The London School of Economics and Political Science

Big data analytics and organisational change. The case of learning analytics

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A thesis submitted to the Department of Management of the London School of Economics for the degree of Doctor of Philosophy, London, June 2019

Declaration

I certify that the thesis I have presented for examination for the PhD degree of the London School of Economics and Political Science is solely my own work other than where I have clearly indicated that it is the work of others (in which case the extent of any work carried out jointly by me and any other person is clearly identified in it).

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Abstract

Much of the Information Systems (IS) literature on Big Data Analytics (BDA) assumes a straightforward relationship between human activity and data, and between data and analytical insights that can be used to steer operations (e.g. Chen, Preston and Swink, 2015; Brynjolfsson, Geva and Reichman, 2016; Yahav, Shmueli and Mani, 2016). On the other hand, researchers also try to understand the role of big data within organisations, the contributions of analytics to strategy and decision-making, and the value of big data and its organisational consequences (Constantiou and Kallinikos, 2015; Abbasi, Sarker and Chiang, 2016; Günther *et al.*, 2017). At the same time, more critical scholars have suggested that the implications of BDA can go beyond decision-making, sometimes twisting or even undermining managerial efforts (Newell and Marabelli, 2015; Galliers *et al.*, 2017; Markus, 2017). This research investigates how BDA systems change organisations that implement them and aims to uncover the resulting organisational transformations.

In line with the Transformational Model of Social Activity (Archer and Bhaskar, 1998; Faulkner and Runde, 2013), it is argued that BDA systems as technological objects change how work is done, and these changes lead to the reproduction or transformation of organisations as social structures. In order to uncover this reproduction or transformation, the concepts of encoding, aggregation and correlation (Alaimo and Kallinikos, 2017) are deployed to analyse how data is produced, and the theory of reactivity (Espeland and Sauder, 2007), originally developed to study university rankings, is adapted to trace the mechanisms and effects of organisational transformation in a case study. The study provides an answer to the question of how organisations are transformed, in unintended ways, through the implementation of BDA systems. The concept of the analytical cage is proposed as a new form of organising emerging from BDA within organisations.

Acknowledgments

I would like to thank the Information Systems and Innovation Group at the Department of Management at the LSE for the support and guidance that were necessary from the very first to the last day of my doctoral training. I am very grateful for the PhD Studentship I received, which was instrumental in completing this work, as well as for other opportunities to develop academically and intellectually.

My thanks go to all faculty who over the years volunteered feedback on my work, among whom I would like to offer special thanks to Cristina Alaimo, Antonio Cordella, Shirin Madon, Maha Shaikh, and Carsten Sørensen for always being available to answer my questions. I would like to thank also my colleagues at the Department, who created a collegial and supportive environment.

Thank you to Aleksi Aaltonen, whose help and support went above and beyond the call of duty and made this work possible.

A heartfelt thank you to my family and friends, whose patience and support I have relied upon over the years. Thank you to my husband Nuno, who provided encouragement when needed and challenged me with questions when necessary.

I am thankful to all the interviewees at the organisation I studied, who very generously volunteered their time and answers.

Finally, I would like to extend my deepest gratitude to my supervisor Jannis Kallinikos. His wisdom, advice, and support changed the trajectory of my intellectual journey forever.

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List of Abbreviations

BDA – Big Data Analytics

IS – Information Systems

LA – Learning Analytics

TMSA – Transformational Model of Social Activity

VLE – Virtual Learning Environment

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Chapter 1: Introduction

1. Introduction

In this chapter, I introduce the problem of Big Data Analytics (BDA) by presenting its[1] background, the central thesis of this research, and the significant ramifications and contributions of this project towards the study of Information Systems (IS) and organisations. I discuss the approach and objectives guiding this research, and I provide the thesis outline.

2. Introduction to the problem area

BDA is rapidly entering organisations and is seen as a way to obtain better, more accurate, previously unavailable data to support decision-making and unlock stores of value. The rapid introduction of analytical systems has taken root particularly in areas where previously data was considered scarce, unreliable or inauthentic. Big data of the social – customer preferences, taste, behaviour – developed rapidly on various social media and advertising platforms, turning social activities such as liking something, adding friends or choosing one music genre over another into data points. Similarly, organisations turned to using big data to record and measure not only their customers' online activities, but also that of their employees, attracted by the promise of better information, faster decision-making and improved organisational outcomes. To reap the promised benefits of BDA, organisations implement various analytical systems to measure diverse aspects of organisational performance, with hope for improvements according to a range of performance indicators.

Together with the deployment of such systems comes the need to not only constantly develop better analytical tools and models, but also implement changes in processes, organisational units, and strategies. IS research has thus far focused on three main areas concerning BDA. First, researchers investigate better analytical tools and statistical models to help organisations and other IS researchers in conducting more efficient and useful analytics (see e.g. Chen, Chiang and Storey, 2012; Brynjolfsson, Geva and Reichman, 2016). The second research agenda concerns the development of the understanding of BDA in strategy and decision-making in order to unpack the links between analytics and strategy, decision-making and value (Constantiou and Kallinikos, 2015; Abbasi, Sarker and Chiang, 2016). Third, and adjacent to

[1] In this work, to improve readability and in line with common usage, I treat data, big data, and data analytics as singular nouns. Whenever I refer to data I collected as a researcher, I use the plural.

these two, is a critical stream of IS research into BDA which emphasises the need to uncover the effects of BDA on organisations, the transformative character of analytics, and the societal consequences of datafication (Lycett, 2013; Newell and Marabelli, 2015; Markus, 2017).

Within this rich body of scholarship, there is a paucity of research investigating the interactions between work with analytics, changes in organisational structures, and wider stakeholder and societal consequences (Günther *et al.*, 2017). In other words, researchers have hitherto focused on understanding either the work level, the organisational level or the supra-organisational level of BDA separately, and not on uncovering cross-level interactions that can both shape how BDA is used and be essential to extracting value from BDA. The present study is an investigation into how work and practices surrounding BDA are contingent upon the organisational structures within which they are embedded while simultaneously leading to both intended and unintended changes in the very same organisational structures. This research is an attempt to complement the existing body of literature on BDA by bridging the agency and structural levels of BDA, in order to uncover the mechanisms by means of which work with analytics shapes organisations.

3. Research approach

The central question of this research is how organisations change, or are transformed, as a result of implementing BDA. To better understand this phenomenon, I studied an organisation that deployed a BDA system to measure the online activities of its customers (i.e. students) and staff. Focusing on the aspect of measuring staff performance, I investigated how work practices changed at this organisation as a result of incorporating BDA in the day-to-day work of various members of staff across several functions. Setting these findings against the organisational background, I unpicked the intended and unintended consequences that led to organisational change.

In order to guide the research, I drew from the Transformational Model of Social Activity (TMSA, Archer and Bhaskar, 1998; Faulkner and Runde, 2013) as a theoretical framework of change within which human agency has a mutually-shaping relationship with social structures, leading to the reproduction or transformation of these structures over time. TMSA provides a suitable framework to capture the coevolution of organisation-level conditions and everyday operations at the level of work practices. In particular, TMSA allows for the investigation of the relationship between structure and human agency as temporally separate phases in mutually constituting cycles. Human agency and social structure are bound by a recursively shaping relationship, and "the reproduction and transformation of social structure is a generally unintended consequence of human action" (Faulkner and Runde, 2013, p. 804).

In order to uncover this reproduction or transformation, the concepts of encoding, aggregation and correlation (Alaimo and Kallinikos, 2017) were deployed to analyse how data is produced, and the theory of reactivity (Espeland and Sauder, 2007), originally developed to study university rankings, was adapted to trace the mechanisms and effects of organisational transformation in the case studied. According to Espeland and Sauder, all measurement and measures may lead to reactivity, i.e. individuals altering their behaviour in reaction to being evaluated, observed or measured. Actors adjust behaviours under measurement, which both affects their actions but also limits the methodological validity of the measurement process itself (Espeland and Sauder, 2007). Therefore, this analytical framing provides a potent lens through which the case can be analysed.

The case study investigated is a UK business school that developed and deployed a sophisticated Learning Analytics (LA) system to monitor teaching and learning practices. LA systems are examples of BDA that focus on the analytics of social data, that is big data concerning users' online activities that constitute a trace or shadow of their socially-embedded behaviours (Alaimo, 2014). In this case, I focused on the use of the LA system by staff and concerning staff activity, rather than student – that is customer – online activity. The use of a single-case research design (Yin, 1994) is justified, as it enables the collection of rich evidence that allows for intensive, contextual understanding of the phenomenon (Flyvbjerg, 2006).

The study involved two stages of qualitative data collection and analysis. The first stage was a pilot study that confirmed the suitability of the theory of reactivity and helped refine the analytical framework. The main data collection took place between March 2017 and August 2018. I collected data in the form of meeting minutes, observation of the learning environment and the LA system, diagrams, websites and blogs, which complemented 29 semi-structured interviews with 31 members of staff from four professional areas across the organisation. In the qualitative data, I traced the processes of big data production and I investigated how different groups of staff changed their work practices as a result of the implementation of BDA through theoretically-derived thematic coding and analysis. I searched for evidence for four reactive effects: redistribution of resources, change in values, redefinition of work and practices, and gaming. I then tried to trace these to four underlying reactive mechanisms: commensuration, self-fulfilling prophecies, reverse engineering and narratives. I identified new effects of discipline, standardisation, and acceleration. Most importantly, the study provided a fruitful ground to search for a comprehensive answer to the question of how changing work practices surrounding BDA transform the organisations within which they are embedded.

4. Research objectives

The study was conceived to provide a number of significant contributions to the field of IS. First, by carefully analysing the production and characteristics of the BDA system data, this research offers a clarification of the distinctive nature of big data as opposed to other forms and types of data. Based on a thorough overview of the literature concerning big data, the thesis teases out the defining characteristics of this phenomenon, and in doing so provides an answer to the two opposing views concerning big data, one making claims concerning the revolutionary nature of big data, and the other stating that big data is a continuation of a longer history of statistics with a few differences in terms of quantity rather than quality. Second, the study allows for the testing and extension of the theory of reactivity into the realm of BDA.

Finally, and most importantly, this research helps provide an answer to the question of how organisations change as a result of implementing BDA. As I analyse and synthesise the data obtained in this study, it is evident that the introduction of BDA systems impacts work practices of various members of staff. Some such impacts are intended and intentional. However, due to the measurement-related nature of BDA, such systems become nexuses of reactive mechanisms (commensuration, self-fulfilling prophecies, reverse engineering, and narratives), and when enmeshed with human agency, they lead to unintended, reactive effects (redefining work and practices, resource redistribution, change of values, gaming, discipline, standardisation, and acceleration). These reactive mechanisms and effects lead to organisational change, as presented throughout the thesis, and lead to the emergence of analytical cages – discussed in depth in Chapter 11.

These findings are significant for organisations that intend to implement BDA. Such organisations need to be aware of the reactivity that can result from the deployment of BDA and, through its mechanisms, lead to intended and unintended effects or consequences. Embracing reactivity can enable organisations to better manage its effects with respect to transforming or reproducing organisational structures, thus extracting more value from BDA. However, the importance of the analytical cage concept goes beyond these considerations and extends to the understanding of new forms of organising present in a datafied organisation.

5. Thesis outline

The thesis is structured as follows:

This chapter provides an introduction to the study by outlining its motivation and scope as well as summarising the theoretical approach taken and the main contributions.

Chapter 2 synthesises background literature relevant to the study in order to present the various mechanisms through which BDA mediates the social world. First, extant literature on Information Systems and BDA is presented in section 2 to summarise the scholarship on the characteristics of big data and delineate the current research at work-practice, organisational and supra-organisational levels. This section is followed by a review of research into measurement and data in section 3, which provides details of the measurement mechanisms, from representation to computation, that are involved in the production of data in BDA. Research into measurement and its relationship with technology is presented in section 4, where BDA systems are presented as new measurement technologies with digital properties that influence the nature of measurement.

Chapter 3 summarises the extant research on education, data and LA, and presents an overview of LA, and highlights the unanswered questions stemming from this nascent literature.

In Chapter 4, the background literature is summarised to carve out the main research question, that is "*how does big data analytics change organisations that implement it?*" as well as supplementary questions arising from the various strands of the literature on measurement and measurement technology. Thus, against the literature reviewed, it is argued that organisational changes resulting from the implementation of BDA at the work level need to be unpacked and understood.

Chapter 5 provides an overview of the theoretical framework guiding this research project. Within the critical realist paradigm, the Transformational Model of Social Activity (TMSA) is presented as a theoretical scaffolding fit to support this study. Within the chapter, the TMSA is reviewed and mapped with key concepts in the research project.

In Chapter 6, the analytical framework is presented. The framework consists of the mechanisms of data production drawn from Alaimo and Kallinikos (2017), and the mechanisms and effects of reactivity proposed by Espeland and Sauder (2009). The suitability of the theory of reactivity in the study of management and information systems is assessed to confirm the validity of this analytical approach to studying organisational change.

Chapter 7 details the methodological approach adopted in this research. It begins by summarising how the retroductive approach (Mingers, Mutch and Willcocks, 2013) drawn from critical realism assists in the process of identifying and validating mechanisms, before moving into an overview of the research design. The pilot study undertaken is summarised, and next a detailed description is provided of the main data collection, coding, and analysis.

Against this background, Chapter 8 presents a thorough description of the case study narrative. The narrative allows for the presentation of the background of the organisation as well as its internal operations. It also discusses the emergence and use of the Virtual Learning Environment (VLE) and the LA system. The picture presented in this chapter is that of a data-based organisation.

Chapter 9 delves into the analytical details of the case. It starts by analysing LA as a BDA system and challenges a range of typical characteristics associated with big data. It then provides an analytical reading of the LA system as a digital technology of measurement. Section 3 of this chapter analyses how LA data is produced through the processes of encoding, aggregation, and correlation.

Chapter 10 focuses on the analysis of data through the lens of the theory of reactivity, first by describing the intentional shaping of teaching and learning practices identified, then by moving into the unintended effects of reactivity, before proceeding to the analysis of the mechanisms of reactivity. The last sub-section summarises the emergent effects of reactivity identified in the case.

In Chapter 11, the findings are summarised and discussed. First, the consequences of measuring the social with BDA are fleshed out. Second, arguments are presented concerning how the theory of reactivity can be tested and extended in the BDA context. Finally, the findings concerning BDA and organisational change are summarised and theorised to provide a comprehensive understanding and an answer to the main research question, leading to the formulation of the concept of the analytical cage as a new form of organising.

Chapter 12 provides a general summary of the findings, lists their implications and contributions, and highlights the limitations of this study. Finally, a set of proposals for further research on the basis of this study is presented.

Chapter 2: Background literature

> "Count what is countable, measure what is measurable,
> And what is not measurable make measurable"
> Galileo (in: Aumala, 1999)

1. Introduction

In this chapter, I present background literature pertinent to the understanding of various mechanisms through which Big Data Analytics (BDA) mediates and shapes the social world it purports to describe. I start by outlining the extant scholarship related to big data and analytics in Information Systems (IS) in order to tease out the main research problem that this project addresses, namely the lack of theorisation of how BDA shapes organisations that implement it. Concurring with the literature reviewed, I argue that BDA should be seen as form of measurement, and in order to contextualise this argument, I present an overview of various theories and technologies of measurement, while arguing for BDA as a technology of measurement with digital properties that influence the essential properties of measurement. I then focus on the mechanisms present in the measurement of the social, and I show how BDA shares these mechanisms, and what new aspects it introduces.

2. Information Systems and Big Data Analytics

In this section, I outline the current understanding of big data characteristics and the processes of its production. After summarising the extant literature on this topic in other fields, I move on to outline contributions to the understanding of the nature of big data from the field of IS. It is an essential step to understand the nature of big data before discussing its analytics. I then discuss BDA specifically and tease out the perspectives on this phenomenon within the IS literature in order to summarise unanswered questions. Although various researchers point towards this issue, it still remains unknown how BDA shapes, transforms and modifies the organisations within which it becomes embedded.

2.1. Characteristics of big data

Data are in essence "the things having been given", as the etymology of the term traced back to Latin conveys (Galloway, 2011, p. 87; Rosenberg, 2013, p. 37). In other languages such as French (*données*) or Polish (*dane*), the word can in fact mean either 'data' or 'given', depending on the context. Data are thus not recorded facts, but rather that which is "remaining after the tide of being recedes" (Galloway, 2011, p. 87). As argued, it may be that data have "no relation to truth or reality beyond the reality that data helps us to construct" (Kallinikos, 1995; Rosenberg, 2013, p. 37).

Much has been written about the particular characteristics of big data that make it stand out in comparison to other forms of data. Doug Laney started with volume, velocity and variety, the so-called three Vs of big data (2001), as the defining characteristics that set big data apart from previous forms of calculative representations of the world. His framework served as a starting point for researchers to build on and add other characteristics they believe make up the phenomenon. Mayer-Schönberger and Cukier claimed that an important characteristic of big data is its exhaustivity, i.e. its ability to capture the entire system rather than relying on samples (2013). This theory has since been undermined (Kitchin and Lauriault, 2015). Dodge and Kitchin discuss the fine-grained nature of big data in terms of its resolution and how it allows for unique indexing (2005). Relationality (boyd and Crawford, 2012) – that is the possibility to cross-reference different datasets through common fields – and extensionality (the ease of adding or changing fields) with scalability (Marz and Warren, 2012) have also been identified as important features of this phenomenon. In fact, it has been pointed out that individual data points produced by users at any given time are almost meaningless (Wilson, 2015) and valueless (Stalder, 2012) until they are linked to other points of data, until they are aggregated (Thatcher, O'Sullivan and Mahmoudi, 2016). While veracity is also mentioned as one of its features, big data can be messy, noisy and uncertain, and contain errors (Marr, 2014). Big data is a type of data whose meaning can be constantly shifting in relation to the context in which it was generated, so it is important to highlight its variability as well (McNulty, 2014). Furthermore, it often does not include any information about the social context in which it was produced (Griswold and Wright, 2004), sometimes referred to as its "lossiness" (Busch, 2014).

In terms of its format, big data can be real-time, near real-time, batch, structured, semi-structured or unstructured (Murthy, Bharadwaj and Subrahmanyam, 2014). It can be both quantitative or qualitative, indexical, specifying attributes or meta-data (Kitchin, 2014b).

In Kitchin and McArdle 2016, the authors summarise the characteristics of big data in juxtaposition to survey and administrative data, claiming that in big data statistical products are specified ex-post, and data is organic, i.e. not designed, gives a higher potential for by-products, is less persistent, huge in volume, potentially much faster and inexpensive (Florescu, Karlberg and Reis, 2014; Kitchin and Lauriault, 2015). The authors claim that the boundary characteristics of big data are velocity and exhaustivity (Kitchin and McArdle, 2016).

Others point out one of the characteristics of big data as a by-product of everyday life practices (Cohen, 2013; Bhimani and Willcocks, 2014; Couldry and Powell, 2014). A number of researchers claim that one of the salient features of big data is that it relies on data that was not initially intended to be used for certain purposes (Puschmann and Burgess, 2014), thus creating "data shadows" (Graham, 2014, p. 6), layers of information about objects, "data fumes" (Thatcher, 2014, p. 1765), or "data footprints" (Lewis, 2015, p. 1). Such "fumes" may come from directed data (censuses, CCTV), automated data (smart meters, loyalty cards), or volunteered data (Wikipedia, OpenStreetMap), as claimed by Cockayne (2016). However, other researchers see data exhaust, i.e. ambient data passively collected for a different purpose that can be recombined with other data to create new sources of value (George, Haas and Pentland, 2014), as just one source of big data – with public data, private data, community data and self-quantification data named as other sources.

Big data has also been studied in terms of the promises it offers and the myths around it (boyd and Crawford, 2012). Big data promises to extend the reach of automation, reduce the need for theory (Kitchin, 2014a), models, and human expertise, expand the realm of what can be measured, and calculate future events and behaviours (Rieder and Simon, 2016). Big data thus can speak for itself "free of human bias or framing", and "any patterns and relationships within Big Data are inherently meaningful and truthful" (Kitchin, 2014a, p. 4). Big data is often seen as offering "a higher form of intelligence and knowledge that can generate insights that were previously impossible, with the aura of truth, objectivity, and accuracy" (boyd and Crawford, 2012, p. 663).

Such promises are regularly debunked in more critical literature on big data. Big data is not exhaustive and does not capture a whole domain, but instead is a representation and a sample "shaped by the technology and platform used, the data ontology employed and the regulatory environment, and it is subject to sampling bias" (Kitchin, 2014a, p. 4). It has been argued that big data often involves convenience samples: "people who bought a certain product, families that are a part of a given government program, (…) books that Google has scanned" and similar (Busch, 2014, p. 1728). As Kitchin proposes, data are always a selection from the total sum of all data available (Kitchin, 2014b).

As a thorough investigation of the process of producing big data shows, it does not arise from nowhere, it is based on scientific reasoning and is generated on grounds of theories containing human bias and framing (Kitchin, 2014a). Thus, there have been calls to study “data assemblages”, that is, “the technological, political, social and economic apparatuses and elements that constitute and frame the generation, circulation and deployment of data” (Kitchin and Lauriault, 2014, p. nd).

While this literature is rich, it does not cover all the characteristics of big data in a comprehensive and unquestioned manner. Many of the claims, such as those concerning the velocity or variety of big data, are not specific enough and seem rather subjective. Other characteristics seem to focus on distinguishing the types and varieties of big data (structured, unstructured, and so on), rather than on uncovering its ontological nature. This is where the extant literature on the characteristics of big data from the field of IS can help clarify and contribute to the understanding of its status.

Essentially, big data is created as an effect of “user participation along narrow and standardised activity types” (Alaimo and Kallinikos, 2017, p. 175) that leave data footprints, and therefore it is a by-product, an exhaust (Alaimo and Kallinikos, 2017). It is imbued with the assumption that anything in this exhaust is worth encoding and storing (Alaimo and Kallinikos, 2017). This points to the conclusion that “we have shifted from the problem of what to save to the problem of what to erase” (Floridi, 2012).

It is also important to point out the difference between “sorting on the way in” in previous data contexts, i.e. where “data is gathered through a carefully laid out cognitive architecture” (Constantiou and Kallinikos, 2015), and “sorting on the way out”, where data “is captured and stored without such a plan and on the assumption that it may be variously used a posteriori” (Constantiou and Kallinikos, 2015), as proposed by Weinberger (2007). The outcome, as pointed out by Leonelli, may be “the serendipitous result of social, political, economic and technical factors, which determines which data get to travel in ways that are non-transparent and hard to reconstruct” at the receiving end (Leonelli, 2014).

Importantly, such data “escape the systematic nature of professional classifications” (Constantiou and Kallinikos, 2015). As argued, “data generation is lifted out of the prevailing expert-dominated cultures by which the information needs of practice fields have been defined” (Kallinikos and Constantiou, 2015, p. 71), and instead large populations of users or technically-minded database administrators carry out the process.

An important characteristic of this big data is its granularity, as it aims to represent the most minute traces of behaviour which can then be used to produce *a posteriori* behavioural patterns

(Kallinikos and Tempini, 2011). The decomposition of behavioural patterns into such granular traces involves a loss of meaning; however, this loss is then compensated by increasing opportunities to aggregate data and subject it to analysis (Kallinikos, Hasselbladh and Marton, 2013).

Data is also “use-agnostic” (Kallinikos, 2013), i.e. its intended uses, which inform the process of data production, may differ from their actual uses in the future: data is not tightly coupled with the uses it may be put to (Kallinikos and Tempini, 2011). Big data exists with “an open-ended potential”, rendering it unbound when it comes to potential explorations and analyses (Kallinikos and Tempini, 2011).

Further, big data is real-time: users’ behaviours are constantly logged into databases which then require algorithms to deal with such dynamic datasets (Constantiou and Kallinikos, 2015). This constant renewal and updating puts emphasis on real-time events, challenges the longer-term horizon and “privileges the present at the expense of past and future” (Constantiou and Kallinikos, 2015). Data logged in real time (Murthy, Bharadwaj and Subrahmanyam, 2014) leads to “nowcasting” (Constantiou and Kallinikos, 2015). Big data enable the regime of futurity, an obsession with the future and its prediction (Ekbia *et al.*, 2014).

Thus, to summarise the characteristics discussed above, the current literature attempts to define and differentiate big data on the grounds of its volume, variety, velocity, exhaustivity, granularity, veracity and use-agnosticity (with other characteristics described above captured through these main seven). One of the most pertinent contributions of IS scholars to the understanding of the big data phenomenon is their focus on the practices of data production. Zooming in on how big data comes to be offers an enhanced view on its characteristics.

2.2. Processes of big data production

The various mechanisms involved in the production of data have become an object of increasing scrutiny in the field of IS. The main issue pertains to how technology translates social interaction into computable objects (Alaimo and Kallinikos, 2017) through the creation of a selected set of actions that become encoded along computable paths (Alaimo and Kallinikos, 2017). Without a doubt, the mediation of the social is possible by means of a complex apparatus and its technical datawork (Alaimo and Kallinikos, 2017). I present a brief overview of these mechanisms in big data production below.

2.2.1. *Encoding*

Alaimo and Kallinikos argue that encoding relies on the formalisation of users, posts, comments, etc. as objects, and on connections between such objects along the lines of pre-established actions, such as following, clicking or sharing (Alaimo and Kallinikos, 2016). This process entails “the programmed disaggregation of individual users in countable actions” (Alaimo and Kallinikos, 2016, p. 83), which in turn allows for easy identification, counting and comparison.

Objectification then allows for the detachment from contexts in which social interactions are normally embedded (Kallinikos, 2009). This leads to the conclusion that data do not just record or measure social activities, but encode them under their own assumptions, following the logic embedded in the database or platform (Ruppert, 2012; Alaimo and Kallinikos, 2016). All attempts at encoding involve an analytical approach, which is inherently related to the existence of a model, a reference domain that allows for the assignment of thus constructed codes to that which is being codified (Kallinikos, 2009). This process is essentially “the comprehensive mapping of reality through the technological generation of huge amounts of data” (Kallinikos and Tempini, 2011, p. 6), which is followed by data reduction and interpretation.

2.2.2. *Aggregation*

Due to the characteristics of data pointed out in the previous section – it is not possible for data not to compromise variety, richness or complexity, thus leading to “abstraction from the messiness of life and contextual detail” (Constantiou and Kallinikos, 2015). “The ghost of abstract or generic descriptions that may carry dubious social relevance” (Constantiou and Kallinikos, 2015) is perceived as a pivotal issue that calls for critical scrutiny. Decontextualisation is, in fact, an essential practice in databases to make data portable, allowing for their integration with other databases. Further, data are subject to recontextualisation and reuse (Leonelli, 2014).

Aggregation is a pivotal step, as individual data may not be meaningful in themselves, it is through aggregation and pattern-finding that they reveal new information (Couldry and Powell, 2014). However, this places much more emphasis on “aggregates or averages and too little on outliers” (George, Haas and Pentland, 2014, p. 323).

2.2.3. Correlation

The process of correlation rests on the principle that data can be combined and recombined within databases (Galliers *et al.*, 2017), and thus the patterns of relationships or similarities can be uncovered. Small, dividual pieces of data are made intelligible by correlating them with other dividual pieces (Cheney-Lippold, 2011). More recently, Hacking added correlating to the list of "engines of making up people" (Hacking, 2006), and it should be further emphasised that big data relies on de-contextualisation in the way it correlates, that is, data are taken out of original contexts and propagated in other contexts (Galliers *et al.*, 2017).

As a result of objectification, it is possible to connect objects and correlate them, while every such link acts as a reductive filter of the complex social reality and channels activities along set paths (Alaimo and Kallinikos, 2016). Correlated data can be then used to provide measurements and classification of behavioural patterns. Correlation often results in the creation of user profiles, which can then be continually updated and changed (Cheney-Lippold, 2011). What is more, as more data about a specific user are received, new computations can be carried out which in turn may change "who the user is believed to be". This leads to a constant feedback loop which becomes a form of control (Cheney-Lippold, 2011).

Correlation results in data being further incorporated into other calculations and becoming parts of other data infrastructures due to the recombinant nature of databases. This correlative nature of data can provide "powerful knowledge that was not available before" (Leonelli, 2014) through the identification of statistical relationships between data values and the shift to patterns (sometimes leading to apophenia, i.e. the perception of patterns where none actually exist) (boyd and Crawford, 2012) simply because "everything counts in large amounts" (Aaltonen and Tempini, 2014). In order to enable correlation, a potent technological infrastructure involving statistical tools and programming in the creation of data as well as computational techniques is required (Ekbia *et al.*, 2014).

2.2.4. Contributions from adjacent fields

Although IS offers a more comprehensive and detailed treatment of the processes involved in data production, other fields contribute to or echo the views presented above. Big data practices are seen as sinking into the everyday: "new regimes of data generation, acquisition, and analysis slip into normalcy – as even the most profound technologies recede from view as they transform into unquestioned amenities of the everyday" (Thatcher, O'Sullivan and Mahmoudi, 2016, p. 2). Such processes involve asymmetrical power relations, they privatise data, "obfuscate the quantification and alienation of data from those who create it" (Thatcher, O'Sullivan and Mahmoudi, 2016, p. 5) and package data into aggregates ready to be purchased and sold. Couldry and Powell state that "many everyday activities now produce data without requiring human meaning-construction" (2014, p. 3) and that individual data points are not meaningful in themselves; however, "taken together, either through aggregation, correlation or calculation, such data provide large amounts of information" (2014, p. 3).

Some researchers highlight the reductive character of data production, pointing to "the need to reduce the dimensionality of complex objects" (Patty and Penn, 2015, p. 1) for the purposes of big data, and that "any process of data reduction necessarily involves choices about measurement" (Patty and Penn, 2015, p. 2). It has been pointed out that "the statistical relationships emerge from the data, but the stable, measurable concepts do not: the concepts are a prerequisite for the existence of the data" (Shaw, 2015, p. 2).

There is an increasing understanding that data is "given by computational storage" (Puschmann and Burgess, 2014, p. 1693), and Bowker notes that in big data "the interpretative work is done inside the computer and read out and acted on by humans" (2013, p. 170). The production of big data involves work, and big data carries out work itself as well. Big data involves "a great deal of social work" that "takes place off-stage, by non-human agents, as a result of processing choices engineered by computers" (Gregg, 2015, p. 44). Big data depends on decisions which are often embedded in previously collected data or tools used to collect it, for example in relation to "the recording, indexing and representation of data and the settings for analysis methods" (Diesner, 2015, p. 1). This brings up the point of standards, and it is claimed that big data "require herculean efforts of standardisation – in data collection, analysis, and interpretation" (Busch, 2014, p. 1736).

