get out of the data. You need to ask people who are good at seeing patterns." - Drew

Participants appeared to be in agreement that **seeing patterns is a skill**. If educators and learners are going to be asked to do it, they felt should receive some support in learning how to do so correctly.

One troubling finding was that educator participants did not have a lot of faith that analytics, even if they were insightful, could actually inform decision-making processes at the institutional level.

> "In my experience it is very difficult to do anything in the OU because there are legions of people telling you how to do it." - Jeremy

> "I think the thing that's come across really clearly in this workshop, among all five of us, is how much it comes down to really, individuals and the thing is, that the University is a mass teaching thing. We are an industrial teaching environment and that's not necessarily compatible with what the gods at the University would like. Whether there's anything that can be done about that, I don't know. Actually one of your questions that came before was how can learning analytics support the individual experience. " - Ivan

This impression appears to link back with transparency around institutional goals. The proposed solution from Ivan, which was shared by several other participants, is to **connect learning analytics more firmly with individual needs and experiences**. In other words, it is important to **create buy-in with people who have agency to make changes.**

9.8 Chapter Summary

This chapter outlined the affordances that participants were able to name for using learning analytics to support their practice. Affordances, as the actionable properties of an object [21], are based on perceptions. Chapter 8 described some of the contextual features that act as *lenses* for participants, influencing what they see and how they see it. This chapter focused on the actual opportunities that participants have experienced or could visualise, in using learning analytics to improve educational experiences.

The chapter began with a discussion of affordances related to student demographic data, data from previous module presentations (legacy data) and other types of information obtained from student applications (see 9.1). Findings suggested that educators in the Arts and Humanities or Social Sciences in particular, were more likely to see this type of data as directly useful to their practice, in particular for **understanding the different educational experiences of particular social groups of learners**. Ultimately, educators who perceived these affordances tended to express an interest in **accommodating any special needs** that might be uncovered. This was particularly true if the educator had the educational priority of learner satisfaction. This section also introduced cohort-comparisons, based on legacy data, as a way of helping educators and learners to **understand prerequisite knowledge that could be important for a given module and for new educators to gain orientation in the faculty.**

The second and largest section 9.2, presented the many affordances that educators and learners could perceive in using click-stream data from tracking activity in the VLE. The majority of affordances were around **exposing patterns in behaviour to *predict and classify learners***. Educators with large class sizes and module team chairs were most interested in predicting weak or at-risk learners. For those with large class sizes, the value-added was the speed at which learning analytics could alert them to problems. For module teams, the value-added was typically described in terms of retention. Some educators, in particular tutors working in the Arts and Humanities, felt that this focuses the University on a reactive, rather than a proactive approach to working with learners. They proposed the identification of mid-range students as a compromise, to learn more about how behaviour changes and to begin looking for warning signs even earlier.

Educators and students enjoyed the idea of *experimenting with VLE data* and viewed this as requiring freedom to both set the parameters of a given query, and aid in the interpretation of any results. Affordances for study tracking and testing assumptions suggested that educators and learners would respond well to software that would allow them to **test and play with assumptions**.

Section 9.3 began by describing how daily social networking experiences helped to ease educators and learners into the topic of social analytics, in particular with regard to following trends and group discussions online. Affordances that educators and learners perceived involved **exploring the staff-student relationship and innovating existing paradigms about the teacher-student connection**. In addition, participants envisioned using social analytics to **form more effective teams and match learners to teachers.** Difficulties or concerns were typically around the potential for misinterpretation and difficulty in stimulating participation without forcing students to contribute.

The next two sections addressed affordances related to learning analytics technologies that are less common in higher education and were not particularly known to any of the participants, Multimodal data (see 9.4) and Web Data from outside of the VLE during normal web-searching activities (see 9.5). Multimodal data, from sensors or eye-tracking devices were typically seen as tools for **assessing learner attention for orientation on a problem, but not for developing intervention on an individual basis.** Web data external to the VLE was valuable to educators as it was the only affordance that gave them **direct access to learner strategy.** Likewise, students were also interested in web data to **explore how other students approach a task and to identify new, relevant resources**.

9.6 provided an overview of how educator activity might be tracked using learning analytics to support student learning. Findings suggested that educators are wary of having their activity tracked, but that learners feel this could improve assessment, as well as student-teacher relationships.

The final section of the chapter presented some general thoughts about affordances. Groupings of influencing factors, affordances and metacognitive activity were presented, which materialised from the data. In addition, the section discussed the direct and indirect benefits of learning analytics, the meaning of "time well spent" and perceptions of accessibility, awareness and training. While some affordances participants mentioned would potentially impact student choices, many would impact *educator* choices. Findings showed that the educator's definition of "time well spent" is integral to their perception of priorities and thus, how and why they would use learning analytics. Educators agreed that the skills required to understand and use learning analytics appropriately required significant training for certain types of individuals with little experience in advanced numeracy. Helping educators to understand the basic ideas behind learning analytics will help them to grasp the more subtle opportunities and challenges that could affect their practice. Participants also believe that it would have an equalising function among educators with and without this knowledge. The findings of this chapter are the central point of the discussion on how learning analytics can mediate learning. Recording participants' experiences and cataloguing the ways in which they consider how they think about their practice assists in modelling how the process of mediation takes place. Overall, it appears that background, experience and goals influence affordances in somewhat predictable ways.

The next chapter will focus on exactly what is being mediated and why that is important for student learning. In addition, it will present some recommendations for other stakeholders involved in learning analytics about how to *capitalise on this predictability* to improve the impact of learning analytics on learning.

Chapter 10

Discussion

> *What engineers do is design for society and if we don't represent society, we're not going to do very well for society. - Roma Agrawal*

The previous chapters presented impressions, experiences and ideas around learning analytics, expressed by the participants in this study. Participants' statements were contextualised by examining their foundational beliefs about both teaching and learning, and in particular, the experience of online education. By connecting affordances with participants' current contexts, affordances had more meaning. The actionable properties that the participants were able to perceive were described not only in terms of what could be done, but also how and for what purposes at a given moment in time. In addition, looking at affordances in this way highlighted the opportunities that some groups would be more likely to perceive as useful, depending on background and experience. Those chapters partially address the research question that has guided this study: **"What impact is learning analytics having on practice and how can it be improved for educators and learners?"**

This chapter serves two functions: to resolve the theoretical discussions brought up within the data and to transform this into the language of learning analytics. First, this chapter returns to the theories of "Mediated Learning" as framework through which to interpret and evaluate the data presented in the previous chapters. The outcome of that exercise is to discuss how"learning analytics" can act as a mediatory agent, a more knowledgeable entity that can support learning. Second, this chapter identifies the indicators that appeared to be most useful to participants and translates them into metrics that can be captured with learning analytics. Understanding how learning is recognised is key to improving existing educational models and establishing impact in learning analytics research. Recommendations are grouped with regard to issues around data collection, interpretation and analysis, and communicating outputs with stakeholders, the three pillars of software development [160].

Section 10.1 examines the evidence from the perspective of Vygotsky's theories of mediated learning. It summarises how learning analytics can best shift thinking about teaching and learning. In addition, it provides some recommendations for learning analytics developers for how to promote positive changes in these areas. Section 10.4 adds the perspective of Feuerstein's Mediated Learning Experiences and the universal criteria that all MLEs will share. Each criterion is used to examine the types of affordances expressed by educators and learners in the context of this study and to evaluate their potential for improving the impact of learning analytics on teaching and learning. Section 10.5 goes more deeply into translating the indicators that educators and learners are already using to understand and monitor various aspects of their practice, into workable metrics. This section includes informal feedback from researchers and developers on the recommendations made in this chapter. Finally, the chapter closes with some reflections on using Mediated Learning as a framework and the extent to which it was able to produce insights useful for addressing guiding questions in this research.

10.1 How Learners Develop

Vygotsky believed that the development of signs, symbols and language is the vehicle by which human beings master more advanced cognitive skills; The need to communicate, creates a need to think about oneself in relation to an"other", which then opens channels for critical thought and reflection. Kozulin argued that, as certain systems of psychological tools persist over time, they become "cultural", perpetuating themselves [26].

The findings of this study described some of the psychological tools, or ways of thinking, that appear to have become cultural for the participants in the study, and which have/had their own mediating effect on how learning analytics can be perceived and utilised (see 8.13). This section examines some of these reciprocal relationships and their consequences for learning analytics.

10.1.1 Self-Selection in the Field

The study suggests that, through socialisation within their given field or profession, a process of self-selection impacts how an individual thinks of affordances of learning analytics and prepares to act on them. This evidence could support the Theory of Formal

Discipline, for example, which states that the study of certain subjects will result in the development of certain cognitive skills [161]. Mathematics, for example, has been shown to influence the development of conditional reasoning over time [161, p 164]. The fields of medicine, law and psychology have also been shown to have significant effects on certain cognitive skills [162]. The findings of this study support the proposition that **individuals carry over strategies from previous educational and professional experiences, which then influence their goal orientation and future strategy choices**. The greatest differences noted in this study were from Medicine and Sociology (see 8.10).

For learning analytics research, this will impact both perceived ease of use and perceived usefulness. Perceived usefulness is dependent on learning analytics dealing with a challenge that the stakeholder finds relevant. Relevance is established through evaluation. For example, the Learning Analytics Acceptance Model was evaluated and validated with only participants with a computing background or experience in analytics. Perceived usefulness was examined only in terms of the role within the institution, not their personal or past professional background [2]. If evaluations were conducted with a more diverse stakeholder group, it might be possible to identify new categories of data that are necessary to collect, new techniques and methodologies around interpretation and analysis, and different applications of learning analytics data. On the basis of those findings, it is highly recommended to **ensure diversity at all stages of the development and evaluation process**.

Recommendations

- Data Collection: Conduct qualitative studies with educators from different faculties to understand their unique data needs.
- Data Analysis: Conduct early pilots with stakeholders from non-technical backgrounds.
- Communication: Ensure effective "translation" of technical terms to non-technical stakeholders.

10.1.2 Perceiving Strategy

The findings presented indicate that exposure to new strategies, in particular through transitioning to a new domain or coming into contact with those who have, produced the greatest level and diversity of metacognitive activity about individual practice. Learners who found themselves in unfamiliar territory appeared to find it easier to spot differences in strategy and goals among their fellow classmates. The importance of witnessing and being exposed to different strategies is mirrored in Vygotsky's theories about learning through the "other". Humans need others to compare these factors and influence them, and our "modifiability and diversity" are what makes humans powerful as a species [16].

This study suggested that learners with special needs are also more conscious of their strategies than other students, perhaps through recognition of their struggles. Learners described becoming more aware of their study habits, strengths and limitations because of some of the support services that are offered to them at the Open University.

Institutions like the OU, which provide flexible distance education, should **be prepared to both accommodate and learn from transitioning learners and learners with special needs**. The OU has reported that approximately 70% of learners work full or part-time while they are studying and that the institution had enrolled more than 20,000 students with reported disabilities in 2015-2016 [1]. The student research participants in this study reflected the strength of this demographic. If transitioning learners and learners with special needs have the greatest insight into their own strategies, then they represent an important group of learners whose behaviours could be significant to monitor.

The findings of this study suggested some possible ways of recognising such learners. Transitioning learners may be most easily identified through integration of information about their professional background and current course of study. In combination of this, transitioning learners might perform initially worse than they expect, or have habits that are different from other students who are not transitioning. Learning analytics can contribute to the strategy development of learners by focusing on the activity of transitioning learners, how they approach the new topic, how they learn from other students and how they change their behaviour.

[1] http://www.open.ac.uk/about/main/strategy/facts-and-figures, Accessed January, 2018

Recommendations

- Data Collection: Harvest more data on the learner's professional and educational background from initial University or course applications.
- Data Analysis: Identify learners transitioning from one domain to another. Look for moments of behavioural change, for example, by analysing VLE data related to indicators such as use of resources, submission style, interaction, tuition payments and quality of work.
- Communication: Consult with students with special needs on learning analytics.

10.1.3 Supporting the Learner Through Design

As providers of distance education, every communication, every resource, also transfers a way of thinking to the learner. It is important to consider that message and what it communicates. As mentioned previously, there is already a strong support for using learning analytics to improve learning design. For example, learning analytics can inform intervention design [163] or the study the effects of learning design on student satisfaction or performance [154].

Findings from this study indicate that educators have a conscious link between what they intend and how they structure their course and that they would most prefer to have learning analytics solutions that resolve real challenges that they are already resolving in a different, less effective way. Similar to learners, educators felt learning analytics should be able to help them make *better* educational choices, not perfect choices. The personal attachment that educators feel toward their teaching approach, suggests that over-standardising course delivery is not likely to be a workable option. Rather, using learning analytics to support **reflection on the appropriateness of certain learning designs for certain subjects, what consequences that has for the student and how they could be innovated** seems to be a more sensible approach [154].

Recommendations

- Data Collection: Harvest more data on educator background and experience.
- Data Analysis: Evaluate learning design more holistically, looking at the confines of the field and the materials, the pedagogical intention of the educator and the impact on learners.
- Communication: Promote standardisation across shared educational goals and needs, rather than wholesale across a given faculty or module.

10.2 How Learners Think

As a necessary first step toward changing thinking and behaviour with learning analytics, the study indicated that it is important to understand how different ways of thinking get established, so that they can be broken down or expanded upon if necessary.

This section deals with how learners conceptualise knowledge and evidence, and how this relates to learning analytics acceptance. 10.2.1 explores how epistemology and strategy connected in the study. 10.2.2 looks at learning analytics as its own object, constituting a specific type of evidence.

10.2.1 Different Tools for Different Jobs

How do learners and educators perceive knowledge and knowing? Asking participants to reflect on how they recognise learning provided insight into how they perceive, "knowledge", where it comes from and how it changes. Examining the variety of affordances, one can get a sense for the types of information that are interesting for certain groups of individuals.

The evidence suggested that, for learners and educators **in the pragmatic grouping, learning is somewhat like prospecting**; a learner uncovers knowledge that exists, waiting to be discovered. Affordances appeared to be about making the prospecting easier; **calibrating tools, automating processes, and taking a more *indirect* approach to impacting learning** with learning analytics (see 9.7.4).

Their more discursive strategies suggested that **for educators and learners in the open grouping, knowledge was viewed as more constructive**; an internal process of competency development in being able to engage with the topic on multiple levels. The affordances associated with the open grouping tended to be more about **providing many chances for interaction and exchange** (see 9.7.2).

For the applied grouping, knowledge appears to be a combination of that which can be uncovered, such as patterns in one's own behaviour or that of others, and that which is constructed *on top of that foundation* through interaction and exchange with others (see Figure 10.1). **Applied learners appear to view knowledge as both fixed and evolving**, which combines the best of both pragmatic and open strategies. For example, learning analytics were perceived to be useful in assisting the process of **sifting through potentially relevant data** on student forums to identify the key conversations. This is a rather pragmatic affordance. When combined (by learners, in particular) *with the intention to analyse discourse*, it appears similar to intentions expressed by participants in the open grouping. Individuals with applied strategies demonstrated that they are aware of different forms of knowledge and performance of knowledge, for which different strategies are appropriate.