All of these contributions point to the fact that the production of big data is imbued with highly subjective and complex decisions and processes which already start at encoding, aggregation and correlation, before data is subjected to more complex analytical work.

2.3. Big data and its analytics

While I defined and contextualised big data in the preceding section, the term Big Data Analytics is commonly used to describe analytical techniques applied to data sets that are large and complex, and require advanced storage, management, analysis and visualisation technologies (Chen, Chiang and Storey, 2012). Big data and its analytics have received considerable attention in IS, with a number of articles, editorials and special issues appearing in leading publications (Abbasi, Sarker and Chiang, 2016). The study of BDA is seen as a continuation of the debate on data warehousing and data mining (Wixom and Watson, 2001;

Watson, Goodhue and Wixom, 2002), and previously some scholars discussed the processes of extracting knowledge from data using data mining (Fayyad, Piatetsky-Shapiro and Smyth, 1996). Meanwhile, Simoudis (1996) looked at the theory and limits of data mining. Some go as far back as linking the current trends in BDA literature to Decision Support Systems and Executive Support Systems (Huber, 1990; Leidner and Elam, 1995).

In order to systematise and synthesise the extant IS scholarship on BDA, I conducted a thorough search of the top eight IS publications from the Senior Scholars' Basket of Journals, as defined by the Association for Information Systems (European Journal of Information Systems, Information Systems Journal, Information Systems Research, Journal of the Association for Information Systems, Journal of Information Technology, Journal of Management Information Systems, Journal of Strategic Information Systems, MIS Quarterly) to identify articles which related directly to BDA, either by referring to this phenomenon in their abstract or in their keywords. This search resulted in 30 articles which directly pertain to this phenomenon. I identified three main streams that current research gravitates towards, with a number of themes in each: Big Data Analytics Methods, Big Data Analytics and Organisations, and Critical Big Data Analytics. I have drawn up an overview of the streams, themes, papers and main research agendas in Table 1, together with the level of analysis which I return to later in this section.

Table 1 Main streams of Information Systems literature on Big Data Analytics

Stream	Themes	Papers	Research Agenda	Level of analysis
Big Data Analytics Methods	- Developing and improving analytical tools - Using big data in IS research	Chen *et al.*, 2012 Agarwal and Dhar, 2014 Goes, 2014 Chen *et al.*, 2015 Brynjolfsson *et al.*, 2016 Ghose and Todri-Adamopoulus, 2016 Ketter *et al.*, 2016 Martens *et al.*, 2016 Müller *et al.*, 2016 Saboo *et al.*, 2016 Yahav *et al.*, 2016	- Investigate better analytical tools to help organisations and IS researchers in conducting big data analysis	Work-practice
Big Data Analytics and Organisations	- Big data and strategy - Decision-making - Organisational consequences - Value	Sharma *et al.*, 2014 Bhimani, 2015 Constantiou and Kallinikos, 2015 Kallinikos and Constantiou, 2015 Markus, 2015 Woerner amd Wixom, 2015 Yoo, 2015 Abbasi *et al.*, 2016 Baesens *et al.*, 2016 Günther *et al.*, 2017	- Understand the role of BDA in strategy and decision-making - Uncover the organisational consequences of big data - Contribute to the understanding of the value of big data for organisations	Organisational

		Lyytinen and Grover, 2017		
Critical Big Data Analytics	- Datafication and its societal effects - Privacy and security - Data quality - Transformative nature of big data	Lycett, 2013 Loebbecke and Picot, 2015 Newell and Marabelli, 2015 Clarke, 2016 Menon and Sarkar, 2016 Galliers *et al.,* 2017 Markus, 2017	- Understand the effects of BDA - Analyse how BDA transforms behaviours	Supra-organisational

First, there are a number of publications on BDA which focus solely on developing increasingly more sophisticated analytical methods to deal with big data. This is evident in publications from the MIS Quarterly special issue on Big Data & Analytics in Networked Business. For example, Brynjolfsson et al. (2016) develop a robust process for predicting behaviours using online crowd-based data, and they evaluate the effectiveness of their model. Similarly, Yahav et al. (2016) introduce a tree-based approach to adjust for self-selection in BDA. Some publications also investigate the use of BDA in IS research (Müller *et al.*, 2016). Most of the literature in this stream calls for more interest in developing increasingly precise and efficient methods to deal with BDA and promotes its usefulness in management and for decision-making. However, we can see that this stream of literature generally does not question the assumptions regarding how analytics can support businesses and organisational operations, assuming a fairly unidirectional relationship of causality between the world and data.

Second, the field of IS has seen a number of publications preoccupied primarily with the impact of BDA on organisations and their decision-making (Abbasi, Sarker and Chiang, 2016). Within this stream, the main themes are concerned with identifying how BDA impact strategic decision-making (Constantiou and Kallinikos, 2015) and how it can extend the strategy 'toolbox' (Woerner and Wixom, 2015). Quite subversively, Lyytinen and Grover revisit the classic "Management Misinformation Systems" (Ackoff, 1967) and posit that "given the new information-rich environments and our nearly limitless capability to collect and analyse data, we may need to re-examine these arguments to correctly frame information systems' contemporary effects on managerial decision making" (2017, p. 206). Another significant theme in this stream pertains to the consequences of BDA for organisations (Bhimani, 2015; Yoo, 2015), with clear calls to research big data consequences because "doing Big Data consequences research is a necessary and valuable complement to two other kinds of Big Data research already underway in the Information Systems field" (Markus 2015, p. 59).

Within the same stream, there has been a growing interest within the IS literature in the value of big data and its analytics. For example, a thorough literature review by Günther et al. (2017) provides a useful overview of what types of value can be associated with BDA and identifies six main debates that highlight how organisations extract value from it, breaking them down into work-practice, organizational, and supra-organizational levels. The authors indicate that "future research needs to empirically examine how different actors within organizations work with big data in practice, how organizational models are developed, and how organizations deal with different stakeholder interests to realize value from big data" (2017, p. 200). Baesens et al. argue for the addition of the fifth V "namely *value*, to complement the 4V framework from a business perspective" (2016, p. 807) in order to put this aspect of BDA at the forefront of research. It is clear that this stream of literature invites research into the consequences of BDA in organisational decision-making to develop a better understanding of the value of BDA in this context.

Third, I have identified a growing body of literature focusing on a more critical outlook on BDA. In this stream, the theme of 'datafication' has received considerable attention, pointing to the fact that this term "is increasingly being used to characterise the reliance of enterprises on data (and their data infrastructures)" (Lycett, 2013, p. 382). While big data is attributed the possibility to empower actions which can potentially provide value, "it should be clear that datafication will unavoidably omit many features of the world, distort others and potentially add features that are not apparent in the first instance" (Lycett, 2013, p. 384). There have been calls within this stream for further research into the societal effects of 'datafication', since the implications of BDA "for individuals and the wider society are less clear" (Newell and Marabelli, 2015, p. 3). Apart from the issues of privacy and security (Menon and Sarkar, 2016), or data quality (Clarke, 2016), much of the literature in this stream points towards the transformative nature of BDA within organisations, as performance measurement and rankings become the infrastructure transforming organisational behaviour (Markus, 2017). In her article, Markus speaks directly to the concern I am preoccupied with, and also makes a clear link to the theory of reactivity which I employ to lay bare the mechanisms by which BDA indeed inform *and* transform organisational behaviours. Within this stream of literature, there are many voices calling for a more thorough analysis of the transformative nature of BDA.

As mentioned before, Günther et al. (2017), following a rigorous approach to reviewing the literature, identify three levels that the key six debates focus on: work-practice, organisational, and supra-organisational. They define the work-practice level as "what individual actors inside organisations do with big data in their day-to-day interactions" (2017, p. 194) and summarise key debates, focusing on the inductive and deductive approaches to BDA, and algorithmic and human-based intelligence. Unsurprisingly, similar debates permeate the BDA literature which aims to investigate better analytical tools to help organisations and IS researchers in conducting analytics. Often rooted in computer science, econometrics, and data science, these studies refine statistical models and develop predictive powers of business analytics to support decision-making in organisations.

At the organisational level, the key debates identified by Günther et al. (2017) focus on centralised and decentralised big data capability structures, and big data-driven business model improvement and innovation. The articles identified at this level are largely similar, as they aim to understand the role of BDA in strategy and decision-making, uncover the organisational consequences of big data, or contribute to the understanding of the value of big data for organisations.

Third, the supra-organisational level of Günther et al. (2017) focuses on controlled and open access to big data, as well as minimising and neglecting the social risks of big data value realisation, and corresponds to the Critical Big Data Analytics stream I summarised above.

I concur with Günther et al. (2017) that research at these levels seems to be developing independently, largely ignoring potential cross-level interactions. The scholars state that "future research needs to empirically examine how different actors within organizations work with big data in practice, how organizational models are developed, and how organizations deal with different stakeholder interests to realize value from big data" (2017, p. 200). Further, the authors encourage cross-level research, as they hypothesise that big data at the work-practice level should go hand in hand with the development of organisational structures and models, as "failure to do so may limit big data value realization by organizations" (2017, p. 202). Specifically, the authors have two propositions concerning potential cross-level interactions between the work-practice and organizational levels: 1a) *To realise value from big data, insights gained at the work-practice level need to be paralleled by the development of appropriate organisational models*; and 1b) *When collecting and analysing data at the work-practice level, analysts and decision-makers are constrained by dominant organisational models*. The authors posit that "realizing value from big data is the result of continuous interaction between work practices, organizational models, and stakeholder interests" (2017, p. 205), and they call for empirical research on cross-level interactions and alignment.

This view that big data influences what it measures is pronounced even more strongly in wider IS literature. Boyd and Crawford quote Du Gay and Pryke, saying that "accounting tools (…) do not simply aid the measurement of economic activity, they shape the reality they measure" (2002, pp. 12–13), and that "big data stakes out new terrains of objects, methods of knowing, and definitions of social life" (2012, p. 665). Lewis notes that the digital contexts in which behaviours take place are recorded and "carry norms that powerfully shape human behavior" (2015, p. 3). This leads, for example, to gaming, i.e. "strategic and selective collection and use of data in pursuit of individual goals", or amplified performativity: "data used to amplify impact of measures on what is being measured" (Galliers *et al.*, 2017, p. 188). In the context of big data, it has been noted that "strategic performance measurement and ranking systems take on new significance as infrastructure intended, not just to inform, but also to transform, individual and organizational behavior" (Galliers *et al.*, 2017; Markus, 2017). Big data "does not simply help us describe 'what is out there' in social identity and social interactions; it deeply shapes them" (Yoo, 2015, p. 63), and thus it actively shapes the world (Yoo, 2015). Following Constantiou and Kallinikos, Yoo states that this is precisely what makes data "such a powerful wold-shaping strategic tool" (2015, p. 63).

Thus, this research project concerns BDA and organisations, and answers the question of how organisations – and work – change as a result of the implementation of BDA.

2.4. Conclusions

I began this section by presenting the characteristics of big data and the processes of its production. I then focused on outlining the three main perspectives on BDA present in IS literature, namely BDA methods, BDA and organisations, and critical BDA. As teased out from literature reviewed, there is a paucity of research concerning the transformations in organisations resulting from the work-practice level deployment of BDA. Literature stipulates that work-practice level insights from working with BDA need to feed into organisational transformations, while at the same time existing organisational structures constrain or limit changes at the work-practice level. However, the nature of organisational transformations and the mechanisms by which they take place remain undiscovered. As it is clear from the IS literature presented above, my research aims to pull together the main issue of the transformative nature of BDA from all three strands in order to leverage the understanding of this phenomenon within organisations. Following Abbasi et al. I agree that "both qualitative and quantitative researchers have an important role to play in rethinking and redefining how big data is collected, prepared, analysed, and presented and in investigating the actual processes and consequences of using big data analytics" (2016, p. X).

3. Measurement and data

I begin this section by developing the argument that current BDA practices are a continuation of the phenomenon of technologies of measurement and thus can be seen as tools of measurement. I present an overview of critical literature on measurement, summarising the various mechanisms of measurement, including representation (3.2.1), commensuration and quantification (3.2.2), numbers (3.2.3), calculation (3.2.4), standardisation (3.2.5), classification, categorisation and aggregation (3.2.6), indices and indicators (3.2.7), rankings (3.2.8), statistics (3.2.9) and computation (3.2.10). These mechanisms are discussed in the approximate order of their increasing complexity, and they can be seen as enabling one another in more or less this sequence. The main position represented by this rich literature is that of the non-neutral nature of measurement and its impact on objects, people and societies. I finish this section by teasing out the problems and questions that such a framing of BDA opens up.

3.1. Big data analytics as measurement

My main argument in this section is that BDA should be seen as a continuation of the line of technologies of measurement, as defined in the next chapter. To support this argument, I review the extant literature supporting this perspective. Numerous scholars propose this view, and I summarise their points below.

Big data analytics is embedded in “a long-standing culture of measurement and quantification” (Rieder and Simon, 2016, p. 2) which can be traced back to the development of statistics and earlier. Big data is historical (Barnes and Wilson, 2014), has a long history (Beer, 2016), and should be contextualised within “the history of social statistics” (Beer, 2016, p. 1). While the type of data and its analytics may be different “the lineage is clear” (Beer, 2016, p. 2). Big data represents “the latest iteration of the desire to find efficiency and meaning in quantitative analysis” (Thatcher, 2014, p. 1768). This led to some arguing that “things are not as different as they might seem” (Barnes, 2013, p. 298), and others trace the push for more data all the way back to scientific management (Andrejevic, 2014). Censuses have also been presented as previous forms of collecting and analysing big data (Nafus and Sherman, 2014). As researchers point out, “we’ve been here before” (Barnes and Wilson, 2014, p. 10). Similar views are echoed in the IS literature (Agarwal and Dhar, 2014; Clarke, 2016; Markus, 2017).

Much of the characteristics of big data can be attributed in general to statistical entities (Kennedy, Poell and van Dijck, 2015). Big data also rely on representation, commensuration, classification, notably aggregation, and other mechanisms of measurement summarised above. Similarly to arguments in the various theories of measurement, big data also "promises to expand the realm of what can be measured" (Rieder and Simon, 2016, p. 4).

It is tempting to see BDA as just a continuation of the history of measurement, and indeed there are strong, significant similarities between how previous forms of measurement operate and how the new BDA measures and remakes the world. These similarities are strong enough to warrant a reading of BDA as a technology of measurement and to apply theories drawn from the sociological analysis of measurement to this new context. I am convinced that this is a fruitful perspective which can enable a new understanding of what BDA is and how it works. However, it would be unjust and potentially misleading to see BDA as just more of the same. I return to this point in the conclusions in this section. Before that, I frame the measurement of the social as a highly contingent process, and I unpack the various mechanisms that it relies on.

3.2. Measuring the social in social sciences

Measurement was born out of the need of the physical sciences to provide evidence for theories and experiments, as discussed in the previous section. In the so-called "hard" sciences, measurement is seen as a determination of a quantity of inorganic or organic matter without any impact on the objects measured (Micheli and Mari, 2014). Within this view, objects can be assessed objectively, and environmental influences can be controlled for (Tsoukas, 1989). While some tenets of scientific measurement were reflected in the overview of mathematical theories of measurement and the realist approaches above, they serve only as a background to the main issue for this project, namely measurement in social sciences.

Measurement in management has long suffered from physics envy (von Hayek, 1989), which leads to the use of models of explanation and theorisation derived from "hard" sciences (Micheli and Mari, 2014), despite some obvious ontological and epistemological differences between objects studied. Scientific measurement cannot impact what it measures, while social measurement deals with organisations – and people – as adaptive systems which change, adapt, are complex and become influenced by the theories informing the measurement process (Micheli and Mari, 2014). Epistemologically, scientific measurement relies on a significantly different mode of explanation to social sciences, and yet management scholars have adopted "the 'scientific' approach of trying to discover patterns and laws, and have replaced all notions of human intentionality with a firm belief in causal determinism for explaining all aspects of corporate performance" (Ghoshal, 2005, p. 77).

In their study of the epistemological foundations of performance measurement and management (PMM), Micheli and Mari point out that PMM relies on the concept of measurement as drawn from scientific experiments and the assumption of measurability of performance, while it remains a social practice. Micheli and Mari point out that extant research often assumes "that all the key properties of measurement, (e.g. objectivity, accuracy, and precision) are unproblematic and can be taken for granted" (2014, p. 148), while most of PMM concerns "social objects (…) which are often complex and difficult to define and measure in their properties" (2014, p. 152), such as stakeholder satisfaction or brand management. Numerous management studies assume that variables outside of interest can be controlled for, that metrics measure actions completely, that there are no disagreements among agents about the contexts and situations, and that agents have an ability to reflect (Numagami, 1998). The authors argue that unlike in natural sciences, organisational PMM is not a straightforward process of determining the value of a metric, but rather of its assignment (Mari, 2007). Thus, "measurement results must be assigned (and not determined) according to the goals for which the measurement is performed, with the consequence that they are adequate if they meet such goals" (Mari, 2007, p. 76). Within this paradigm, measurement results are of an informational and not empirical nature, a measurement result is not an intrinsic characteristic of a property, and measurability depends on the current state of knowledge of the property and the availability of experimental conditions (Micheli and Mari, 2014).

Thus, I adopt the view of measurement of the social as a "form of insight, rather than the (actual or potential) 'true knowledge'" (Micheli and Mari, 2014, p. 149). Below, I outline various mechanisms by which this "insight" into the social can be obtained.

3.2.1.Representation

Following the information-theoretic approaches to measurement presented in the previous section, it is fruitful to draw from IS literature on the representative nature of information in order to better expose the nature of the relationship between measurement and the objects measured. As discussed in the previous section, measurement is seen as information, and thus a further analysis in this direction can provide additional insights into this phenomenon.

Drawing from Heidegger (1977), Kallinikos sees information as a selective and discriminatory representation of things, states and processes, different from cognition and the symbolic mediation of the world (1995). This representation is selective because it objectifies specific properties or facets of the world, thus abstracting from "the totality of things and events which it reduces in order to survey and master them" (Kallinikos, 1995, p. 118). Comparing it to physical decomposition, Kallinikos states that representation "dissolves the interior texture of the things and states which it renders visible and calculable" (1995, p. 119), and by reconstructing the world through information, it does so "from the horizon of human intention" (1995, p. 119). Following Heidegger, Kallinikos states that "representation always proceeds by (re)constructing the world from particular standpoints" (1995, p. 121). By extension, we can conclude that "massive mediation of reality and sociality by expansive grids of data and information tokens" (Kallinikos and Tempini, 2011, p. 2) takes place (compare with: "a number, like a photograph, seems a piece of reality, rather than an interpretation of it", Sontag, 1977, p. 4).

It is worth noting that information is essentially productive, that is, it contains "novel descriptions" of the objects it describes, extending their existence. In this sense, information "partakes in the construction of reality" (Kallinikos, 2006, p. 103). This, in turn, leads to the "self-propelling" nature of information where "producing information out of information" takes place (Kallinikos, 1995, p. 106), thus deepening the selectively representational mechanism of information. Information is also perishable and disposable, which paradoxically "makes information useful and useless at the same time" (Kallinikos, 1995, p. 108).

Seen from this perspective, measurement as information provides a selective, deductive, abstractive, subjective, reductive representation of objects it measures. This important contribution from IS literature provides a link between seeing measurement as information, but also serves as an important starting point to understand the mechanisms involved in the representation of the world through measurement, it being a type of information.

3.2.2. Commensuration and quantification

Measurement entails not only representation but also translation of qualities into quantities – commensuration. In other words, it involves "the transformation of different qualities into a common metric" (Espeland and Stevens, 1998, p. 314). Commensuration is a mechanism that "encompasses all human efforts to express value quantitatively" (Stevens and Espeland, 2004, p. 375).

Commensuration is thus a process that transforms qualities into quantities, and difference into magnitude. It is essentially relative, that is, it creates new relations between objects and their attributes (Espeland and Stevens, 1998). The creation of such relationships "unites objects by encompassing them under a shared cognitive system" while distinguishing them "by assigning to each one a precise amount of something that is measurably different from, or equal to, all others" (Espeland and Stevens, 2008, p. 408). This results in the judgment of parts instead of wholes. Thus, difference or similarity becomes a magnitude, an interval, and allows for comparability. On one hand, commensuration renders distinctive characteristics of objects less visible, but at the same time it brings into view certain parts and aspects of objects (Stevens and Espeland, 2004) and new forms of unity, and new, more precise distinctions are created (Espeland and Lom, 2015). This results in the generative character of commensuration: it allows for comparison, stratification, perception of differences and judgment; it permits "scrutiny of complex or disparate phenomena in ways that enable judgment" (Espeland and Stevens, 2008, p. 415). Following Latour (1993), it has been argued that commensuration, a by-product of measurement, creates relations that did not exist before, and once these relations emerge it is no longer possible to see the world in the same way as before.

The essential part of commensuration is the simplification of information. The processes of organising, integrating and eliminating information are inherent in commensuration (Espeland and Sauder, 2007). Vast amounts of information are rendered irrelevant, and instead, simplified, single measures rely on decontextualised information (Espeland and Stevens, 1998). It is thus easier to access and process information, and "simplification often makes information seem more authoritative" (Espeland and Stevens, 1998, p. 17). Researchers argue that simplification may obscure assumptions and arbitrariness, and limit uncertainty and contingency (March and Simon, 1958), and as a result information may be perceived as more robust (Espeland and Stevens, 1998, p. 17). Thus rendered information, deprived of its original context, is more portable, enables numbers to circulate and opens up possibilities for the recreation of their meaning, by "building them into new contexts", and reinterpretation (Espeland and Stevens, 1998, p. 18).

Commensuration relies also on normalisation. This process requires the development of specific categories that allow for a mechanised decision-making process in turning qualities into quantities (Espeland and Stevens, 1998). Normalisation allows for comparison (Sauder and Espeland, 2009, p. 72), turning acts and behaviours into comparable data points. In turn, this allows for differentiation and the creation of a hierarchy (Sauder and Espeland, 2009, p. 73) between the number of clicks, length spent on a particular page, and so on. Normalisation, as Sauder and Espeland argue, leads to homogenisation and exclusion (Sauder and Espeland, 2009). Normalisation also defines what is normal and "creates the experts who maintain the boundaries" (Sauder and Espeland, 2007, p. 5). The effects of commensuration mean that some aspects of life become less visible or relevant; what can be discussed changes, as does what is valued and how (Espeland and Stevens, 1998). The mechanised decision-making opens up the possibility of conducting further "machinations" (Heidegger, 1973) with the measurements.

As Espeland and Stevens state, "most quantification can be understood as commensuration because quantification creates relations between different entities through a common metric" (Espeland and Stevens, 1998, p. 316). Quantification is sometimes used in literature interchangeably with commensuration (see Espeland and Lom, 2015), but more often it corresponds to a broader trend towards an increased reliance on a numerical representation of objects, people, and the world, and is "fundamentally about creating units that can be counted and described numerically with the aim of putting them in some order" (Rottenburg *et al.*, 2015, p. 7).

Espeland and Stevens point to the fact that quantification simplifies, excludes and integrates information, and by doing so it "expands the comprehensibility and comparability of social phenomena in ways that permit strict and dispersed surveillance" (Espeland and Stevens, 2008, p. 415), thus giving rise to monitoring or governing "at a distance" (Miller and Rose, 1990) and legitimising quantification as an "instrument of state power" (Shore and Wright, 2015b, p. 22). This "technology of distance", as Porter states, "minimizes the need for intimate knowledge and personal trust" (1995, p. IX) because "mechanical objectivity serves as an alternative to personal trust" (1995, p. XX), introducing impersonality, suggesting objectivity, and abstracting individuality (1995, p. 32). This makes quantification a strategy of intervention rather than just description: "the quantitative technologies used to investigate social and economic life work best if the world they describe can be remade in their image" (1995, p. 43). Porter explains that quantification works by objectifying, creating a superficial transparency, and implementing hierarchies (1995).

Quantification is often embedded in larger social processes (Espeland and Stevens, 2008) and thus disappears from sight (Rottenburg *et al.*, 2015), but it nonetheless requires considerable work. Who does this work matters, as authors suggest quantification may lead to reapportioning of power by engaging technical experts who gain a new-found influence (Merry, 2011).

Thus, measurement can be seen as a specific kind of information that transforms qualities into quantities, therefore enabling new relationships, comparisons or "machinations" through non-trivial amounts of work. By doing so, it enables judgment, ordering, governance and monitoring "at a distance".

3.2.3. Numbers

If commensuration and quantification allow for the representation of qualities as quantities, it is important to consider numbers that represent these quantities as an important mechanism enabling measurement to happen. Numbers participate in the process of ordering and in representing that order as value, therefore giving them a dual role: ordering and valuing, which is often conflated in the everyday and scientific uses of numbers (Adkins and Lury, 2012). This leads to the fact that "what counts – in the sense of what is valued – is that which is counted" (Badiou, 2008, p. 2). As the French philosopher of numbers Alain Badiou explains, numbers provide a norm for all (2008). In his approach, Badiou claims that objects and people are plural in nature, but once turned into a number, they are forced into singularity. Thus, "no-one can present themselves as an individual without stating in what way they count, for whom or for what they are really counted" (2008, p. 2). This idea speaks yet again to the fact that to turn something or someone into a number means to simplify or reduce complexity. Numbers as entities are "reductive, selectively compressing and framing life and ideas in patterned ways" (Espeland and Lom, 2015, p. 18).

This is why numbers are never innocent (Sayer, 1984): they do not stand for themselves, but are the result of a prior theorisation; they are essentially theory-laden, they speak for assumptions they embody, as they emerge from social institutions or organisations with their agendas and interests.

Yet numbers hold a privileged position in society and command certain authority, as it is often believed they are accurate or valid in their representations (Anderson and Fienberg, 1999; Desrosières, 2001). They help solve problems (Porter, 1995), and they have long been associated with rationality and objectivity (Daston, 1992). Especially in Porter (1995), the rise of numbers can be traced back to the cult of impersonality, the push towards reducing the human element, and valuing formalised principles over subjective interpretation to attain mechanical objectivity (Daston and Galison, 1992). In this light, numbers are seen as factual, neutral, and certain.

Porter explains, contrary to some mathematical theories of measurement presented above, that numbers do not occur naturally, that there is much work involved in applying numbers to nature and that, to apply numbers, it is necessary to remake nature (1995). "[O]nce numbers are deployed, they transform nature further by creating new categories for understanding the world and new entities to fit those categories" (Espeland and Stevens, 1998, p. 1115). Numbers create new things and transform meaning, and thus "create and can be compared with norms, which are among the gentlest and yet most pervasive forms of power in modern democracies" (Porter, 1995, p. 45).

Numbers are seen as entities that allow for new operations, that is, "to travel, to make possible comparison, conversion, and exchange, to be stored, to inform, and to make sameness and difference" (Day, Lury and Wakeford, 2014, p. 127). Numbers make it possible to size, shape, and give form to value (Day, Lury and Wakeford, 2014). In their fascinating insight into numbering practices, Day et al. identify zooming, folding, scoring, pausing, knotting, accreting, diffracting and edging among the things that can be done to numbers (2014) which cannot be done to objects or people themselves. Numbers have the capacity to order things, to create bonds of uniformity that did not exist before: one can add oranges and apples if one wants to know how much fruit there is. Numbers enable comparisons of dissimilar objects, but they can also sort out components and decompose things (like velocity into time and distance or population growth into fertility and mortality, Cohen 1982).

In this sense, again, numbers as products of measurement are productive (Beer, 2016). They allow for the generation of new outcomes through new processes which previously were impossible to carry out on the object or person measured. However, drawing from Badiou's philosophical take, numbers also force some form of unity, singularity on objects or people who do not fit into such form. Thus, representing something as a number is a transformation, a mutation of its intrinsic nature in order to make it fit into a fixed format.

3.2.4. Calculation

As stated above, giving measures the shape of numbers allows them to be subjected to a range of calculative practices. These, too, have been a point of interest for researchers across sociology. Calculation involves "a progressive reduction of complexity" (Starr, 1980, p. 40), which means that some information is lost while some is created, partially dictated by technical and in part by social criteria. Whoever carries out calculation is engaged in "a kind of interpretation, choosing a language for inquiry and analysis" (Starr, 1980, p. 40). Just like photographs (cf. Sontag, 1977), numbers and calculations do not just reproduce reality, they contain and enforce specific views and interpretations.

Calculative practices "enable new ways of acting upon and influencing the actions of individuals" (Miller, 2001, p. 379) by altering the power relations they shape and are embedded within. This line of thought is particularly prominent in the analysis of calculative practices that make economic processes visible and measurable as the economy (Callon, 2010) or in accounting, where "management accounting seeks to affect the conduct of individuals in such a way that they act freely, yet in accordance with specified economic norms" (Miller, 2001, p. 380). Miller in particular provides a lucid description of the evolution of calculative practices in accounting and emphasises that calculation of costs is linked to the development of the ideas around costs and costliness of activities, “altering the way in which it is thought about” (2001, p. 393). In his words, “calculative instruments of accountancy presuppose and recursively construct the calculable spaces that actors inhabit within organisations and society” (Miller and Power, 2013, p. 561). Higgins and Lerner also link to these literatures to ground their arguments on “calculating the social” through standardisation, as explained in more detail below (2010). Calculative and statistical processes behind the production of measurement are “the product of a determinate process of production of knowledge governed by a determinate system of concepts” (Starr, 1980, p. 37), therefore reflecting presuppositions and theories about the nature of society (Starr, 1980, p. 1). In fact, it has been pointed out that calculative data production is imbued with social relations (Starr, 1980) and creates new forms of work organisation (Miller and O’Leary, 1994). Just as in accountancy, in other contexts calculative practices are “intrinsic to and constitutive of social relations, rather than secondary and derivative” (Miller, 2001, p. 392).