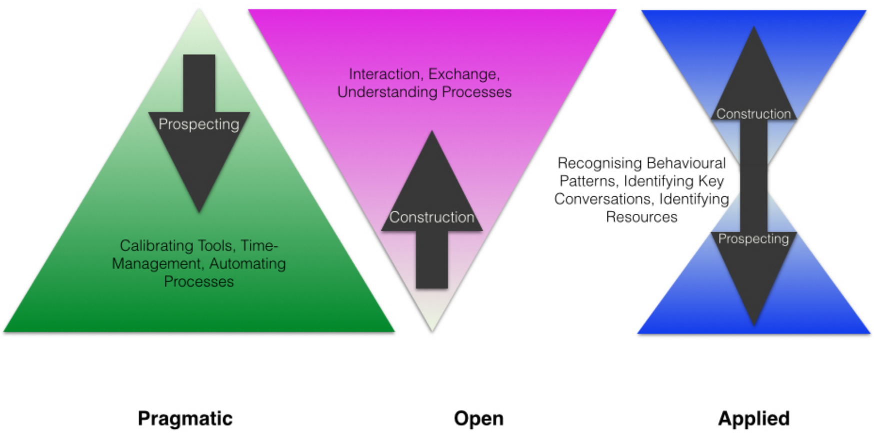

FIGURE 10.1: Learner Conceptions of Knowledge

With regard to learning analytics research, the consistencies in some of the behaviours or interests that are associated with a pragmatic or open strategy might make it possible to **predict what type of conceptual development a student might need at a given moment in time**, in order to put them on equal footing with their classmates. If a student displays no time management in submitting assignments but appears to have a lot of interaction with other students, for example, this may indicate that the student has activated an open strategy. If a student submits regularly with adequate performance, but does not engage with other students, this may indicate the presence of a pragmatic strategy. In order to seriously consider strategy as an indicator, institutions must consider which information is important to collect and harvest about a learner's background and experience. Figure 10.2 provides an initial set of indicators for identifying learner strategies from combinations of performance, interaction and communication metrics. Qualifying words such as "limited" and "considerable" refer to educator and learner discretion in how such terms should be interpreted. This implies **the need for clustering processes on such information to help create some useful ranges**.

Pragmatic Strategists	Open Strategists	Applied Strategists
limited contact with the tutor	considerable contact with the tutor	contact with the tutor when necessary
limited contact with other learners	considerable contact, also informal contact with other learners	participation in key conversations
consistent performance (high, low or mid-range)	erratic behaviour and performance	consistent performance (mid-range or high)

Figure 10.2: Indicators for Recognising Different Learner Strategies

Many learners that fell into the applied grouping, were transitioning learners. This makes sense, as many of these learners have had to develop complex epistemological positions in order to do well transitioning between domains as was discussed in 10.2.1. Understanding this process of transition may offer important clues about how it takes place and how to encourage it in other learners.

In addition, it is worth considering the *educator's* own background and how their own interdisciplinary approaches open new strategic visions. Online education, and particularly open education, attracts different types of individuals to the field. The Open University appeals to different technological, sociological and pedagogical interests. Rather than identifying common interests among all stakeholders, **learning analytics research could focus on identifying and serving specific needs of specific communities or types of stakeholders**.

Recommendations

- Data Collection: Harvest more information on learner interactions with their tutor and other peers.
- Data Analysis: Identify and cluster patterns of behaviour and performance that may illuminate the current strategies of learners, such as consistency or continual fluctuations.
- Communication: Focus on identifying and serving specific needs of specific communities or types of stakeholders.

10.2.2 Accepting Learning Analytics as Evidence

What counts as evidence and who decides? The findings suggest that educators and learners tend to cluster around a few different educational goals and strategies, which are influenced by their educational and professional backgrounds. This appears to impact **the extent to which learning analytics will constitute acceptable "evidence".** The belief structures that governs an individual's particular goals and strategies, prime the individual for how to perceive evidence. For individuals with advanced numeracy or computing in their background, learning analytics were not difficult to process as a plausible vehicle for good evidence. As mentioned previously, learning analytics emerged from computer science and educational data mining, which involved a certain set of psychological tools. Educators with no background in computing or analytics are less likely to "speak the same language" and express more fears about whether or not learning analytics could be adequately interpreted at all.

However, a promising finding of this study indicates that **fears around learning analytics could be mitigated through exposure to them, regardless of whether the experience was particularly fruitful or not**. Even participants that reported negative experiences with learning analytics, such as Lucy, continued to feel confident that learning analytics can illuminate something significant. She describes learning analytics as an extra-observational tool, that is sometimes useful and sometimes not. The general interest in exposing "unknown unknowns" supports this as well, suggesting that learning analytics have unrealised potential that is recognisable. Finally, the same effect was noticed after the exploratory interviews, when the researcher was able to discuss her own ideas about learning analytics with the participants from the exploratory interviews. Sharing her own reflections on using learning analytics to support critical pedagogy, sparked additional conversations with participants about new affordances. As mentioned in 7.7, this effect is what helped to clarify the purpose of the focus groups to explore learning analytics without preconceptions related to specific tools, just thinking about the information learning analytics can provide.

The findings above indicate that learning analytics may be mediating learning even by simply introducing some individuals to the concept of operationalisation. Considering how something could be measured, educators were able to see more possibilities for *what else* could be measured with the same methodologies. **Conducting operationalisation exercises, even those that are very complex, could provide insights into creating more intuitive learning analytics tools**.

In addition, to help educators inspire one another, **forming interdisciplinary teams can help to shake persistent assumptions about learning analytics**.

Recommendations

- Data Analysis: Allow for experimentation in the operationalisation process with different indicators with diverse stakeholders.
- Communication: Provide early, interdisciplinary experiences with learning analytics.

10.3 How to Support Learning

In this study, potential impact was measured in terms of the extent to which the participant could conceive of a personal application for the insights that a particular affordance might offer. The richest affordances were those in which the participant could describe how having similar insight in the past actually changed or would change behaviour. **The cognitive and conscious behavioural shift is learning impact**, in comparison to impacts on the “performance of learning”. Learning impact is the focus of this study.

This section focuses on how participants shifted their thinking or behaviour and how learning analytics can leverage or mobilise these factors. This leads to a final caution in subsection 10.3.5, which addresses the pitfall of confusing affordances (how something *could* be used) with intention (knowing how something *would* be used).

10.3.1 Identifying Student Goals Through Query

The evidence suggests that **the learner's goals really are at the centre of the educational experience and that useful interventions require access, of some sort, to this information**. Most of the intentions that educators had in classifying learners, for example, were really about looking at behaviours that might be more helpful in identifying the learner's goal, to understand what they were perceiving as the learner's strategies. Educators reported that once they were aware of what the learner's goal was, they would be better equipped to encourage the learner to stretch it. If the learner does not choose to stretch, at least the learner can be encouraged to maintain their current achievement level. Unfortunately, **educators reported that they are missing information about students' goals**.

At the moment, educators gather information on learner goals from what the learner tells them and what they can observe in the learner's behaviour. When they do not have even this much information (for example, with large class sizes), educators described feeling in the dark, preparing for everything and fearing that they are delivering less than they could. Much of what educators hoped to achieve with learning analytics was about amplifying and extending their existing practice of **identifying what learners need and want to know**. Affordances around analysing prerequisites and setting expectations were about calibrating learners' goals to be more realistic and achievable, once again, focusing on the *indirect approach* to compensate for the lack of information.

For learners, goals were much more contextualised and nuanced. Goals were sometimes formed on the basis of life experiences, such as motherhood or retirement, *conditions that will not soon change.* Regardless of what the educator would hope for the student, the evidence indicates that if the student has decided on a certain path, it will be difficult to deter her.

Students in sub-optimal conditions will continue to study. However, learners did experience having their goals *shaped* through different learning strategies. **Meaningful comparisons** with the self, with others and with the discipline were able to shape learners' self-conceptions, in particular when these comparisons were **on their own terms**. Learning analytics were perceived as an opportunity for **noticing subtle shifts in learner behaviour that indicate they are consciously acting on feedback**.

Learning analytics for non-formal learning are able to offer some insights in this regard. For example, the AFEL project, mentioned in the literature review of this thesis, involved tracking individual behaviour online and suggesting to the user what their goal might be based on their activities. The simple question implied by this is: *"is this what you [the user] intended to do?"* [41] **Looking at how learners react to simple queries such**

as this may provide insight into the level of consciousness behind students' strategies, as well as alerting educators to changes. This could come in the form of an alert or regular notification/reflection question, to help provide an additional data point for interpreting learners' actions.

Another way of gathering insight into conscious decision-making is to gather information on what students feel is important to know. The ADA service, a digital assistant created to support students at Bolton College [2], tracks the kinds of queries that students submit to the system, to analyse gaps in understanding or communication channels. It also provides personalised and adaptive feedback. This simultaneously **provides a useful service to the student and delivers extremely useful insights about what students know and do not know**.

In learning analytics research, the need for customisable, adaptive feedback is typically realised in the form of an interactive dashboard. This tool can enhance its power by making two adjustments. **Combining the customisability of learning dashboards with a way of tracking learner queries and confirming any changes in behaviour by asking the student to confirm it**, would provide the reciprocal information of understanding where learners have gaps in their strategic understanding and what assists them in making changes.

Recommendations

- Data Collection: Collect information on the questions learners ask. Collect learner verification of system outputs.
- Data Analysis: Appeal to learner verification of system outputs (predictions, etc.), through use of prompts, to establish learner awareness and conscious behavioural change.
- Communication: Include verification prompts in learner and educator dashboards. Inform tutors of changes in learner behaviour and apparent goals after verification of system outputs.

10.3.2 Ensuring Relevance Through Agency

What is likely to be relevant? This is still a question that learning analytics may help to answer, even if it is personal. Useful analytics are those which "surprise and compel, and

[2] http://aftabhussain.com/ada_goes_live.html

thus motivate behavioural change" [24]. The previous subsection described some of the shared ways in which learning processes generally change and adapt. **Helping learners to develop more cognitive flexibility is an area where learning analytics can help to impact learning directly.**

Inside of that, however, **students still need to anchor their development on something that is important to them**. The findings suggested that agency plays a much bigger role in learner success and strategy formation than educators realise. **The evidence indicates that while educators hoped to empower learners to make good choices, learners hoped to be empowered to make good on the choices they've already made.** Information that learners were likely to find useful typically depended on goals that were personally relevant for their learning experience: a) what they hope to gain overall from studying b) what they hope to gain from the module or class itself. Occasionally, those needs coincided with what educators wished for students to do, but only when the student had personally understood the value of the activity toward achieving their goals.

Statements from students also demonstrate their desire for **concrete, timely, relevant feedback that *take into account the realities of their lives***. Educators, however, do not always feel that they have enough information to provide contextualised, personalised feedback.

What is interesting, however, is that agency was also an enormously important aspect for educators, who expected to be supported in delivering the learning design that they feel is most appropriate. While educators appeared open to exploring the impact of their pedagogical approaches, they also hoped to have more control over what data is collected and how it is interpreted. The findings suggest that **agency may be the quickest path to relevance, and thus to perceiving an actual affordance in using learning analytics**.

For learning analytics development, enhancing agency could mean creating more personalised dashboards, but possibly, more personalised tools as well. Using learning analytics for **identifying more subtle changes in learner behaviour would allow educators to better assess learners in the absence of information about their goals**. Research indicates that customisable dashboards are what both educators and learners want[164][85]. However, research shows that the customisation process itself requires a familiarisation phase, especially for computer novices [164]. Personalised tools, which go a little further in allowing an individual to develop their own indicators to analyse, can support the processes of reflection and regulation. The DDART platform, for example, allowed learners to develop their own indicators from examining their trace data, which improved their ability to regulate their behaviour. However, evaluations indicated that developing indicators can be difficult [165]. This suggests, once again, that training in the area of operationalisation will be important for learning analytics development.

Recommendations

- Data Collection: Identify the indicators that are important to learners. Collect data relevant to those indicators.
- Data Analysis: Explore common patterns and trends to enhance learning models and bundle indicators for novice users.
- Communication: Consult diverse stakeholders to create customisable learning analytics dashboards, but provide familiarisation phases in implementation.

10.3.3 Utilising Association and Examples

As mentioned previously, Vygotsky argued that self-consciousness arises through comparison with the "other." Vygotsky's notion of the Zone of Proximal Development (ZDP) describes the learning potential of an individual with the assistance of a more knowledgeable individual [26] (or perhaps entity, in the case of learning analytics platforms). This has direct and indirect features. Some mediating effects are direct, in the form of instruction or scaffolding procedures that help learners to develop inquiry skills and clarify their strategies [26, p 20]. Other mediating effects are indirect, in the form of exposure or spontaneous insight. However, not every experience of exposure will have a positive mediating effect, as Smagorinsky argued [106]. Scaffolding experiences of exposure as learning experiences is more likely to result in the development of cognitive strategies, which are useful in formal learning [26, p 21]. This suggests that novice users of analytics platforms will require some assistance in understanding and using the insights provided. If learning analytics is to be a mediatory agent, or represent the "more knowledgeable other", there must be some common language.

Findings related to transitioning students show that conscious contact with other learners is the mechanism that they relied upon most to actually change a strategy. This means that, if a learner has already developed a general set of learning strategies, as many OU learners will have done in their previous or current professional life, conscious contact with new strategies can help them transform or replace certain strategies when necessary. Students act incidentally, in group assignments or student chat rooms and on the forum, but they do not often interact with the clear purpose to explore and exchange information about learning strategies. In particular, students with pragmatic strategies, who reported less conscious contact with other students, reported some difficulty in adapting new learning strategies when they were struggling. This was especially true if they did not have a particularly interactive tutor to provide expert guidance. However, the research literature is ambiguous on this point, as some studies argue that participation expressly *improves* performance [166], whereas others indicate that it is *not interacting* that has a *negative* effect on learning [167].

In light of the findings of this study, this ambiguity makes sense. If the student requires a new strategy, but has no conscious contact with other learners or is not aware of her need for the strategy, she will have difficulty making that transition. If, in addition, her tutor is not helpful, then she is even less likely to make a positive transition to a more useful strategy. **This study implicates the way in which interaction is facilitated and for what purpose as the influencing factors on the level of impact it can have on student learning**.

To improve the likelihood of new strategy development, social learning analytics can first help to **identify some general strategies that are useful**. Second, social learning analytics can **assist learners in becoming more aware of their needs through making meaningful comparisons**, and in particular by giving them access to a wider selection of strategies. Finally, social learning analytics can help to improve and optimise social networks, helping the learner **identify more knowledgeable peers able to assist with new strategy development**.

Tutors also have an important role to play in providing the conscious contact that some students need in order to shift their strategies, especially when the learner is entering a new domain with a pragmatic strategy set. Learning analytics that help to **track educator activity and intervention** would provide much needed insight to a very important aspect of the learning process. The findings of this study suggest that this may be true, even if only the educator has access to this data.

It appears from the findings that the "more knowledgeable entity" does not need to be present. Many students spoke about wanting to have an example of an assignment or text, something that could help them to understand, at least at the beginning, what will be expected of them. Other students wanted to have insights into how other students approached assignments. For example, one of the affordances of learning analytics on web data that is external to the VLE (see 9.5) was having access to other learners' web histories as they prepared an assignment. The realisation that each person will approach the task slightly differently, and that it would be possible to have access to some part of this process, was interesting for both learners and educators.

For educators, **finding more efficient or more effective ways of resolving *existing* problems** was a primary concern. This typically translates into identifying best practices, which is not the same as drilling down on specific issues of importance. Findings from the exploratory interviews demonstrated that a "problem" is only a problem for an educator, if it represents a challenge directly related to their individual learning design and pedagogy. The study found that **different pedagogical positions could be clustered into some reasonable groupings, clarifying sets of needs and possibilities that might be relevant for subgroups of educators**.

Recommendations

- Data Collection: Collect web histories and examples of work from different learners and experts. Collect social data from learner use of histories and examples from other learners and experts. Collect information on tutor interaction with learners.
- Data Analysis: Have users rate and annotate examples they find useful. Identify workable learning teams and support networks based on goals and strategies.
- Communication: Provide ample training and support, especially for novice users. Anchor evaluation experiences on existing problems.

10.3.4 Reaching for High-Hanging Fruit

How can you assess knowledge? All of the above leads to the very complex issue of assessment. Assessment featured quite often in the data, involving relationships between the University as an entity and the educators, the module teams and the associate lecturers or tutors, the educators and the students. Educators were generally unhappy with assessment and many felt that the current ways they assess their students were inadequate for the job. This was particularly true for educators in the Arts and Humanities or Social Sciences, especially those with a goal to develop strong minds. That appears to translate to students in similar domains, who struggle to recognise their learning with traditional assessment and performance markers. Findings indicated that **assessment in the Arts and Humanities, as well as Social Sciences require more creative methods of analysing text and identifying best practices for which general skills are expected to be developed, such as argumentation and critical thinking.** This is not a surprising finding. This division has been noted before in education, for example, with the concept of "multiple intelligences" and the development of linguistic *versus* numeric skills [168]. Educators and learners acknowledge that assessment of linguistic skill is time-consuming and complex. They see opportunities for learning analytics to provide the **innovative technologies necessary for harvesting this high-hanging fruit of educational data**.

Already in 2011, Ferguson and Buckingham Shum illustrated that it would be possible to use learning analytics techniques to identify exploratory dialogue in synchronous chats [169]. In the same year De Liddo, Buckingham Shum, Quinto, Bachler, and Cannavacciuolo demonstrated how learning analytics could support qualitative data collection about student discourse and argumentation [170].

These types of tools are reminiscent of wishes expressed by individuals in the applied grouping to understand the shape and structure of discourse, where certain conversations or conflicts are occurring. Many smaller analytics tools that have been researched and developed, which accomplish what many educators felt would be useful in assessing more complex skills, such as academic writing [171] and discourse [172]. However, research indicates that students are not likely to use them, unless they are perceived as useful or necessary, and "embedded" in their coursework [173]. With regard to "perceived usefulness", findings implicate a domain-relationship as a factor in what a learner would perceive as important. As an effect, that value is communicated by the educator to the student through the pedagogical approach. This is important when one considers the Mediation of Meaning in 10.4.4.

It also suggests that it is important to **start with the educator and make a convincing argument for embedding such tools in the every day processes of learning**. In terms of approaching and working with educators, the findings of this study indicate that having stakeholders work in interdisciplinary teams on learning analytics might be more helpful in disseminating useful knowledge to less knowledgeable individuals. In addition, the influx of novices may generate some creative ideas from outside of the disciplines closest to learning analytics (such as computer science and statistics).

Recommendations

- Data Collection: Collect textual data from learner assignments.
- Data Analysis: Use existing research to provide ways of analysing more complex skills that impact success such as critical thinking and academic writing.
- Communication: Encourage educators and tutors to fully embed the process of reflecting on learning into the regular activities of the class.

10.3.5 Differentiating Affordances and Intentions

Why are such tools, as those described in the previous paragraphs, not more common place for educators in an institution like the Open University? The findings of this study, along with the research literature, suggest that many tools educators might need already exist in some form. If they exist and they are not being used, there are a few possible explanations. However, the educators and learners in this study suggested that if tools are not being used it is mostly likely because they are failing to meet the real requirements of educators, with regard to the information needed to make an important judgement. **Requiring educators to base their evaluations on personal, real-life scenarios will be more likely to produce evidence of intent to use**.

10.4 How to Change a Mind

The previous section highlighted the places where learning analytics could mediate important educational processes related to identifying, influencing and transitioning between systems of thinking ("psychological tools"). Smagorinsky claimed that a positive mediation will not always be successful, in particular if the learning environment is not intentional and trustworthy [106]. In addition, as Feuerstein argued, it is possible to *perform* learning without the continued development of advanced cognitive skills [17].To determine if an environment is trustworthy and differentiates between learning and the performance of learning, it requires some additional reflection.

Assessment has already been discussed as a frustrating element of the educational experience. Assessing learning as something separate from the *performance* of learning is a central conflict that faces all educational institutions. Kozulin wrote:

> "We often tend to confuse literacy in a generic sense with a special type of analytic literacy that is supposed to be a goal of formal education. Not every type of literacy leads to the cognitive changes observed by Vygotsky and Luria (Luria, 1976). Moreover, even literacy acquired in the nominally formal educational setting does not necessarily lead to the cognitive changes unless this literacy is mediated to a student as a cognitive tool.[26, 25]"

When the output looks very similar, **learning and performance can be differentiated by examining the educational context**. Feuerstein's criteria for mediated learning experiences provide a framework for determining, at the very least, **whether the appropriate conditions for learning have been met**, as a complementary feature to actual performance.

This section discusses the affordances proposed by research participants in relation to the three universal criteria proposed by Feuerstein, which *all mediated learning experiences will share*. 10.4.2 addresses Mediation of Intentionality and Reciprocity. It describes the affordances of learning analytics that communicate an intent for the student to learn, as well as an interest in the student's processes over outcomes. 10.4.4 explores Mediation of Meaning, and the ways in which learning analytics can help to convey or support learners' understanding of why something is important, should happen, or be done. 10.4.6 probes Mediation of Transcendence, and affordances that go beyond the goals of specific educational interactions to help the learner see the larger picture. Each of these sections has a message for institutions, researchers and developers about creating learning analytics that are more likely to mediate (and this impact) student learning.

10.4.1 The Applied Grouping

Before beginning this part of the discussion, it is useful to point to a particular group of interest from the data, which shaped the development of arguments below, learners with applied strategies. The previous chapter explored how the hybrid strategies of the applied grouping allowed them to connect with learning analytics in novel ways. The affordances of learning analytics that were expressed by members of this grouping resulted in the highest levels of metacognitive activity (see 9.1). This group represents an **interesting and insightful target group for learning analytics exposure and evaluation**. Transitioning learners from the applied grouping provided some additional evidence of how new learning strategies are adopted, which is ultimately how Vygotsky and Feuerstein believed that learners grow [19][17]. Due to their ability to stimulate metacognitive activity, **more of the affordances that fall into the applied grouping are also those which have the greatest mediatory potential**, as the following subsections will demonstrate.

10.4.2 Mediating Intentionality and Reciprocity with Learning Analytics

Intentionality is the spark that ignites the mediation process. Feuerstein likened this to calling a class to attention and signalling that the learning process has begun [16]. Feuerstein argued that if a particular object is intended to be used as a cognitive tool, that intention must be communicated very clearly to learners. Reciprocity is the companion to Intentionality, in communicating to the learner that there is value in sharing the processes by which they learn, rather than their outcomes [16] [19]. Together, they ensure that mediated learning is a *mutual process*, which Feuerstein felt provides the learner with the best chances of success [19][20].

Online classrooms already have difficulty mediating intentionality and reciprocity in the same way as a bricks and mortar institution. In a physical classroom, the teacher can come in, stand at the front of the class and tap on the chalkboard or flip the lights on and off if the classroom is noisy and the pupils appear unsettled. Silence is a sign of attention. In an online classroom, at least for educators from the exploratory interviews and focus groups, silence is potentially a sign of *disinterest*. Without the disruption/silence dynamic of a physical classroom, *how do online educators and learners perceive a mutual process? How can learning analytics support this?*

Findings of this study showed that **transparency** was a factor in how educators and learners perceived learning analytics affordances. This was particularly noted with regard to the intentions of the University. Students and educators tended to connect learning analytics with cost-saving measures, which breaks the perception of mutual process. **Having a clear chain of responsibility** was also an important issue, in terms of who is asking the questions and why. Not knowing who the beneficiaries are, appeared to create barriers in how useful educators and learners perceived learning analytics to be. Ethical considerations, too, appeared to be focused around the potential for misinterpretation or misapplication, for example, to reduce quality and keep costs high for students. The evidence suggests that if educators and learners could be assured of benevolent usage, they would be more willing to supply their data. **Mediation of Intentionality and Reciprocity can be improved by dealing with these transparency issues and clarifying responsibilities**.

Intentionality and reciprocity can also be mediated by **allowing learners to engage with the institution and with educators on the subject of learning analytics**. Findings of this study suggest that even just pointing out to educators and learners that certain activities can be mapped and measured elicited metacognitive activity about practice. Getting the learner to verify claims that the system is can encourage their participation and increase the validity of the system's insights.

Most educators admitted that they make mistakes and that they could learn something about their own practice from the data. This indicates that they are open to having their activity *interpreted* by others. However, they are less open with how it is *applied.* Findings indicated that educators are less willing to share data, if they believe it could be used to evaluate their performance based on measures to which they do not relate. Still, understanding, in the same way as learners, the ways in which they are responding to learning analytics insights, would be an important piece of the puzzle to resolve.

10.4.3 Affordances for Mediating Intentionality and Reciprocity

Which of the affordances that educators and learners named meet this particular criterion? Affordances that stop short of involving the learner or educator in any conscious aspect of the *process* would be automatically excluded. However, most named affordances did have *potential* for examining mutual process of intention and response. Prediction, for example, has a very clear intention and reciprocal request; at-risk learners should be identified and the tutor should intervene. The findings of this study indicate, however, that the strength of the prediction could be improved, if some part of the request was made directly of the learner. More specifically, this study suggests that a query, such as asking the learner if they are aware of a given trend in their activity, if they intend to continue or if they need help, might help to close the loop more effectively, between learning analytics and impact. Identifying the learners who do and do not exhibit behavioural changes after verifying or rejecting system outputs can provide some useful insight into what processes or conditions support behavioural change.

Likewise, complex sociological studies have the intention to examine other contextual features that are relevant for learning and it is expected that the institution will do something about it. The mediatory potential of such studies, affording to the findings presented in this thesis, could be improved if learners were *also* aware of the many factors that potentially influence their educational experience. In addition, comparison with a selection, so long as that selection is relevant to the learner, is also intentional and reciprocal. Conversely, affordances such as assessing participation, understanding withdrawal and assessing learner attention, as they were described by participants, were not typically affordances that would mediate intentionality and reciprocity. Either, there was no clear request that the learner perceived (in particular when their participation or attention was required), or there was no clear intention behind it.

The affordances that provide the closest mutual process of learning exchange through learning analytics can be found among the applied grouping. Affordances that involved investigating the educator and student relationship, tracking one's own patterns of study, or looking into the patterns of others relied most closely on mobilising the individual for a social benefit.

To gain their support, findings suggest that educators and learners would like to be in control of how their data is applied. **During the initial stages of learning analytics research, institutions should consider developing tools that support familiarisation and personal exploration, providing exposure without requiring access to the data**. This would give educators and learners time to become familiar with learning analytics approaches enough to provide a useful consultation on how they could be used to evaluate activity on an institutional level. This suggests that learning analytics can learn some lessons from the health sector about innovative approaches to protecting sensitive data, for example, through cryptography protocols around clustering partitioned data from distributed databases [174][175]. However, intentionality and reciprocity are a frame. Mediation of meaning and transcendence are still necessary to understand exactly what is being communicated through the mutual learning process.

Recommendations

- Data Collection: Collect verification and response rates to system outputs from both learners and educators.
- Data Analysis: Perform cluster analyses on recommendations, verification and subsequent user behaviour. Develop more meaningful predictive patterns. Research new technologies regarding data storage and distribution.
- Communication: Make a clear use case for why gathering data is important. Ensure that this use case benefits those who contribute their data. Make all stakeholders visible.Develop student-facing dashboards for tracking study habits and outcomes, identifying and verifying goals and strategies.

10.4.4 Mediation of Meaning

Presseisen argued that Mediation of Meaning is about finding “the generator of the emotional, motivational, attitudinal, and value-oriented behaviors of the individual” [16, p 15]. The findings of this study indicate that this generator is found in the individual’s background and life circumstances, which set a few systems in motion that can be difficult to change.

This study proposes that the motor for change is in having access to *new* strategies that may assist the learner in accomplishing their own goals. With this in mind, **Mediation of Meaning will involve communicating the importance of certain activities toward the learner’s own goals**.

The findings of this study suggest that a few general learning analytics that are able to **meaningfully group and support different constellations of individuals** can help to anchor new strategies on existing knowledge (Mediation of Transcendence) and **promote conscious contact**. As has been previously mentioned, learners appeared more likely to seek out students with similar goals to obtain information on strategy. Learning analytics could both support and influence this process, for example through algorithms such as k-nearest neighbours, which helps to classify like-students. This technique is already used in predictive analytics, for example, in informing the models involved in the predictions generated by OU Analyse [51].

Mediating meaning in online learning gives social learning analytics a much higher value than it appears to have currently in impacting the practice of educators or learners. Educators are only one bridge that learners have to understanding the value and importance of knowledge and strategy. In a physical classroom, students can absorb strategy knowledge from students they trust “in the back of the classroom”, as one participant said. Finding ways of recreating that informal space within the structure of the University is a difficult challenge. **Mediation of meaning can be improved by analysing and fortifying bridges between students and with educators, in a way that focuses on the learner’s goals.**

10.4.5 Affordances for Mediating Meaning

Which affordances are best able to mediate meaning? Once again, any affordances that do not speak to the goals of the individual are not likely to mediate meaning, because the value is not easily apparent. **Affordances that build awareness of value or work with existing values are most promising for mediating meaning.** The most immediate approach is to allow the individual to experiment with, model and test their own assumptions, because the value is internal. For example, affordances around testing assumptions, tracking one's own study, and comparisons against specific selections of others are all driven by the individual's own perceived goals. Affordances that are based on idealistic goals cannot be assured of their ability to mediate meaning, even when those idealistic goals are very sensible, such as high performance or retention.

In connection with the above, findings of this study suggested that rather than time-management or setting expectations, which educators felt constituted a more reasonable approach to learning to study, students seemed to feel that accessibility and coping strategies would be more valuable. This indicates that **mediating meaning can be also be improved through affordances of learning analytics that address what *learners* perceive as critical aspects of their ability to participate in education**.

With this in mind, there are many affordances that participants mentioned, which potentially pass this second test. Almost all of the affordances from the pragmatic grouping in Figure 9.3.4 could mediate meaning if they were directed at the users than can benefit from this type of information. However, there are some that will not likely mediate learning. As has been mentioned above, setting expectations is an affordance that educators expect learners to benefit from, but which learners do not say they want. Likewise, assessing participation was considered important for educators in implementing their learning design, but this kind of design was not perceived as useful for some students. Additional work would be necessary to convince learners that do not feel they benefit from interaction that interaction is useful. This study suggests that affordances around **social analytics, in particular those that examine the expert-novice relationship, will appeal to the most students, even those with different motivations and goals** (though for different reasons). Learners want examples, from tutors or from peers. Tools that allow them to filter those examples in a meaningful way will be helpful.

This study observed evidence of two paths through which Mediation of Meaning might best be achieved. First, learning analytics could potentially automatically recommend strategies based on the goals the system can recognise. For example, through learning analytics, a tool could identify and communicate to the learner what their goal appears to be, based on their activity. The AFEL project [41] is an example of this functionality. Once the learner has verified or refuted the presented goal, it would be possible to suggest to the learner whether their activities are helping them to achieve that goal. Tools like nStudy [43] and click-stream analytics would have improved value. For example, if a learner has consistently fallen within the 10% of her class in her performance, it may be useful to ask her, "Is this your goal?". It may even be possible to ask follow up questions, such as "Do you want to improve it?" to gather extra information that would be helpful to know in understanding learner motivations and actual behaviour. **Learning analytics can mediate meaning more efficiently by helping the learner to identify goals, and monitor them as they change**.

The second avenue for development, with regard to mediation of meaning, would be to **focus on *general* strategies that are important toward achieving *any* goal**. For example, the findings of this study suggest that knowing how to make conscious use of other students and tutors is a general strategy that is useful for developing new strategies, as well as gaining access to specific strategies that are useful in the short-term. **Social analytics could facilitate conscious contact by appealing to learners for whom any interaction is useful, as well as those who want more targeted support**. Using the example above, the learner's goal was to be in the top 10% of her class, having access to learners with the same goal may allow her to make a more relevant comparison of strategies.

Recommendations

- Data Collection: Collect response rates (from both learners and educators) to learning analytics recommendations and prompts. Collect user verification of system outputs.
- Data Analysis: Identify patterns of expert and novice behaviour relative to different system tools and applications. Use non-parametric statistics on demographic, legacy and VLE data (such as k-nearest neighbours) to identify classes of learners who exhibit similar responses to system insights in terms of their goals, priorities and background. Apply social analytics to support classifications and create learning exchange groups.
- Communication: User the learner's own goal to motivate by exposing the learner to successful strategies demonstrated by learners who share their goals and certain key aspects of their background.