Continuing this line of thought, Doria (2013) sees calculation as being infused with practices such as measurement, ordering, arrangement, classification, manipulation, control and translation. It is a political process which shapes organisational structures and practices and defines the identity of individual and collective actors. Doria points to the progressive nature of calculation, stating that it started with rendering things as measurable, calculable objects, then with seeing people as states in statistics, and now it is turning selves into individual characteristics which become commoditised and turned into resources (2013). People thus become objects of calculation, and act upon themselves and can be acted upon. Doria is primarily preoccupied with the measurement of quality of life and presents an overview of how quality became a calculable object (Doria, 2013). The author draws from Heidegger and his concept of calculative thinking coinciding with the perfection of modern technology, in which through cybernetic control “man and things both become standing reserves, available for all forms of mastery and enhancement” (Doria, 2013, p. 4). Thus, people become annexed to this calculative regime and become submitted to “a universe of calculation” which they themselves have created (Doria, 2013, p. 5).

In his “Speaking against number: Heidegger, language and the politics of calculation”, Elden develops his argument, drawing again from Heidegger, concerning the move from logos to ratio, from words to mathematics, and the resulting ordering of the world (2006, p. 117). Elden summarises Heidegger’s main arguments and concludes that “mathematics is an abstraction, an extraction from, an extractive looking at [Heraussehen] being. There is therefore a khorizein, a separating, between mathematics and being” (Elden, 2006, p. 129). Heidegger claims that traditional philosophy has neglected or forgotten the question of being, and as a result human beings have become less preoccupied with it (Elden, 2006). Elden summarises Heidegger's diagnosis of this condition by restating three things that cause people to forget being: calculation, acceleration and massiveness, where the latter two are dependent on the first (2006, p. 139). According to Heidegger, calculation is grounded in mathematics and set into power by the machination of technology, and thus technology is dependent on calculation. Heidegger claims that calculating, discovering the world by measurement is a feature of modern technology (Heidegger, 1977). Elden restates that "this sense of calculation requires all things to be adjusted in this light" (2006, p. 140). As Heidegger states himself, "all calculation lets what is countable to be resolved into something counted that then can be used for subsequent counting. Calculation refuses to let anything appear except what is countable. Everything is only whatever it counts. (…) Such counting progressively consumes numbers, and is itself a continual self-consumption" (Heidegger, 1998, p. 235).

Apart from clear links between calculating and technology, Heidegger also emphasises the productive and self-referential nature of numbers. Therefore, calculation can be seen as a (previously impossible) set of operations carried out on (measurement) numbers which are derivative in relation to beings and yet serve as instruments that shape and influence the interpretation of these beings.

3.2.5. Standardisation

The link between calculative practices and the need to improve or enhance is not new (Doria, 2013). Thus, calculation can be seen as an enabler of standardisation and normalisation. Standards "are typically deemed laudatory; they are something one aspires to live up to" (Timmermans and Epstein, 2010, p. 71), and yet standardisation is derogatory and "connotes a dull sameness" (2010, p. 71). Standardisation can be seen as "a process of constructing uniformities across time and space, through the generation of agreed-upon rules" (Bowker and Star, 1999; Timmermans and Epstein, 2010, p. 71). Standards are bigger than one community, they enable things to work together across space, time, and metrics. They are often developed and supported by external bodies and nested within other standards (Lampland and Star, 2009). Standards can substitute other forms of authority and fill in the gap to coordinate activity (Brunsson and Jacobsson, 2000), and although they are often created by experts, with time can substitute the same experts by embedding authority in rules and systems and not in professionals (Brunsson and Jacobsson, 2000).

Although they often start as formally or legally negotiated and created entities, they often "sink below the level of social visibility, eventually becoming part of the taken-for-granted technical and moral infrastructure of modern life" (Timmermans and Epstein, 2010, p. 71).

Yet each standard implies a "script" (Akrich, 1992), that is a description of various roles of groups of users and their skills, motivations, requirements, tools, etc. While standardisation can be seen as a soft form of regulation (Brunsson and Jacobsson, 2000), it also stratifies, elevates some stakeholders and submerges some (Timmermans and Epstein, 2010). In other words, "each standard achieves some small or large transformation of an existing social order" (Timmermans and Epstein, 2010, p. 83).

Creating standards involves a lot of work by multiple stakeholders. They are built collectively and require buy-in (Timmermans and Epstein, 2010). However, standardising also requires work to make different entities "commensurable, calculable and thus standardisable", and to enact distinctions (Higgins and Lerner, 2010, p. 208). Standardisation is never complete or finished (Barry, 2001); there is an ongoing labour of comparison (Pollock, 2010). To standardise means to create sameness and distinction at the same time, as it serves to later classify and categorise (Bowker and Star, 1999).

Standardisation is an essential component of measurement precisely because of its dual nature: it sets aspirational standards, and yet it gives rise to sameness; it helps to identify similarities, but at the same time it creates distinctions and differences. It is also an ongoing process which can never be complete.

3.2.6. Classification, categorisation and aggregation

In their seminal book, Bowker and Star (1999) emphasise that to classify is human, and all cultures at all times have produced classification systems. In a striking description of classification of people into races during Apartheid, Bowker and Star expose the complexities and inner workings of the process of classification (1999) and point to its inherently social nature. They define classification as "a spatial, temporal, or spatio-temporal segmentation of the world" and identify classification systems as "sets of boxes" (Bowker and Star, 1999, p. 10) into which things can be put to be further subjected to work. Classification systems act to "stabilise the world in particular ways" (Kress, 2010, p. 122). Through the cases of the International Classification of Diseases (ICD) and race classification and reclassification under apartheid, the authors lay bare the precise mechanisms of creating classifications, classifying and re-classifying, and the work attached to these processes as well as their consequences. Classifications may appear natural or in line with a given human context, but may appear forced and heterogeneous when seen from a different perspective (Bowker, 1996). Thus, classification is never neutral (Shore and Wright, 2015b).

Similar ideas are presented by Hacking (Hacking, 2006) in his famous notion of "making up people". Hacking claims, using suicide rates, that recorded motives for some types of suicides did not exist before the practice of counting them as such came to be (2006, p. 161). Hacking claims that "new slots were created in which to fit and enumerate people. Even national and provincial censuses amazingly show that the categories into which people fall change every ten years. Social change creates new categories of people, but the counting is no mere report of developments. It elaborately (…) creates new ways for people to be" (Hacking, 2006, p. 161). Categories then became resilient black boxes, official and increasingly real (Porter, 1995). As researchers point out, "once categories are in place, people's behaviour increasingly conforms to them" (Espeland and Stevens, 1998, p. 331), highlighting the powerful nature of classes and the process of classification. Categories can be then seen as disciplinary techniques operating by classifying and categorising individuals into populations (students, criminals) governed through spaces of enclosure (Ruppert, 2012), such as schools and prisons (Deleuze, 1992). Classification is also present in verbal language and the cultural practices of grouping and making sense of reality as natural categories (Rosch, 1973) that are tasked with providing maximum information with minimum cognitive effort: knowing that something belongs to a certain category reveals much more information about it.

Through the tracing of the development of medical classifications and the ICD, Bowker describes how the need to classify is intrinsically linked with the development of the state: "large modern states have (…) found themselves forced into developing complex classification systems in order to promote their political and economic smooth functioning" (1996, p. 51). To maintain a good classification system, a huge amount of information is needed, no information is irrelevant, and the state's need for information is effectively infinite (Bowker, 1996, p. 53). Thus, Bowker points to the relationship between state-building and the development of information systems, showing through the history of ICD and the development of information-processing technology "the imbrication of the technological configuration and the form and the use of the classification system" (1996, p. 57).

Increasing reliance on information systems allows for aggregation within classifications or categories. Going back to Foucault (2008, 2009), in the 18th and 19th centuries, collectives were given calculable, statistical reality as a result of censuses of the population. It was the aggregation of students or criminals from individuals to populations which then enabled the further examination of such classes. This meant that new classes led to the formation of new objects, such as "the population characterised by a mean and a standardized dispersion" (Hacking, 2006, p. 142). This propelled the growth of statistics.

Measurement can then be seen as a set of practices that enables the classification, categorisation and aggregation of entities for the purposes of further manipulations.

3.2.7. *Indices and indicators*

Indices and indicators "are rapidly multiplying as tools for measuring and promoting reform strategies around the world" (Merry, 2011, p. 52). They are a "specific technology of quantification" (Rottenburg *et al.*, 2015, p. 18). The authors give several examples, such as the Body Mass Index (BMI) or Human Development Index (HDI), to explain that indices and indicators work by aggregating a few different measurements: "obesity cannot be determined just by measuring weight; it must also be related to height, age and sex" (2015, p. 19). By conflating different factors into a single number, indices tempt with their simplicity. Yet in the collection of chapters edited by Rottenburg and colleagues in "A World of Indicators", various authors point towards the use of indices and indicators by governments in particular, and the push towards accountability and regulation in quantitative terms. On one hand, say Rottenburg et al., "accountability measured by indicators is supposed to make it easier for outsiders to understand, monitor and evaluate the actions of politicians, state actors and national or transnational organisations. (…) On the other hand, quantitative forms of accountability devices assist people with political and/or extensive economic power, who have been given the task of working in the interest of a specific or wider public, to make decisions in an increasingly fast and uncertain working environment" (2015, p. 23). In the same collection, Wendy Espeland argues that indicators are created through the dynamic relationship between simplification and elaboration, they erase narratives, remove "the persons, places and trajectories of the people being evaluated by the indicator and the people doing the evaluation" (2015, p. 56).

While often seen as promoting transparency and accountability (see e.g. Mathiason, 2004), progressing "indicization" constitutes a form of pressure to conform (Kelley and Simmons, 2014). Indices and indicators become "technologies of power" (Hansen, 2012).

Indices and indicators shed a slightly different light on the issue of measurement. They act by putting together measures of different aspects, or sometimes of completely different things. As a result, they produce measurement outcomes that are increasingly less transparent and straightforward to interpret.

3.2.8. *Rankings*

Rankings can be distinguished from other indices and indicators because they not only measure and classify, but also order (Shore and Wright, 2015a). They have been studied most prominently in the context of education, and especially at US law schools (Sauder and Lancaster, 2006; Stake, 2006; Sauder and Espeland, 2007; Espeland and Sauder, 2009). Rankings rely on criteria that are surrogates for quality, they are poorly defined and they present data in a misleading way: "they appear accurate and validated, but they actually throw away information" (Stake, 2006, p. 247), trying to present differences between ranked institutions on a normalised scale of a ranking, while such normalisation of distinctions is hardly ever the case. At the same time, important criteria that are not incorporated in rankings are devalued. Such distortions can be further compounded as future decisions are made on their basis (Stake, 2006).

Rankings are abstract, concise, portable, travel widely and are easy to import into new places (Sauder and Espeland, 2009, p. 71). They can lead to several negative consequences, including loss of organisational trust (Power, 1994; O'Neill, 2006), elaborate gaming strategies (Shore and Wright, 2000), a culture of compliance and large compliance costs, including appointing specialists busy with creating positive (mis)representations of performance (Miller, 2001), defensive strategies, and deprofessionalisation (Shore and Wright, 2015a).

Rankings studied by Espeland and Sauder become the devices (in the sense proposed by Ruppert 2012) that give rise to reactivity, that is, same individuals altering their behaviour in reaction to being evaluated, observed or measured. Actors adjust behaviours under measurement, which both affects their actions but also limits the usefulness of the measurement process itself (Espeland and Sauder, 2007). Reactivity as a theory is a continuation of the performativity discourse (and by extension, the scholarship of Hacking on interactivity and "making up people", 2006), but rather than putting solely the effects of the recursive relationship between what is being described and what describes into focus, reactivity aims at uncovering the mechanisms that give rise to these effects as well as their consequences. The mechanisms and effects of reactivity are further discussed in the theoretical framework chapter.

Rankings, thus, are a particular type of indicator that also creates relationships of order, of being higher or lower in a ranking. This is different from indices because it creates competition between ranked bodies: for one to score higher, another one has to score lower, unlike in indices where it is possible for more than one body to obtain a particular score. A ranking as a form of measurement creates interdependencies between ranked bodies unlike any other practice.

3.2.9. Statistics

Statistics is often understood as "the collection, classification, analysis, and interpretation of numerical facts or data" (Kish, 1987, p. 598) and thus is not only a continuation of these previous practices of measurement, but also adds complexity to the processing of measurement data by relying on probability calculations and predictions. Desrosières identifies four perspectives on what statistics are, pointing towards their: metrological realism, pragmatism of accounting, the use of statistics for argumentative purposes, and the explicit admission of the constructed, conventional and negotiated definition of measured variables (2001).

The development of statistics led to a new conceptualisation of cognition as statistical computation (Hodge, 1991), and the more general reliance upon statistics became "the taming of chance" (Hacking, 1990). Hacking distinguishes between three uses of statistics, namely descriptive, inferential and modelling (1992), but concludes that in all three uses "the data were not passive, awaiting collection, they were moved, ordered, coerced" (1992, p. 140). A similar thought is echoed in a fascinating story of the development of statistics presented by Stigler (1999), who details how specific statistical tools such as, for example, least squares, were discovered and propagated. By these accounts, statistical tools emerge through negotiation and development, and are far from being objective, stable and universal. Statistics are "the product of a determinate process of production of knowledge governed by a determinate system of concepts" (Hindess, 1973, p. 56), and they reflect presuppositions and theories about the nature of society.

According to Hacking, statistics enabled the creation and emergence of new sentences, classes, law-like sentences, objects, explanations, criteria and intersubjectivity (Hacking, 1992). Thus statistics also has a "creative power" (Porter, 1995).

Historically, statistics evolved in a close relationship with the development of the modern state (Starr, 1980), especially for the purposes of conscription, tax collection and surveillance. Census is one of the first instruments of state power and social control, dating back to ancient times (Starr, 1980; Kittler, 2006). The increasing amounts of data required far more advanced processing, so the development of the state meant the need to develop statistics further (Porter, 1995). With time, official governmental statistics become black boxes that are hard to discredit or open (Desrosières, 2002), giving them legitimacy and guaranteeing their survival over time.

One of the most important distinctive features of statistics is that they enable calculating probabilities and making predictions concerning the future based on the measurement of variables in the past.

3.2.10. Computation

Although computation is not traditionally discussed in the context of measurement, I believe a short mention of computation is justified here, as measurement, all the way from representation to statistics, increasingly relies on technological computation. This is also where the field of IS can contribute to a fuller understanding of measurement practices at play in the modern world. Computation “entails the relentless analytic reduction of the composite character and complexion of the world” (Kallinikos, 2009, p. 183). Technological operations reconstruct basic objects, redefine the processes through which they are ordered, identified, and made accessible. They also change the profiles of skills and expertise needed (Kallinikos, Hasselbladh and Marton, 2013). Technology, and thus computation, embodies technological functions created by humans that obtain “an operational independence from social agents” (Kallinikos, Hasselbladh and Marton, 2013, p. 401). Computation relies on design, technological functions, operational links, and instrumental prescriptions (Kallinikos, Hasselbladh and Marton, 2013).

Quite a shift takes place from relying on “fuzzy semantic organization of ideas present in living heads” to “the gridded, disjoint and frozen forms by which knowledge is fed into digital machine” (Kallinikos, 1995, p. 127). Technological computation implements a specific regulative regime through specific functionalities and procedures it is imbued with (Kallinikos, 2011). Technology shapes what people do by means of functional simplification/closure and objectification/automation (Kallinikos, 2011). Functional simplification and closure are realised through a set of operations “lifted out of the surrounding institutional and organizational complexity to which they belong, with the purpose of their reconstruction as simplified causal and procedural sequences, sealed off from their environments” (Kallinikos, 2011, p. 23). Technology thus reduces complexity, reduces inferences from the outside, and embodies operations away from social contexts in material devices and objects. Once closed and sealed off, operations become automated sequences of steps in pre-arranged technological sequences (Kallinikos, 2011). One of the consequences of this regulative regime of technology is the fact that technological information processes become installed “at the heart of activities that were once predominantly performed on the basis of professional criteria” (Kallinikos, Hasselbladh and Marton, 2010).

These processes have a non-trivial impact on the practices of measurement when conducted via computational means. Measurement practices carried out with the help of computation become functionally enclosed, objectified and automated.

3.3. Big data analytics and mechanisms of measurement

So far in the previous section, I attempted to provide an overview of the characteristics and processes involved in big data production. I have done so in order to facilitate the mapping of BDA onto the processes of measurement. Below, I present a table summarising in what way BDA relies on similar processes of measurement as other forms of measurement of the social, and in what way it is different, derived from the literature. The literature highlights that there are non-trivial differences between the hitherto tradition of measurement (how technologies of measurement worked and how measurement was constructed and used) and BDA. Glossing over these differences may conceal, rather than reveal, the mechanisms and effects of BDA at play. I therefore suggest that it is equally important to study what is different in BDA. Few researchers have discussed this issue in a critical manner, namely hinting that the increased use of computation and the digital form of big data is what distinguishes big data from previous forms of measurement (Agarwal and Dhar, 2014; Rieder and Simon, 2016). However, these remain unpacked and rather thinly studied. Thus, I intend to assign equal importance to studying both the differences and similarities between BDA and other forms of measurement. In the next section, I review literature that highlights shifts in the nature of BDA as a technology of measurement.

Table 2 Big Data Analytics and mechanisms of measurement

Mechanism of measurement	Short definition	"Small data" example	Big data analytics		Big data example
			Similarities	**Differences**	
Representation	Mediation of reality by selective, abstractive and objectifying information, reconstructing the world "from the horizon of human intention" (Kallinikos, 1995, p. 119)	A photograph (Sontag, 1977), list, table	Similar process of mediation	Information is digital, representation is limited to the boundaries of the digital	'Like' on Facebook as a representation of engagement or preference (Alaimo and Kallinikos, 2016)
Commensuration and quantification	"The transformation of different qualities into a common metric" (Espeland and Stevens, 1998, p. 314) relying on simplification of information and normalisation; "most quantification can be understood as commensuration because quantification creates relations between different entities through a common metric" (1998, p. 316)	Comparable-worth programmes commensurating skill and pay levels between traditionally female and traditionally male occupations (England, 1992)	Big data analytics as a nexus of commensuration and quantification	Transforming digital representations of quality into various metrics interpreted and changed locally; quicker to accommodate change in space and time; digital infrastructures facilitating commensuration	TripAdvisor's Traveller Rating and Popularity Index (Jeacle and Carter, 2011)
Numbers	Forms of singularity which order and help value objects, and allow new operations, i.e. "to travel, to make possible comparison, conversion, and exchange, to be stored, to inform, and to make sameness and difference" (Day, Lury and Wakeford, 2014, p. 127), they are entities rather than processes	Stars and rosettes awarded by AA in the UK (Orlikowski and Scott, 2014)	Numbers as a form of symbolic capital	Numbers stand in for the content they represent (e.g. a list of friends who like a status becomes '8 people like this', Grosser 2014); easy to obtain from databases	Enumerations of 'likes', comments and other reactions on Facebook (Grosser, 2014)
Calculation	"Calculation lets what is countable to be resolved into something counted that then can be used for subsequent counting. Calculation refuses to let anything appear except what is countable. Everything is only whatever it counts. (…) Such counting progressively consumes numbers, and is itself a continual self-consumption" (Heidegger, 1998, p. 235)	Census (Rose, 1991)	Social actions made countable are then counted and used for counting	Social actions are made countable as an effect of user participation along standardised activity types (Alaimo and Kallinikos, 2017), and a host of calculations are conducted on top of these actions	Enumerations of 'likes', comments and other reactions on Facebook (Grosser, 2014)
Standardisation	"A process of constructing uniformities across time and space, through the generation of agreed-upon rules" (Bowker and Star, 1999; Timmermans and Epstein, 2010, p. 71)	ISO 9000 standard (Timmermans and Epstein, 2010)	Creating uniformities across time and space	Uniformities are more dynamic and are a result of aggregation of numbers of non-expert users	IMDB ratings as a standard-setting device (Bialecki, O'Leary and Smith, 2017)

Classification, categorisation and aggregation	Classification as "a spatial, temporal, or spatio-temporal segmentation of the world" and identify classification systems as "sets of boxes" (Bowker and Star, 1999, p. 10)	Medical classifications and the ICD (Bowker and Star, 1999)	Assignment of objects or people into categories or classes, and their aggregation	Depends on user involvement; observation and research skills; encoded in data	PatientsLikeMe (Kallinikos and Tempini, 2014)
Indices and indicators	Work by aggregating different measurements and conflating different factors into a single number	Human Development Index (HDI) (Rottenburg *et al.*, 2015)	Aggregating different sources of information into a single, non-competitive number	Constantly, dynamically changing sources and resulting scores, a "participative measure of dynamic participation" (Day et al. 2014: 138)	Klout score (Gerlitz and Lury, 2014)
Rankings	Order ranked entities on a normalised scale, create relationships of order	U.S. law school ranking (Espeland and Sauder, 2007)	Creating relationships of order between ranked entities	Quality of the ranking depends on and improves with the quantity of user contributions	TripAdvisor's Popularity Index (Ye *et al.*, 2014)
Statistics	"The collection, classification, analysis, and interpretation of numerical facts or data" (Kish, 1987, p. 598) for statistical inference or prediction	Determining movie preferences based on gender (Wühr, Lange and Schwarz, 2017)	Statistical treatment of data	Use of sophisticated statistical techniques and computation with a pronounced emphasis on prediction	Netflix recommendation system (Fleder and Hosanagar, 2009)
Computation	The use of computational tools characterised by "an operational independence from social agents" (Kallinikos, Hasselbladh and Marton, 2013, p. 401) for calculative purposes	US 1880 census (Zittrain, 2008)	The use of computational tools for calculative purposes	Not only operational, but also interpretational and agentive independence awarded to computational tools	Self-driving cars (Chen and Huang, 2017)

3.4. Conclusions

In this section, I argued that BDA should be seen within the much longer history of measurement. I supported my argument in favour of treating BDA as a continuation of the history of measurement by drawing from the growing body of literature on big data. I provided an overview of mechanisms of measurement at play and their consequences as studied in the mostly sociological literature. It is important to note that while this section analyses the various mechanisms of measurement separately, in reality they are often interrelated, interwoven and interdependent. I posited that the framing of BDA as a technology of measurement provides a new perspective that can strengthen our understanding of this phenomenon. Yet, the precise mechanisms in which big data and its analytics are involved for the purposes of shaping the world and organisations have not yet been analysed and uncovered. Set within the longer history of measurement, big data influence what they measure, yet we still do not have a full understanding of this phenomenon. Through contributions from various fields, but most notably IS, we have a better understanding of how big data encodes behaviours and events from the real world, how it aggregates and correlates them, and how the process of BDA shapes the world in return. However, the precise workings of this shaping remain under-theorised. This is where I would like to offer my contribution to the understanding of this phenomenon.

4. Measurement and technology

In this section, I present an overview of a range of theories pertaining to measurement, namely mathematical theories, operationalism and conventionalism, realist accounts, model-based theories and information-theoretic approaches, in order to contextualise the study. In light of these theories, I flesh out the evolution of technologies of measurement and their characteristics and applications in order to trace their changing nature. Finally, I posit that digital measurement technologies, such as BDA systems, while sharing many traits explored in the following section, also introduce significant differences as compared to previous technologies of measurement. Specifically, the literature reviewed indicates that while past technologies of measurement aimed to ensure objectivity, reliability, precision, coherence and acceptance, new technologies of measurement undermine these characteristics through their digital ontology. This background is essential to understanding the impact of BDA systems on measurement as a phenomenon.

4.1. Theories of measurement

The study of measurement, now located primarily within the discipline of philosophy of science, has been taken up by a number of scholars with differing backgrounds and interests, from mathematics (e.g. Helmholtz, 1887; Moscati, 2016), through psychology (e.g. Stevens, 1946), philosophy (Trout, 1998, 2000), to information theory (Hartley, 1928; Shannon and Weaver, 2001), economics (Boumans, 2005), accounting (Ijiri and Jaedicke, 1966) and management (Bagozzi, 2011; Burton-Jones and Lee, 2017).

While these scholars would usually approach the issue of measurement from the perspectives of their own disciplines to highlight and emphasise different aspects, in their work we can find alignment with the main theoretical thoughts on measurement. Namely, the main strands of modern philosophical approaches to measurement are as follows: a) mathematical theories of measurement, b) operational and conventional view, c) realist accounts, d) model-based accounts and e) information-theoretic accounts (Tal, 2017). These strands tell the story of the trajectory of the discussion and do not contradict each other, but rather focus on different aspects and elements of measurement. Broadly speaking, while scholars, within mathematical theories, are primarily concerned with the mathematical foundations of scales, operationalists and conventionalists deal with the semantics of terms used in measurement, realists deal with the ontology of measurement, and the model-based and information-theoretic approaches primarily focus on the epistemology of measurement (Tal, 2017). This is not the only attempt at organising the scholarship around measurement (see for example Micheli and Mari, 2014, who propose three periods in relation to the study of measurement: metaphysical, anti-metaphysical and relativistic, or Mari 1997, who juxtaposes the classical position to the modern one). However, this typology by far seems to be the most encompassing one, transgressing the boundaries of respective disciplines.

In what follows, I present short and compact overviews of these five strands of scholarship, focusing specifically on the way in which they perceive what I term technologies of measurement, often referred to in the literature as measurement tools, measuring instruments, measurement devices or measurement systems. In doing so, I do not attempt to present a complete investigation of the broad and varied scholarship, but rather tease out the perspectives scholars in these strands take on the technologies of measurement in order to construct an argument about the role of BDA systems as technologies of measurement.

4.1.1. Mathematical theories of measurement

Broadly speaking, mathematical theories of measurement view measurement as the mapping of qualitative empirical relations to relations among numbers. Such approaches set out to identify the assumptions underlying mathematical structures as descriptions of the empirical world and evaluate their suitability and limits (Tal, 2017). Within this scholarship, the prevalent nascent idea of measurement was that it relied on assigning numbers to magnitudes (Helmholtz, 1887; Russell, 1903), and was best expressed in the definition stating that measurement is "the process of assigning numbers to represent qualities" (Campbell, 1920). Under this assumption, most researchers within this strand focused on the questions of adequacy of assignment and the conditions under which it can take place. Within this scholarship, the empirical conditions of quantification focused primarily on numbers as well as constructing the right tools that allow the right mathematical relationship while "assigning numbers" to qualities to be maintained.

The work on the classification of scales by Stevens (Stevens, 1946, 1951) earned a notable mention in this strand. Four types of scales, namely nominal, ordinal, interval and ratio, differ, according to Stevens, in terms of the transformations they can undergo without loss of information. While the classification was generally accepted, Stevens' work opened up a wider debate on what constitutes measurement, and whether classification and ordering were indeed measurement operations (Tal, 2017). For Stevens, measurement was the "assignment of numerals to objects or events according to rules" (Stevens, 1951), and he claimed that any consistent and non-random assignment counts as measurement in the broad sense (Stevens, 1975). While they could be seen as technologies of measurement, scales within this strand were mostly discussed in terms of their faithfulness in representing the relationships between numbers, rather than the relationship between the empirical world and the scale.

The most influential mathematical theory of measurement to date is the Representational Theory of Measurement (Krantz *et al.*, 1971; Suppes *et al.*, 1989; Luce *et al.*, 1990), which sees measurement as the construction of mappings from empirical relational structures (empirical objects with certain qualitative relations) onto numerical relational structures (Krantz *et al.*, 1971). Representational Theory of Measurement (RTM) has its roots in the philosophy of mathematics and the changing understanding of numbers, which were at that time no longer believed to be features of the real world (Michell, 1993). RTM offered a tenable view that scales have different representational adequacy, which in turn gave rise to a host of statistical representations of measuring systems and their output data (Tal, 2013). This approach is one of the foundational paradigms in statistics (Hand, 1996). At the same time, RTM was and is still met with criticism, most pertinently in the discussion in relation to the fact that it "reduces measurement to representation" (Heilmann, 2015, p. 787), often ignoring problems such as measurement error and the construction of reliable measurement instruments (Michell, 1990, 1995; Boumans, 2005). In fact, in order to counter the shortcomings of RTM, the science of metrology arose, with contributions mostly from engineers who focused on measurement in relation to instrumentation (Michell, 2007). This mostly engineering approach called for the description of measurement to include the structure of the measurement process comprising three components: the measurand, the measuring system and the environment (Mari, 1997). It also gave rise to other fruitful approaches discussed below, relying on the shift from the truth-based view of measurement to a model-based view (Michell, 2007).

The surprising absence of the study of measuring systems, or instruments, within RTM and its thin treatment in the mathematical theories of measurement more broadly has a number of potential explanations – including a limited interest in measurement instruments (see Rossi, 2007) – but the need to study the role of measurement technologies within the theory of measurement has been pointed out by a number of scholars (Gonella, 1988; Mari, 2000). While the absence of a theoretical treatment of the technologies of measurement in the mathematical tradition does not reveal insights concerning this phenomenon, it is nonetheless symptomatic of the assumptions held, namely that technologies of measurement are transparent and objective, and as such do not justify theoretical concerns.

4.1.2. Operationalism and conventionalism

Operationalists and conventionalists see measurement as a set of operations that shape the meaning or regulate the use of a quantity term (Tal, 2017). In this view, terms such as "length" or "unemployment rate" depend on choices made by humans with respect to how a given quantity is measured (Tal, 2017).

Operationalism is the view that the meaning of quantity terms is determined by the set of operations used for their measurement (Bridgman, 1927). It became particularly influential in psychology. Stevens, for example, argued that psychological concepts have empirical meanings only if they stand for concrete operations (Stevens, 1935), and this allowed psychologists to justify the conclusions they drew from experiments (Feest, 2005). This view gave rise to logical positivism, a school of thought which argued that only those statements that are empirically verifiable are meaningful (Tal, 2017). Operationalism, however, came with specific problems, notably the automatic reliability of measurement operations that was one of its assumptions, which ultimately led most philosophers of the semantics of quantity terms to avoid taking this approach (Tal, 2013).

Conventionalism, in turn, accepted the conventional aspect of measurement while "resisting attempts to reduce the meaning of quantity terms to measurement operations" (Tal, 2013). Conventionalists accepted that some aspects of measurement are conventional, that is, dependent on a consensus among people. As an example, Poincaré argued that the processes used by scientists to mark equal durations, e.g. pendulum swings or the rotation of the earth, are chosen based on the scientists' preference rather than facts of nature (Poincaré, 2007). The usefulness of conventionalist approaches was highlighted with respect to creating opportunities for debate around phenomena.

Within both of these approaches, measuring instruments are regarded as black boxes producing readings, and it is assumed that they "define" the measured quality (Berka, 1983). Therefore, they are of no particular interest to researchers working within this perspective.