10.4.6 Mediation of Transcendence

The above sections argued that to mediate intentionality, reciprocity and meaning, the future direction of learning analytics research should focus on **how to make learning analytics more personal, dynamic and mutually beneficial for the institution, educators and learners**. **Mediation of Transcendence is a type of insurance policy that improves the quality of information in a highly personalised and**

dynamic setting. As mentioned previously, transcendence is mediated when the mediatory agent goes "beyond the scope of a particular interaction", to "widen the scope of interaction" [16, p 14]. Transcendence is what allows a person to **organise new knowledge into existing structures**. Without it, learning transfer is difficult to achieve.

Essentially, **mediating transcendence is about communicating context, which this study concluded was an important feature for new strategy development**. One achievable area of influence that learning analytics could have would be in **helping learners to see how their *strategies* fit within a larger context of other students in their in their module, in their degree program, or even in their domain** (which was important for novices). Through understanding context, individuals are able to anchor information on familiar concepts, identify outliers, observe the interactions of different factors, many general strategies that are important for learning. Presseisen wrote:

> "Feuerstein (1990) notes that transcendence is seldom, if ever, observed among animals who rather model behavior of particular and discrete intentions alone, very much limited by the organism's primary instinctual needs. Transcendence, for Feuerstein, is the most humanizing of the universal parameters [16, pp 14-14]"

Findings of this study about how specific strategies impact student learning suggested that being focused on achieving only specific goals may put new strategy development at risk. The framework of mediated learning would propose that this is because the conditions for transcendence are not met. In the study, when the student had module specific goals, such as to pass a specific test, their strategies were generally around understanding what that particular test would be assessing and making judgements about how to efficiently process material. This is a good strategy that can be repeated for a generally good outcome, so long as the student's ability to assess the situation is adequate (awareness), or they have contact with a more knowledgeable peer or tutor that is helping them (interaction). If the student is lacking in that general ability to assess, or has little contact with a tutor or peers, it is difficult for a student to contextualise their own goals and strategies well enough to know what is missing and how they can fix it.

The same is true for educators, when they find themselves in the position to interpret and act on learning analytics. It may be difficult for some educators to understand the wider context of learning analytics and thus, its strength as evidence. For example, where prediction falls short is in informing a larger cognitive strategy for what to do in the future to prevent the same occurrence. The evidence of this study demonstrated that sometimes the educator knows what to do, but sometimes they do not and it is this **missing larger strategy, for educators and learners, that impede the performance of prediction** as an affordance of learning analytics that can impact learning.

10.4.7 Affordances of Mediating Transcendence

Of the affordances that educators and learners named, which are best able to mediate transcendence? This study concluded that **affordances that specifically address general or contextualised strategy development will be those that best mediate transcendence**. Affordances around study tracking and self-regulation, for example, help learners to view their behaviours as part of a larger strategy for success (whatever this means)[39][43], which is already part of the challenge. All educators in the study agreed that self-regulation is a skill that students need and are expected to develop through their course of studies. As this study concluded, however, **there is very little place inside of higher education to assess and correct learners' strategy development**. It was not generally a formal part of the curriculum, nor were students' skills in this area formally assessed (with the exception of students with learning support).

Self-regulated Learning Theory shares many of the same principles that have been cited throughout this paper as being important for learning, such as emphasising agency and reciprocity in learning [5]. Learning analytics researchers have connected with this theory to create holistic sets of tools [176], as well as customisable dashboards and personal learning environments [177] for self-regulated learning, using learning analytics as a way of promoting awareness and reflection. In the long-term, these projects will reach the potential to mediate transcendence by **providing structure and organisation to educational strategy data**.

Learners, however, report that they need more help accessing that cycle of self-regulation. Becoming aware of learning as a strategy is a first step, followed by the understanding that there are different strategies that produce different results. With regard to the above, one of the simplest ways of mediating transcendence was in identifying and cataloguing different study behaviours. This was an affordance that learners were keen to see realised. In particular, the technology behind tools like nStudy [43], which capture trace data, was interesting for learners in a somewhat surprising way. Learners reported that, if some of the details of classmates' web histories and resource use were made available, for example, they would have a useful point of contact to consider different research strategies. Knowing the task and the first places a learner goes to start resolving the task can provide specific information for general strategy development, such as does the learner start with the materials or a general web search? Do they look at source material? How deeply do they go into the topic?

As long as the affordance, with its intentions and requests, aids in widening the scope of the interaction, it will have improved changes of mediating transcendence. Engaging learners and educators in the process of interpreting and verifying learning analytics claims and insights is not only reciprocal and meaningful, it also directs the reflection process away from the individual and back toward the process of discovery. As the findings of this study suggest, even small or negative experiences with learning analytics are sufficient to improve a stakeholder's awareness of learning analytics and their potential power.

Though experience of learning analytics does begin to train these skills, educators and learners, any direct beneficiaries of learning analytics insights, should still receive a foundation in computing and numeracy that is necessary for understanding both the potential and limitations of learning analytics. **Specific and prolonged training will help educators to understand certain functions of a given software, which will improve impact**.

Recommendations

- Data Collection: Collect information on students who both verify a system output and exhibit a behavioural change as a result. Collect information on students who verify a system output and do not change their behaviour.
- Data Analysis: Seek patterns in precipitating events or behaviours that precede behavioural change. Seek patterns in precipitating events or behaviours that precede verification without behavioural change. Conduct mixed-methods research to develop models of behavioural change on the basis of learning analytics insights. Share and verify these models with learners.
- Communication: Invite all stakeholder groups to be involved in the verification process to a reasonable extent. Communicate organisational changes that are made on the basis of insights and recommendations. Embed the processes of self-regulation into learning management systems and classroom curricula. Improve training in advanced numeracy and analytics for all student-facing staff and central academics.

10.5 Identifying Software Requirements

Identifying software requirements in learning analytics research is an iterative and cyclical process (see Figure 10.3). Clow described the learning analytics cycle as an extension of other cyclical learning and reflection theories, for example from Kolb, Schön and Laurillard, which emphasise how reflection leads to future decision-making [4]. For learning analytics to operate in a "closed loop", Clow suggests that there needs to be a) a clear evaluation of what has been done in response to learning analytics and b) evidence of how these responses are borne out in the subsequent data collection and analysis phases. What did users expect and were their expectations met? Requirements elicitation is an important part of understanding expectations.

For requirements analysis, Yang and Tang have suggested that focus groups, questionnaires and experimentation with initial prototypes are part of the first stage in gathering requirements from end users. During subsequent stages, the key stakeholders typically respond to a prototype and provide enhancement suggestions, while satisfaction with current features is measured [178]. This is a common practice in gathering learning analytics requirements as well. As has been highlighted before in this thesis, however, this process can risk conflating technology acceptance with learning analytics acceptance. For the purposes of understanding the conceptual value of learning analytics, this thesis did not involve responding or reacting to a prototype. Instead, it deployed a qualitative approach, highlighting instead what it is that educators and learners want to know about learning, and whether or not the information they could use to support them is being currently collected already.

Dyckhoff also distilled requirements qualitatively by assessing different case studies involving learning analytics and analysing the research questions that these case studies intended to answer [179]. The diversity of these requirements supported her conclusion that learning analytics tools must have a high degree of personalisation with a "flexible and extendable set of research questions"[179]. The findings of this thesis suggest that what is being framed as highly personal might also reflect professional standards or is shaped by professional experience and mindset. **The application Mediated Learning at the point of collecting user requirements made it possible to group requirements into different clusters, demonstrating that what is relevant may be somewhat predictable**. The findings of this thesis also suggest that learning analytics should focus on improving end users' **existing strategies first**, as this is what educators and learners value most. This meets the requirements of mediating meaning described in the previous sections, which are critical for gaining buy-in and contextualising impact. Greller Drachsler [180] concluded that intentional pedagogy is visible in the way that an educator interacts with learning analytics tools and technologies. The authors do not extend this to examine whether or not there are patterns, such that pedagogy might become *detectable* by looking at certain choices or behaviours. Knowing what an educator appears to be trying to achieve improves the value of a highly personalised tool, which is part of the contribution of the study presented in this thesis.

The codes and descriptions that emerged from the data often produced some indicators of concepts that were important to the participants. By considering what is available to collect, given the sources of data accessible, it is possible to develop workable software requirements for tools that perform the functions that participants suggested in the exploratory interviews analysed in chapter 7 and the focus groups presented in chapter 9 on Affordances.

The previous sections and chapters have already highlighted several examples of learning and learning process indicators that could be translated into metrics. Researchers and developers can start from those indicators to improve data collection, support the development of stronger predictive and descriptive models, advance learning assessment techniques and create buy-in from a greater number of potential stakeholders.

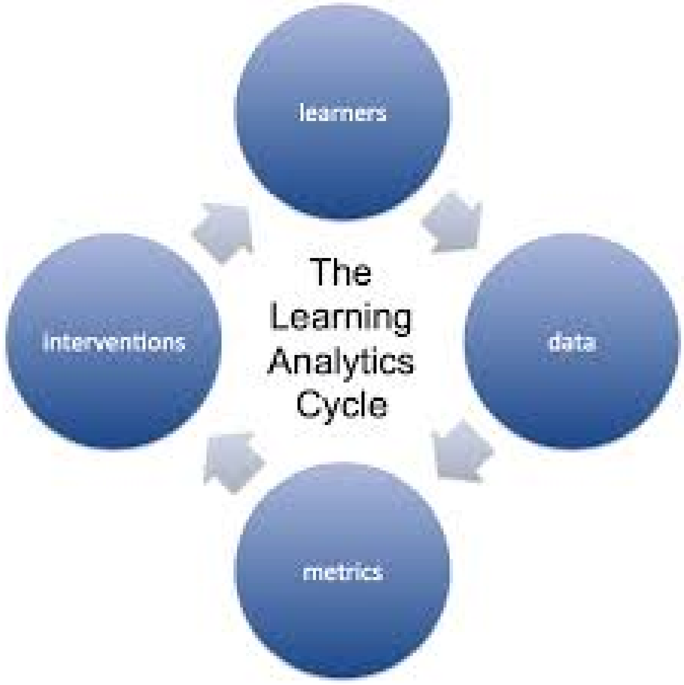

Figure 10.3: Learning Analytics Cycle (Clow, 2012)

This section expands on some of those examples, using codes and descriptions from the previous chapters to make some more specific recommendations with regard to classification of learners, prediction, social analytics and assessment, four of the most common applications of learning analytics in higher education. This section shapes a pathway for future work.

10.5.1 Overview

Before descending into the details, it is useful to consider the top-level system requirements that would be necessary for learning analytics systems to engage with educators and learners as a mediatory agent. A "more knowledgeable entity" should be able to help model and scaffold effective learning strategies. This thesis has helped to distil what should be available to educators and learners, in terms of the information they need to make better educational choices. Figure 10.4 presents those top-level requirements for systems that want to help mediate learning. Mediation of Intentionality and Reciprocity, Meaning and Transcendence were universal criteria that should be present in all learning analytics systems, as described in the previous sections. The requirements to capture all relevant metrics and perform the relevant analyses are broken down further in subsequent diagrams below. Multi-modal analytics have been left off of the relevant metrics in this diagram, based on reported learner and educator perceptions that multi-modal data was not particularly important. As this thesis is focused on what is important to educators and learners right now, it is expected that this could change. Web analytics are included because of the importance they had for learners in understanding the behaviour of their peers, but they do not need to be built into the system. Rather, the system should be able to integrate web analytics on learning analytics platforms.

With this birds-eye view of the system, it is easier to explore the ways in which different concepts were operationalised in the sections below.

10.5.2 Useful Classes of Learners

Some learners were determined through the evidence to be important targets for learning analytics research because they can highlight how certain processes of change occur. For example, it has already been recommended to consult with learners with special needs as important contribution to learning analytics research and development. A group of interest that also arose in the case study was the "mid-range learner". Educators and learners were concerned that learning was difficult to detect among learners that perform averagely, because the the effort and strategies of the student are less immediately visible. Some of the examples educators gave were inconsistent performance and engagement, and erratic learning habits, related to when they spend time logged-in, when they submit their assignments and when they participate in discussion. If learning analytics could make the identification of mid-range learners possible, some educators felt that this could offer important insights into learning patterns and the the impact of interventions. This would potentially offer **an even earlier warning system for at-risk learners, before they become at-risk**.

In addition, to mid-range learners, the findings suggest that it is important to identify transitioning learners to explore their strategy formation and development. In addition, learning analytics that are focused on transitioning learners shifts the focus away from what some educators in the study described as "educational triage" and contributes more directly to investigating how learning analytics can optimise learning. **To help identify transitioning learners, it is necessary to know more about their educational and professional background**, which is information that was important for the pragmatic and open groupings as well. It will be important to collect and integrate this data.

Figure 10.5 illustrates some of the indicators associated with identifying each class of learner. The qualifying terms that educators use, such as "limited", "erratic" and "considerable" are representative of each educator's or learner's own judgement in comparison

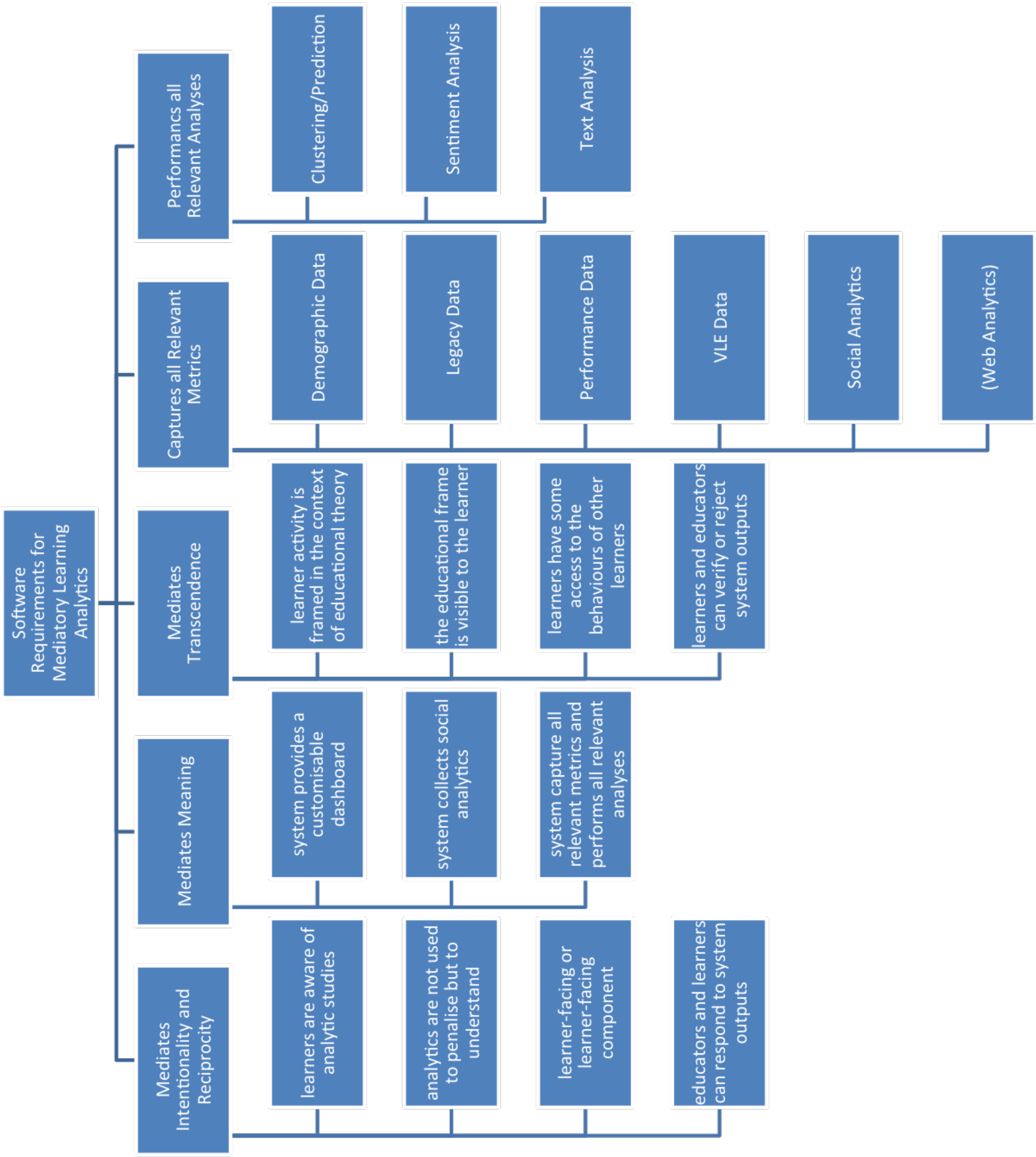

FIGURE 10.4: Software Requirements for Mediatory Learning Analytics Systems

to other information. In some cases, information may not be available or possible to integrate fully in an ethical way, such as previous academic performance. However, information needs should be considered in terms of what kind of "answer" is required. For example, in the case of student past performance, information is only needed in terms of the question "Has there been a change?" The educator does not need to have access to the complete set of student grades.

Transitioning Learner	Mid-range Learner
the learner has moved from one academic or professional domain to a different academic domain	the learner has erratic learning habits
the learner has poorer outcomes initially, relative to their own previous academic performance	the learner has inconsistent outcomes
the learner has periods of increased contact with other students	the learner has inconsistent interaction with other students

FIGURE 10.5: Indicators of Transitioning and Mid-range Learners

Incorporating some new techniques for **identifying and documenting the behaviours of learners who could be useful to track** could improve the power of existing techniques like prediction and automatic recommendation systems. In addition, **developments in cryptography might offer new ways of interrogating databases**, for example, using zero-knowledge proofs or other type of verification method that does not require unmasking the data [181]. Zero-knowledge proofs allow for verification of data without the need for accessing the entire data set, allowing educators and learners to interrogate data without exposing the data of other learners.

10.5.3 Metrics for Recognising Learning

Both educators and learners who participated in this study provided some indicators that they already find useful in their practice. In figure 7.6, educators described how they recognise learning, through getting a sense of the willingness to learn, positive feedback, social interaction, demonstration of skill and even their own perceptions. Figure 10.6 illustrates a translation of these indicators into software requirements (the second, longer row) and the associated metrics that educators described under each indicator.

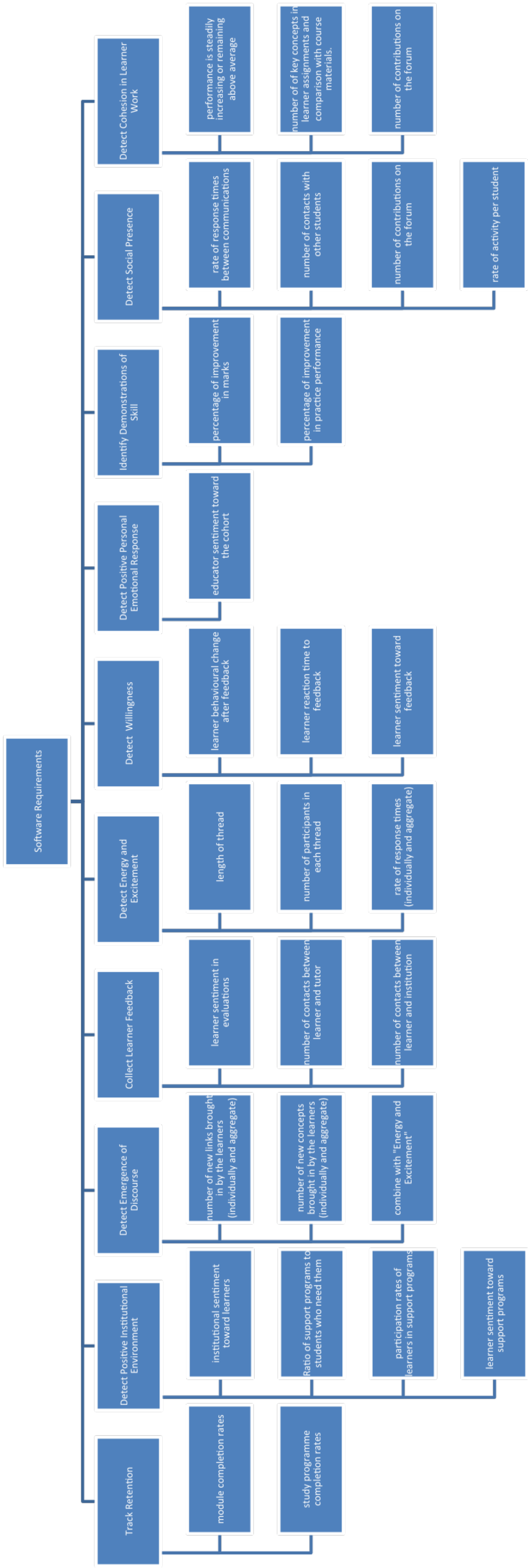

Figure 10.6: Metrics for Recognising Learning

One can see from the figure that there are many non-textual features of learner activity that are useful to track regarding communication, interaction, energy and excitement. Several requirements, however, do require more complex technologies to gather data, such as performing semantic sentiment analysis on communications on student fora and in email exchanges. Semantic data can be gathered about "morphology, semantics, discourse analysis with emphasis on polyphony and dialogism, thus providing reliable support for both tutors and students across a range of educational settings" [182]. Sentiment analysis can gather information that is important for understanding student attrition [183], supporting the emergence and maintenance of discourse [184] and more generally obtaining a sense of the feelings and attitudes toward a given subject [185]. Exploring sentiment in this way will help to provide more robust data to support emotional indicators, such as intuition and positive feelings toward the learner cohort.

Learners described the ways in which they recognise their own learning, which was summarised in a table in figure 8.9, including comparisons against oneself and others, sensing coherence in their work and performing well on assessments. They had their own indicators, such as doing better than a certain selection of students, or obtaining a specific mark, or feeling like they had access to discourse on a subject to support their process of recognition. As such, most of the metrics are already listed in figure 10.6. For learners, it is more about what kinds of analyses are performed on the data, which makes the difference. The metrics necessary for performing theses analyses are presented in figure 10.7.

10.5.4 Requirements for Improving Learner Classification and Modelling

Several examples of classifying learners have already been presented within the data. Figure 7.12 illustrated one participant's description of how to classify learners by engagement. Figure 10.5 proposed some indicators for classifying transitioning and mid-range learners, and figure 10.2 suggested some indicators for classifying learners by strategies.

From the affordances that participants described in using learning analytics to impact their practice, educators and learners named a number of indicators they would gather from the various sources of data that could be available to them. Figure 10.8 looks at the data collection and analysis that educators desire from each data source. Data that has already been referred to in a previous column is then shaded in grey, indicating that it is a data need that is shared between two or more data sources and should be a priority for research and development. The most important data to collect, according to this figure is learner verification on learning analytics insights. This suggests that **a**

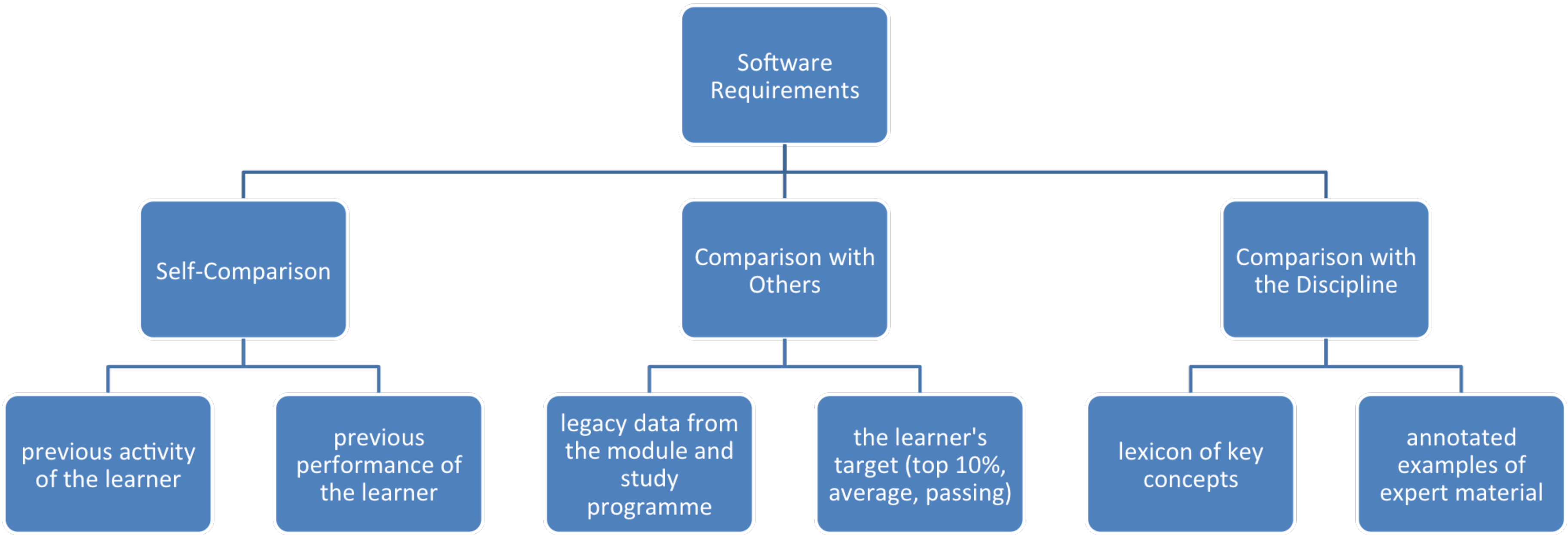

FIGURE 10.7: Additional Learner Metrics for Recognising Learning

student-facing dashboard is a must-have for any learning analytics initiative. Without knowing why a learner agrees or disagrees with a particular system output, or how they found it helpful, at least connecting a verification of a claim with a behavioural output helps to reduce the relative "noise" in identifying patterns in learning behaviour.

All of the data mentioned in figure 10.8 can be combined to test the various indicators that educators and learners referred to in the data chapters of this thesis. For example, in chapter 9, educators Ivan and Jeremy elaborated an idea of a "shell tool" that would **allow educators to experiment with different models, and to select indicators that they would like to track on the basis of these models**. The requirements presented in figure 10.8 can provide some introductory steps in developing more complex and stronger indicators to expand upon what educators and learners provided in figure 7.6.

In addition, learners Jonah, Harriett and Ora all spoke independently about having the ability to track and make sense of certain features of their own online activity and habits. **Students could also select the indicators that are most interesting for them and receive data analyses on the basis of those indicators.**

Combined with the frequency distribution in figure 7.7, researchers and developers can work on further developing these basic models with the educators for whom specific indicators are important. For example, the findings of this study suggested that educators with the goal to develop strong minds were missing data about the emergence of discourse and excitement or energy in the classroom. Starting from the data collection requirements in figure 10.6, researchers and developers can consider consulting with members of the Arts and Humanities or Social Sciences to further explore and refine research outputs. This represents an area of future research, to gain further perspectives, and work with educators and learners to better refine the metrics or test different models based on educator and learner needs.

10.5.5 Requirements for Improving Assessment

In general, semantic analysis of learner and educator written contributions, communications and assignments can provide some of the valuable data for assessment that some educators required. Research on semantic sentiment analysis of Twitter data, for example, can provide clues on how to explore short contributions that include informal language and irregular usage of words [185], which is common in online educational exchanges. In an increasingly international and interdisciplinary online education environment, the analysis of data based on standard lexicons may no longer be sufficient to adequately explore student contributions to learner fora.

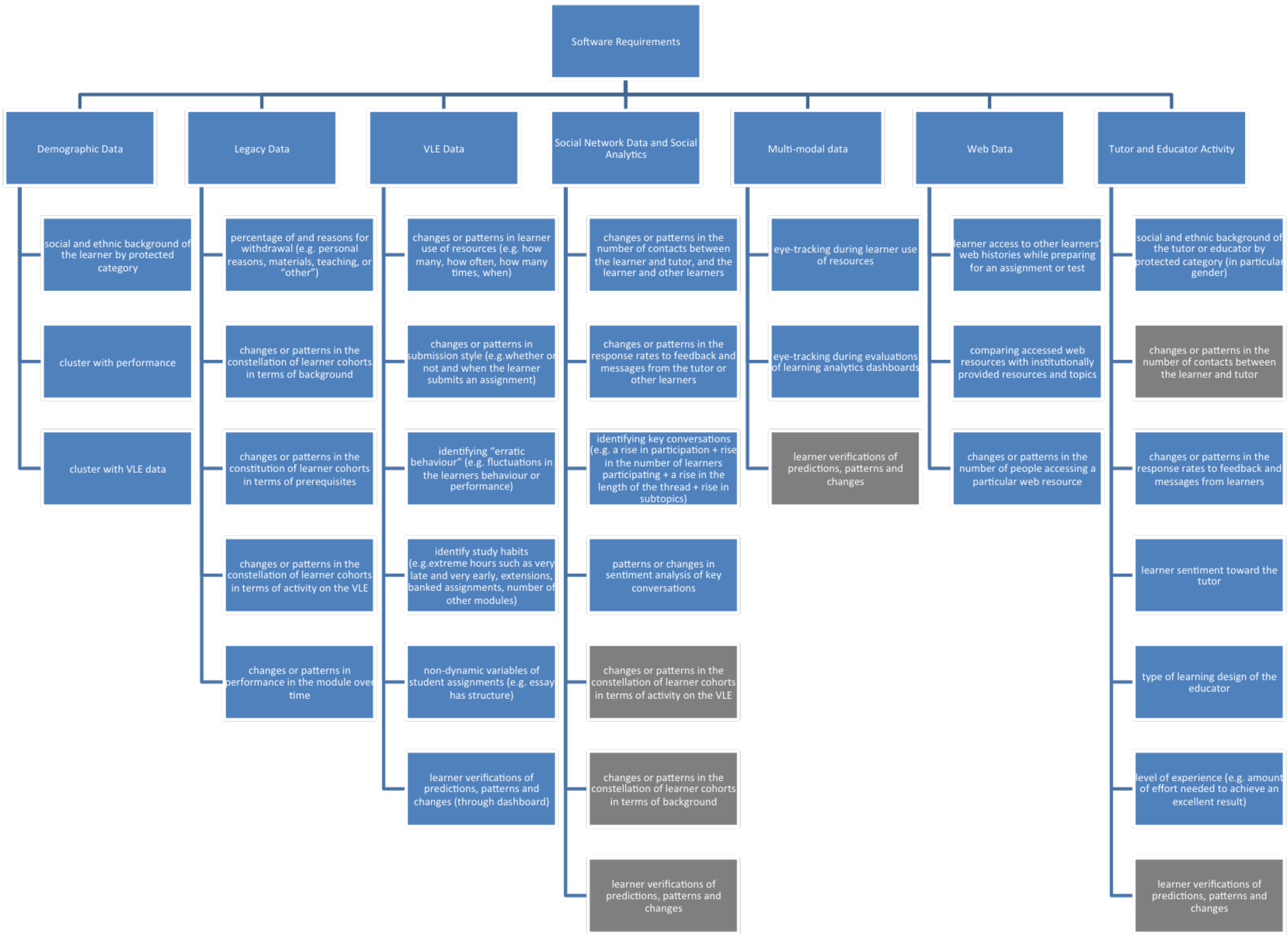

FIGURE 10.8: Requirements for Data Collection and Analysis

In addition, as two social science participants remarked, analysing a written assignment, such as an essay, has presented a considerable challenge for educators and researchers, up until now. Text semantics that explore more complex concepts such as cohesion have helped to elaborate classical models that typically include only text syntax and vocabulary, such that their accuracy is considerably improved [186].

10.5.6 Evaluating Learning Analytics Tools for Mediating Learning

To meet all requirements for mediating learning, learning analytics tools and technologies should satisfy all universal criteria, collect all relevant data and perform all relevant analyses. One area of future research would be to more fully vet the learning analytics tools and technologies that exist. Figure 10.9 is an initial example of how the performance of learning analytics platforms can be compared to the requirements presented in Figure 10.4.