4.1.3.Realist accounts

Realists see measurement as the estimation of mind-independent properties or relations (Tal, 2017). Measurable properties are seen as independent of the beliefs and conventions of measurers and the methods used for measurement. Estimation is used to highlight that measurement results are only approximations of true values (Trout, 1998, p. 46). Within the realist view, to measure means to obtain knowledge about properties, and not to assign values to objects. Observable objects can offer insights into non-observable properties, but this presupposes background theory. Thus, realists often emphasise the theory-laden nature of measurements (Tal, 2017).

Within this account, phenomena are intrinsically quantitative (Mari, 2005), and measurement is deployed to determine pre-existing properties (Mari, 1997). This view is perhaps best encapsulated in the definition of measurement: "a process of empirical, objective assignment of symbols to attributes of objects and events of the real world, in such a way as to represent them, or to describe them" (Finkelstein, 2003). Such views, as argued, are often adopted by management scholars, who often assume that "variables other than the ones whose variation we would like to observe are perfectly controlled for", that "the empirical scales measure the constructs completely", and that "there is no cognitive disagreement among social agents about the definition of the situation" (Numagami, 1998, p. 4).

Within realist accounts, most philosophers argue for the realism not only of the reality of relations between objects, but also of properties that are measured (Trout, 1998, 2000). Such realists would argue that some measurable properties exist independently of human beliefs and conventions, and thus can be used to explain, for example, the reliability of measuring instruments (Tal, 2017). Realists explain that different measurement procedures required by different tools often yield similar results because they are exposed to the same facts (Trout, 1998, p. 56). Realist accounts would also claim that it is only possible to construct measurement apparatuses and analyse measurement results if guided by theoretical assumptions about causal relationships (Tal, 2017).

Since the realist accounts are primarily preoccupied with the ontology of measurement, the studies of the technologies of measurement within this account focus mostly on the role of such tools as estimators of true values: “the length of a column of mercury is a thermometric property [that] presupposes a lawful relationship between the order of length and the temperature order” (Byerly and Lazara, 1973, p. 23). However, in any other sense, measuring instruments are not of significant interest to the realists.

4.1.4. Model-based accounts

Particularly since the beginning of the 21st century, a new wave of scholarship of measurement emerged, focusing on the relationships between measurement and theoretical and statistical modelling (Tal, 2017). Model-based accounts assume that there are two levels to measurement: a concrete process in which the measured object, the instrument and the environment interact, and a theoretical or statistical model of that process, in which the model is an abstract representation based on simplifying assumptions (Tal, 2017). Model-based accounts attempt to clarify the epistemological grounds for measurement, and by doing so investigate, among other things, instrument design and calibration (Frigerio, Giordani and Mari, 2010).

With the basic assumption of measurement involving interactions between the system under measurement, the measurement system and an environment, model-based accounts also emphasise the role of secondary interactions, such as between the measuring instrument and reference standards (Mari, 2005). Measurement is thought to represent these interactions with a set of parameters and to assign values to a subset of parameters based on the results of the interactions (Tal, 2017).

Model-based accounts distinguish between instrument indications (i.e. the readings, or the properties of the measuring instrument in its final state after the measurement is complete, such as digits on a display or bits stored in a device's memory) and measurement outcomes, the results, or knowledge claims about the values of quantities attributed to the object (Giordani and Mari, 2012). One of the central claims of the model-based accounts is that inferences from indications to outcomes in measurement are not straightforward and depend on a number of theoretical and statistical assumptions about the object under measurement, the instrument, the environment and calibration (Tal, 2017). Models, seen as abstract representations of systems are necessary to infer outcomes from instrument indications. What is more, as model-based theorists emphasise, indications produced by the same measurement process may be used to establish different outcomes depending on the modelling of the measurement process, e.g. which environmental features are considered, or which statistical assumptions are implemented (Mari, 2003).

Model-based approaches have been used in economics, where some philosophers interpret certain economic models as measuring instruments (Boumans, 2005) because they produce relations between inputs and outputs of measurement. Another area where model-based views were adopted is psychology, where the measurement of psychological attributes such as intelligence does not yield itself to mappings proposed by, for example, the Representational Theory of Measurement (Wilson, 2013).

4.1.5. Information-theoretic approaches

The model-based view led to the important conclusion that measurement outcomes "are obtained from indications by a chain of inferences, and the particular inferences drawn depend on the particular theoretical and statistical assumptions" (Tal, 2013). Thus, it opened up several new questions as to the nature of measurement. Accepting the role of theoretical and statistical assumptions, van Fraassen argued that measurement "is a means of gathering information about an object" (van Fraassen, 2008). Specifically, "measurement is an operation that locates an item (already classified as in the domain of a given theory) in a logical space (provided by the theory to represent a range of possible states or characteristics of such items)" (van Fraassen, 2008).

Within this approach, the mapping of measurement indicators to outcomes began to become a matter of information transmission (Tal, 2013). Such an account draws an analogy between measuring systems and communication systems. Just like in a communication system, a message (input) is encoded into a signal, sent to the recipient and then decoded (output), and the accuracy of transmission depends on the communication system and the features of the environment (Tal, 2017). Similarly, measuring instruments or technologies of measurement can be seen as interacting with an object in a given state (input), encoding the state into an internal signal, and converting the signal into a reading (output), where the accuracy of measurement depends on the instrument and the environment (Tal, 2017). The information entity, according to this view, is produced "by properly representing the outcome of a physical interaction between the object under measurement and a measuring instrument in a specific environment" (Giordani and Mari, 2012, p. 2146). Within this view, to measure "does not necessarily mean to associate empirical objects with numbers, but more generally, with information entities" (Frigerio, Giordani and Mari, 2010).

Thus, the task of any measurement system is to "associate a symbolic entity, assumed as a measurement result, with the thing under measurement, thus generating a link between the empirical realm of things and the informational realm of symbols" (Mari, 1997, p. 86). Information-theoretic approaches not only emphasise the role of a measurement instrument, but also propose that measurement instruments act as filters, comparators and classifiers. As a filter, a measurement instrument interacts with the object under measurement with respect to a given quantity, as a comparator it produces a comparison with a set of measurement standards through this interaction, and as a classifier it creates classes of objects sharing similar measurement results (Mari, 1997; Giordani and Mari, 2012). On the output end of the measurement instrument, it is tasked with associating a symbol with an output of measurement, i.e. creating a formal representation of the information collected (Mari, 1997). Measuring instruments are also believed to "make a contribution to what we observe" by way of directly affecting the quantity observed or contaminating the result by way of design and construction inadequacies (Jones, 2013, p. 108).

As for the environment, a common view would be that measuring instruments may be sensitive to environmental factors, and because usually the comparison between the object of measurement and the standard is asynchronous, the measuring system may operate as "a memory unit and it might not be perfectly stable in this function" (Giordani and Mari, 2012, p. 2146). It is believed that "all measuring instruments and measuring systems experience sources of error" (Jones, 2013, p. 110).

The information-theoretic approach has been adopted, for example, in the study of accounting measurements (Ashton, 1977), where the role of the measurer has also been emphasised (Ijiri and Jaedicke, 1966). In a similar vein, some studies in IS have posited that measurement practices are problematic (Burton-Jones and Lee, 2017).

Information-theoretic approaches are currently believed to be key to the future of the epistemological study of measurement. Indeed, some of the most recent definitions of measurement emphasise that “measurement is a specific kind of evaluation, an operation aimed at associating an information entity, the result of measurement, with the state of the system under measurement” (Mari, 2003, p. 17). Some philosophers of measurement call for more detailed studies of the relationship between information and modelling, and to contextualise the study of measurement within the rich literature on information from other fields.

4.1.6. Conclusions

This brief overview of the different theories of measurement employed by a range of researchers in a variety of fields showed differing foci of interest and approaches to the ontology and epistemology of measurement. In terms of their treatment of the technologies of measurement, mathematical theories, as well as operationalism and conventionalism and the realist approaches, offer a rather meagre theorisation of the measuring instruments and tools, and never a complete treatment. This is most likely due to the fact that such views are not primarily concerned with the problematisation of measurement. However, model-based views and especially the information-theoretic approaches offer a much richer narrative around the role of the technologies of measurement within measurement as such. The table below synthesises the perspectives that these theories propose in relation to the technologies of measurement.

Table 3 Theoretical perspectives on technologies of measurement

Tradition	**Mathematical theories of measurement**	**Operationalism and conventionalism**	**Realist accounts**	**Model-based accounts**	**Information-theoretic approaches**
Views on measurement	Measurement is a process of assigning numbers to represent qualities	Measurement as a set of operations that shape the meaning of a quantity term	Measurement is an estimation of objective properties or relations	Two levels of measurement: 1) actual measurement, 2) a theoretical model representing what is measured	Measurement as a transfer of information through inference from an object to its measurement
Views on technologies of measurement	Absent from theorisation, thus seen as unproblematic	Black boxes producing readings according to determined operations	Tools as estimators of true values, largely untheorised and considered unproblematic	Emphasis on the study of interactions between measuring instruments, environment, standards, and the measured object.	Measurement instruments are sensitive to environmental factors, they act as filters, comparators and classifiers and as such need to be studied.

Drawing from the literature proposed for the above purpose, the following understanding of a technology of measurement as an information system is synthesised in Figure 1 below.

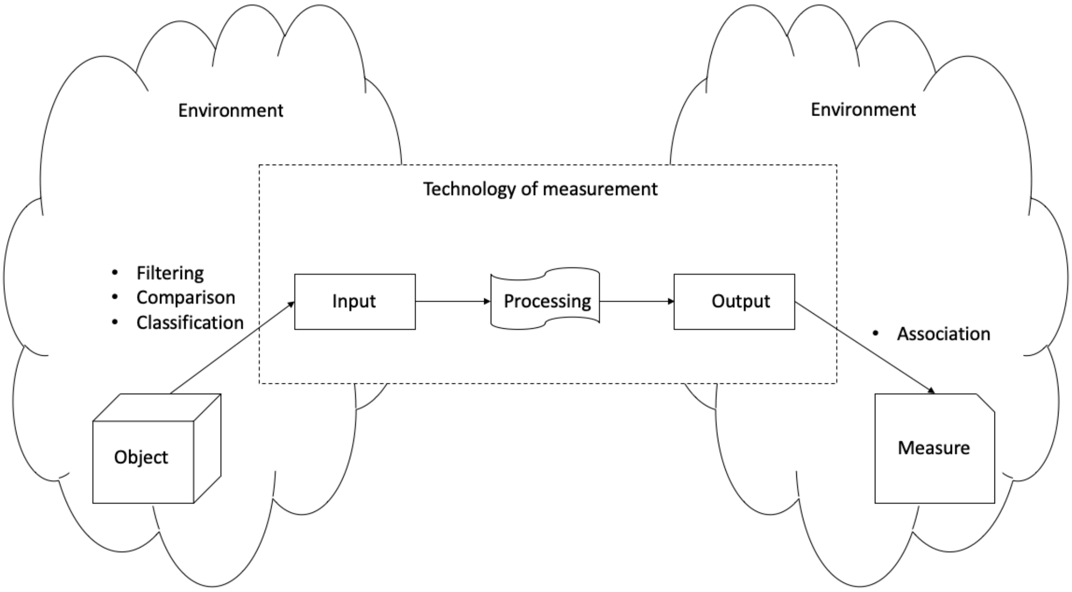

Figure 1 Technology of measurement as an information system

4.2. Overview of the technologies of measurement

With the above considerations as a starting point, I refer to measuring devices, tools, instruments and systems as technologies of measurement to offer a single term, but also to link such technologies to the wider discourse presented in the following sections. In this section, I present a brief overview of the characteristics of such technologies of measurement derived from an analysis of their development and evolving nature. In short, technologies of measurement moved from using body parts, through using measures of body parts, to using objects as points of reference through the creation of standards and their embodiment in objects, to the development of statistics and computing. Generally speaking, this evolution corresponds to the different primary uses of such technologies, from simply the collection of measurement data, through its storage, to collection, storage and processing of such data. The survey of measurement literature allowed for the identification of several qualities desirable in technologies of measurement – namely objectivity, reliability, precision, coherence and acceptance. In what follows, I trace the trajectory of the development of some technologies of measurement to exemplify the above.

4.2.1. Body parts as technologies of measurement

“Man is the measure of things”, a statement by the ancient Greek philosopher Protagoras (Kula, 1986; Mari, 2003) has of course its metaphorical meaning of objectivity, but serves as a useful starting point in the discussion of the development of the technologies of measurement. As Kula explains, the first people used themselves and their bodies to measure the world (1986): feet, shoulders, fingers, hands, and so on. At this stage, they referred to their own body parts and used them as guidelines: "your finger" was noted down as a measurement unit in medical prescriptions (Kula, 1986). The anthropomorphic tools of measurement were used primarily to take, or collect, measurements by comparing the object under measurement with the most suitable body part (Scotti, 2016), or sometimes other bodily function, such as the distance that the human voice travels (Kula, 1986). With time, people seemed to have started to realise that most feet or fingers were different, and such differences led to significant complications in trade. Additionally, it was difficult to multiply or create systems (a step did not have to have a constant number of shoulders, as Kula explains). In an attempt to overcome these problems, many kingdoms and tribes often used body parts of their kings and rulers as measurement standards (Scotti, 2016). This move represents the need for the technology of measurement to be objective and reliable, that is, it ought to regularly produce the same measurement indications.

However, this solution was still seen as lacking universality, and therefore the need to create a standard, or abstract foot or shoulder, emerged (Kula, 1986). Local communities developed, through experience, varied processes of measuring and standardising body part units of measurement, giving rise to a wide number of differentiated measurement systems which, while serving local communities well, were separate and very localised (Kula, 1986). A fascinating example of such a standardising process is a picture and a description from a 1535 book which depicts a group of 16 men outside a church (Stigler, 1999, p. 361). The first sixteen men leaving the church in a random order were lined up so that the sizes of their feet could be added up to determine a standard length of a rod, measuring 16 feet. Apart from the local community showing at least intuitive awareness of a number of statistical concepts, this example emphasises the role of acceptance of a measurement (Stigler, 1999).

A standardised measure was required for communities to move away from relying on their own body parts to embody measurement units in objects. This change also reflects the changing nature of technologies of measurement, from merely collecting measurements to storing them.

4.2.2. Objects as technologies of measurement

With civilisations evolving, using body parts as the basis for measurement eventually proved insufficient (Scotti, 2016). For example, it was difficult to measure land or crops by making references to body parts (Kula, 1986). The need to count large numbers of livestock also tested the boundaries of body parts as tools for measurement. Instead, people started using objects to perform and record measurements. The clay balls used in Mesopotamia to count sheep or stones and clay tables used to record measurements with pictograms, lines or symbols were among some of the first uses of objects (Himbert, 2009).

For objects to be accepted, they had to convey authority, they had to be objective and reliable. This is why local authorities became involved in setting such standard objects (Scotti, 2016). Kula (1986) provides fascinating insights into the importance of measurement objects for early Medieval communities, with local rulers or religious leaders serving the role of guardians of proper measurement, and merchants often conducting the measurements of goods sold and bought in churches. Thus, objects embodying standard measurements of length or weight would often be stored in churches or other authoritative institutions, and fraudulent uses of measurements led to punishment, evidenced by holy texts of several religions (Himbert, 2009). The Romans, for example, certified measurement standards and stored them in Rome in the temple dedicated to Iuno Moneta, with certified copies of such standards distributed to temples in each town of the Roman Empire (Scotti, 2016). Such spread of standard objects of measurement facilitated trade and cohesion within communities.

However useful as objective and reliable measures, objects initially lacked precision, similarly to body parts. At the same time, science began to prove that it was possible to discover new phenomena through measurement using new instruments (Himbert, 2009; Scotti, 2016). Outside of interests of governments and rulers, the scientific world began its quest for precision in measuring instruments. The "scientific revolution" in the 16th and 17th centuries saw, for example, Galileo establishing, through measurement, that the velocity of a falling body is proportional to the duration of its fall (Himbert, 2009). Indeed, Galileo himself described his measurement process and instruments as follows: "a piece of wooden moulding or scantling, about 12 cubits long, half a cubit wide, and three finger-breadths thick was taken (…), having made this groove very straight, smooth and polished, and having lined it with parchment (…) we rolled along it a hard, smooth and very round bronze ball (…) noting the time required to make the descent" (Gallileo, 1963 quoted in Koyré, 1953). Koyré points out the lack of precision of such a measurement and provides a detailed description of scores of scientists working on improving this particular measurement instrument, as well as other developments leading to the invention of a pendulum clock as a quest for precision feeding back into scientific discoveries (1953). Such attempts, however, were for years confined to the world of science, with limited interest from governments and rulers (Scotti, 2016).

The French revolution, which brought about significant modifications in the organisation of public authorities, is often seen as the single biggest trigger of attempts at creating objective, acceptable, reliable, accurate and precise measures. Philosophers (e.g. Condorcet), politicians (Talleyrand) and people from all over the country called for the creation of a uniform system of measurement (Himbert, 2009). However, in the true spirit of the revolution, though with contributions from the scientific world, the proposed system was aiming more at universality ("for every human being and forever", as Talleyrand said in his speech at the Constitutional Assembly in 1790, (Scotti, 2016)) than unification. This gave rise to the establishment of the French metric system and the definition of the metre (Himbert, 2009). Between the years 1792 and 1799, two French academicians set out on a journey to triangulate the meridian between Dunkirk in France and the Spanish southern coast, and to this date their original data are available at the Observatory of Paris, with information given on the repeatability, reproducibility and computations performed (Himbert, 2009). The metre, then stored as a metal rod, became the basis of the Metre Convention and the establishment of the International Bureau of Weights and Measures, as well as the current universal system of units (Scotti, 2016). Since then, measures have improved in terms of their precision and objectivity, no longer being mapped to the human body, as well as other characteristics.

4.2.3. The development of statistics and computing

The period between 1800 to 1850 saw a large increase in the amounts of data and information gathered, mostly to control and administrate states in a centralised way, and to improve and rationalise production, or improve health and education (Himbert, 2009). This shift is often associated with the increased general belief in the power of measurement (Kula, 1986) and is not separate from the "avalanche of numbers" associated by Hacking (1990) with the rise of statistics. This was the age when statistics, i.e. the collection of facts about states (Starr, 1980, p. 10) (Starr 1980: 10), developed with a need to rely on incomplete data about samples rather than whole populations. More emphasis was put on the coherence of statistics as a technology of measurement, that is, the links between statistical measures and the world that they attempted to capture and their stability over time (Morgan, 2001; Himbert, 2009). Statistics needed specific tools to collect data, and thus various survey, experimental and observational techniques were developed to enable samples to be collected. Notably, censuses were regularly collected by states in attempts to capture entire populations, rather than customary samples.

While a detailed treatment of the development of statistics is outside the scope of this work, it is worth noting that the growing amount of data resulting from statistical processes culminated in the processing of it exceeding human capacities. The invention of the first computer by Herman Hollerith was a direct response to the needs to compute and compile the results of the 1880 US census (Zittrain, 2008).

Since then, computers have been increasingly in use to collect, store, and process a wide range of measurement outcomes: "the explosion in the production and circulation of information and data, including its archiving and manipulation, and the role of search engines, data mining systems, sensing systems, logging software and tracking and tagging devices" is of interest to several researchers (Adkins and Lury, 2012, p. 5). The most recent investigations into the nature of measurement bring in the issues of digital measurement, or the intersection between the digital and non-digital worlds (Aumala, 1999; Tal, 2013). Aumala, for example, focuses on the use of virtual measuring instruments comprising sensors, data acquisition units and computers, and points towards the fact that "flexible data processing gives the possibility of constructing virtual instruments (…) which can be tailor-made for the particular application" (1999, p. 45). Aumala also indicates that "today it is exceptional to process information by analogue means" (1999, p. 48), and that most measurements are converted to digital formats. He also draws attention to the increased use of measurement systems instead of separate measurement equipment, and to the rise of distributed measurement. However, such approaches are rare.

4.2.4. Evaluative infrastructures of the internet

The internet is a prime example of digital forms of measurement. The more tangible part of valuative devices, such as rankings, ratings, reviews, and tagging, is analysed by Kornberger (2017) within the wider context of evaluative infrastructures – that is, methodologies (presupposing assumptions about what is valuable and the calculative practices of evaluation, Miller, 2001) and technologies (depending on material evaluation devices measuring, quantifying, comparing and calculating values, Karpik, 2010) of valuation distributed across innovation networks. Kornberger investigates the development of such evaluative infrastructures in parallel to distributed information systems and brings in examples to support the argument that such infrastructures not only make values visible but also constitute new values (e.g. the number of Twitter followers as a form of social value). Kornberger highlights how evaluation devices "represent regimes of valuation that categorize and hierarchize products emerging from distributed innovation systems" (2017, p. 184), and how "virtually anything (downloads, citations, references, etc.) can serve as raw material for valuations" (2017, p. 184).

The theme of evaluative infrastructures is further developed by Kornberger et al. by applying it to analyse platform-based organisations (Kornberger, Pflueger and Mouritsen, 2017). In the paper, the authors trace the role of accounting practices in the organisation of platforms and outline the mechanisms through which they work, highlighting the role of relationality, generativity and distributed control with centralised power. In such infrastructures, accounting and counting is no longer done by professional accountants but by the system itself, composed of programmers, users and algorithms (Kornberger, Pflueger and Mouritsen, 2017). The authors highlight that the development of many evaluative infrastructures is made possible because of big data, and call for the analysis of big data through the exploration of evaluative infrastructures that result from and enable them. They claim that "big data for instance is an important precondition to and outcome of the development of evaluative infrastructures" (Kornberger, Pflueger and Mouritsen, 2017). Thus, distributed systems imbued with evaluative infrastructures are the most recently emerging forms of technologies of measurement and of great interest to this study.

4.2.5. Conclusions

In this section, I aimed to cursorily outline the history of the development of the technologies of measurement to underline how the purposes of the use of such technologies changed over time, and to summarise the key characteristics of technologies of measurement. These characteristics namely included their objectivity, reliability, precision, coherence and acceptance. This section sets the scene for my subsequent proposed argument regarding the changing nature of technologies of measurement.

4.3. Towards new technologies of measurement

In their article on special measures sociologists Lisa Adkins and Celia Lury draw the field's attention to "an ongoing expansion of the social by way of techniques of mediation, measurement and valuation" (2012, p. 5) through data. As they say, data "moves, flows, leaks, overflows and circulates beyond the systems and events in which it originates" (2012, p. 6). They add that in such practices, "numbers are created as ephemeral products, designs for intervention; to be purchased, not as indices, but as symbols" (2012, p. 10). While I provide a more detailed argument for the treatment of data, and big data in particular, as a form of measurement in the following section, if we accept this as true for now, we see that Adkins and Lury's description of data as a technology of measurement brings in a very different perspective in comparison to how measurement was construed in the past.

As hinted in the nascent literature on digital measurement above, the move from analogue to digital measurement has significant consequences for the ontology and epistemology of measurement (Aumala, 1999; Tal, 2013). In order to shed light on this aspect and further expose the changing nature of the technologies of measurement, for example BDA systems, I propose to analyse what happens when such technologies become digital artefacts (Kallinikos, Aaltonen and Marton, 2013).

Digital artefacts are incomplete and in the making (Garud, Jain and Tuertscher, 2008; Zittrain, 2008). They have an "ambivalent ontology" (Kallinikos, Aaltonen and Marton, 2013, p. 357) as they lack stability and plenitude. Digital artefacts differ from physical entities in a number of ways: they are editable (it is possible to modify and update them continuously and systematically), interactive (offering the possibility to explore information through the responsive and loosely bundled nature of the digital artefact), open and reprogrammable (they can be accessed and modified by another digital artefact or users), and distributed, i.e. "seldom contained within a single source or institution" (Kallinikos, Aaltonen and Marton, 2013, p. 360).

Taking the idea of BDA systems as technologies of measurement, their interpretation and analysis as digital artefacts presents an interesting vantage point and opens up a series of questions on the changing nature of technologies of measurement. Conversely, placing the discussion of BDA systems against the backdrop of the scholarship on measurement enables us to sharpen the distinctions and focus the debate. For example, seen in the light of the characteristics of digital artefacts (editability, interactivity, openness and reprogrammability, and distributedness), it is interesting to consider how the characteristics of emerging technologies of measurement change. While analogue technologies of measurement were constructed to increase their objectivity, reliability, precision, coherence and acceptance through sometimes painstaking processes of scientific discovery, standardisation and universalisation, what are the desired qualities of digital measurement technologies? How does the openness and reprogrammability of BDA systems shape the characteristics of this technology of measurement? How does the ambivalent ontology of digital measurement artefacts impact the epistemology and ontology of measurement through data itself? I return to these questions in the analysis section.

4.4. Conclusions

In this section, I used the extant scholarship on measurement to tease out its treatment of the technologies of measurement in order to provide a background for the study and systematise the characteristics of measurement technologies as well as their changing uses throughout history. With this discussion, I proposed to reinterpret digital measurement technologies (with BDA as an example) as digital artefacts in order to suggest this framing as a fruitful lens in order to outline the changing nature of measurement through data. More specifically, this framing highlights a shift in the characteristics of the technologies of measurement resulting from the digital ontology of BDA.

5. Conclusions

Overall, the rich body of literature presented above serves as a background to the main problem identified. As evident from the IS literature synthesised, various scholars suggest that there are some unintended, or at the very least unenvisaged, organisational changes and transformations resulting from the implementation of BDA. However, such changes are not analysed, and their provenance is not looked at systemically. BDA systems are often seen as novel methods of measurement and generating data. Thus, section 3 offered an insight into the various processes involved in the measurement of the social that takes place within organisations. Section 4 offered an overview of the development of technologies of measurement to position BDA systems as new, digital technologies of measurement.

Chapter 3: Education, data and Learning Analytics

1. Introduction

In the previous chapter, I presented an overview of background literature depicting the various mechanisms of measurement present in Big Data Analytics (BDA). In this chapter, I investigate the evolution of Learning Analytics (LA) as a form of educational measurement to provide a background for the case study conducted and link it with the wider debates around BDA identified. I describe the functioning and format of LA systems, and then I present three strands of emergent LA literature on 1) tools and techniques, 2) LA and changing organisational practices, and 3) a critical outlook on LA. I finish this section by summarising questions emerging out of this literature and I contextualise LA as a continuation and sub-type of BDA.

2. History of educational measurement

Educational measurement has a long and interesting history, dating back as far back as to the first forms of educational instruction (Wilbrink, 1997). Researchers in educational evaluation have a keen interest in uncovering the developments in measurement, assessment and evaluation of educational progress over the years and across cultures. For the purposes of this thesis, only a brief overview of some of the most important developments at the crossroads of education and measurement are outlined (for a more detailed treatment, see e.g. Bullough, 1978; Deutsch, 1979; Gascoigne, 1984; Berkey, 1992 and others).

The purpose of this overview is to track the developments in educational measurement in order to situate them in a rich and changing social context. As is the case for all measurement, educational measurement is not an objective, imposed system, but rather a product of the changing society (Kula, 1986). Following the presentation of the development of educational measurement in the Middle Ages, through the Renaissance, to the modern day, I provide an equally brief summary of the emergence of the most recent developments to serve as a background to the problem of big data infrastructures in education. I then provide a thorough description of such infrastructures currently in place and give examples of some of their applications and consequences.

2.1. Measuring education in the Middle Ages

Education in the Middle Ages was largely related to teaching students to remember sacred texts, as knowledge was understood back then as knowing something by heart (Riché, 1989). The clear religious motivation, coupled with the scarcity of manuscripts, forced students to learn Latin grammar in order to be able to read Latin texts (Wilbrink, 1997). As such, learning constituted repeated reading of grammar books, some of them dating back to the Roman Empire, often written in the form of questions and answers (Wilbrink, 1997).

The measurement of educational progress and success took a very similar form. Students were asked to recite lines from the texts they had learned by heart, or answer questions from particular grammar books (Wilbrink, 1997). Universities measured students' progress in this way as well, demanding simple answers to simple questions about the memorised material (Lewry, 1982). Assessment was carried out orally. This form of measurement was still dominant in the 19th century (Foden, 1989), and even today assessment, to a certain extent, is still based on providing the right answers to the types of questions known beforehand (Wilbrink, 1997), albeit in the form of a standardised test rather than oral examination.

The Western Style Education, with important principles of the curriculum and school organisation, were developed by Joan Cele from Zwolle, then a Hanseatic town, between around 1375 and 1415 (Wilbrink, 1997). As a result of dividing the student cohort into classes and forms, Cele introduced biannual examinations for promotion to a higher form, and is credited with creating the European model of the graded school, including examinations for promotion and merit-based ranking (Wilbrink, 1997).

A poignant example of the role of assessment and measurement is the Medieval University of Paris, where the master praised the best performing students and criticised the worst performing ones on a daily basis, thus making assessment an intrinsic part of the student experience (Wilbrink, 1997). One of the main responsibilities of the master was to decide when students were ready to take a public and formal examination, which comprised a series of questions that tested knowledge of the required books, an impromptu lecture and participation in a public disputation (Wilbrink, 1997). As an important distinctive feature of medieval universities, they "were the only institutions (…) to link teaching and examinations closely together" (Verger, 1992). In order to pass the exam, students had to hear the lectures on a given topic several times, and university regulations stipulated the recommended number of lectures each student should attend, thus turning repetition into the most natural form of university education (Wilbrink, 1997).

Medieval universities awarded merit based on social status. The ranking for each examination was not based on academic merit, but rather on social merit by birth, and only later by the length of study (Schwinges, 1992). While academic merit was an important part of the daily practice at universities, it was not recognised in the ranking order when it came time for the examination (Wilbrink, 1997).

2.2. The Renaissance turn to ranking systems

One of the biggest challenges of education in the Middle Ages was to encourage students to focus on studying. Punishment was one of the first means introduced to this end, and was dominant throughout the Middle Ages, empowering schools and universities to punish students even for misbehaviour outside of the school setting (Wilbrink, 1997).

Humanists, helped by the innovations of Cele in the 14th century as well as an overall eagerness to learn in the Renaissance (Scaglione, 1986), proposed a system of motivation based on competition and reward. This took the form of awarding the best class students and dominated in western education into the late 19th century.