The small "n" icon represents the nStudy [3] program and the small person icon represents the OU Analyse platform [4]. One can see from the figure that nStudy is stronger in creating a reciprocal relationship between learners and learning analytics, while OU Analyse performs more of the analyses necessary to parse large amounts of educational data. The two initiatives together would meet many of the requirements that educators and learners felt were important, and which are necessary for mediating learning. Evaluating additional tools and collecting insights from their developers on how these tools might be improved is a next step following this research.

10.5.7 Feasibility of Software Requirements

While it was outside of the scope of this research project to perform a complete evaluation of the recommendations presented in this thesis, the initial ideas and opinions were sought from three experts within the learning analytics research field. These individuals have expertise on predictive analytics, learning dispositions and using learning analytics to understand learning design. Each of these experts was asked for some informal feedback on the recommendations provided in this chapter. In addition, they were asked for their thoughts on data collection, analysis and communication around learning analytics, and to review the indicators and metrics that emerged from the data.

With regard to analysis, one researcher working on predictive analytics reported that attempts to use machine learning techniques to explore strategy led to "messy data".

[3] https://www.sfu.ca/edpsychlab/nstudy.html
[4] http://kmi.open.ac.uk/projects/name/ou-analyse

Features and Options	Mediates Intentionality and Reciprocity	Mediates Meaning	Mediates Transcendence	Captures All Relevant Metrics	Performs All Relevant Analyses
Learner Awareness of Learning Analytics	n				
Learning Analytics not used to penalise	n				
Learner-Facing Component	n				
Reciprocal Interface	n				
Customisable Dashboard		n			
Collects Social Analytics		n			
Captures All Relevant Metrics					
Learning Framed in Educational Theory			n		
Educational Frame Visible to Learner			n		
Learner Access to Other Learners' Activities			n		
Demographic Data					
Legacy Data					
Performance Data					
VLE Data					
Web Analytics				n	
Clustering/Prediction					n
Sentiment Analysis					
Text Analysis					

nStudy OU Analyse

Figure 10.9: Comparison of Mediatory Potential: OU Analyse and nStudy

With all factors considered, students appeared too individualistic for meaningful classifications. However, with the assistance of some indicators that can provide a way of reducing the amount of data that is being included in the analysis, it may be possible to improve models and set some parameters for analysis. If educators and learners can describe more clearly exactly what they are looking for, it may be possible for learning analytics to find it.

A researcher that had experience liaising with different faculties on the issue of learning analytics confirmed different faculty perceptions that had been noted in the data. For example, this researcher had experienced similar resistance from educators with little to no background in either numeracy or computing, and the wish for more independence and knowledge of the processes behind analytics from STEM and other computing faculties. He also said that he faced more ethics and privacy concerns than were reported in my study, and that he had noted a tendency regarding the age of a course and increased resistance to change. The researcher had used an activity chart as a way of introducing people to what learning analytics can do. Based on the recommendations made in this thesis, activity charts should be assessed to ensure that they represents activities that are relevant to the educators involved, not just one type of educators group.

One researcher has expertise in using learning analytics to examine learning design and learner disposition. He proposed that the "strategic approaches" presented in this thesis might be connected to learner disposition, but also to the institution itself. He said that much of how students progress has to do with how the university does things, which explains the focus on shaping macro-level interventions to improve learning design and retention. He also spoke about academic resistance, to technology, to change. In particular, he spoke about tracking educator activities as something that would be very difficult to convince educators was useful. Resistance to technologies like learning analytics, which transform complexities into ordinal numbers, attract fear of misinterpretation [187]. Sometimes this fear is justified, because complexities are "misconstrued as calibrated ordinal variables"[188][189]. This lends support to the statement that educators need to be able to trust in the data they have been given.

10.6 Mediated Learning As a Framework

Mediated Learning as a framework produced some heuristic tests for assessing the potential for learning analytics to impact learning.

- Does the tool or approach support agency, especially of learners?
- Does it communicate why information is or could be important?

- Can it widen the scope of interaction in meaningful ways?
- Can it do all of the above?

Mediated Learning also helped to answer the questions that were highlighted as gaps in the literature review. This section goes briefly through each of these questions and evaluates the answers concluded by this study.

10.6.1 What is the relationship between learning analytics and pedagogy? How can it be managed?

This study demonstrated how commitment to pedagogy, in particular over time, can have an influence on goals, strategies and thus, perceptions of learning analytics. It also suggested how psychological tools might be agitated and influenced by learning analytics that promote conscious contact and exchange, especially around general learning and teaching strategies. Looking at learning analytics as a mediatory agent presented an opportunity to explore their impact on psycho-social aspects of learning, rather than the technological aspects.

To manage pedagogical influences, mediated learning suggests that new approaches and strategies should not be allowed to become stagnant, and to encourage educators and learners to experiment with new ways of accomplishing the same thing.

10.6.2 How can learning analytics help to detect and optimise goals?

Mediated learning highlighted that it is not so much goals as strategies that need to be optimised, as these are sometimes indefinitely borrowed from a previous domain or profession. The theory provided a way to understand how transitioning learners make their way from one system of psychological tools to another, to better understand what is necessary to know in order to correct strategy problems in other types of learners.

Feuerstein's criteria provided a way of evaluating those approaches and checking learning potential (measured by metacognitive activity) with mediation potential (measured by comparison with the universal criteria).

10.6.3 How can learning analytics help capture and optimise the learner-educator relationship?

Mediated learning focused the attention a bit more on the educator once again, in technology-enhanced learning. It served as a reminder of the incredible importance that educators have in shaping learning experiences. The **affordances that learners named for helping to match educators and learners, or track educator activity are currently untapped potential in learning analytics development**. Once again, it might be possible to build support for these types of tools by keeping the data with the educator while the impact of such tools is evaluated.

10.6.4 How important is learning analytics literacy in the every day performance of the educator?

Learning analytics do not exist in a purely theoretical space as this study simulated. They are always intertwined with a specific tool, with specific purpose, functionality and design. However, all of this constitutes a language, textual and symbolic, that is not easily grasped by those without insight into that system of psychological tools.

This study was able to demonstrate that learning analytics is both shaping education and educators. A lack of foundational knowledge about the principles behind learning analytics leads to fear and resistance. Fortunately, the study also illustrated that those fears can be relieved through experimentation and ownership. **Concerns about sharing data, misinterpretation and misapplication of data are generally resolved if the user sees a direct link** between what data is being collected and for what it will be used, in the best case, when they can decide this for themselves.

10.6.5 Limitations of the Framework and Future Research

Though not as "over-socialised" in comparison with Activity Theory [190], Mediated Learning is very much based on the socio-cultural. It does not appear to account for individual giftedness or progression beyond what is socially or environmentally available [191]. Liu and Matthews also argue that mediated learning does not account for special needs specifically, in terms of how to make a social interaction something worthwhile.

During the course of this study, understanding and accounting for special needs were affordances that were possible to organise within the theory as a type of psychological tool. For example, performing complex sociological studies was an affordance associated with the open grouping, which included many educators who fell into the pedagogical category "developing strong minds". Links were identified between the values of the educator's discipline and the perceived value of accommodating different needs. However, what Liu and Matthews refer to, is something more general, in terms of concrete ways of accommodating special needs in the actual process of mediating learning. However, the entirety of Mediated Learning Theory can be framed as a theory of accommodation. The attention to intentionality, reciprocity, meaning and transcendence is exactly about ensuring that the message is received by the learner, whoever they are and with whichever skills.

This presents an opportunity for future research, to understand if the field of learning analytics makes appropriate provisions for recognising and accommodating special needs, as a mediatory agent. For example, how would social analytics accommodate learners with social anxieties? How would student-facing dashboards address issues like dyslexia or dyscalculia[5] among potential users? It is not that learning analytics cannot or does not address some of these issues, but they are generally not incorporated into models. The Open University, as a strong supporter of learners with special needs, should partner with these learners to understand more about their experience and how learning analytics can support them.

Giftedness may or may not have been relevant to the study. If gifted learners are simply faster at enacting the same strategies as other learners, or if they have existing strategies that other learners might not know, the framework of mediated learning still applies. If gifted learners have skills that cannot be transferred or improved, then mediated learning cannot explain the behaviour and influence of gifted students.

Gifted students may be one of the groups that are worth trying to study specifically with learning analytics research. *What do gifted students do that other students do not? How do they make use of resources? How do other students benefit from their presence in the classroom? What challenges do they present?* The study of gifted students could provide some orientation on cognitive development that is currently missing from the literature on learning analytics research.

In addition, this study did not provide a way to address or structure many of the temporal aspects involved in learning. In the exploratory interviews and focus groups, the only dimensions of time that appeared to be relevant were immediacy and volume. For example, participants stated that feedback should be as immediate as possible. Tutors and Modules Teams said that intervention should happen as soon as possible after the problem has been identified. In addition, educators and learners spoke about not having enough time, being short on time, etc. However, none of this could be particularly incorporated into Mediated Learning Theory. One reason for this might be that Mediated Learning is not necessarily procedural or didactic, though it seems to be. There are principles and structure to Feuerstein's concepts of Mediated Learning Experiences [19][20] that can be translated into didactical approaches, but *type* and

[5]Dyscalculia is a learning difficulty associated with numeracy (see http://www.bdadyslexia.org.uk/dyslexic/dyscalculia)

technique of mediation are two different things. However, learning analytics may be able to provide that extra context. One area of future research would be to go more deeply into techniques of mediation using learning analytics, to get at those temporal elements.

Finally, this study implicated previous experience and background as a likely influence on goals and strategies. While participants checks were conducted, the evidence was cross-referenced with the literature and other similar studies. The delineation of the groupings that emerged from the data, if they are to become tools for classification, must be more robustly validated. These findings could be further explored and validated using a survey instrument with a wider sample of educators and learners. *Do the three groupings stand up to scale? Can some of what learners and educators perceived be seen in their traces in the VLE and online?* These would be two important questions for immediate future research.

10.6.6 Limitations of the Research Design

In addition to the above-named theoretical limitations, the study also produced limitations resulting from the initial research design. Missing institutional perspectives, for example, make the picture of learning analytics at the Open University less complete. In addition, with access to several well-known researchers in learning analytics, this should have formed an additional stakeholder group participating in this study. Unfortunately, time and other resources would not permit it. An immediate and elaborative addition to this study would be to share the findings with those missing stakeholder groups and gather their reactions and responses to this information. This has been included into the publication schedule of the researcher heading into the post-doctoral phase.

In addition, with the number of participants in the study, choosing not to use a digital form of record management was time-consuming and cumbersome. Additional analyses of participant statements may have been possible through using software such as nVivo [6], which is specifically for qualitative research. While this does not impact the over-all quality of the work, it may have impacted the scope.

10.7 Chapter Summary

This chapter applied the framework of Mediated Learning to demonstrate how learning analytics can mediated the learning process, filtered through the prism of other human

[6] http://www.qsrinternational.com/nvivo/what-is-nvivo

beings and technology. It presented several recommendations and guidance notes, for both researchers and institutions, on improving mediatory effects.

11.1 retraced the path of the study, from the critical review to the methodology. 10.1 identified self-selection in the field as a particular challenge of learning analytics and how to manage it through interdisciplinary exchange. In addition, it addressed epistemological diversity and how facilitating reflection on operationalisation might support researchers in helping to legitimise learning analytics as a source of evidence. 10.3 looked more closely at how transitioning learners changed strategies and behaviours to accommodate a new domain. It suggested that asking learners to verify learning analytics insights, in particular about what is presumed to be conscious behaviour change, would greatly improve the value of learning analytics for all stakeholder groups. 10.3.3 and 10.3.2 described the importance of associative examples, and how learning analytics can help to identify and categorise them. In particular, the findings suggest that identifying more subtle behavioural changes would be most useful in supporting agency through learning analytics. 10.3.4 examines the potential of "high hanging fruit", and the importance of embedding learning analytics tools in the curriculum. 10.3.5, discussed confusing affordances with intention. It supported previous author's claims about the necessity for deeper collaboration [105] and proposed the development of more experimental tools in learning analytics research.

Section 10.4 applied the universal criteria to the affordances that participants expressed in the context of this study to evaluate them. 10.4.2 outlined factors and potential affordances that can demonstrate a mutual learning-teaching process. 10.4.4 discussed how learning analytics can help to communicate the importance or value of some strategies over others. 10.4.6 presented mediation of transcendence as the insurance policy that ensures personal, dynamic environments also remain grounded in a wider context.

Chapter 11

Concluding Remarks

In the Universe, there are things that are known, and things that are unknown, and in between there are doors. - William Blake

What impact is learning analytics having on practice and how can it be improved for educators and learners? In learning analytics research, understanding, documenting and evaluating impact is a persistent problem [4]. It is a **socio-technological** problem, in that learning is very difficult to define and represent coherently [14], learners are difficult to access, and they have private motivations that effect how one should interpret their behaviour [3] [15]. Impact is also an **ethical** problem. Learning analytics must anticipate the consequences of actions not yet taken, and how one can mitigate any associated challenges [65]. Finally, learning analytics is an **epistemological** problem. Even if it were possible to identify and collect all of the evidence one would like to have, it is still necessary to identify ways to parse the abundance of data available [89] and apply it meaningfully, in order to understand impact.

To bring together the socio-technological, ethical and epistemological aspects of learning analytics' impact, the study presented in this thesis used Mediated Learning [16][17] as a framework for **examining impact potential**. Affordance Theory [21] provided a mechanism for examining how perception links with metacognition. More specifically, affordances illustrated the **recognisable action potential** that educators and learners could perceive. Metacognitive activity, however, demonstrated that the individual was aware of how to *apply* information [119]. The study took a qualitative approach [140] in investigating the problem, to unpack some more of those context variables that influence learning analytics adoption and acceptance. This was determined to be an exploratory study, to develop theories around how to actually understanding learning analytics as a mediator. For this reason, the study applied Grounded Theory [130] to design a research study able to gather different perspectives on education and learning. Semi-structured interviews and focus groups [140], were the vehicle by which those perspectives were contributed and analysed. Participants contributed information on what they are trying to achieve in education and how they recognise it, to understand more about how learning analytics can assist and improve those processes. To organise participant contributions, the evidence was transcribed and coded, using an inductive, qualitative analysis of the transcripts.

Chapter 10 provided a summary of the main findings of the thesis (see 10.6) in relation to the given framework of Mediated Learning. In addition, several recommendations for future work have been provided, alongside recommendations and limitations of this research (see 10.6.5 and 10.6.6). This chapter presents further opportunities for future work and some final reflections on the study. 11.1 reviews the objectives of this study and reviews some of the key literature and research questions that framed this study.

11.1 Research Objectives

The research question named in the introduction to this chapter was divided into three parts: what is known currently about impact, how that compares with perceptions and finally, what can be done to enhance or increase positive impacts. This section summarises the chapters of these thesis that address these three components.

11.1.1 What is already known

Chapter 2 of this thesis explored the genesis of learning analytics, and how analytics and "big data" are already shaping the educational landscape through policy [29] and skill requirements [32]. In addition, it presented concerns that this has happened without proper attention to the socio-cultural aspects of educational technology [53]. With regard to tools and technologies, the chapter reviewed the state-of-the-art of learning analytics most typically applied within higher education. The chapter included some of the perceptions that have already been gathered about learning analytics' impact. Critiques of learning analytics presented in the chapter highlight some generic difficulties of exploring impact, such as the necessity for reflexivity to be embedded in everyday practice [61]. In addition, it argued that technological and financial deficits shape the kind of experience an institution may have with using learning analytics [66].

Chapter 3 discussed what is missing from learning analytics research and how some of those gaps could be filled. For example, what is meant by optimising learning? Does it mean the same as improving efficiency [38]? How do learning analytics fit into a wider pedagogical structure [4]? What are the consequences for the conceptual development of learning analytics, if it cannot be separated from its tools and technologies? Finally, how can one create stake-holder buy-in? The chapter argued that it is a challenge to determine what is relevant to different stakeholders enough to answer these questions. Educators have different needs and may find tools overly complex [9], while students may require a higher level of customisation due to dynamic and variable goals [91]. Evaluation also remains difficult outside of authentic settings without a firm foundation in educational theory [3] [74][73]. Learning analytics acceptance my require a way of dividing the different features of larger systems of data management from specific tools or technologies [92]. Other forms of evaluation might be necessary, as well. Usability studies are implicated as potentially counterproductive [94] in examining some types of learning impact. Finally, the chapter highlighted some of the known challenges in learning analytics training, knowledge transfer and acceptance. It presented future visions about a more cohesive structure to learning analytics research, more fruitful communication and collaboration, and improved learning analytics literacy [105].

11.1.2 Framing the Gap

It was determined through the literature review that deeper perspectives from educators and learners were required to understand the mechanics of how learning analytics can lead to cognitive and behavioural change. Asking educators and learners to describe what they are trying to achieve, how they recognise it and how they control it, was proposed as a way of understanding where points of contact with learning analytics might be most effective.

In Chapter 4, Mediated Learning was adapted as an exploratory and evaluative framework, to **assess the potential of different learning analytics tools and technologies for impacting practice**. Vygotsky's theories on the development of psychological tools and the role of the "other" in learning [16] were proposed as a way of understanding psycho-social levers in perceptions of learning analytics. Feuerstein's theories about Mediated Learning Experiences and the universal criteria they all share [16], was chosen to provide a way of assessing the potential of learning analytics to shift certain thematic areas into focus.

The scope of this research was to examine in more detail the different perspectives of educators and learners toward learning analytics. In addition, a main objective was to understand more about how they would or do actually use learning analytics to support everyday aspects of their practice. As the study concerned itself with individual perspectives and everyday experiences, it was determined to be appropriate for a qualitative investigation. Chapter 5 presented the reasoning behind choosing a Grounded Theory approach [130] and the formats of qualitative interview and case study. In addition, the chapter introduced Affordance Theory as a way of getting at realistic perceptions of learning analytics and connecting them to practice.

Affordance Theory argues that the affordances of an object are driven by perception [21]. Perception, according to Vygotsky, is shaped through conscious exposure to the "other", which Feuerstein believed could be regulated through a Mediated Learning Experience (MLE) [16][17]. This study demonstrated that affordances of learning analytics are also driven by perceptions of them, and those perceptions are influenced by other people and entities around the individual, in potentially predictable ways.

11.1.3 Understanding Impact

As affordances are ideas, it is difficult to know how much they reflect real desires and needs. Simply because a participant could perceive an action possibility for learning analytics, did not necessarily mean that the affordance was valuable or would be used. In addition, having a personal example provided better granularity for seeing dimensions of impact, for both the immediate and long-term future. Focusing on the production of metacognitive activity through affordances was way of qualifying whether or not an affordance has high potential for impact or not. If a participant could imagine to use learning analytics for a specific task or query that was personally important for practice (Intention), this was viewed as a strong indicator of potential impact. Affordances were then examined in more detail with their given context, to see which factors appeared particularly important and how its value could be enhanced, both for those that currently find it valuable and those who need more convincing.

11.2 Contributions of this Thesis

This thesis involved an investigation of the determinants of perceived usefulness from a social constructivist perspective. The scope of the research included an examination of relationships between learning analytics, performance expectancy, effort expectancy, social influence and facilitating conditions within a specific context.

The following represent the contributions this thesis has made to knowledge:

- The recognition of departmental epistemology as a new exogenous mechanism of learning analytics acceptance. This contributes to theories of context at the organisational level.
- The connection between learners' and educators' conceptual models of learning, and perceived usefulness of learning analytics tools and technologies.
- Guidance on how to develop feelings of affinity and perceptions of usefulness among potentially resistant stakeholders.

In terms of methodological contributions, this thesis makes the following contributions:

- The use of Mediated Learning Theory as an evaluative framework for a) assessing the potential for impact and b) understanding learning analytics as a mediatory agent.
- The use of Affordance Theory to establish perceived usefulness in connection with "real-life" problems or circumstances.

These contributions resulted in **a set of heuristics to test learning analytics approaches for their robustness in being able to mediate learning.** These heuristics can be tested and applied in different institutions to help shape their learning analytics initiatives.

In addition, it was possible to **translate what educators and learners perceive as useful into software requirements and metrics that would important to capture**.

11.3 Outlook

The future work in learning analytics has been interspersed throughout chapter 10, as recommendations for the development of the field, in particular with regard to Mediating Learning and related educational theory. However, this section addresses some additional possibilities in the broader disciplines touching learning analytics research.

11.3.1 Future Work in Education and Learning

Education is a wide field, with it's own exponentially large set of sub-fields. This study contributed findings that are immediately relevant to educational philosophy and educational theory, which could warrant future research.

With regard to educational philosophy, this research study produced some evidence in support of the Theory of Formal Discipline [161], which argues that studying a particular discipline over a period of time shapes a person's cognitive development in some predictable ways. In some cases, these developments can be highly productive. Medicine and psychology, for example, have been shown to produce effects in statistical and methodological reasoning. In addition, studying law had been shown to improve reasoning in the logical of the conditional [162]. **Using learning analytics to perform longitudinal studies on learners' behaviours and performance online would help educational scientists to understand more about how learning strategies are formed and shaped through the educational experience**. Such studies could investigate whether or not learning analytics support or reject this theory, and whether they can help demonstrate when and how learning changes take place.

Concerning educational theory, this thesis has already made a contribution to mediated learning, in evaluating it as a preliminary assessment and forecasting tool, looking at potential impact. In addition, it would be possible to frame the affordances provided in the context of this study with other educational theories. For example, Self-Regulated Learning Theory describes the different areas and phases of regulation [39]. It addresses the actions that the learner takes, from orientation and planning, to monitoring and controlling learning. The objects of control are thinking, feeling, behaviour and context [39]. As was mentioned in 10.6.5, this study did not address some of the temporal issues of learning. **Looking at affordances from the perspective of self-regulated learning, it is possible to see how learners perceived affordances that could be mapped to this theory and used to understand techniques of mediation that can lead to specific, self-regulatory actions**. This may be important for the development of tools like nStudy [43], which are student facing, strategic and based on self-regulation. It would also help to contextualise tools like the platform developed in the AFEL project [41], which rely on learners confirming learning analytics propositions. In fact, this study proposed learner validation of learning analytics insights as a recommendation for future development. It would be a very useful area of future research to **investigate the impact of learner validation on their own behaviour, and on what can be understood about what learners are thinking and doing more generally**. Another broad area for future research would be to go more deeply into technology and learning analytics acceptance. Agency links back to relevance, in that the agent wants to do something that is important to them. Future research could **explore receptiveness, specifically toward harvesting high-hanging fruit with learning analytics, such as evaluating assessment and identifying learner strategies for self-regulation.** The findings of this study indicate that to properly mediate learning experiences, learning analytics in higher education should be much more personal, holistic and interactive than they are currently. Since the kinds of tools that educators and learners were looking for do already exist in some form, one can ask, why are they not more widely adopted? There are some questions that are difficult to resolve, but the answer to this one may have something to do with what is perceived as relevant. This study concluded that data must address goals, challenges and strategies of the individual to drive action. There are some domain-based and profession-based characteristics that influence perceptions of relevance. This study also argued that impact is likely to be evaluated in the stakeholder's own framework. Either the stakeholder will need to expand their framework to understand learning analytics, or learning analytics researchers must develop tools that can work inside of different stakeholders' frameworks. This study suggested that harvesting high-hanging fruit is viewed as a middle space, because this is where more agreement in the usefulness of learning analytics will be found. Those that are already knowledgeable of analytics and analytic techniques will see the value. Those that need need more convincing would be more likely to see value in high-hanging fruits. **Harvesting high-hanging fruit can lead to the convergence on some common areas of engagement and research**.

While this study did not go extensively into ethics, because they were not often mentioned, especially once the focus groups began, it is clear that relevance is not only a cognitive but an ethical issue. The willingness to share information increased with perceived usefulness and transparency. This suggests that ethical and privacy issues could be mitigated if institutions always ensured a direct benefit to the person supplying the information. **Experimenting with the cost-benefit ratio for learners, and how this drives their engagement with technology**, would be another area of future research, that could contribute to the development of educational software that will have impact.

11.3.2 Future Work in Data Security, Management and Cryptography

In light of how important agency is to users and data protection is to the institution, it would also be useful to experiment with different ways of storing and sharing data. For example, Blockchain technology, the distributed record ledger behind the cryptocurrency Bitcoin, may offer some insights into **how to store and manage educational**

records more dynamically. Educators and learners in this study spoke about learning processes as being dynamic. Studies are disrupted often by personal and professional lives. **Blockchain would improve the flexibility of the institution to award certifications and credits in smaller increments**. Educators perceived that students who banked their assignments tended to return to their studies. They simply wished that the student would return with improved competencies. **Blockchain could provide a mechanism for pushing out very small, but certifiable transactions**. This is useful for validating specific skills, which may be more appropriate for distance learners, like those at the Open University.

11.4 Conclusion

The study concludes that learning analytics can better mediate learning when they support the agency of the stakeholder in collecting, analysing and even storing the data. The closer the agent is to the student (in the best case the agent is the student), the greater the potential is to mediate learning. The study also pointed to potential weaknesses in self-selection, with regard to learning analytics research and development. The language of learning analytics can be alienating to individuals without advanced numeracy or computing in their background, which leads to a potential lack of diversity among adopters and evaluators. In addition, it is not always clear for which purposes and for whom information is gathered through learning analytics. This is counterproductive to mediating learning through learning analytics.

Learning analytics must be embedded in a larger vision and strategy, with regard to curriculum and institutional trajectory. This must be communicated clearly to all stakeholders and become a part of new institutional processes. Researchers have already come quite far in the development of tools and technologies that all kinds of educators and learners can appreciate. This study suggest that the reasons why these tools are not reaching their full potential within institutions have to do with epistemological barriers that influence institutional will, to move forward with learning analytics development and to invest in harvesting some of the high-hanging fruits that have been promised in the literature.

It is the general recommendation of this thesis that to improve the mediatory impacts of learning analytics, **institutions will have to show interest in making learning analytics a regular part of the teaching and learning process**. Educators and learners should be trained to see the types of learning insights that analytics can provide. Engagement with learning analytics should be facilitated through experimentation and supporting agency. Impact should be evaluated reciprocally, in terms of what learning analytics propose, and educators and learners confirm. Finally, both educators and learners should remain close consultants to the learning analytics research community and participate in the development of the field.

Appendix A

Open Codes for Exploratory Interviews

In the following tables, the open codes that emerged from the data are represented on the right side of the table under the heading "Open Codes/Subcategories". Open codes often became subcategories of larger thematic categories. Descriptions of those categories are given.

Major Categories	Description	Open Codes/ Subcategories
Communication	Challenges in both non-verbal and verbal communication with students	- Lack of visual referencing - Lack of feedback from learners
Interaction	Challenges in group dynamics and context for communication	- Difficulties creating community -Difficulties generating discussion
Institution	Challenges inside of the educational institution	- Pressure to work quickly - Confusion of roles
Background	Challenges arising from a lack of information about the learner before entering the learning environment	- Learner diversity - Lack of information about existing knowledge or previous experience
Progress	Challenges related to measuring learning	- Progress is difficult to interpret - Assessment is flawed
Dynamic Agency	Challenges related to "moving targets" such as choice and individual decision making, which is not static	- Transience of learner goals - Learner patterns of peaks and troughs
Ethics	Challenges associated with ethical dilemmas	- Data protection - Ethics about retention
Realities	Challenges that cannot be resolved	- Social change in use of technology - Change in structure of education
Goal of Education	Participants' description of the purpose of education	- Learner Satisfaction - Developing Strong Minds - Preparing for Practice

Table A.1: Categories and Subcategories of Educator Challenges

Major Categories	Description	Open Codes/ Subcategories
Willingness	The sense that a learner has the desire to engage	- Reciprocity in the classroom - Learner response to feedback
Retention	The learner is retained in the course of study or the module	- Retention in modules - Retention in study programmes
Cohesion	The learner's work "makes sense"	- The learner can engage on the topic - The learner's work is well-rounded
Social Presence	The learner brings their whole self into the classroom	- Learners supporting other learners - Learner active participation
Demonstration of Skill	The learner is able to prove a new skill	- High marks - Successful practicals
Positive Learner Feedback	The learner communicates that they have learned something	- Written evaluations - Emails and informal conversations with learners - Gifts from learners
Positive Institutional Environment	The presence of tools and systems that logically should support student learning	- Institutional attitudes that are learner-centred - Support for learners
Positive personal emotional response	An own sense that the class or individual students are learning	- Intuition - Joy
Excitement/Energy	Learners are interactive such that the speed and quality of contributions is dynamic	- Long message threads - Quick response time - Increased participation
Emergence of Discourse	The learners' interactions result in meaningful discourse	- New ideas - Transfer of ideas

Table A.2: Categories and Subcategories of Educator Desired States

Major Categories	Description	Open Codes/ Subcategories
Willingness	A sense that the learner is engaged and invested in the process of learning	- Response to feedback - Change in behaviour after feedback
Positive Learner Feedback	Anything that the educator can learn about sentiment	- Positive evaluations -Informal contact -Gifts/appreciation
Emergence of Discourse	The discourse is expanded or emerges through learner interaction	- Introduction of new ideas - Effective knowledge transfer
Excitement or Energy	The sense of excitement and energy in the classroom	- Long threads - Quicker responses - More participation
Cohesion	Sense-making in arguments	- Work is well-rounded - Learner can engage
Social Presence	The learner brings their full self to the learning experience	- Support other learners - Active participation
Demonstration of Skill	Learners' ability to prove their knowledge	- High marks - Good practicals
Retention	Percentage of learners who stay enrolled	- Learners compete their module - Learners complete studies
Positive Personal Emotional Response	The educator's own reflections on their emotional state	- Positive intuition - Joy
Positive Institutional Environment	The general sense that learners are well looked-after within the university	- Attitudes are learner centred - Support for learners is more than adequate

Table A.3: Categories and Subcategories of Educator Data Needs

Major Categories	Description	Open Codes/ Subcategories
VLE Data	Data that is available about the learner's activity in the Virtual Learning Environment.	- Log-in Data - Trace Data -Use of Resources
Institutional Analytics	Data available through institutionally implemented pilots or other learning analytics initiatives	- Predictive analytics - Retention studies
Social Media/Forums	Data available through social media platforms and student forum	- Learner sentiment on the platform/forum - Learner social role - Learner interaction
Home-grown Analytics	Analyses performed by the educator directly on a chosen set of data	- Home-grown participation assessments - Home-grown group assessment
Consulting Colleagues	Asking colleagues for advice or support	- Module team meetings - Support from Data Wranglers
Qualitative Data	Data collected through observation of the class and classroom dynamics (on- and off-line)	- Paying attention to silence - Emails and informal conversations with learners - Gifts from learners
Self-Report	Data collected directly from students	- Feedback forms - Emails -Evaluations
Personal Reflection/Intution	Data collected from one's own sense that the class or individual students are learning	- Intuition - Joy - Excitement

Table A.4: Categories and Subcategories of Educator Data Sources

Major Categories	Description	Open Codes/ Subcategories
VLE Data	Data that is available about the learner's activity in the Virtual Learning Environment.	- Log-in Data - Trace Data -Use of Resources
Institutional Analytics	Data available through institutionally implemented pilots or other learning analytics initiatives	- Predictive analytics - Retention studies
Social Media/Forums	Data available through social media platforms and student forum	- Learner sentiment on the platform/forum - Learner social role - Learner interaction
Home-grown Analytics	Analyses performed by the educator directly on a chosen set of data	- Home-grown participation assessments - Home-grown group assessment
Consulting Colleagues	Asking colleagues for advice or support	- Module team meetings - Support from Data Wranglers
Qualitative Data	Data collected through observation of the class and classroom dynamics (on- and off-line)	- Paying attention to silence - Emails and informal conversations with learners - Gifts from learners
Self-Report	Data collected directly from students	- Feedback forms - Emails -Evaluations
Personal Reflection/Intution	Data collected from one's own sense that the class or individual students are learning	- Intuition - Joy - Excitement

Table A.5: Categories and Subcategories of Affordances for Course Creation and Development

Major Categories	**Description**	**Open Codes/ Subcategories**
Learner Background	All information about the learner's education and experience upon entering the classroom	- Previous studies - Barriers - Professional background
Goal of the Learner	Information about what learner's want to achieve and why	- Learner desire - Leader needs - Classifying goals
Change	The importance of knowing when and how things change	- Recognising change - Documenting change

Table A.6: Categories and Subcategories of Affordances for Learner Context and Disposition

Major Categories	Description	Open Codes/ Subcategories
The Academic Fitbit	Affordances for a personal educational activity tracker	- Student-facing - Real-time feedback
The Crystal Ball	Affordances for gaining information that learning analytics can provide that one cannot anticipate	- unknown-unknowns -
Cohort Analysis	Affordances for examining effects of the group on the learner and the learner on the group. In addition the learner's perception of the group dynamics	- Group constellation - Leveraging Group Dynamics - Cohort level emotional analysis - Creating collaboration
Interaction/ Communication	Affordances for sensing excitement and energy in the classroom	- Key conversations - Prioritising and organising conversations - Other sensory and visual data
Recognising Complex Skills	Affordances for more granular examination of learner activity online	- Finding new resources - Questioning - Making argumentation visible
Other Measurements of Learning	Affordances for other ways of measuring learning	- Support other learners - Active participation

Table A.7: Categories and Subcategories of Affordances for Imaginary Uses

Appendix B

Open Codes for Case Study

In the following tables, the open codes that emerged from the data are represented on the right side of the table under the heading "Open Codes/Subcategories". Open codes often became subcategories of larger thematic categories. Description of those thematic categories are given.