However, in order to reward students and allow them to compete, their results had to be somehow identified and made comparable (Wilbrink, 1997). This reward system gave rise to a "bookkeeping system of points or notae" (Wilbrink, 1997) and was the driving force behind the development of the 19th century marking systems. As we learn, in 1559 in Geneva, "classes were divided into decuriae not by age or social rank but by merit and achievement (…) and punishment for intellectual sluggishness could take the typical form of nota asini or nota sermonis soloecismi" (Scaglione, 1986). Notes were awarded for good behaviour or deducted for academic mistakes or bad behaviour (Wilbrink, 1997). A similar system persisted in Jesuit schools, where competition and ranking were at the heart of education, and students' "results [were] listed publicly in order of merit" (Scaglione, 1986).

The schools of the Brethren maintained an elaborate system for ranking students based on merit, where examinations were used to determine the ranking. Students could challenge their placement, which could lead to a contest between the challenger and the next highest ranking student (Wilbrink, 1997).

At the turn of the 18th century, written examinations replaced the oral ones, although they were still almost exclusively based on factual recall (McArthur, 1983). In England, notably at Cambridge, with the competitive nature of university education, candidates were ranked according to achievement on public lists of honours candidates (Wilbrink, 1997).

It is important to note that the Renaissance ranking systems did not award grades. They were purely based on ordering students in the rank of their relative achievements, from the weakest students to the best performing ones. It was common to keep notebooks for this purpose, where students would note down all their notae, as well as those of other students (see Rudolph, 1977 for an example from Harvard). The system was met with a fair amount of scepticism even at that time, pointing to the neglect of students further down in the rankings, as well as certain ethical issues arising in competition for prizes, such as fraud or lying (Wilbrink, 1997).

2.3. The 19th century marking systems

The exact moment and reasons for ranking systems being replaced by marking systems is yet to be discovered (Wilbrink, 1997). However, this shift is often associated with the increased general belief in the power of measurement (Kula, 1986) and is not separate from the "avalanche of numbers" associated by Hacking (1990) with the rise of statistics. It is believed that this first "datification of education" (Williamson, 2015, p. 3) may be a result of the industrial revolution as "people reached for quantification when chaos from a massive shift in the sociotechnical world ensued" (Ambrose, 2015).

While the ranking systems were still the dominant practice in the first half of the 19th century, the first case of marked examination papers in England dates back to 1836, at the Mathematical Tripos at Cambridge, while "earlier examiners and moderators tended to rely on impression" (Rothblatt, 1982, p. 14). Thus, the move to the marking systems may be linked to the demands for objective assessment of increasingly competitive examinations in Oxford and Cambridge (Rothblatt, 1974). This level of objectivity required that the curriculum be narrowed down, in order to facilitate a mark-based assessment and justify the assignment of specific marks based on the curricular content (Rothblatt, 1974). High marks were still artificially kept scarce to reflect the achievement of ranking as first or second in order of merit (Deutsch, 1979).

While marking systems differ between countries, they all embody the move from a subjective ranking system to a seemingly more objective way of measuring progress by assigning a mark on a scale.

2.4. Educational measurement and the state

The rise of modern states in Europe is credited with influencing the critical period in the development of educational measurement in the early 19th century (Wilbrink, 1997). While university enrolment in the preceding centuries was low in many countries and examinations were scarce or farcical (Engel, 1974), the developing modern states needed to control the numbers and quality of civil servants, as family, wealth and relations were no longer a decisive factor in obtaining lucrative governmental positions (Fischer and Lundgreen, 1975). The state thus had to try to "get a hold on the universities and their examinations" (Wilbrink, 1997). As in other areas where statistics became dominant, also in education they originated "as a means, not of gathering quantitative data, but of surveillance" (Starr, 1980, p. 10).

In England, the modern Senate House examination at Cambridge, later known as the Mathematical Tripos (Gascoigne, 1984), and similar university examinations have been identified as a role model for the civil service examinations. In this period, assessment "became a serious matter" (Wilbrink, 1997). It was no longer just a case of honour and placement in a ranking, but it could decide somebody's personal and professional future; educational measurement and assessment started playing a different role than previous didactic purposes, and it encouraged students to focus only on what they would likely be tested on (Wilbrink, 1997). Due to the weight of the outcome of assessment, the process had to seem more exact and objective. Therefore, examiners were no longer siding with the student, like medieval masters, but became distanced from their pupils and served the purposes of the state (Wilbrink, 1997).

This, in turn, led to the development of a host of objective educational tests, with the first example dating back to 1864 in England (Kelley, 1927). By the end of the 19th century, teachers were accused of teaching for the test "devoting weeks of preparation and drills to extant editions of upcoming exams" (McArthur, 1983, p. 3).

However, this was not the only way in which the state extended its control over education through measurement. With the rise of statistics, as it was first used in German and English to mean facts about states (Starr, 1980, p. 10), governments began collecting educational statistics, at first limited to tabulations of school attendance and costs (McArthur, 1983). With the development of statistical methods and progress in so-called "mental tests", a new approach to educational testing was developed (McArthur, 1983, p. 6), combining a variety of factors to assess and calculate potential educational attainment.

This critical period is characterised by a visible turn to a more managerial approach to education (Thompson and Cook, 2014; Selwyn, 2015) and the propagation of "governing by numbers" (Rose, 1991). Importantly, the state's involvement broadened the extent to which measurement was present in education. It was no longer just the student whose achievement was being measured, but the state became more interested in measuring teachers, schools and the overall efficiency of the educational system (Thompson and Cook, 2014).

2.5. The rise of standardised testing

Increasing statistical rigour in the first decade of the 20th century has proven that statistical methods and data sources for educational measurement needed "thoughtful improvement" (McArthur, 1983, p. 7). By 1910, a number of tests emerged, including English, spelling, handwriting and arithmetic, and "there followed a phenomenally creative period during which testmakers developed instruments for virtually every aspect of educational practice" (Cremin, 1961). As reported by the American National Council of Education in 1913, it has only been the "beginning to have measurement undertaken in terms of standards or units which are, or may become, commonly recognised. Such standards will undoubtedly be developed by means of applying scientifically derived scales of measurement to many systems of schools. From such measurements it will be possible to describe accurately the accomplishment of children and to derive a series of standards" (Strayer, 1913).

A decade later, multiple-choice and true-false tests were first introduced (as discussed in McCall, 1922; Monroe, 1923). While these tests and their results were coherent and valid from the statistical perspective, their reliability and validity was often questioned by educators and education researchers (McArthur, 1983). With the progress of educational testing, the majority of issues around the validity of findings remained unresolved, while standardised tests started gaining ground, becoming commonplace, along with a suite of other statistical tools to measure students, teachers and schools.

The main goal of standardised testing became the production of performance data for the purposes of accountability (e.g. Lingard, 2011). Linked with educational policy-making, standardised testing emerged as "the chief instrument of educational governance" (Tröhler, 2010, p. 6). The key change in this period was the move to assessments producing numerical data that hold institutions and individuals accountable (Thompson, 2017). As argued by Power (1997), this use of accountability represents a trust in the audit mechanism, rather than people working for organisations. The majority of educational systems use standardised test data, in an aggregate form, for a variety of reasons (Thompson, 2017).

2.6. Educational measurement and ICT

Without a doubt, Information and Communication Technology (ICT) has benefitted education greatly in a number of ways, from e-learning, through access to resources, to better insights

(Dawson, Heathcote and Poole, 2010). In the area of interest for this project, ICT enabled increased computerisation and capacity to shift from paper-based, or even computer-based but discrete forms of assessment to "online, continuous learning analytics of digital data" (Thompson, 2017, p. 3). The development of computerised adaptive testing (CAT) introduced "prediction methodologies to reduce the length of the test without sacrificing accuracy" (Hwang, 2003, p. 218). Intense efforts have been made, notably in Australia with the National Assessment Program – Literacy and Numeracy, to shift to online, adaptive standardised testing. There seems to be a wide-spread acceptance that "test data [is] a pure and accurate fact of the world" (Thompson, 2017, p. 4), and this belief dominates school policy and reform. It appears that there is a consensus that data obtained this way can aid evidence-based policy-making to lead to more effective interventions in policy, administration and teaching as well as learning (Thompson, 2017).

However, standardised tests were not the only source of data. Schools and universities alike, fuelled by the possibilities awarded by ICTs, continued gathering data on all aspects of their activities. In 1979 in the UK, the Survey Research Department at The Open University amassed data spanning ten years covering the progress of thousands of distance learning students over a variety of courses and at several stages in the academic year (McIntosh, 1979).

Later developments, such as Virtual Learning Environments (VLEs) and Massive Open Online Courses (MOOCs) contributed to the developing need for institutions to collect data (Andrews and Haythornthwaite, 2007; T. Anderson, 2008).

2.7. The emergence of database infrastructures

Standardised tests became an important source of data in the field of Educational Data Mining (EDM), which in turn traces its roots back to Knowledge Discovery in Databases and is primarily "concerned with the development of methods and techniques for making sense of data" (Fayyad, Piatetsky-Shapiro and Smyth, 1996, p. 37).

In turn, enterprise ICT systems utilised by universities proved to be important resources for transactional and operational data, giving rise to the practice of academic analytics (Dawson, Heathcote and Poole, 2010). Academic analytics (AA), arising in the early 2000s, focused mostly on data aggregation for the purposes of refining reporting, marketing and attracting additional sources of revenue (Dawson, Heathcote and Poole, 2010). It draws heavily from business intelligence.

The third strand, Learning Analytics (LA), is focused on measuring teaching and learning activities, as explored in more detail below, for the purposes of improving the associated processes.

Together, these three data sources are often seen as the emergent database infrastructures in education, understood as “an assemblage of material, semiotic and social flows, or practices: (1) that function to translate things into numbers (datafication), (2) that enable the storage, transmission, analysis and representation of data using algorithmic logics and computational technologies, (3) that embed data usage into other assemblages, (4) that produce relational topological spaces through practices of classification, measurement and comparison (…), and (5) that produce, in the combination of these processes, new social practices and new problematisations of the social” (Sellar, 2015b).

While EDM is primarily technically-focused and AA has strong roots in business intelligence, both of these fields have been extensively studied both from the educational as well as technical perspectives. However, LA being the newest development, it remains a new field with nascent research, as outlined in the following section.

3. Learning Analytics

LA has a number of definitions with different emphases, as summarised by van Barneveld et al. (2012): from the students’ perspective, it is sometimes defined as “the use of data and models to predict student progress and performance, and the ability to act on that information”, “the collection and analysis of usage data associated with student learning; [to] observe and understand learning behaviors in order to enable appropriate intervention”, or a set of tools enabling “teachers and scholars to tailor educational opportunities to each student’s level of need and ability”. For educational departments, LA is “the use of predictive modelling and other advanced analytic techniques to help target instructional, curricular, and support resources to support the achievement of specific learning goals”, and “it might be used as well to assess curricula, programs, and institutions”. Institutions themselves use LA to gather “input from multiple databases and, when conjoined with appropriate queries, can pull data and create a real-time slice of an organization’s training metrics.” Institutions can see LA as “a set of activities an organization does that helps it understand how to better train and develop employees” (van Barneveld, Arnold and Campbell, 2012, pp. 21–28). However, the most common and accepted definition of LA is “the measurement, collection, analysis, and reporting of data about learners and their contexts, for the purposes of understanding and optimizing learning and the environments in which it occurs” (Siemens, 2013, p. 1382). This definition has been extended to include academic analytics, focusing more on the institutional level (Long and Siemens, 2011).

The practice of LA evolved around two main ICT-related trends: ICT integration into teaching and learning, often through Virtual Learning Environments (VLEs), and related developments in online learning as well as increased availability of VLE tracking data (Macfadyen and Dawson, 2010). Some practitioners and researchers in the field likewise argue that the development of big data further accelerated LA (Clow, 2013; Daniel, 2015). It is believed that VLEs accumulate vast amounts of data which could be valuable for analysing students' behaviour and results (Romero, Ventura and García, 2008).

LA data is increasingly used for a range of applications, summarised in the table below.

Table 4 Uses of Learning Analytics identified in literature

Source	**Application of LA**	**Explanation**
Papamitsiou and Economides, 2014; Sin and Muthu, 2015	Performance prediction	Predicting student performance by analysing interaction in VLE
Picciano, 2012; Papamitsiou and Economides, 2014; Sin and Muthu, 2015	Attrition risk detection	Detecting the risk of dropping out by analysing students' VLE data
Sin and Muthu, 2015	Data visualisation	Using data visualisation techniques to easily identify trends and relations
Sin and Muthu, 2015	Intelligent feedback	Providing intelligent and immediate feedback to students to improve their interaction and performance
Sin and Muthu, 2015; Sclater, 2017	Course recommendation	Recommending new courses to students based on data about their activities
Picciano, 2012; Sin and Muthu, 2015	Student skill estimation	Estimating students' skills
Papamitsiou and Economides, 2014; Sin and Muthu, 2015	Behaviour detection and modelling	Detecting student behaviours to improve models
Papamitsiou and Economides, 2014; Sclater, 2017	Resource recommendation	Recommending educational resources to students, sometimes known as adaptive learning
Picciano, 2012; Sin and Muthu, 2015; Sclater, 2017	Institutional decision-making	Improving decisions
Picciano, 2012; Sclater, 2017	Curriculum design	Informing course design

In the following section, I outline how this data is gathered, processed and disseminated (my division into these steps corresponds to how the LA process is often described in the literature, e.g. Romero, Ventura and García, 2008, albeit simplified): data collection, data processing and data dissemination.

3.1. Data collection in LA

Modern VLEs have the capacity to record and store every action performed within the environment in a tracking log (Macfadyen and Dawson, 2010). Off-the-shelf VLEs, such as Moodle or BlackBoard, have a tracking function built in, and custom-made VLEs almost exclusively come equipped with similar functionalities (Romero, Ventura and García, 2008). Such logs track all VLE activities, such as reading, writing, taking tests, performing tasks or communicating with peers (Mostow *et al.*, 2005) in the form of time-stamped numbers of clicks, all stored in the university data warehouse. For example, a commonly used VLE, Moodle, keeps detailed logs of student and staff activities (Rice, 2006) in 145 interrelated tables (Romero, Ventura and García, 2008). Frequently logged data includes number of clicks, time spent on the site, average visit duration, last activity, number of videos viewed, time spent on videos, numbers of words posted on the forum, etc. (Ho, 2017).

This data is coupled with information about users' profiles (such as demographic information, Clow, 2012; Ho, 2017), academic results and interaction data (Romero, Ventura and García, 2008; interaction data is often seen as a basic unit of learning data in VLEs, Agudo-Peregrina *et al.*, 2014). Another type of data sometimes collected in LA is self-disclosed data, for example students' moods or attitudes (Buckingham Shum and Crick Deakin, 2012). Macfadyen and Dawson exemplify the detailed level of tracking: "while this study opted for 'chat room entered' as the key variable for chat room use, the PowerSight kit offers seven other chat-related variables that record user participation in the chat resource" (Macfadyen and Dawson, 2010, p. 591). Among practitioners, there is an attitude of trying to collect as much data as possible, to gather "any data [they] can get their hands on" (Jones, 2015). Further, there is little collaboration between education scholars and teaching staff and professionals responsible for designing and executing data collection for the purposes of LA (Clow, 2014). It is worth adding that such data is logged in real time, all the time, for all types of users in the VLE.

The main driving force behind this approach is the belief among LA proponents that VLE tracking data is a way of measuring educational progress and is closely related to how students learn and perform (Siemens, 2013; Yu and Jo, 2014; Daniel, 2015).

3.2. Data processing in LA

The data collected is then subjected to a range of processing types. Preprocessing involves cleaning and transforming data into an appropriate format, for example using a database administrator tool (Romero, Ventura and García, 2008). Preprocessing tasks are usually carried out by administrators or professional services staff (Romero, Ventura and García,

2008) and may include data cleaning, user identification, session identification, path completion, transaction identification, data transformation and enrichment, data integration and data reduction. This first step involves a range of manipulations around the data collected, and there seems to be a lack of understanding in the literature as to how these tasks are carried out and by whom.

Such preprocessed data then undergoes further processing, not unlike approaches seen in big data analysis. There is a host of tools, such as DBMiner, MultiStar, EPRules, KAON, Synergo/ColAT, GISMO, TADA-Ed, O3R, MINEL, CIECoF, Simulog and more (Romero, Ventura and García, 2008). The primary areas of analysis of this data include prediction, clustering, relationship mining, or discovery with models (Baker and Yacef, 2009), coupled with the creation of user profiles, modelling of knowledge domains, trend analysis, personalisation and adaptation (Bienkowski, Feng and Means, 2912), and more (see e.g. Romero and Ventura, 2013; Siemens, 2013). Other statistical tools include classification, association rule mining, sequential pattern mining or outlier analysis (Romero, Ventura and García, 2008).

Such data processing is either conducted with the use of external software or performed by professionals with a specific set of skills focusing on statistics and data analysis. This stage is often conducted with no engagement from educational academics or practitioners.

3.3. Data dissemination in LA

The direct outputs of LA are often deemed inaccessible to wider audiences (Clow, 2014), who may lack data science training or understanding of statistical approaches. Such outputs are often delivered to interested stakeholders through dashboards (Verbert *et al.*, 2013), with emphasis on data visualisation. Data visualisation may include spreadsheet charts, scatter plots or 3D representations, and may be produced with the use of specific visualisation tools, such as CourseVis, WebCT or GISMO (Romero, Ventura and García, 2008). Such objects are often generated by professionals with data analysis backgrounds and by their very nature involve reduction and simplification (Romero, Ventura and García, 2008). It is also common to produce reports based on LA outputs for further dissemination within departments.

Such data can later be used, for example, to improve course design (Daniel, 2015) or design interventions aimed at reducing drop-out rates (Macfadyen and Dawson, 2010), or for a range of other potential applications as depicted in Table 4. As proponents of LA argue, the possibilities and potential of such data is already big and will develop over the next few years, as LA spreads across institutions (Daniel, 2015).

3.4. Example of LA

One of the examples of LA often discussed in the literature is the Open University with its OU Analyse, an LA system employed school-wide, albeit solely for monitoring student learning. The Open University provides online education in the form of several hundred courses delivered to more than 200,000 students, who primarily access study materials through a VLE. OU Analyse is an LA tool that combines student demographic data (including age, previous education, and gender) and student VLE daily activity data, representing individual actions such as participation in forums, resources accessed, etc. (Herrmannova *et al.*, 2015).

Each week these two sources of data are used to build predictive models: Bayesian classifier, classification and regression tree, and k Nearest Neighbours (Kuzilek *et al.*, 2015). Following this statistical treatment of data, “a list of students at risk of not submitting the next assessment is sent every week to the course chairs and the student support team, who are responsible for contacting and supporting the students” (Kuzilek *et al.*, 2015). Predictions based on this data are available through the OU Analyse dashboard. For example, OU Analyse data can be used to assess the likelihood of failure for specific classes of demographic attributes (such as new student, male, no formal qualification or continuing student, female, HE qualification) coupled with the number of clicks in the VLE. OU Analyse data is also used to suggest recommended activities to students (see Figure 2 below).

Figure 2 OU Analyse - student overview page. Source: Kuzilek et al. 2015

In 2014, some courses at the Open University asked to receive predictions of students' expected scores, not just an indication of a potential pass or failure. Since then, this information has been used to motivate students to improve their final results, in particular in second and third year courses (Kuzilek *et al.*, 2015).

OU Analyse data can also be used to improve the effectiveness of instructional material available in the VLE, and teachers are encouraged to adapt their materials based on LA outputs (Clow, 2014). In order to facilitate the use of this data, the Open University created a data wranglers unit, which employs data scientists who turn OU Analyse outputs into reports and communicate their findings to wider staff (Clow, 2014).

The Open University being just one example, the setting is symptomatic of the wider practice of LA. Such databases and systems are used for fine-grained measurement of student activity and attainment as well as the effectiveness of teachers and institutions.

4. Learning Analytics literature

Research in LA is developing rapidly. As of 2019, there were several regional LA conferences (Annual Learning & Student Analytics Conference, Learning Analytics Network), one international conference (LAK), a journal (Journal of Learning Analytics), two societies, and a number of funding schemes to support research in this area. Having analysed a large body of the literature in this field, I identified three main strands: Learning Analytics Methods, Organisational Impacts of Learning Analytics, and Critical Learning Analytics. I present these strands below and outline the main open questions.

4.1. Learning Analytics methods

The strongest body of research focuses on LA in practice and the development of successful tools, techniques and methods for the purposes of LA. Such papers most often report on the outcomes of applying particular analytics techniques (as mentioned above) to datasets (Papamitsiou and Economides, 2014; Daniel, 2015) and focus on developing better models (e.g. Gašević *et al.*, 2016). A good example of this is a paper by Macfadyen and Dawson, which concludes that the "findings indicate that a regression model of student success, developed using tracking variables relevant to the instructors' intentions and to online course website design (tools implemented to allow content delivery, and/or student engagement, and/or assessment & grading, and/or administration) combined with measures of time on task (variables indicating number of log-ins and time spent online) explains more than 30% of the variation in student final grade" (Macfadyen and Dawson, 2010, p. 596).

The literature in this strand assumes an unproblematic relationship between data and what they encode, often stating for example that "interactions [are] represented as data log records" (Agudo-Peregrina *et al.*, 2014, p. 544) or stating that "learning analytics approaches typically rely on data emanating from a user's interactions with information and communication technologies" (Gašević *et al.*, 2016, p. 68). It is not uncommon to read assumptions such as "because data mining is not a separate act to normal user behaviour, the information retrieved is also highly authentic in terms of reflecting real and uninterrupted user behaviour" (Greller and Drachsler, 2012).

Despite these attempts, researchers in this strand conclude that "there is no consensus yet on which interactions are relevant for effective learning" (Agudo-Peregrina *et al.*, 2014; Tempelaar, Rienties and Giesbers, 2015), and that "despite the growing number of studies on learning analytics, there is no agreement on which interaction data may be meaningful – or even if interactions have any pedagogical or educational value" (Agudo-Peregrina *et al.*, 2014,

p. 544). Other researchers agree that "it remains an ongoing challenge to formulate indicators from the available datasets that bear relevance for the evaluation of the learning process" (Greller and Drachsler, 2012). Researchers conclude that "predictive power of our LMS remains low: the multiple correlations of all six performance indicators converge to a value of about 0.2, indicating that no more than about 4% in performance variation can be explained by (…) track data" (Macfadyen and Dawson, 2010; Agudo-Peregrina *et al.*, 2014; Tempelaar, Rienties and Giesbers, 2015). Some researchers believe that "simple clicking behaviour in a LMS [VLE] is at best a poor proxy for actual user behaviour of students" (Tempelaar, Rienties and Giesbers, 2015). This led some to conclude that "although there is a vast potential in this field, there remains much work to be done to build the theoretical and empirical base that provides clear evaluative procedures for matching observed student interaction behaviours with course- and program-level learning goals and outcomes" (Lockyer, Heathcote and Dawson, 2013, p. 1441).

4.2. Organisational Impacts of Learning Analytics

The third main strand of literature related to LA focuses on the organisational impacts concerning the introduction of such systems. Most notably, researchers within this strand highlight that LA applies not only to tracking student activities online, but it also monitors what various members of staff do, and that the consequences of such systems go beyond just student-facing activities. In fact, a number of stakeholders can be impacted by the introduction of LA: faculty, researchers, department heads of programme directors, deans, executives, learning systems staff, learning content and support staff, and administration staff (Elouazizi, 2014). However, thus far research has not provided much detail of how they could be impacted.

Researchers note that the use of LA presupposes a move to online teaching as "it is almost a requirement that transaction processing be electronic rather than manual and (…) it is important that instructional transactions are collected as they occur" (Picciano, 2012, p. 13). This creates a push towards online learning and greater reliance on VLEs (Picciano, 2012; Sellar, 2015b). A broader infrastructure for data collection has to be developed and maintained (Sellar, 2015b), and thus teacher practices may need to change to fit into this infrastructure, which points towards significant changes that LA brings into what teachers or lecturers do. Some point towards the fact that feedback output from LA "can be used directly to trigger actions and interventions without involving a teacher at all" (Clow, 2013).

A certain preference towards numerical, measurement data in institutions has been noticed. It has been pointed out that "substantial resources are going toward learning analytics (…); it is entirely unclear, though, whether the resources spent on data analytics will lead to as much educational benefit as other possibilities" (Rubel and Jones, 2016, p. 154).

Other researchers focus on the need to develop and introduce new roles in the educational setting to support the applications of LA. Clow discusses how a whole Data Wranglers unit was created at a university in the UK to support and popularise the use of LA data (2014). Some point to the development of dashboard applications, which teachers and students have to learn how to use (Verbert *et al.*, 2013). As shown in the preceding section, data collected for the purposes of LA undergoes a host of transformations which involve decisions that can have impacts on the output dataset. Such decisions are taken by professionals with backgrounds in statistics or computer science before they reach teaching staff or researchers. Even such professionals agree that there is no agreed, established way of processing data, and there is a visible lack of learning models that can be used to improve data processing (Clow, 2014). At this stage, LA data is essentially black-boxed and subjected to transformations hidden from view to those who could contribute to its improvement. As pointed out, it is rare to find educational researchers or teaching staff who are also proficient in computer-scientific or statistical approaches (Clow, 2014).

While still nascent, this strand of research points towards broader changes within organisations and the entire sector (Elouazizi, 2014) that the introduction of LA may entail.

4.3. Critical Learning Analytics

Critical literature concerning LA, coming mostly from the field of pedagogy, higher education studies and sociology, focuses on several core issues surrounding the uses of LA.

First, such researchers show the shortcomings of approaches widely adopted in the LA methods strand, pointing out that "many recent LA technologies are detached from pedagogical experiences and practices" (Drachsler, Stoyanov and Specht, 2014). Authors emphasise the need to go beyond "a series of clicks and page visits" (Drachsler, Stoyanov and Specht, 2014) because "the actual learning remains an inherently autodidactic and invisible process" (Beaudoin, 2002, p. 152), explaining that students not only differ in their learning strategies, but may also be adapting them as they learn (Nijhuis, Segers and Gijselaers, 2008). In a paper by Friend Wise et al., it has been reported that even students "pointed out that there is much they [LA data] don't capture" (Friend Wise, Zhao and Hausknecht, 2013, p. 52). Researchers draw attention to the measurement imprecision of such systems (Piety, Hickey and Bishop, 2014) and emphasise the need for human involvement, "which increases the possibility of error and manipulation" (Piety, Hickey and Bishop, 2014). Conversely, some researchers call for more human input into LA and more reflection in decision-making (Friend Wise, 2014). Some researchers even conclude that numbers are not enough (Beaudoin, 2002) and that LA data only "concern a small range of fairly well understood pedagogical practices that engender student engagement" (Gibbs, 2010, p. 5), therefore providing no new insights.

Second, some researchers are preoccupied with the issues of privacy and ethics surrounding data use. For example, Picciano points out that "since learning analytics requires massive amounts of data collected on students and integrated with other databases, colleges need to be careful about privacy, data profiling, and the rights of students in terms of recording their individual behaviors" (Picciano, 2012, p. 18). There is a related concern that such data may end up in the hands of private companies or governments (Picciano, 2012) and that it can be de-anonymised (Swenson, 2014); the issue of data ownership in the context of LA is also problematised (Pardo and Siemens, 2014). Researchers are concerned about the consequences of classification in such systems (Buckingham Shum and Crick Deakin, 2012; Shum Buckingham and Ferguson, 2012; Swenson, 2014; Rubel and Jones, 2016) and how students may end up being profiled. They point out that "data processes that might seem mundane and procedural are often significant and highly powerful social practices (e.g. processes of observing, measuring, describing, categorising, classifying, sorting, ordering and ranking)" (Selwyn, 2015). LA systems have a bearing on who makes decisions about learning: they legitimise some knowledge and data but not others, they give voice to some students and not others, and they validate some student stories but not all (Swenson, 2014). Institutions are also facing ethical dilemmas regarding whether to always act on the data they have (Clow, 2013; Slade and Prinsloo, 2013), as sometimes interventions resulting from faulty learning diagnoses may result in resentment and demotivation (Slade and Prinsloo, 2013).

Third, much of the critical literature on LA points to the fact that reliance on such systems "is not only transforming the ways in which schooling gets done, but also affects the production of knowledge about schools and systems" (Sellar, 2015b, p. 765), pointing out, for example, that since interactivity is what generates data, this may lead to changes in how teaching material is presented to foster more interactivity (Swenson, 2014). LA technology is seen as "an interactive agent in the production of data, because some of the data arises from a complex interaction product between the learner and the digital learning environment as well as from co-production of data by the learner, environment and social context" (Gibson and de Freitas, 2016, p. 6). Researchers call for the perception of digital data as "playing a key part in defining as well as merely describing 'the social'" (Selwyn, 2015). It has also been pointed out that LA relies on commensuration, which often involves decontextualisation and oversimplification of educational contexts (Sellar, 2015a), and the "abstraction of education" (Thompson, 2017, p. 2).

Some researchers highlight that LA results in "a reconfiguration of the sense of 'education'" (Thompson and Cook, 2017, p. 2) by using data to "render social processes and social relations more knowable and, it follows, more controllable" (Selwyn, 2015). Not without issue is the matter of the speed that LA introduces to the educational context: "it appears that for many engaged in education, the size [of data] is less compelling than the promise of the speed at which results can be processed" (Thompson and Cook, 2017, p. 4). While promising, this also means that there is an imperative of activity and engagement imposed on the users of such systems, and that this entails that no tasks can ever be fully completed (Haythornthwaite, de Laat and Dawson, 2013; Thompson, 2017; Thompson and Cook, 2017). This is symptomatic of control societies, and some researchers see LA systems as "a technology through which an entirely new education policy-making logic can be deployed" (Thompson and Cook, 2014, p. 704). This is also seen as something that could affect students: "analytics could disempower learners, making them increasingly reliant on institutions providing them with continuous feedback, rather than developing meta-cognitive and learning-to-learn skills and dispositions" (Shum Buckingham and Ferguson, 2012, p. 19).

Relatedly, some researchers flagged up the possibility that students and staff may alter their online behaviours if they are aware of institutional surveillance (Gibson and Jakl, 2013; Slade and Prinsloo, 2013). As Rubel and Jones state, "as individuals become more aware of the existence of the mass of data about them and the purported and actual ends to which it has been put, they may consciously change their behaviors based on who or what is recording data about them" (Rubel and Jones, 2016, p. 147). Researchers bring up this "general risk in learning analytics", stating that it may lead to "optimising to a metric that does not reflect what is more fundamentally desired as an outcome" (Clow, 2012, p. 135). Using LA data may lead "to the gaming of the system: 'learning and teaching to the analytics' to maintain performance indicators that do not genuinely promote meaningful learning" (Shum Buckingham and Ferguson, 2012, p. 19). In some cases, "proxies of learning and constructs associated with learning can cease to be good measures. As a comparable analogy to teaching to the test rather than teaching to improve understanding, learning analytics that do not promote effective learning and teaching are susceptible to the use of trivial measures such as increased number of log-ins into an LMS, as a way to evaluate learning progression" (Gaševic, Dawson and Siemens, 2015, p. 65).

Thus, LA researchers in this strand call for more educational research into the consequences of the uses of LA data, the organisational cultures that have formed around the use of data, and how data work can be more efficiently and fairly arranged in the educational context (Selwyn, 2015).

4.4. Conclusions

Taken together, the three strands of LA literature summarised above, namely Learning Analytics methods, Critical Learning Analytics and Organisational Impacts of Learning Analytics point towards significant questions. First, it is unclear what methods, tools and techniques can be used in successful LA, as there are still debates around meaningful variables to be included in the models. Second, there are significant issues around the privacy, ethics, and wider consequences of the use of LA, including students and teachers potentially altering their behaviours in response to the introduction of such systems. Third, it has been signalled that LA may impact organisational practices and the organisation of work. All these three areas have been discussed mostly theoretically, with few empirical studies. It is also interesting to note that LA literature can be closely aligned to the three main strands I identified in IS literature on BDA.

Indeed, LA is often seen as the application of BDA to the context of education (Fritz, 2011; van Barneveld, Arnold and Campbell, 2012; Clow, 2013). According to one definition of LA in the literature, LA means that "big data concepts and analytics can be applied to a variety of higher education administrative and instructional applications" (Picciano, 2012, p. 13). Selwyn admits that "while less discussed than the high-profile areas of 'Big Data Science' and 'Business Intelligence', it is also worth acknowledging the ways in which education has been subjected to a similar digitally driven 'datafication'" (Selwyn, 2015). It thus seems justified to treat LA, as I do, as a sub-field, a specialised application of BDA discussed in preceding sections.

5. Conclusions

In this chapter, I presented background literature on the use of data within the context of education, tracing its history from the Middle Ages to the most recent uses of LA. This chapter is essential to provide the context for the case study undertaken in this research project. Taken together, Chapters 2 and 3 summarise various strands of literature that help delineate the problem studied.

Chapter 4: Research Questions

As evident from the literature presented above, there are several strands of literature contributing to the overall understanding of the interplay of Big Data Analytics (BDA), measurement, technology, and education. The literature surveyed represents bodies of comprehensive research undertaken in the respective fields and on particular topics. Each of these strands leaves unanswered yet similar questions.

Information Systems (IS) literature on BDA offers an important contribution by identifying the processes of big data production which BDA relies on. From within the field, several voices raise the issue that BDA impacts that which it is supposed to describe or measure. The three strands of IS literature identified, however, do not open this problem up and do not offer explanations, but there is a strong indication in research to investigate how working with analytics leads to organisation-wide changes. Thus, the emerging questions can be outlined as:

- How does big data analytics change the organisations that implement it?
- What are the mechanisms by which such shaping occurs?
- What are the effects of such shaping?
- What are the intended and unintended organisational consequences of this shaping?

Section 3 in Chapter 2 covered a body of diverse literature on measurement of the social with the aim of systematising various processes of measurement, from representation to computation. To relate to various voices claiming that BDA is a continuation of more established processes of measurement, this chapter outlined the arguments to support these statements. However, there are several areas which call for a further inquiry, namely what are the characteristics of BDA systems as technologies of measurement? What measurement practices does BDA rely on? And what differentiates BDA from previous technologies of measurement?

The literature on measurement and technology in Section 4 of Chapter 2 builds up the understanding of various theories of measurement and the evolution of technologies of measurement over centuries. It concludes with the move away from analogue towards digital measurement and the emergence of digital technologies of measurement, among them BDA, which are not yet well researched. Thus, this leads to several questions emerging, namely what the ontology of digital technologies of measurement, including BDA, is and how these digital technologies of measurement change the nature of the measurement process itself.

Finally, the last strand of literature reviewed in Chapter 3 focused on analysing measurement in the context of education, and placed Learning Analytics (LA), a sub-field of BDA, against this backdrop. The LA literature surveyed provided a useful and fruitful background for understanding these systems, and allowed for the formulation of specific questions which remain unanswered:

- How does Learning Analytics shape teaching and learning practices?
- How does the work carried out at educational institutions change as a result of implementing Learning Analytics?
- What are the organisational changes that emerge after the implementation of Learning Analytics?

Taken together, these questions helped me to formulate the overarching research question guiding my research project: *how does the application of big data analytics interact with or shape the phenomenon it purports to describe and predict, and what are the organisational consequences of such interaction and shaping?* The literature reviewed and the research gap identified are summarised in Figure 3 below.

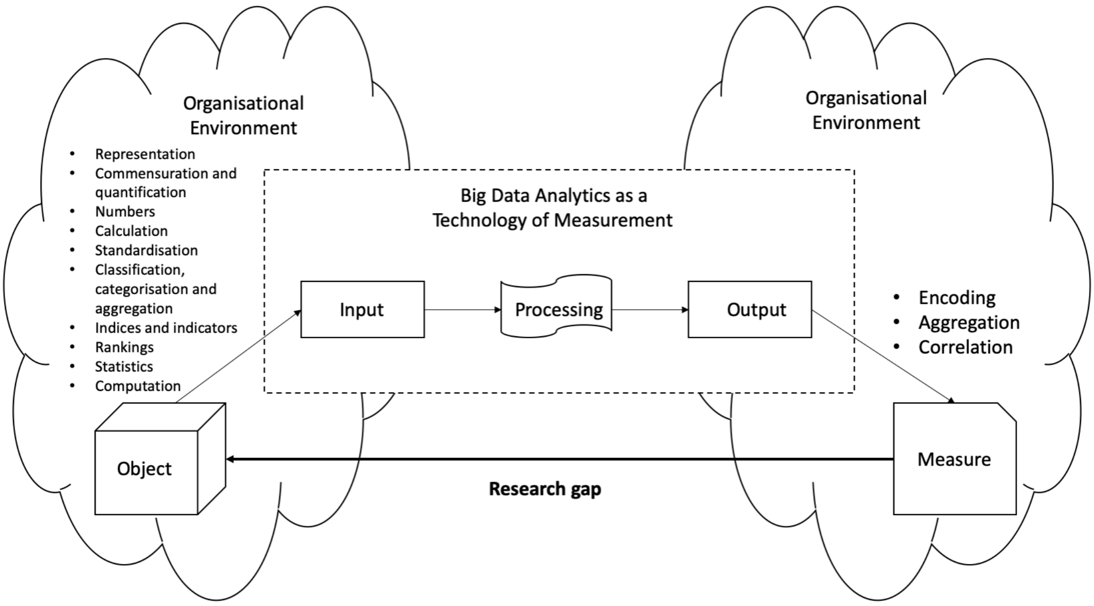

Figure 3 Proposed theorisation of the field with research gap

In the next section, I present the theoretical framework I propose to deploy in order to yield data needed to answer the emerging questions and thus the overarching research question.

Chapter 5: Theoretical framework

1. Introduction

In this chapter, I will focus on outlining the theoretical underpinnings that serve as an ontological scaffolding for my research project. Drawing from critical realism, supported by a further explanation of the Transformational Model of Social Activity (TMSA) and morphogenesis and morphostasis, I construct the theoretical framework to support my study. I frame the problem of organisational transformations resulting from the work carried out with Big Data Analytics (BDA) as an issue of the interplay between structure and human agency, and how their interactions lead to transformations and reproductions of structure.

2. Critical realism

In its ontological foundation, this research project accepts that there is an existing, causal reality independent of the observer, following Bhaskar's conceptualisation of critical realism (Bhaskar, 1978, 1979). At the same time, a critical realist ontology "allows for one reinterpretation of the activity (…) as implicitly predicated upon natural and social realism as well as the concepts of structures and generative mechanisms" (Smith, 2006, p. 191), thus providing a greater, more robust explanatory power than other, conflicting ontological stances. Initially developed by Bhaskar as a philosophy of the social sciences, critical realism first preoccupied itself with finding out "what properties do societies and people possess that make them possible objects of knowledge for us" (Archer and Bhaskar, 1998, p. 13). This question evolved into an approach that focuses on "what the world must be like to generate a particular phenomenon" (Smith, 2006, p. 199).

Within critical realism, this world is stratified between the real, the actual and the empirical (Archer and Bhaskar, 1998). At the level of the real, mechanisms come to play to generate events. At the level of the actual, these events may – or may not – occur, while at the level of the empirical, a subset of these events may be observed or experienced (Mingers, Mutch and Willcocks, 2013). Within this stratification, the real is where mechanisms, events and experiences reside, and "the picture of the real is thus one of a complex interaction between dynamic, open, stratified systems, both material and non-material, where particular structures give rise to certain causal powers, tendencies, or ways of acting" (Mingers, Mutch and Willcocks, 2013, p. 796), often referred to as "generative mechanisms" by Bhaskar (1979, p. 170).

Critical realist researchers “take some unexplained phenomenon and propose hypothetical mechanisms that, if they existed, would generate or cause that which is to be explained” (Mingers, Mutch and Willcocks, 2013, p. 797). Within critical realism, “a mechanism is basically the way of acting or working of a structured thing” (Lawson, 1997, p. 21) which may not be visible or empirically observable, but its potentialities may still exist, no matter whether they are exercised or unexercised (Archer and Bhaskar, 1998). In other words, physical objects or social processes “possess causal or emergent powers which, when triggered or released, act as generative mechanisms to determine the actual phenomena of the world” (Lawson, 1997, p. 21). Therefore, the main aim for the researcher is to “use perceptions of empirical events to identify the mechanisms that give rise to those events” (Volkoff, Strong and Elmes, 2007, p. 835). Through observation and engagement with events at the level of the empirical, I hope to theorise the mechanisms operating at the level of the real, through what Bhaskar calls retroduction, which I expand on further in the following section.

Critical realism was taken up by IS researchers as a fruitful approach to study the nature of social reality in conjunction with the role of technology (Faulkner and Runde, 2013). There are a number of IS studies that deploy this stance to study social phenomena affected by technology (Mutch, 2002; Mingers, 2004; Smith, 2006; Dobson, Myles and Jackson, 2007; Volkoff, Strong and Elmes, 2007; de Vaujany, 2008; Bygstad, 2010), while fewer analyse “how the non-human world, and the world of technological objects in particular, may be implicated” (Faulkner and Runde, 2013, p. 803) in the relationship between social structure and human agency. As claimed by Smith, “an example of this type of theorizing of the artefact has been done by Kallinikos (2002, 2004, 2005)” (Smith, 2006, p. 205). In his work, Kallinikos uncovers the “distinctive forms” (Kallinikos, 2005, p. 189) “through which technology constrains and enables human behavior at the moment of human-technology interaction and beyond” (Smith, 2006, p. 205). Therefore, to understand the interaction between people and technology, the researcher has to “move beyond the human-technology interface to uncover the core properties of technology and how malleable they are” (Smith, 2006, p. 205).

3. Transformational Model of Social Activity

One of the approaches within critical realism is the TMSA, which depicts how society is organised, reproduced and transformed (Faulkner and Runde, 2013). TMSA represents three aspects of the social: human agency, social structure, and the relationship between them. People, according to Bhaskar, largely act intentionally, while the “genesis of human actions

[is] lying in the reasons, intentions and plans of human beings" (Bhaskar, 1989, p. 79). Nevertheless, unconscious drivers of human behaviours also exist (Bhaskar, 1989, p. 97). Such unconscious drivers, or dispositions and capacities, "involve the propensity to respond appropriately to pre-existing rule structures" (Faulkner and Runde, 2013, p. 804).

Agency encompasses human capacities (abilities), dispositions (propensities or inclinations), and activities (manifestations of capacities and dispositions in operation). The *duality of praxis* (Bhaskar, 1989) means that human activities are generally consciously directed at some goal, but their impact on social structures is generally unconscious and unintended (Runde *et al.*, 2009).

People and, as discussed below, technologies occupy social *positions* in organisations. Positions are associated with specific routines, purposes and duties which are underpinned by various rules that define the positions (Runde *et al.*, 2009). A social position is a status that, when assigned to an entity, confers a social identity to that entity within a community and, as a result, gives people "the propensity to respond appropriately to pre-existing rule structures" (Faulkner and Runde, 2013, p. 804).

Within TMSA, social *structure* underpins and shapes the activities of people, but cannot be reduced to them and exists prior to the activities it conditions. It is "reproduced and transformed through human activity rather than created by it" (Faulkner and Runde, 2013, p. 804). As Bhaskar explains that "social forms are a necessary condition for any intentional act, that their pre-existence establishes their autonomy as possible objects of investigation, and that their causal power establishes their reality" (Archer and Bhaskar, 1998, p. 358). Bhaskar contends that pre-existing social forms entail a transformational model of social activity, and that the causal power of social forms is mediated through human agency (Bhaskar, 1979). Bhaskar is "inclined to give structures (…) a stronger ontological grounding and to place more emphasis on the pre-existence of social forms" than Giddens[2] (Archer and Bhaskar, 1998, p. 359).

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[2] In explaining the relationship between individuals and society, Giddens posits that "structure and agency are a mutually constitutive duality" (Jones and Karsten, 2008, p. 129), and thus social phenomena are products of both of these elements, as humans draw from structure in their actions and at the same time through these actions produce and reproduce social structure. Yet also Giddens argues that structure exists only in the instant of action, which sometimes attracts criticism for focusing too much on "what people do" (Giddens and Pierson, 1998, p. 81).

TMSA thus posits that human agency and social structure are bound by a recursively shaping relationship, and that "the reproduction and transformation of social structure is a generally unintended consequence of human action" (Faulkner and Runde, 2013, p. 804). In other words, TMSA suggests that the social actions of individuals are shaped by social systems through socialisation, but the very same actions reproduce and transform these social systems.

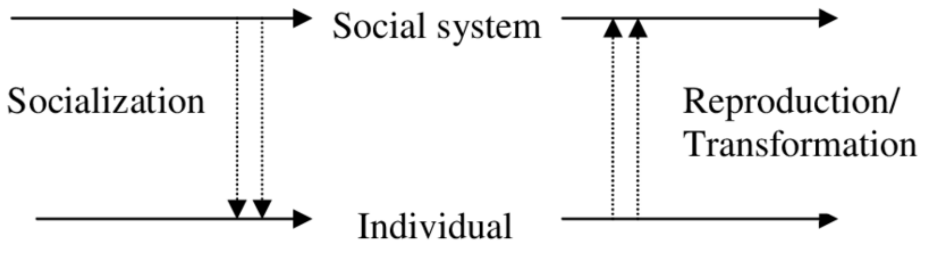

Figure 4 Bhaskar's original TMSA model. Source: Archer and Bhaskar, 1998

Bhaskar's original TMSA model, depicted in Figure 4, evolved to incorporate features and revisions, notably from Archer's morphogenetic approach (Archer and Bhaskar, 1998), discussed below.

In this elaborated version, TMSA presupposes temporality: "TMSA has a 'before' (pre-existing social forms), a 'during' (the process of transformation itself) and an 'after' (the transformed)" (Archer and Bhaskar, 1998, p. 361). This approach argues that because of human agency over time, structures are discontinuous, and "once they are changed, then subsequent activities are conditioned and shaped quite differently" (Archer and Bhaskar, 1998, p. 373).

Important and relevant to this study is a development of the TMSA by Faulkner and Runde, who include technological objects within the model. Technological objects are structured (composed of distinct, organised parts) continuants (present at every point in time of their existence) with at least one use assigned to them collectively by members of a community (2013). The authors claim that, just as human actors, technological actors can also occupy positions, with two significant differences. The authors say that "although they occupy social positions, technological objects do not have practices in the way that human actors do" (Faulkner and Runde, 2013, p. 809) thus their reproductive or transformative capacity does not come from their affordances and capacities but from "their being implicated in the structured human activities in ways that are relatively stable over time" (Faulkner and Runde, 2013, p. 809). The second difference is the fact that technological objects do not attract rights and responsibilities through their social positions, but it is "incumbent on the human actors that are using or otherwise implicated in the use of the objects concerned to behave in accordance with" these rights and responsibilities emanating from social positions (Faulkner and Runde, 2013, p. 809). Thus, within TMSA and critical realism in general, technological objects occupy "social positions broadly analogous to the positions occupied by human actors, by virtue of which they have an agentive function assigned to them and, flowing from this, acquire a distinct technical identity" (Faulkner and Runde, 2013, p. 810). In turn, these positions become embedded in human action and lead to reproduction or transformation largely in accordance with TMSA, with two important reservations above.

In IS, TMSA was keenly taken up as offering a balanced approach to "the interaction between human agency and social structure in the emergence, reproduction and transformation of social phenomena" (Runde *et al.*, 2009, p. 2) without focusing more on either aspect. TMSA has since been successfully deployed to develop "a general framework within which to think about technological objects" (Runde *et al.*, 2009, p. 1) and subsequently enriched to "introduce into this model a theory of the technical identity of technological objects and how such objects come to be part of the social world" (Runde et al. 2009: 1-2). After "importing technology into TMSA" (Faulkner and Runde, 2013, p. 808), this model offers a compelling scaffolding to connect human agency, technology and structure, and is further elaborated upon by Faulkner and Runde to account for "non-material technological objects" (Faulkner and Runde, 2013, p. 811). For this reason of the careful treatment of the identity of digital, or non-material, objects, as well as the equal positioning of agency and structure, I adopt TMSA as the theoretical backbone of this study.

With this in mind, TMSA is deployed in this research project as a way of understanding the positioning and role of technologies of measurement, and BDA in particular, drawn into the activities of human actors transforming and reproducing social structures that pre-exist them. Thus, in the language of TMSA, employees working with BDA become human actors with agentive capacities to transform or reproduce the structure, the organisation that houses social structures enabling and constraining this agency, and BDA is the technological object.

4. Morphogenesis and morphostasis

Before proceeding to the next section, I would like to shed more light on the morphogenetic and morphostatic approach developed by Archer (1995), which fed into TMSA and added its temporal aspects. As Archer explains, "the 'morpho' element is an acknowledgment that society has no pre-set form or preferred state; the 'genetic' part is a recognition that it takes its shape from, and is formed by, agents, originating from the intended and unintended consequences of their activities" (Archer, 1995, p. 5). Morphogenesis, corresponding to transformation in TMSA, is thus "those processes which tend to elaborate or change a system's given form, structure or state" (Archer, 1995, p. 1). Its opposite is morphostasis, or reproduction in TMSA: "those processes which tend to stabilize and recreate a system's given form, structure or state" (Archer, 1995, p. 1).

Archer's approach posits that the processes of reproduction and transformation of human agents and social structures take place over time and have a complex temporality. She sees these changes as a set of cycles with differing time frames, from structural conditioning of the individual who is historically situated (structure), through social elaboration of this individual (action), to structural elaboration (reproduction or transformation), each taking place with a different temporality. Importantly, "phenomena at different levels change at different paces" (Mutch, 2010, p. 509).

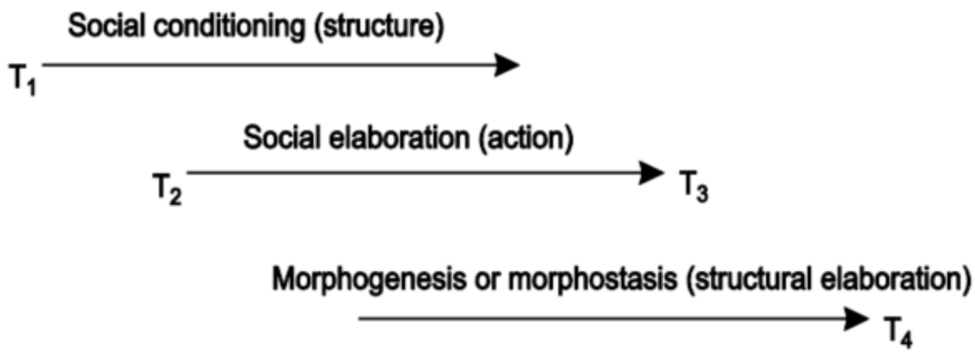

Figure 5 The morphogenetic cycle. Source: Archer and Bhaskar, 1998

At T1, structural factors shape the social context that agents exist in: "these results of past actions are deposited in the form of current situations. They account for what there is (structurally and culturally) to be distributed and also for the shape of such distributions" (Archer, 1995, p. 201). Between T2 and T3, actions are shaped by prior structures, and at T4 morphogenesis or morphostasis may take place as an elaboration of structures, as depicted in Figure 6.

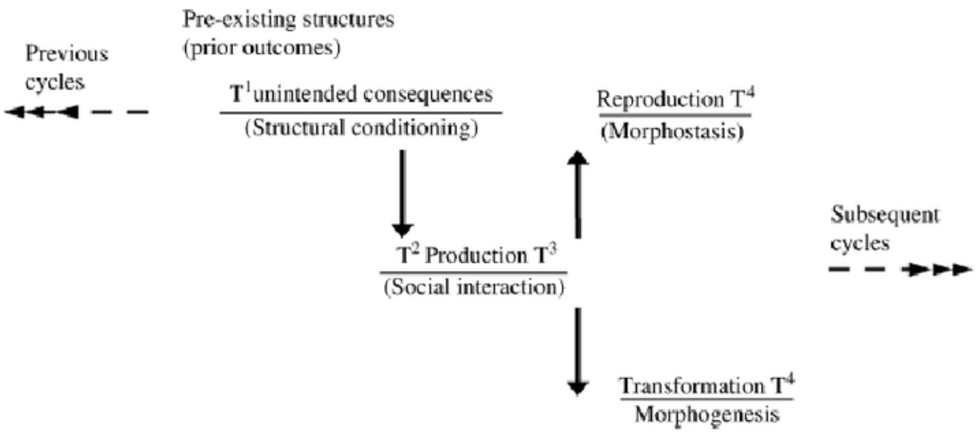

Figure 6 Transformational Model of Change. Source: Archer and Bhaskar, 1998

Archer proposed a clear analytical separation of agency and structure, and argued that structure and action operate over two different time periods, with assumptions that “structure logically predates the action(s) which transform it” and “that structural elaboration logically postdates those actions” (Archer, 1982, p. 468). Archer argues that action “takes place in a context not of its own making” and that agency “exerts two independent influences, one temporal, the other directional. It can speed-up, delay or prevent the elimination of prior structural influences” (Archer, 1982, p. 470). Temporality is essential in the morphogenetic approach, and therefore Archer argues that the structuring process “can only be grasped by making distinctions between the ‘before’, ‘during’ and ‘after’” (Archer and Bhaskar, 1998, p. 359). Thus, Archer puts significant emphasis on temporality. Echoing her, Mutch claims that “time is of central importance”, and therefore, methodologically, it is important to study “the unfolding of events over time as the key to the isolation of causal mechanisms” (2010, p. 509).

In IS, the morphogenetic approach was taken up as a way of avoiding the conflation of structures into agency evident in Giddens’s structuration and later approaches (Mutch, 2010). Starting with the morphogenetic approach, Mutch developed an argument around technology rendering structures more durable in “both time and space” (2010, p. 510), and claimed that “a morphogenetic approach supports the focus on the importance of the attention to the interplay over time between the material features of technology and aspects of organizations” (2010, p. 517). Archer’s work on morphogenesis and morphostasis fed into Bhaskar’s formulation of the Transformational Model of Social Activity (Archer and Bhaskar, 1998).

Temporality of structural transformation and reproduction, as proposed by Archer, complements the description of TMSA above. It is from its elaborated version, including the aspects of time, that I intend to draw in this study.

5. Conclusions

In this chapter, I presented the theoretical foundations of the research project, which is rooted in critical realism ontologically and epistemologically. Drawing from the Transformational Model of Social Activity, I explained how I intend to analyse the organisational changes resulting from BDA implementation by positioning organisations as structures enabling and constraining human agency at the work level. The interaction of structure and agency leads to reproduction or transformation of both in time. Big data analytics, as a technological object, is interwoven with human agency, and both the system and humans occupy social positions. The technological object, through its technological identity, shapes human agency, and in turn human agency changes the social position and thus the identity of the object. What is unique in this scenario is that the technological object contains data-based descriptions of the activities that the users of the system engage in. Shaped in this way, together with the technological object, human agency has the capacity to reproduce or transform the structure. A summary of key concepts with their applications to the case is presented below.

Table 5 Key TMSA concepts and their application in this research

TMSA concept	Definition	Application on research site
Agency	Human capacities, dispositions and activities	How staff work with the BDA system
Social position	A status based on routines, purposes and duties underpinned by rules allowing people to respond to structures	The BDA system and its users and their roles, routines, purposes, duties and rules stemming from the organisation
Social structure	Pre-existing, autonomous form underpinning and shaping the activities of people	The organisation as a whole with its structuring capacity
Technological object	Structured continuants assigned a use by a community and thus possessing identity	The BDA system analysed
Reproduction	Human agency generally unconsciously and unintendedly stabilising the present social structure	Unintended, reactive consequences of actions of staff reinforcing the organisation’s structuring capacity in its current form
Transformation	Human agency generally unconsciously and unintendedly elaborating on or changing the present social structure	Unintended, reactive consequences of actions of staff leading to the transformation of the organisation’s structuring capacity in its current form

Chapter 6: Analytical framework

1. Introduction

In order to attempt to provide a response to the main research question guiding this project, I propose to deploy an analytical framework allowing me to analyse data about how Big Data Analytics (BDA) systems describe, or encode, social activity and how they then interact with or shape the very social activities they claim to merely describe. This framework, as described in detail below, enables me to explain how technological objects become interwoven with human agency in a mutually-shaping relationship, and consequently how the object and agency together contribute to the reproduction and transformation of the organisational structure. To do this, I propose to employ the concepts of encoding, aggregation and correlation as mechanisms by which this purported description takes place, and to deploy the theory of reactivity, which yields insights into how BDA systems may be reproducing or transforming organisations. These two approaches, together, will form the analytical framework that will guide data analysis. Below I present the details of how this analytical framework is applied.

2. Translating social activity into big data

In order to understand how social activities, including teaching and learning, become translated into big data, I propose to utilise the three processes identified in IS literature as processes of big data production. They were described in detail in section 2.2 of the preceding chapter, and to avoid repetition, I will summarise the three processes here.

Encoding is the process of formalising users and their activity as objects along pre-established actions (Alaimo and Kallinikos, 2016). For example, on social media platforms users and their social activities become disaggregated into countable clicks, likes, views, which allows us to identify, count and compare with ease. In other words, encoding entails the objectification of people and their social activity and corresponds to the mapping of reality through data.

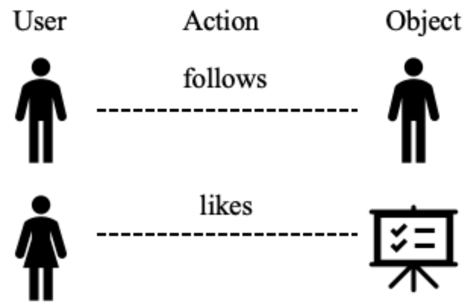

Figure 7 The codification of social action (Alaimo and Kallinikos, 2016)

Aggregation relies on adding together individual encoded data points and looking for patterns revealing new information. It is an attempt to generalise data about people and their social activity (Alaimo and Kallinikos, 2016). Aggregation relies on prior encoding in the sense that without encoding users and their activities as predefined data points, it would be far more difficult, if not impossible, to aggregate the diverse world of people and behaviours.

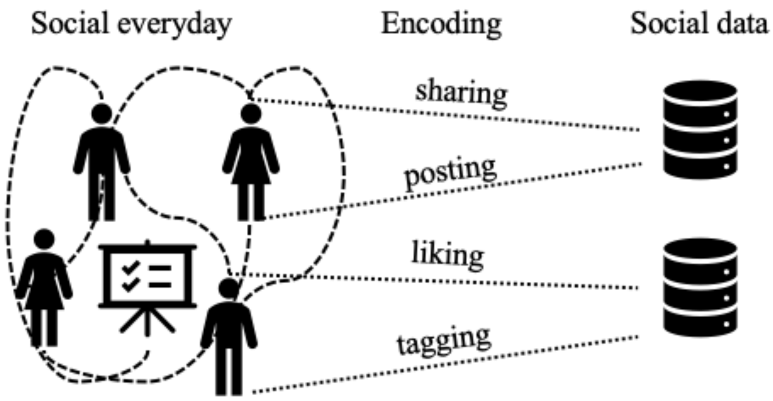

Figure 8 Social life made computable (Alaimo and Kallinikos, 2016)

Finally, correlation is the process by which aggregated users and their actions can be compared, contrasted and otherwise processed to look for patterns. This relies on further datawork (Alaimo and Kallinikos, 2016).

Taken together, these processes are "depicting the contours of a new, computationally empowered, representation of the social" which in turn enables further computational processes (Alaimo and Kallinikos, 2016, p. 20). In other words, this is how data is produced based on the activities and actions it captures. Within the context of the present study, this data is produced based on the activities of students and employees who are also the users of the system themselves. The data captured about their teaching and administrative practices is fed into a BDA system that then processes and displays this data to the employees themselves, their colleagues, and managers. I use encoding, aggregation and correlation to lay bare how these activities are computationally rendered in the BDA system.

3. Big data analytics and organisational transformation

With the processes summarised above, it is fair to say that big data produced about social activities already carries some assumptions, is limited or shaped by platforms which enable such processes, and in short is just a version of complex human agency. However, as pointed out in the literature review and emerging research questions, this very same big data is then fed back into the activities it was only meant to describe, and in turn this changing human agency has an effect on the reproduction or transformation of the organisational structure. In order to fully understand how this happens, the theory of reactivity offers a potent analytical scaffolding.