Major Categories	Description	Open Codes/ Subcategories
Educational Background	The past education or training of the participant	- Previous educational training - Advanced knowledge of numeracy - Faith in numbers - Experience in discourse
Professional Background	The skills a participant acquired on the job or in any other work-related capacity	- Experience with computing - Experience with numbers - Experience with strategy
Triggers (Students Only)	The life situations learners describe as impacting their decision to study at the Open University	- Returning after retirements - Returning after having a family - Having a disability - Being a new student
Goals	What the learner hopes to gain or achieve from the learning experience	- Learner aims - Module specific goals - Module agnostic goals
The Tutor	The influence of the presence of tutors in the educational experiences of learners	- Tutor feedback - Tutor responsibility - Tutor character
The Institution	The influence of institutional mission and values on learners and on teaching	- Distance learning - Social inclusion as a mission - Using innovative technology - Flexibility toward students
The Discipline	The influence of the discipline on learners and on teaching	- Expectations of learners - Access to experts
Pedagogy (Education Only)	The influence of educators' pedagogy on learners and on teaching	- Educational aims - Belief structures - Perspectives on the purpose of education

Table B.1: Categories and Subcategories of Participant Context

Major Categories	**Description**	**Open Codes/ Subcategories**
Personal Development	Aims associated with learning to develop oneself, whether it is enjoyable or not and regardless of where it leads	- Betting oneself - Being the best - Module agnostic goals
Qualifications	Aims associated with needing qualifications for specific types of work	- Specific job prospects - Being "good enough" - Module specific goals
Joy of Learning	Aims associated with getting pleasure out of learning experiences, whether they are successful or not	- Enjoyment in learning - Enjoyment as motivation - Module agnostic goals

Table B.2: Categories and Subcategories of Learner Aims

Major Categories	**Description**	**Open Codes/ Subcategories**
Comparison with the Self	Comparisons between any previous state, set of behaviours or outcomes around a single individual, with a current state, set of behaviours or outcomes of that same individual	- Comparison with Previous Marks - Comparison with Previous Performance of a Skill - Comparison with Previous Emotional State - Comparison with Previous Social State -Comparison with Previous Well-Being
Comparison with Others	Any comparisons involving groups of students in a single module, a course of study, a department, a faculty, or the University as a whole	- Comparisons between Cohorts - Comparisons between the Individual and the Cohort - Comparison with a Selection of Students - Retention
Comparison with the Discipline	Any statements around proving competence by comparing a learner with some aspect of the discipline	- Comparisons with experts - Comparisons with expectations of learner ability
Coherence	Perceptions of the learner having a sense for the domain and the ability to navigate it	- Appreciation of the Domain - Sense-making Arguments - Access to Discourse
Marks	Fixed ideas of a good and bad mark, that are not directly related to comparisons with other students or past performance	- Assignment Marks - Test Marks - Overall Marks
Recall	Aspects of the institution of the Open University that impact learning and teaching experiences	- Remembering Key Concepts - Retaining Written Information
Feedback	Any information about learning that is gathered from human sources outside of the individual	- Direct Feedback from the Tutor - Direct Feedback from other Students - Indirect feedback from other students

Table B.3: Categories and Subcategories of Learner Recognition of Learning

Major Categories	**Description**	**Open Codes/ Subcategories**
Pragmatic Strategy	A strategy for doing what is necessary to achieve a specific goal in learning	- Limited contact with tutor - Limited contact with other learners - Consistent performance
Open Strategy	A strategy for exploring new territory	- Considerable contact with tutors - Considerable contact with other learners - Informal contact - Erratic behaviour
Applied Strategy	Any statements around proving competence by comparing a learner with some aspect of the discipline	- Contact with the tutor when necessary - Participation in key conversations - Consistent performance (mid-range or high)

Table B.4: Categories and Subcategories of Learner Strategy

Major Categories	Description	Open Codes/ Subcategories
Facilitator/Guide	A strategy for doing what is necessary to achieve a specific goal in learning	- Limited contact with tutor - Limited contact with other learners - Consistent performance
Innovator/Frontiersman	A strategy for exploring new territory	- Considerable contact with tutors - Considerable contact with other learners - Informal contact - Erratic behaviour

Table B.5: Categories and Subcategories of Focused Intentions

Major Categories	Description	Open Codes/ Subcategories
Facilitator/Guide	A strategy for doing what is necessary to achieve a specific goal in learning	- Limited contact with tutor - Limited contact with other learners - Consistent performance
Innovator/Frontiersman	A strategy for exploring new territory	- Considerable contact with tutors - Considerable contact with other learners - Informal contact - Erratic behaviour

Table B.6: Categories and Subcategories of Educator Self-Image

Measurement Data	Thematic Codes/ Affordances	Open Codes/ Intentions
Demographic Data	Complex Sociological Studies	- Understanding the experience of specific groups of learners - Accommodating their needs
Legacy Data	Cohort Comparisons	- Identifying key prerequisites - Interpreting performance - Gaining orientation in the Faculty
VLE (Clickstream) Data	Testing Assumptions	- Experimenting with analytics - Creating different streams of educational content
	Predicting at-risk learners	- Improving Retention - Distributing resources - Intervening quickly - Identifying the mid-range student - Timing interventions
	Study Tracking	- Self-discovery - Modelling learner behaviour - Monitoring effort and strategy
	Recognising Patterns in Behaviour	- Identifying ``pinch points" - Improving retention
	Identifying Potential Anxiety	- Recognising more subtle changes over time, quickly - Helping learners to develop good study habits
	Understanding Withdrawal	

Table B.7: Categories and Subcategories of Affordances

Measurement Data	Thematic Codes/ Affordances	Open Codes/ Intentions
	Classifying Learners	- Improving retention - Intervening quickly - Identifying skill gaps
	Setting Expectations	- Understanding learner trajectories - Exposing ``unknown unknowns" - Creating different pathways for success - Helping learners to identify goals - Helping learners to identify strategies - Identifying ``best practices" - Delivering targeted content
	Evaluating assessment	- Helping learners to identify goals - Helping learners to identify strategies
	Comparison with a Selection	- Exposing arbitrary aspects of assessment - Providing more complex tools to build competencies
		- Identifying best practices - Providing access to new, relevant strategies like the ``back of the classroom"
Social Network Data and Social Analytics	Exploring Staff-Student Relationship	- Interpreting impact more precisely

Table B.8: Categories and Subcategories of Affordances Continued

Measurement Data	Thematic Codes/ Affordances	Open Codes/ Intentions
		- Matching educators and students
	Identifying Key Conversations	- Extracting major topics - Structuring and representing student discourse - Determining quality and trajectory as well as quantity of conversations
	Assessing Participation	- Understanding influence and how conversations are shaped - Tracking student participation - Exploring cohort-level dynamics of attention, interest and communication
	Forming Successful Peer Groups	- Distributing resources and accommodating different needs
Multimodal Data	Analysing Learner Attention	- Using noise sensing, eye-tracking and other types of sensory data - Identify moments of attention and distraction
Web Data	Cataloguing Research Behaviours	- Using other learners' research behaviours as a model - Developing new strategies and approaches
Tutor and Educator Activity	Identifying Educator Subgroups Matching Educators and Students Evaluating Interventions	- Understanding aspects of the tutor relationships that impact learning and teaching experiences.

Table B.9: Categories and Subcategories of Affordances Continued

Appendix C

Research Instruments

The following appendices include the research instruments used to recruit participants to the study and guide our conversations in the exploratory interviews and focus groups. Figure C.1 is an example of the recruitment letter sent to participants before the exploratory interviews. Figure C.2 is the letter sent to educators before the focus groups. The consent form for focus participants is found in Figure C.3. The letter initially used to recruit students to the focus groups is presented in Figure C.4. After unsuccessful recruitment, the letter was amended to to attract more learners. These amendments are presented in Figure C.5.

Knowledge Media Institute

Dear lecturers, tutors, module chairs and other pedagogical staff,

I am contacting you about taking part in a qualitative research study about the affordances of learning analytics for self-regulated learning. The study will be carried out by myself, under the supervision of my doctoral supervisors, Dr. Alexander Mikroyannidis and Prof. Harith Alani at the Open University's Knowledge Media Institute (KMi). This study aims to collect information about how online instructors understand their students' learning processes (in particular, how learners exercise control over their own learning) and their beliefs about how learning analytics can support this process. The contribution you will make to our understanding in these areas is greatly appreciated.

If you are interested in thinking more about how students develop learning strategies and how learning analytics can contribute to this process, we invite you to return the attached consent form to the email address given below. The interview would last for between 0.5 - 1 hour. For research purposes only, the interview will be recorded. Recordings will never be made public and will be stored in a safe location in accordance with the Data Protection Act until the research project has been concluded and the data can be destroyed. Specific information that could make you identifiable will not be used in any resulting publications.

I hope that you are interested in participating in this study. If you have any questions or would like to know more about the research, you can contact me on +447586101985 or by email, tracie.farrell-frey@open.ac.uk.

Yours sincerely,

Tracie Farrell Frey

Knowledge Media Institute
The Open University
Berrill Building
Walton Hall
Milton Keynes
MK7 6AA

The Open University

Figure C.1: Educator Recruitment Letter (Exploratory Interviews)

Knowledge Media Institute

Dear lecturers, tutors, module chairs and other pedagogical staff,

I am contacting you about taking part in a focus group for a research study about the affordances of learning analytics for self-regulated learning. The study will be carried out by myself, under the supervision of my doctoral supervisors, Dr. Alexander Mikroyannidis and Prof. Harith Alani at the Open University's Knowledge Media Institute (KMi). This study aims to collect information about how online instructors understand their students' learning processes (in particular, how learners exercise control over their own learning) and their beliefs about how learning analytics can support this process. The contribution you will make to our understanding in these areas is greatly appreciated.

If you are interested in thinking more about how students develop learning strategies and how learning analytics can contribute to this process, we invite you to return the attached consent form to the email address given below. The focus group would last for between 1.5 - 2 hours on the OU campus, with 5-10 other individuals. Interested participants would have a choice of several dates for their convenience. For research purposes only, the focus groups will be video recorded. Recordings will never be made public and will be stored in a safe location in accordance with the Data Protection Act until the research project has been concluded (latest December 2019) and the data can be destroyed. While participation in the focus group cannot ensure complete anonymity, as it is a collaborative event, specific information that could make you identifiable will not be used in any resulting publications.

I hope that you are interested in participating in this study. If you have any questions or would like to know more about the research, you can contact me on +447586101985 or by email, tracie.farrell-frey@open.ac.uk.

Yours sincerely,

Tracie Farrell Frey

Knowledge Media Institute
The Open University
Berrill Building
Walton Hall
Milton Keynes
MK7 6AA

The Open University

Figure C.2: Educator Recruitment Letter (Focus Groups)

The Open University

Knowledge Media Institute

Consent form for persons participating in a research project

Affordances of Learning analytics for Self-Regulated Learning

Name of participant:

Name of principal investigator(s): Tracie Farrell Frey, supervised by Alexander Mikroyannidis and Harith Alani

1. I consent to participate in this project, the details of which have been explained to me in my invitation letter.

2. I understand that my participation will involve recording my participation in a focus group 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, 4 weeks after the focus group has taken place . 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. 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 safe location and will be destroyed after five years;

    f. I have been informed that I will be participating with 8-10 other individuals, such that complete anonymity cannot be secured, but 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 **Focus Group** 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:

Tracie Farrell Frey, Knowledge Media Institute, Email: tracie.farrell-frey@open.ac.uk

HREC http://www.open.ac.uk/research/ethics/human-research

FIGURE C.3: Focus Group Consent Form

Dear [Recipient Name]

I am contacting you about taking part in a focus group for a research study about how students learn and behave in online learning environments. The study will be carried out by myself, under the supervision of my doctoral supervisors, Dr. Alexander Mikroyannidis and Prof. Harith Alani at the Open University's Knowledge Media Institute (KMi). This study aims to collect evidence of how students understand their own learning processes and how institutions can support that self-knowledge. The contribution you will make to our understanding in these areas is greatly appreciated.

We are seeking 30 participants at the moment to make 3 focus groups of 8-10 people. All participants will receive a 10£ voucher for their time. If you are interested in thinking and talking about how you learn and develop learning strategies, we invite you to return the attached consent form to the email address given below.

Please note: the focus groups will last approximately 1.5 - 2 hours and will be held online. Interested participants would have a choice of several dates for their convenience. For research purposes only, the focus groups will be video/audio recorded. Recordings will never be made public and will be stored in a safe location in accordance with the Data Protection Act until the research project has been concluded (latest December 2019) and the data can be destroyed. While participation in the focus group cannot ensure complete anonymity, as it is a collaborative event, specific information that could make you identifiable will not be used in any resulting publications.

I hope that you are interested in participating in this study. If you have any questions or would like to know more about the research, you can contact me on +447586101985 or by email, tracie.farrell-frey@open.ac.uk.

Yours sincerely,

Tracie Farrell Frey

Knowledge Media Institute
The Open University
Berrill Building
Walton Hall
Milton Keynes
MK7 6AA

Figure C.4: Learner Recruitment Letter

"Dear [Recipient],

How do you know when you are learning? How much do you know about your own challenges and strengths as a learner? How does it feel to be an online learner? What information would help you to understand more about how learning works for you?

If you can imagine to speak about any of these topics in a small group of other students, you are invited to take part in a focus group for a doctoral research project. You can help to support student-led research and earn a 15£ voucher for sharing your experience from the comfort of your own home.

I sent an email to you previously, describing my research and asking for participants. I am attaching this email below. If you have already responded, thank you so much for wanting to take part. If you haven't responded yet, I am happy to answer any questions or concerns you might have, so feel free to get in touch.

Speaking directly to students is one of the most important ways that researchers and institutions can do sustainable, effective work around improving the learning experience for students. Your participation is absolutely essential to this particular project. You don't need any particular experience, you just need to be willing to discuss the subject with a group of other learners for 45-60 minutes. As mentioned below, the focus group will be held online and the dates will be decided in small groups, so that they are convenient for all participants.

If you are interested in taking part, please contact
Tracie Farrell at tracie.farrell-frey@open.ac.uk."

Figure C.5: Revised Learner Recruitment Email

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