The theory of reactivity was first developed and proposed by Espeland and Sauder (Espeland and Sauder, 2007) as they observed unforeseen changes in US law schools after the introduction of law school rankings published by US News. The authors posit that public measures recreate social worlds "because people are reflexive beings who continually monitor and interpret the world and adjust their actions accordingly" (Espeland and Sauder, 2007, p. 2), and measures are reactive because "they change how people make sense of situations" (Espeland and Sauder, 2007, p. 10). As proposed by Espeland and Sauder, all measurement and measures lead to reactivity, that is, individuals altering their behaviour in reaction to being evaluated, observed or measured. Actors adjust behaviours under measurement, which both affects their activity but also limits the usefulness of the measurement process itself: "measures elicit responses from people who intervene in the objects they measure" (2007, p. 2), or in other words "measures cease to be good once they become targets" (Strathern, 1995, p. 4). It is believed that the reactive reaction to public measures changed "the fundamental activities of schools, transforming, for instance, how actors make decisions, do their jobs, and think about their schools" (Sauder and Espeland, 2009, p. 64), with such changes described by scores of authors (see Elsbach and Kramer, 1996; Johnson, 2006; Espeland and Sauder, 2007; Morriss and Henderson, 2008).

In the case of US law schools, rankings led to significant changes in legal education, with rippling effects on distribution of resources, decision-making and defining status (Johnson, 2006; Stake, 2006; Espeland and Sauder, 2007). In some cases, the introduction of public measures such as rankings can even threaten core identities and functions within organisations (Elsbach and Kramer, 1996). For example, Stake (2006) outlines several ways in which rankings change what law schools do and how they work, from tweaking the admission processes and encouraging applicants with no realistic chances of acceptance to boost selectivity rates, to hiring their own graduates to score higher on employability. Such effects at the organisational and structural level, argues the author, mislead the public and the institution, but also have the further-reaching effect of homogenising education (Stake, 2006). Further, higher education institution leaders have witnessed how rankings, or rather the reactivity thereto, have influenced missions, strategies, personnel, recruitment, and public relations of organisations (Hazelkorn, 2007, 2008). Rankings have become a policy instrument and proxy for competitiveness (Hazelkorn, 2014), and several authors point out that their impact continues to grow (Hazelkorn, 2007; Rauhvargers, 2014), to the point that rankings play a disciplinary role in which “national systems and individual institutions are both disciplined by the system of assessment and learn to discipline themselves by implementing its norms” (Pusser and Marginson, 2013, p. 558). Measures become “the master determining the worth of the university” (Lynch, 2015, p. 194), and they are inscription devices that constitute what they appear to represent (Rose, 1991). Rankings and other measures are being used for broader purposes than originally intended and are bestowed with more meaning than the data alone might bear.

Over the years, and in parallel to the development and spread of rankings in higher education, more and more research has been carried out in this field. There are several criticisms launched at rankings, among them the normative assumptions embedded in them (Marginson and van der Wende, 2007), lack of statistical significance (Saisana and Hombres, 2008), and minimising inter-institutional differences (Marginson and van der Wende, 2007). Further, rankings are used to measure wealth and prestige rather than actual quality (Espeland and Sauder, 2009; Pusser and Marginson, 2013), and thus legitimise inequitable distribution of public resources, including funding, subsidies, and infrastructure development (Pusser and Marginson, 2013). As such, rankings “stop being neutral measures of school quality and start transforming the characteristics of the schools they evaluate” (Espeland and Sauder, 2009, p. 18).

The theory of reactivity offers a link between individual actions – human agency – and transformations at the organisational level – structure – resulting from them, therefore aligning itself with the TMSA approach proposed above. It explains how, through a range of mechanisms described below, rankings impact individual practices which in turn change organisations.

3.1. Mechanisms of reactivity

Rankings studied by Espeland and Sauder become the devices (in the sense proposed by Ruppert 2012) that give rise to reactivity. While the authors do not question the reductive representation afforded by rankings, they are primarily preoccupied by the way rankings become reactive, that is, the way they feed back into the schools they are supposed to only rank. Placed outside of organisations they rank, carrying out "surveillance from a distance" (Sauder and Espeland, 2009, p. 71), rankings impact organisations by means of four main mechanisms: commensuration, self-fulfilling prophecies, reverse engineering, and narratives.

Commensuration, the transformation of different qualities into a common metric (Espeland and Stevens, 1998), aims to translate complex processes into single figures (Miller, 2001), often relying on the simplification of information and making heavy use of normalisation (Sauder and Espeland, 2009). Commensuration works by changing the locus of attention by creating new relationships and obscuring others (Espeland and Stevens, 1998), and it can "render some aspects of life invisible or irrelevant" (Espeland and Stevens, 1998, p. 314). For a more detailed treatment of commensuration, see Chapter 2, section 3.2.2.

The second mechanism is self-fulfilling prophecies. These are "reactions to social measures [which] confirm the expectations or predictions that are embedded in measures" (Espeland and Sauder, 2007, p. 11). Espeland and Sauder explain that "a self-fulfilling prophecy occurs when an expectation, once defined as real, amplifies or confirms the prophecy's effect". They argue that self-fulfilling prophecies give rise to reactivity because the expectations embedded in measures "encourage behavior that conforms" to the measure (Espeland and Sauder, 2016, p. 31). In other words, in the case of US law school rankings uncovered by Espeland and Sauder, law schools were seen performing to the measure, so a tier-three school would act increasingly more like a tier-three school (Sauder and Lancaster, 2006; Stake, 2006; Espeland and Sauder, 2007).

Third, reverse engineering is defined as "the process of working backward through the construction of a completed object or artefact to gain knowledge about how it works" (Espeland and Sauder, 2016, p. 33). In the case of US law school rankings, this means reverse engineering the rankings formula. This mechanism means that "administrators learn to think about the rankings not only in terms of their overall rank, but the individual factors that constitute the composite score" (2016, p. 33). As a result, they stop thinking about the institution as a whole, but rather as a collection of interrelated, discrete, measurable units whose functioning can be changed and influenced according to the ranking formula. In the words of Espeland and Sauder, once law schools "figure this out, they can make decisions about the types of changes to adopt and how resources might be most effectively deployed to optimize their rank" (Espeland and Sauder, 2016, p. 34).

The final mechanism of reactivity is the narrative, that is, "a story, told from the point of view of one or more narrators, that features characters, a sequence of events, a scene, and a plot involving some conflict or problem" (Espeland and Sauder, 2016, p. 36). They usually start with a catalyst that stimulates events or changes, e.g. higher or lower than expected metrics. Narratives about rankings can be celebratory or defensive, often including causal explanations for increases or drops in rankings. They often offer context and interpretation, and are rich in detail about time, place, and additional information, therefore becoming more memorable. Repeated at various levels of seniority and across many functions, narratives become powerful vehicles of a school's identity and thus influence activities and behaviours in line with the predominant narrative.

3.2. Effects of reactivity

Apart from the mechanisms of reactivity, Espeland and Sauder also identified several effects of reactivity in law schools they studied and categorised them into four major groups: gaming the system, redistribution of resources, redefining of work and practices, and change of values (Espeland and Sauder, 2007).

Those who are being measured may resort to gaming the system, that is "manipulating rules and numbers in ways that are unconnected to the motivation behind them" (Espeland and Sauder, 2007, p. 29). Broadly speaking, "gaming is about managing appearances and involves efforts to improve ranking factors without improving the characteristics the factors are designed to measure" (Espeland and Sauder, 2007, p. 29). The ways US law schools started doing this was, for example, by negotiating with universities to pay their own utilities, such as electricity, rather than have them paid by the university as before, because then this amount could be put down as their spending and in turn influence the ranking (for more examples, see Stake 2006).

Redistribution of resources as an effect leads to withdrawing or limiting resources in one area of an institution and re-directing them to another one (Espeland and Sauder, 2016). At US law schools, this meant, for example, cutting funding for libraries and diverting it to advancement or marketing departments, which can have positive effects on rankings (Stake, 2006). At other higher education institutions this may lead to hiring "well-paid ranking experts to work out strategies to improve ranking positions" (Rauhvargers, 2014, p. 39). Other authors also mentioned developing better management tools or introducing new academic programmes (Hazelkorn, 2007).

Redefinition of work and practices describes how work is being changed as a result of reactivity (Espeland and Sauder, 2016), for example by focusing the curriculum on passing the bar or preventing academic staff from going on sabbatical in autumn, as this may impact staff-to-student ratios (Stake, 2006), or changing the way admissions are processed (Espeland and Sauder, 2016). Other authors pointed to reorganisation of structures and increased attention to how work carried out by individuals affects rankings (Hazelkorn, 2007).

Change of values pertains to the effect that measurement has in giving additional validity and weight to what is being measured, because "what cannot be measured cannot be verified" (Aaltonen and Tempini, 2014, p. 106). If measurement impacts what is being valued and what deserves attention (Espeland and Stevens, 1998), then one of the effects of reactivity is the change of what is seen as value in education (Stake, 2006), thus leading to changes in how investments are made (Espeland and Stevens, 1998, p. 319) and impacting organisational cognition (Sauder and Espeland, 2009, p. 72). Other authors have also pointed to increased value attributed to data fed into rankings at higher institutions (Hazelkorn, 2007).

A summary of the mechanisms and effects of reactivity is presented in Table 6 below.

Table 6 Reactive mechanisms and effects (Espeland and Sauder, 2007; Sauder and Espeland, 2009)

Mechanism	**Operation**	**Effects**
Commensuration	Transformation of different qualities into a common metric (Espeland and Stevens, 1998), translating complex processes into single figures (Miller, 2001), often relying on simplification and normalisation (Sauder and Espeland, 2009).	Changing locus of attention by altering relationships (Espeland and Stevens, 1998), creating visibility and invisibility (Espeland and Stevens, 1998).
Self-fulfilling prophecy	Reactions to measures which confirm the expectations embedded in measures (Espeland and Sauder, 2007) which in turn encourage behaviour that conforms to them (Espeland and Sauder, 2016).	Performing to a measure as seen in the case of US law schools (Sauder and Lancaster, 2006; Stake, 2006; Espeland and Sauder, 2007).
Reverse engineering	Working backward through the construction of a completed measure to understand how it works (Espeland and Sauder, 2016).	Actors stop thinking about the institution as a whole, but rather as a collection of discrete, measurable units whose functioning can be changed according to the formula.
Narrative	A story featuring characters, events, scenes and plots involving a conflict or problem (Espeland and Sauder, 2016); can be celebratory or defensive, often including causal explanations for changes.	Repeated at various levels of seniority and across many functions, narratives become powerful vehicles of identity and influence actions and behaviours in line with the predominant narrative.

3.3. Extending the theory of reactivity

So far, I have described the ways in which I intend to deploy the theory of reactivity in the context of BDA. By doing so, I intend to test the applicability of the existing theory in a new context. However, the study also offers an interesting opportunity to expand and reframe the model of reactivity.

Of course, while the theory of reactivity is a fruitful approach to begin mapping out of the recursive relationship between data and the world, it is important to investigate the differences between the original setting in which the theory of reactivity was developed and the context of BDA. Law school rankings which served as the primary context for Espeland and Sauder operated externally to the organisations they ranked and measured, and they reduced these institutions to single digits within rankings compiled by external, independent institutions. BDA operates internally within organisations on top of IT systems designed or appropriated for their use and represents social phenomena as data through the mechanisms of encoding, aggregation, and correlation. Thus, the reactivity of BDA has its sources within the organisation and offers more complex ways of commensurating value.

In the context of BDA, the devices that cause reactivity are essentially placed within the organisations, invoking powerful disciplinary mechanisms and pointing to the panoptic nature of such systems (see e.g. Woodcock, 2017). BDA systems placed within organisations mean that someone from within the organisation is watching, creating opportunities for internal struggles and power imbalances. This is rather different from rankings compiled by independent bodies, as it introduces power dynamics within the same organisation with potential struggles between different stakeholders, or even giving rise to conflicts over the LA system.

Second, in BDA, the device giving rise to reactive mechanisms and effects is an IT artefact which codifies or encodes specific behaviours by the rule of code (Lessig, 2006), rather than human assessment as in rankings. Contrary to the context of rankings, it is not humans who compile the comparison of universities according to a set of much-discussed criteria, but rather it is the code within BDA. Code has fundamentally different properties and characteristics than complex – but more social than technical – processes of ranking-making in the study of Espeland and Sauder (2007). Code used in BDA replaces the human work involved in ranking-making. Within the context of the study, this is an important qualifier, which I will explore in the discussion chapter.

Third, rather than producing ranking numbers, BDA encodes some behaviours as computable actions within the systems, making them easier and quicker to track. The characteristics of big data, notably its claimed real-time nature, mean that the data are actionable nearly immediately after they have been produced, unlike in the case of rankings where they are published at set intervals and with specific delays. BDA can thus produce reactive effects at a much quicker pace than rankings, and it is important to notice that if reactivity happens quicker, changes in human agency happen quicker, and as a result organisations become transformed at a faster rate.

Fourth, rankings in the original theory of reactivity are first and foremost produced for an external audience that uses them to scrutinise and compare organisations. In the context of the LA system studied, this is not the case. Indeed, many if not most BDA applications are hidden from outside view, or their outputs are selectively made available to concerned audiences.

A final note concerning the applicability and potential extensions to the theory is related to the intention with which rankings and BDA systems are deployed. Rankings were not intended to exert disciplinary powers or introduce changes into the organisations they were comparing (Espeland and Sauder, 2007): their intention was to simply order the organisations according to a set value system. Arguably, BDA systems are deployed in order to measure and influence behaviours through predictions, recommendations and personalisation, i.e. they are often deployed precisely to make students and staff change behaviours, albeit I draw a very visible distinction between conscious and intentional changes and the unintended consequences. This is further echoed in the TMSA, where the difference between intentional, conscious agency and unintentional, subconscious reproduction and transformation is emphasised. Therefore, some social activities will intentionally draw from the organisational structures that entrench measurement and behavioural change, but others will be unintended and result from the interaction with the technological object. This is an important consideration to keep in mind with respect to the results of the study.

These are some of the main qualifying differences which outline the principal contrasts between the original study that led to the formulation of the theory of reactivity and the present research. These differences are likely to lead to possible modifications, additions and expansions to the original theory in order to fully realise its explanatory potential in the context of BDA, both with respect to mechanisms and effects.

3.4. The theory of reactivity in management and information systems

The theory of reactivity offers a potent lens through which the mechanisms and effects of measurement on organisations can be studied. Concepts such as commensuration, self-fulfilling prophecies, reverse engineering and narratives help uncover the processes by which reactivity happens, while gaming the system, redistribution of resources, redefinition of work and practices, and change of values help group the resulting effects.

The theory of reactivity has been developed through Espeland and Sauder's seminal study of law school rankings (2007). Since then, reactivity has been deployed to study the rankings of other educational institutions (Bowman and Bastedo, 2009; Hazelkorn, 2011; Goglio, 2016), including business schools (Gioia and Corley, 2000; Willmott, 2011), corporate reputation rankings (Schultz, Mouritzen and Gabrielsen, 2001; Kelley and Simmons, 2014; Sekou Bermiss, Zajac and King, 2014), or valuation online (Jeacle and Carter, 2011; Orlikowski and Scott, 2014; Beuscart, Mellet and Trespeuch, 2016). Notably, Orlikowski and Scott deploy the concept of reactivity, and specifically commensuration, to study valuation on online travel platforms. Similar tropes are picked up by Jeacle and Carter, and van der Vlist, who deploys commensuration to study big data processes within Facebook (2016). An insightful recent discussion focuses on how organisations navigate between multiple rankings by balancing how they conform and transform (Pollock *et al.*, 2018). This study is a continuation of a previous investigation of how firms respond to being rated, which also deploys the concept of reactivity (Chatterji and Toffel, 2010) with the aim of extending the findings to for-profit institutions. Pollock et al. (2018) argue for a more nuanced treatment of reactivity as part of organisational response to multiple rankings, and propose reactive conformance and reflexive transformation as explanations of how organisations respond to rankings.

Thus, although a theory primarily rooted in sociology, reactivity proved to be a potent framework also in the field of management. In the papers cited above, the theory of reactivity elucidated a number of studies looking into unintended changes and transformations within organisations as well as how organisations become reactive to the ways they are measured and assessed, which is directly related to the main question guiding this research project. By applying this theory to the study of BDA, I hope to confirm whether the same mechanisms that are typical of rankings and other means of valuation also give rise to reactivity in BDA, i.e. whether they transform the world of people and their social activities.

4. Conclusions

In this chapter, I set out to present the theoretical framework I intend to employ in order to analyse my data in response to the main questions asked in this project. Therefore, it will also serve as my analytical framework. Thus, I intend to code and analyse my data along the following theoretically-derived model of analysis presented in Figure 10 below.

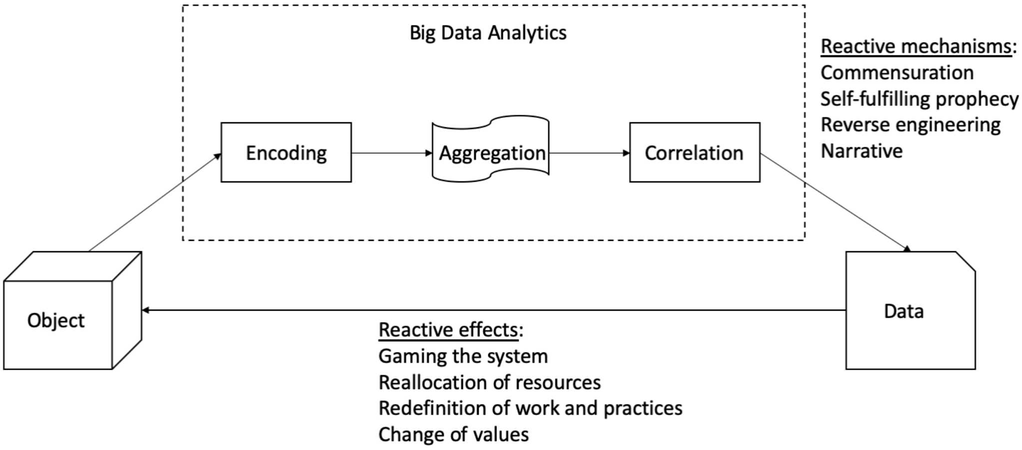

Figure 9 Model of analysis adopted in the study

In line with this framework, data about people and their social activities is produced by way of encoding, aggregation and correlation within the BDA system. In this study, this data is produced based on the activities of employees who are also the users of the system themselves. The data captured about their teaching and administrative practices is fed into a BDA system that then processes and displays this data to the employees themselves, their colleagues, and managers. As users access the BDA system, I hypothesise that they react to the data about the world contained therein by the mechanisms of commensuration, self-fulfilling prophecies, reverse engineering, and narratives. These effects may have tangible effects on the BDA system itself, the agency of the users, and the organisational structure through a range of reactive effects going beyond just the intended uses of the system. The following section contains a statement of methodology employed throughout the study, which outlines how this theoretical framework was used to bridge the case study with the questions asked.

Chapter 7: Methodology

1. Introduction

In this chapter, I will focus on outlining the methodological underpinnings shaping my study. Drawing from critical realism, I propose retroduction as an epistemological foundation for this study. I then describe the qualitative research design, data collection and data analysis strategy deployed in this project through an exploratory pilot study (results summarised in Appendix 1) and a single exploratory case study aimed at answering the main research question of this project: *how does big data analytics change organisations that implement it, and what are the consequences of such change?* I draw from an implementation of a Learning Analytics (LA) system at a higher education institution.

2. Retroduction

In the critical realist tradition, the observer's access to the world is limited and mediated by perceptual and theoretical lenses (Mingers, Mutch and Willcocks, 2013). Without a doubt, if required to adopt a theoretical lens to experience the world, a researcher is bound to select a lens that gives hope to answer the questions posed (Robson, 2011). As I would like to argue, both the ontological stance I take and the theoretical framework of reactivity are aligned in the sense that they both point towards the existence of mechanisms which generate events or effects. In consequence, my methodological decisions are built upon these foundations, and my theoretical perspective assumes a critical inquiry into the 'how' and 'why' (Yin, 1994).

Both for the purposes of the critical analysis and to yield relevant data to answer my research questions, I engage in a retroductive process methodology. Retroduction is what allows the researcher to move beyond the experience of empirical phenomena to hypothesising about the unobservable (Downward and Mearman, 2002). As these authors argue, following Bhaskar, this step is essential in critical realism studies to move from pure descriptions to the identification of potential causal mechanisms. It is inevitable that there may be several mechanisms that could potentially lead to the generation of the events, therefore it is essential to propose competing explanations which can be eliminated or supported further in the research process. With the aim of eliminating alternative explanations, the researcher is invited to adopt the DREI approach: describe the events, retroduce explanatory mechanisms, eliminate false hypotheses, and identify correct mechanisms (Mingers, Mutch and Willcocks, 2013).

The first phase of description focuses on understanding the phenomenon under study. The second phase, the actual retroactive analysis, involves hypothesising about the possible mechanisms that could have generated the phenomena observed. The third phase involves elimination of false hypotheses and identification of correct mechanisms (Zachariadis, Scott and Barrett, 2013). In my study, I used the following methods within the retroductive process.

Table 7 Retroductive methodology deployed in this research

	Retroductive step	**Method**
1.	Description	Pilot study, observation, interviews
2.	Retroductive analysis	Coding and analysis
3.	Elimination of false hypotheses	Interviews and further analysis
4.	Identification of correct mechanisms	Validation interview with senior management

First, in order to describe the phenomenon, I observed how the system is used and I derived an understanding of how it works and shapes the activities of users through the pilot study and interviewing. I then attempted to retroduce the potential mechanisms that cause these activities through coding and analysing my data, and through further interviews I put these mechanisms to the test. Finally, through presenting some of my findings to senior representatives within the organisation, I confirmed the identification of correct mechanisms and revised some incorrectly identified mechanisms.

3. Research design

Within this research project, I adopted a qualitative research design, since it seems to be most aligned with the research question asked. An investigation of "how" in this case calls for developing a thorough and in-depth understanding of the organisation and big data technology embedded in it. The very question asked, concerning how an organisation that implemented BDA is shaped by the system – thus a social phenomenon – calls for a research strategy allowing for an in-depth, contextual explanation which a qualitative approach is most likely to yield. This strategy allows for the development of an understanding of complex and interwoven contexts for which questions or hypotheses are difficult to formulate a priori. The qualitative research design requires a careful application of methods and procedures to ensure quality and validity of findings. Triangulation of data, validation, and thorough description are the most such prominent tools in guaranteeing internal and external validity (Flick, 2004; Bauer and Gaskell, 2007).

Further, I employ a single case study approach. As argued by Yin "a case study is an empirical inquiry that investigates a contemporary phenomenon within its real-life context, especially when the boundaries between phenomenon and context are not clearly evident" (Yin, 1994, p. 13). Considering the problem area and the research questions this project aims to answer, this approach seemed the most appropriate, as the case study enables "continuous interaction between the theoretical issues being studied and the data being collected" (Yin, 1994, p. 69). Below I present the reasons for selecting a case study approach for this study.

First, the problem area I set out to tackle has not yet been studied in a comprehensive and exhaustive manner. By way of a case study, I look to take an explanatory approach (Yin, 1994). A case study approach provided for an opportunity to build a rich, contextual understanding of the phenomenon (Flyvbjerg, 2006). What is more, in this case, the study of the phenomenon within its context was especially promising. For these reasons I also undertook a holistic case study (Yin, 1994).

Second, my primary aim was to test or extend the existing theory of reactivity into the context of BDA. I constructed an analytical framework to guide data collection and analysis (Yin, 1994), and through the analysis I undertook to generalise back to theory. This is also the reason for choosing a single case study approach of a representative case: I set out to test "a well-formulated theory with a specified clear set of propositions as well as the circumstances within which the propositions are believed to be true" (Yin, 1994, p. 38). The case I selected is representative of "a typical project, a firm believed to be typical of other firms, a representative example" (Yin, 1994, p. 49).

Third, case studies have a strong tradition in information systems research. They allow us to study the use of information systems within wider organisational or societal contexts – precisely where there are no clear boundaries between the phenomenon and the contexts (Cornford and Smithson, 1996). Finally, I set out to study a contemporary phenomenon over which I have very little control. This eliminates several other research methodologies which are better suited to study, for example, historical events (archival analysis or history), or strictly controlled variables (e.g. experiments).

Therefore, my empirical investigation involved a single, holistic, extended case study of an organisation that deployed BDA, specifically a higher education institution and its learning analytics (LA) system. The selection of the case study was convenience-based from a pool of institutions with an LA system in place. I attended a number of LA workshops and conferences in 2016 and identified a number of potential higher education institutions that had an LA system in place. Other potential case study sites were identified through contacts with academics. As described in detail in the next chapter, the selection of this particular higher education institution (referred to as the School) for this study was based on several factors. First, the institution developed its own LA system in-house and integrated it well with other sources of data, thus providing for a thorough and robust system to study at the most developed and comprehensive scale, as compared to other institutions considered. Second, the in-house development team was available to be interviewed and observed in relation to the system developed, aside from the users of the system. Third, this particular institution was willing to learn more about the impact of LA on their organisational structures and willing to develop this area further based on research. They therefore supported the research project and ensured that I had access to the School's systems and staff. The proposed research project was put forward to the ethics approval board at the School and obtained full approval on 24/05/2017.

While the selected case is representative of other institutions deploying LA systems and, as such, "the lessons learned from these cases are assumed to be informative about the experiences of the average person or institution" (Yin, 1994, p. 49), it is important to note the implications of this choice for research design and analysis. A first and obvious implication is the fact that LA systems are a subset of BDA systems and are deployed at higher education institutions which are often not-for-profit or otherwise non-typically commercial enterprises. This can have a moderating effect on the use of the system in question as well as its purposes. Second, the particular School selected for this case study was motivated to understand its use of LA partially due to the fact that it was keen to implement it to an even greater extent. Also, the general approach to using data at this School was, overall, positive and enthusiastic, which could have a bearing on the results. Third, this particular School has an in-house software development team which is largely behind the development and integration of the LA system, unlike other institutions that largely implement off-the-shelf VLEs and do not hire software developers[3]. Thus, the bottom-up push towards the wider implementation of the LA system may be a result of the interests of the development team. Finally, this particular School is a highly competitive business school attached to a university. It is internationally ranked and emphasises its ambitious international goals. Such business-school thinking, combined with high ranking stakes, may differentiate the selected School from other, more traditional university settings.

I focused on studying the organisation in areas specifically related to the LA system for an extended period of 12 months, starting with a pilot study in February-March 2017 and

[3] Many UK-based universities develop their learning analytics capabilities in conjunction with JISC, as part of the Learning Analytics initiative, JISC 2018.

deploying the full case study subsequently, running from May 2017 to May 2018. I developed a case study plan (Robson, 2011) and maintained a regularly-updated case study database (Yin, 1994) to ensure internal validity of the project. More specifically, I maintained a secure storage space where I stored all documents received or obtained as part of the case study with a clear attribution of the source and date, all screenshots of the system, as well as an interview log with details of the interviewees, interviews, meeting and workshop notes, recordings, transcripts, and consent forms signed by all interviewees. In the remaining part of this thesis, I use this case study to describe a representative or a typical case to capture the conditions of a commonplace situation (Yin, 1994).

Table 8 Summary of research design

Research design	Exploratory pilot study	Explanatory study
Research phase	Pilot study in an organisation that implemented an LA system	Single explanatory case study of an organisation that implemented an LA system
Timing	March 2017	March 2018 to August 2018
Sample selection	Convenience-based at the organisation selected purposively	Snowball sampling at the organisation selected purposively
Data collection	Semi-structured interview, focus group, observation	Semi-structured interviews, observation, document collection, notes, diagrams
Data analysis	Thematic coding	Thematic coding
Output	Pilot study report	Case study narrative and analysis sections
Quality criteria	Data triangulation	Validation interview, data triangulation

4. Pilot study

The pilot study was conducted in February and March 2017 and, at the preliminary stage of the research project, the pilot study served as an opportunity to explore the feasibility of the study on a smaller scale before expanding it, and to test the theoretical and analytical framework, as well as to produce a pilot study report which was submitted to the relevant management to seek full approval for the project. The pilot study relied on gathering data from four sources: interviews, LA system analysis, a focus group and data analysis in the period between February and March 2017. The pilot study focused on a module taught at the School and involved an interview with the module leader, analysis of the use of LA in this module, a focus group with students, and the analysis of data generated in this period in LA. The outputs of the pilot study included a recorded interview and interview notes, screenshots of LA, focus group slides, focus group recordings and notes.

The main goal of the pilot study was to test the applicability of the theoretical framework adopted for the study, as well as to test the proposed analytical framework. Although rooted in the literature, the assumption that LA leads to reactivity was a hypothesis, so the pilot study was conducted in order to confirm whether such mechanisms and effects do indeed take place in such environments in a preliminary fashion before starting the full research project. The details of the pilot study are reported in Appendix 1.

The pilot study confirmed the validity and feasibility of the proposed approach. The findings from the pilot study were used to refine the interview guide and enhance the analytical framework before proceeding to the main data collection.

5. Main data collection

The main period of data collection took place between May 2017 and May 2018 and included observation, interviewing, and document analysis, as well as a group interview. As per the retroductive approach described above, I used the findings from the pilot study, observation and the first interviews with the most active users of the system to build up my understanding and description of the case study. Further interviews were used to further nuance my understanding, and the final group interview helped to validate the findings.

Relying on snowball sampling, between June and September 2017, I carried out 31 semi-structured interviews (Robson, 2011) with 29 members of academic, teaching, administrative, and software development staff at various levels of seniority within the School to understand how LA is used, what effects it generates, and what reactive mechanisms can be found at play. Snowball sampling started with a small pool of key informants who recommended other subjects to interview (Alasuutari, Bickman, and Brannan, 2008) and finished when informants were not able to recommend anyone else who had any experience working with the LA system and who had not been interviewed before, which meant a point of saturation had been reached. The interviewees included assistant and associate professors, teaching fellows, senior teaching fellows and professorial fellows, operations directors, programmes managers, assistant registrars, administrative officers, teaching and learning consultants and technology utilisation consultants, technology integrators, and information systems consultants, who were all informed of the purposes of the interview and signed relevant consent forms. The interviews lasted on average 49 minutes, with the shortest one lasting 24 minutes, and the longest one 85 minutes. In the interviews, I asked about the use and experience of the VLE, and specifically about the use of data collected and made visible in the LA system, for example by enquiring how different interviewees use these data, whether they experienced any problems or issues with them, and whether they had noticed any changes since the system was rolled out at the institution. The interviews were semi-structured with areas for discussion derived from the theoretical framework, and later transcribed. A typical interview guide used is presented in

Appendix 2. These interviews helped me to revise my understanding of generative mechanisms and eliminate false or unsupported hypotheses as per the DREI framework. During the interviews, I frequently observed how the interviewees used the system, and I took notes of this in interview notes. Each interview is thus accompanied by a set of interview notes. Observation presents itself as a good way to study small groups (Robson, 2011) and also allows for the study of non-verbal, spatial and extra-linguistic behaviours (Smith, 1991) pertinent to the research question. The informants also supplied me with a range of diagrams, documents, and screenshots that helped contribute to my understanding of the system. I was also given access to the system myself and could experience it first hand as an observer.

In the interviews, I was effectively observing perceptions of analytics of the different parties, which are not necessarily the same as actual behaviour. However, perceptions inform people's understanding of behaviours and also shape the behaviours themselves, especially in the case of reactivity (Espeland and Sauder, 2016).

I further complemented the interviews with analysis of documentary evidence from IT strategy meetings obtained from a senior employee at the School. The documents consisted of sets of agendas and minutes from meetings of the IT strategy group at the School, as well as outlines of proposed IT projects. The group includes a number of stakeholders across different functions with interest in the IT capacity of the School. The terms of reference of the group state that its role is to, among others, "formulate and maintain a desired direction and framework for technology developments, including development/procurement strategy, and exploitation of central University systems" (M_001). The group meets on average every two months. Through access to the agendas and minutes, I was able to trace the development of narratives around the system and contextualise my understanding of the LA system.

Finally, I presented my preliminary findings from the study to a group of senior managers in May 2018, who were also available to answer, challenge and validate my proposed explanatory mechanisms. This group interview with seven participants, all at the level of Dean, lasted 30 minutes and helped me to identify and confirm the correct mechanisms at play. A summary of all the data collected is presented in the table below.

Table 9 Summary of data sources, types, and quantity

Source	**Amount and type of data**	**Period of collection**	**Code in the database**
User interfaces of the VLE and LA system	Access to the VLE and LA system on selected teaching modules, observation notes and screenshots	March to September 2017	S_001 to S_025

Semi-structured interviews	31 interviews with 29 informants, totalling 1,528 minutes; transcripts and interview notes		June to September 2017	I_001 to I_029, INotes_001 to INotes_029
	Professional area	No. of interviews		
	Administration and professional services staff	13		I_APS
	Teaching staff (no research activity)	9		I_Teaching
	Technical staff	5 (2 shared roles)		I_Technical
	Academic staff (research with some teaching)	5		I_Academic
Minutes from the IT Strategy Meetings	30 sets of minutes from formal meetings from meetings held between 2013 and 2016		September 2017 to February 2018	M_001 to M_030
Group interview with Senior Management	1 group interview with 7 senior managers lasting 29 minutes; transcript		April 2018	GI_001
University and School website and blogs	13 web pages		August 2018	SCH_001 to SCH_011

Thus, while aiming to generalise our findings back to the theory, I have ensured strong construct validity through the use of multiple source of evidence, as well as reliability by maintaining a case study protocol and database (Yin, 1994).

6. Coding and analysis

In the spirit of the DREI approach within critical realism, I was engaged in coding and analysis as I was still collecting data, ensuring a recursive relationship between my analytical efforts and further data collection. While I was the only researcher coding the data, I carried out coding twice to increase validity: once when I was conducting the study, and again from scratch 12 months after I finished interviewing. I employed thematic coding to report experiences, meaning, and the reality of participants (Robson, 2011) and coded observation notes, LA diagrams and screenshots and interview transcripts using nVivo. I generated initial codes from the literature review and the analytical framework and applied them to the data collected. This theoretically-derived coding scheme included a set of codes for the intended uses of LA. I relied on the theory of reactivity to derive codes for the mechanisms and effects of reactivity at play while remaining open to potential new mechanisms emerging. The coding scheme used is presented in Appendix 3. A visual snapshot of the distribution and relationship between codes is presented below in Figure 11. Different colours represent codes grouped together, and the size of each box corresponds to the number of instances coded to a particular code.

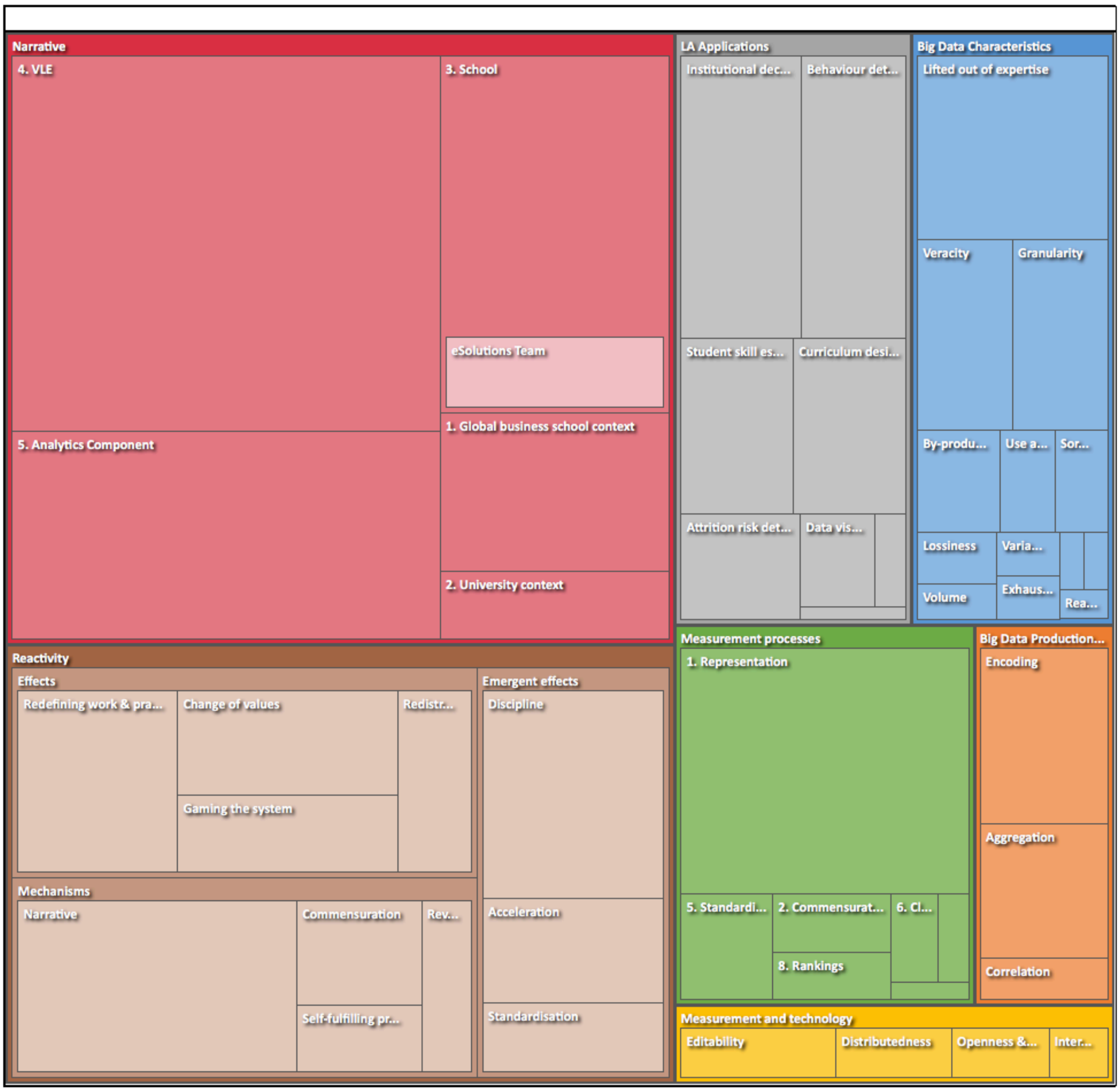

Figure 10 Distribution of codes in data

I then identified emerging themes and constructed thematic networks allowing for integration and interpretation (Robson, 2011). Some excerpts of this approach are presented in Table 10 below.

Table 10 Tracing theoretical codes to emerging themes and data

Number of excerpts	**Example excerpts**	**Emerging theme**	**Theoretical code**
20	"[LA] detracts from the job of educating" "The move towards e-learning"	1. Changes in teaching and teaching-related practices 2. Move towards e-learning 3. Restructuring materials	Redefining work and practices
13	"If I look at the online tracking of staff engagement and people are repeatedly not doing what they're supposed to be doing, they'll be on the blacklist and they won't have the contract renewed; it's a really cut and dried thing"	4. Decisions on tutor contract extensions and termination 5. Bigger team 6. Investment in non-faculty and teaching staff 7. Changes to job positions	Resource re-allocation

	"Changes have become measurable and this is why more power and more investment has gone into non-faculty"		
18	"We employ teaching fellows because they have that focus on teaching rather than being research-focused" Move away from "treating them [students] like an adult learner" to "hand holding to the extreme"	8. Increasing importance of student feedback 9. Move away from treating students as adult learners	Change of values
13	"People who actually previously didn't bother to do that, will use a little of their valuable time, which could be actually spent getting an education, they'll actually use that time to play the game" "It's not really indicating that they've probably completed that page, it's indicating that oh, I'd better do this otherwise the programme team will get on to me"	10. Gaming 11. Reputation and impression management	Gaming the analytics
14	"Check online tutors' participation and without having to go all the way down the discussion boards and see if they're participating. I can just view under the staff activity who's doing what they should be doing or not" "For us, it's enabling us to keep a very much closer handle on those students and provide the personal experience that they think that they're paying for which I don't believe we could consistently provide before the current version of [VLE] because we didn't have that data"	12. Changes within the same cohort 13. Quickly identify underperforming staff	Acceleration with data

In this approach, I treated each unit of data collection (e.g. a datum, an interview, a module) as a unit of analysis (Yin, 1994). The process of data analysis was essential in identifying potential mechanisms in the retroductive process and at the last stage, in identifying the correct mechanisms. This method of analysis seemed to be appropriate for the questions posed in this research project, as it focuses on identifying the mechanisms of data production in LA.

7. Conclusions

As a single case study, the research project is exposed to a variety of issues related to validity, especially construct, internal and external validity, and reliability. To mitigate the potential issues around construct validity, I used multiple sources of evidence (observation, document analysis and interviewing). I used pattern-matching across these sources to increase internal validity, and I relied on a case study database to ensure reliability (Yin, 1994). In terms of ethical considerations, the project was approved by the School's board of ethics, and each interviewee received a copy of a Participant Information Sheet and signed a consent form. It is worth pointing out that the project, by way of extending an existing theoretical approach, is intended for analytical generalisation rather than statistical generalisation for exploratory purposes (Yin, 1994).

Thus, in this chapter I presented the methodological underpinnings of my research project. Taking critical realism as my ontological standpoint, I fleshed out the elements of this approach that were pertinent to and influenced my study, and I also argued that through the DREI approach, critical realism provides epistemological guidance in this research. I have also discussed my strategy for data collection and analysis as well as outlined how I mitigated against the issues of validity and reliability of my findings.

Chapter 8: Case study narrative

1. Introduction

In this section, I outline the broader context of the case study at the sector level, the university level, the School level, and in relation to the VLE and finally the LA system. To do so, I present a thorough description drawing from interview and documentary data. Some of the numbers and factual data in this chapter have been altered to retain the anonymity of the organisation. The description of the case is an essential step to present the phenomenon studied in context, and it is especially relevant for case studies where the boundaries between phenomenon and context are not clearly evident (Yin, 1994, p. 13). Furthermore, as I set out to study how the implementation of the LA system impacted the work of individuals and the wider institution, the phenomenon of reactivity crosses the boundaries of just the LA system, or just the organisational setting.

2. Business school educational context: a numbers game

The sector within which the School operates is not only higher education in general, but specifically business school education at an international level. In this section, I outline relevant aspects of the higher education context and the business school context.

2.1. Competitive landscape of higher education in the UK

As part of a higher education institution established in the United Kingdom, the School and the University it is attached to are subject to pressures similar to those faced by other educational institutions in the country. As per the University's own admission, the university business model in the UK is under stress (SCH_001). As a result of changes in government funding provided to universities, which took place around 2012, universities receive less funding for teaching activities and effectively charge students higher fees for degrees awarded. This is widely perceived in the sector as a driver towards a more consumer-like treatment of students. Similarly, akin to other institutions, the University feels that its traditional activities are no longer sufficient to support the current business model in higher education (SCH_001). Therefore, in its strategy the University decided to turn to adding new activities, providing new financial possibilities (SCH_001).

In order to ensure value for money for students, who in 2019 pay in the region of GBP 9,000 per year for their undergraduate degrees, the British Department for Education introduced the

Teaching Excellence and Student Outcomes Framework (TEF), which is an assessment of the quality of undergraduate teaching in higher education institutions in the UK. The goal of the Department for Education is to triage institutions into three ratings: gold ("provision is consistently outstanding and of the highest quality found in the UK Higher Education sector"), silver ("provision is of high quality, and significantly and consistently exceeds the baseline quality threshold expected of UK Higher Education"), and bronze ("provision is of satisfactory quality") (Department for Education, 2016, pp. 46–47), and to link the respective tier to the decision whether to allow a given institution to increase tuition fees or not. Institutions are assessed through six core metrics and have to submit a 15-page provider submission. The metrics draw from the following sources of data: student satisfaction from teaching, selected outcomes from National Student Survey, retention based on Higher Education Statistics Agency (HESA) UK Performance Indicators, proportion of students in employment or further study 6 months after graduating as reported by the Destinations of Leavers from Higher Education (DLHE) survey.

The National Student Survey (NSS) itself is an important mechanism at universities in the United Kingdom, as its percentage score came to reflect student satisfaction with teaching and often serves as an important factor when students make decisions concerning their university choices. The NSS is a survey of all final year undergraduate students in the UK and is conducted by Ipsos MORI on behalf of the Office for Students and the funding bodies. The questionnaire covers 27 questions pertaining to the learning experience, including questions about teaching, learning opportunities, assessment and feedback, academic support, organisation and management, and learning resources. Results of the NSS are published every year and most institutions comment on the results in internal and external communications (Office for Students, 2019).

The proposed TEF assessment was surrounded with controversy and met with criticism within the sector in the UK. The vice-chancellor of the University himself published an open letter outlining his concerns regarding the metrics used in the TEF and the potential impact of the framework on the recruitment of international students (SCH_002).

The first trial year results of the TEF were published at the time of the case study, and there has been some reflection on the impact of the classification of the University in interviews conducted (e.g. I_APS_024). The University was awarded silver status in 2017, and it was commented in the official award that the University achieves "excellent outcomes for its students… with an institutional culture that facilitates, recognises and rewards excellent teaching" (SCH_002), and that the University offers "high quality physical and digital resources underpinned by significant and sustained investment" (SCH_003). In the official communications concerning the award, the University commented that the award is a continuation of high quality of teaching throughout its history, seemingly evident through the University's consistent ranking among the top 10 UK universities "since league tables began", and in the top 50 universities in QS World Rankings (SCH_002).

While the metrics feeding into TEF are still under consideration, Jisc, the UK higher education sector's main technology body proposed to develop a national learning analytics service that would enable participating universities to warehouse, compare and benchmark LA data. As of 2016, the initiative was still in its early stages, but 70 institutions in the UK have expressed their interest in participating in the project (Havergal, 2016). Jisc's chief innovation officer expressed the goal of Jisc's learning analytics platform as "hoping to become part of the TEF ecosystem", therefore feeding LA data into the TEF framework (Havergal, 2016).

With around 130 universities in the United Kingdom, rankings and the TEF framework add pressure to an already very competitive environment, where institutions find themselves fighting for and wooing students.

2.2. Competing as a business school

The landscape becomes even more competitive in the narrower sector of business school education. Predominantly teaching business and management, business schools usually function as departments of universities. Business schools usually offer courses at undergraduate and postgraduate levels, and notably a range of Masters of Business Administration (MBA) degrees, which attract high tuition fees and are often seen as significant sources of income for their home institutions. Business schools work in highly competitive environments, and the best among them compete at a transnational level. Indeed, most notable business school rankings rank institutions globally. A typical international business school is likely to be ranked by the Financial Times, the Economist, Forbes, QS, Good University Guide, The Guardian, América Economía, Bloomberg Businessweek, Corporate Knights, and more. In most cases, business schools are ranked separately for their different programmes, such as Global MBA, Online MBA, Executive MBA, Masters in Management, and executive education.

Taking the example of the Financial Times's Global MBA ranking, a business school would be usually required to submit a set of data to the ranking institution on a regular basis for assessment. The participating schools have to meet entry criteria and be accredited by Equis or the AACSB. The Financial Times "surveys alumni three years after completing their MBA" and requires at least a 20% response rate (Ortmans, 2018). The ranking comprises 20 different criteria: 8 of them are based on alumni responses and make up for 59% of the weighting; 11 criteria are based on school data and comprise 31% of the weighting; the remaining research rank criterion counts for 10% of the weighting. Among alumni criteria, measures taken into account include average income three years after graduation and salary increase. As the Financial Times explains, “FT also collects information from schools on their current faculty, newly enrolled students and the latest graduating class. School criteria include the diversity of staff, board members and students by gender, nationality and the MBA’s international reach” (Ortmans, 2018).

Currently there are around 60 business schools in the United Kingdom, of which around 10, including the School studied, are internationally recognised and rank consistently high in international rankings. The School states that “we recognise that rankings are one way to profile our progress towards fulfilling [our] vision, and are proud to participate in the major global business education rankings” (SCH_005).

There are three main accreditation bodies awarding recognition to selected business schools known as the Triple accreditation: the Association to Advance Collegiate Schools of Business (AACSB) based in the US, the Association of MBAs (AMBA) based in the UK and EQUIS (EFMD Quality Improvement System), an EU-wide institution. The accrediting bodies set their own criteria and standards, and their accreditation is often used as a symbol of quality and recognition by the institutions awarded.

Business schools are predominantly research-focused institutions. As such, they are not only subject to rankings based on the quality and value of their teaching, but also on various research-related metrics. Notably, business school academic staff are expected to publish in highly-ranked academic journals as set out by the Association of Business Schools Academic Journal Guide. Journals are ranked on a scale from 1 to 4*, where journals ranked at 1* “publish research of a recognised, but more modest standard in their field”, while 4* journals are “journals of distinction” (Association of Business Schools, 2015). The classification process for journals takes into account, among other things, “the mean citation impact scores”, “the number of times the journal was cited as a top journal”, and “the length of time a journal has been established”. Academic publications count for individual academics whose promotions are often linked to the number of publications, as well as for business schools as institutions, as publications feed into other rankings. In the UK, one such ranking is the Research Excellence Framework, which ranks universities in the country based on the quality of research, from one to four stars. A one-star institution would publish research of “quality that is recognised nationally in terms of originality, significance and rigour", while a four-star institution publishes research of "quality that is world-leading in terms of originality, significance and rigour" (Association of Business Schools, 2015).

Even this brief outline of some of the forces shaping the business school educational context presents an environment significantly governed by numbers, rankings and classifications. It is against this backdrop that universities and business schools have to survive and carve out a space for themselves, which is also the case for the University and the School studied. In order to survive and flourish, the University and the School have to engage in this numbers game to the point of allocating resources to a "rankings taskforce" (I_APS_024). During the case study, the School also developed an add-on in its VLE, which was often referred to by the interviewees as the "feedback on feedback" system (e.g. I_Technical_001), whereby students can give feedback on the feedback they received from academics, as assessment and feedback received low scores in the NSS for the School in the preceding year. Another notable example is the creation of a certificate for recent graduates who are unemployed "to improve University rankings" (M_014) by engaging such unemployed graduates in postgraduate study.

It is important to bear in mind the pressures and highly metricised conditions the University and School operate under during the ensuing discussion about learning analytics.

3. The University setting

The University is a public research university founded in the 20th century in the UK as part of the government initiative to expand and improve access to higher education. It has four faculties with over 30 departments, and overall has around 30,000 full-time students and nearly 3,000 academic and research staff. It has a robust level of income, a quarter of which comes from research grants and contracts. It is a young university that "has made outstanding progress in a very short time" (SCH_001), and has quickly established itself among the top universities in the UK.

The University is the overall umbrella institution for the School, but there is a significant separation between the University and the School, both in terms of the physical infrastructure and campus, and the digital offering. While working within the University framework, the School maintains a significant degree of autonomy and separation. For example, the wider University uses Moodle as its learning environment (S_009), unlike the School, which developed its own VLE. The separation and difference are clear to students, as one interviewee reported "what students have said to us though it's comparing what they have with what other departments have got, ‘I don’t even know how I’d be able to track my degree if I didn't have [VLE]’” (I_Technical_001). Similarly, students at the School are provided different usernames and email accounts than University students “following a very bad experience using ITS-provided usercodes” (M_010). The separation causes frictions for students at some contact points, as “the most important change (...) was the decision of the Library to stop supporting the use of [the School’s] usercodes. This happened a number of years ago without any notice or discussion and effectively meant that students would now have to use both their [School] and ITS usercodes” (M_010).

From the perspective of the digital infrastructure, the School maintains a “technical separation” (M_006) from the University, which in a reported case of a security breach “acted as a natural firebreak and prevented [the School] from suffering any direct impact” (M_006). This also means that the University has a separate ITS department, and the School has its own IT team. The extent of this separation is perhaps best exemplified through the struggle to share information following the above-mentioned security breach: “Requests to share [IT] code went unanswered. This meant that [the School] staff had to write applications ‘from the ground up’ even though functionally identical code already existed in ITS” (M_006).

The School is based in a separate building and maintains a strong, separate branding from the University. The School makes significant profits every year and contributes these profits back to the University.

4. The School

The School itself has a strong brand and reputation, and in just under 50 years it “has become one of the world’s elite business schools providing top-class programmes for ambitious people” (SCH_004). It also holds the Triple Accreditation, and 5* research rating. It prides itself in its research (“we strive for excellence in research and can genuinely claim to be home to some of the world’s best researchers”, SCH_010), teaching, recruiting “the brightest students” (SCH_010), producing “the most valuable graduates” (SCH_010) and “breaking new ground” (SCH_010). The School has about 6,000 students across more than 40 programmes in management education and employs around 400 members of staff. It belongs to the Faculty of Social Sciences at the University.

The School’s vision is to be Europe’s leading University-based business school (SCH_006), and to develop transformational ideas and people. This vision is supported by a mission statement envisaging the development of cutting-edge research, providing a transformational learning experience, and working in partnership with policy and practice (SCH_006).

The undergraduate programme runs around 100 modules per year with varying audiences and configurations, including students taking joint degrees, students from other departments of the University, or exchange students from other foreign institutions (SCH_007). Modules delivered vary in size from core modules with several hundreds of students to specialised electives with as few as a dozen of students. Typically, the undergraduate programme attracts students from more than 50 countries each year, and usually around 50% are UK/EU students (SCH_007). The entry criteria for the undergraduate programme are very high, as the School requires AAA results from A Levels and international equivalents. All modules are supported by the Undergraduate Office. There have been interesting attempts at supporting the Undergraduate Office in estimating the number of applicants for the courses available by "quantifying the intentions of university applicants with Google Analytics" (M_017). It was a short research project carried out by two academics at the School to "investigate whether data on the number of visits to course pages on a university website could help us forecast the total number of applications to the undergraduate course in question. Such forecasts may be useful to university management when making a range of policy decisions relating to admissions, including questions about promotion of different courses and changes of entry requirements" (M_017). This pilot study was met with interest at the School (M_014), especially from the admissions team.

The postgraduate programme is aimed at students with four years of management experience. Students come from a variety of nationalities and represent over 50 different countries on the Distance Learning MBA. The School receives nearly 10,000 applications to postgraduate master's degree courses every year, of which it accepts around 1,000, meaning it has a highly-selective admissions rate (S_021).

Teaching and learning activities are of strategic importance to the School. One piece of evidence for this is the suggested prioritisation of IT development projects, where administrative projects were "parked to make time available to work on initiatives directly linked to Teaching and Learning" (M_023). Similarly, measuring student performance for learning outcomes is strategically important for the School (M_017), and the School engaged in the Assurance of Learning exercise as part of their submission to AACSB. The School's approach to learning and technology is best summarised in a report from a Technology Away Day held in 2014 (M_013): "education is now more about an experience and a process. There is a shift in emphasis from the transfer of content to the design of learning activities".

Technology is seen as a tool that can “help deepen learning” (M_013), and to do so, several approaches were identified, including increased attention to the design of teaching, encouraging experimentation, and reviewing administrative systems and structures. During this Technology Away Day it was concluded that the School needs to “construct a narrative such that innovation and digitalization appeals to self-interest and is not just seen as more work” (M_013) among its staff. There was another Teaching and Learning Away Day planned “which would review the strategy around T&L, but crucially for teaching” (M_012). The School has an Associate Dean for Blended Programmes, who is responsible for running distance learning and face-to-face MBA programmes (I_Teaching_002), upon being interviewed she related how the Teaching and Learning Away Day progressed: “So when I came in, because I have a teacher training background, I was like, ‘Right, these are teacher training events. Let’s get [Technology Utilisation Consultant] from downstairs. Let’s get [Teaching and Learning Consultant] from Teaching and Learning. And let’s go in a lab and let’s try stuff out.’ So, about a year ago, we introduced them to the moderation tool, which is the tool that I was just clicking on there. And [Technology Utilisation Consultant] did a sort of treasure hunt thing with the teachers in the lab. We had about 40 of the…there’s about 60 teachers. So we’ve had about 40 of them there which is good because some of them live in Australia, which means that they don’t necessarily come. But in that treasure hunt is a fantastic exercise where he got the tutors to look at their own module that they run. So you had different groups of people in the room looking at their own modules. He got them to click on the moderation, and then they started exploring. And within there, they can see staff activity.” (I_Teaching_002). It is therefore evident that there is emphasis on deploying technological tools for the purposes of teaching and learning.

4.1. Senior Management

The current Dean is an internationally recognised researcher, and held a full professorship at the School for a number of years, taking up a number of administrative posts. The Dean is supported by a Senior Management Group (SMG) who advises the Dean on strategic and operational matters, and to ensure alignment between activities and the School’s mission (SCH_009). The SMG comprises, among others, the Chief Operating Officer, Chief Financial Officer, Pro-Deans (including for Faculty and Teaching & Learning), a number of Associate Deans (e.g. Information Technology Solutions, Pedagogy), the Director of Teaching & Learning, and Director of Executive Education.

4.2. Technology Strategy Committee

Especially in the work of the Technology Strategy Committee (TSC), teaching and learning activities seem to be high on the agenda, as they regularly appear in discussions in meeting minutes. The TSC evolved from a more technical role (M_004) to "a representative body established to take an integrated and strategic approach to the provision of technology to support the research, teaching, and administrative and external activities of the School. TSC recommends, plans and approves all major areas of technology development for the School and unify the technology development planning and prioritisation environment within the School" (M_014). The TSC meets roughly every two months and includes representatives of the IT team, non-academic operational managers, and key academics, including the Associate Dean for IT Solutions, the Chief Operating Officer, e-Learning, representatives of degree programmes, Academic Services, the Finance Office, Human Resources and Marketing & Communications, among others. The TSC aims to "make recommendations to the [School's Senior Management Group] on the School's technology strategy and policy" (M_014), as well as develop and submit recommendations on resources required to "implement and support user-inspired, value-adding technology solutions for the School" (M_014). In the words of one interviewee, "anyone can propose a project for development" (I_Technical_001) to the TSC, who then will "consider development proposals in the light of School/group strategies and the strength of the associated business cases IT environments, responsive & proactive support" (M_014). Most projects requiring significant development and IT resources need to be approved by the TSC following submission of a project proposal, although some projects originating with the Senior Management Group or within the IT team itself do not go through this process (I_Technical_012). Examples of projects approved and overseen by the TSC include: "2010-03-C Bulk export of resources in [VLE]"; "2011-05-B Upload of MBA applicant data"; "2012-05-B Redevelopment of [School's] website"; "2013-02-A Online Signature repository"; "2014-01-A PG Exam Board", and similar (M_019). A typical project proposal includes a statement on the project sponsor, manager and originating group, a description of the project purpose, including envisaged deliverables, a business case including financial impact, compliance requirements, synergies and deadlines, and a project completion sheet (M_019). The TSC is also a forum to share ideas and events around technology concerning the School. For example, in 2013 two members of the TSC went to another university and "made a number of presentations of various e-learning tools and systems to faculty and management. Their key task was to highlight best practice that helped [the School] to advance their own e-learning capabilities, with [Host School] aiming to follow a similar model. The presentations were well received and [the School] clearly has a very good reputation at [Host School]" (M_006).

As the Technology and Strategy Committee draws together representatives from different groups at the School concerned with the development of technology, its makeup offers insights into key technology-related roles. Aside from a high-level Associate Dean for IT Solutions, the school has a Head of Applications Development, Head of IT environments, IT Services, an e-Learning team (renamed to the Teaching and Learning Support team during the case study), and the IT team, which includes applications development staff, a Technology Utilisation Consultant, Information Systems Consultants, and Technology Integrators, who work part-time within the IT team and part-time with programme teams. The e-Learning team consists of around 16 members of staff at the Teaching and Learning Officer, Consultant or Coordinator level. There is a sub-team of two members of staff focusing on producing online teaching resources, and the team also has a full filming studio to support the development of videos (I_Teaching_002). Technology Integrators play a vital role in ensuring that all technological developments are communicated properly to programme teams, and that all members of staff are aware of and trained in the use of different IT systems (I_Teaching_002).

4.3. The IT team

The IT team is of strategic importance at the School ("Been finding out all the latest exciting things that are possible and then working with the IT team who do all the architectural stuff and getting their help in actually creating the tools, the things that we need to make our course number one in the world. But it's currently number two in the world" I_Teaching_002). It employs around 17 members of staff in a number of areas, from services support to application development ("the rest of them are actually coders and are producing applications" I_Technical_001). Academics and other members of staff often turn to the IT team for help and recognise the role played by the team at the School: "And the team downstairs in the [IT team], the guys that do the architecture, they are so open to questions. Every time I go there to ask a question, I learn something new. It's fantastic" (I_Teaching_002). The team often empowers staff: "So, what I do is I go down to my friends down in [IT]. I say, 'I need a dev site.' They create me a dev site, and then I write straight into the dev. So here's an example of one my dev sites. So, I just write straight in. I have full editing access and I write straight in here. So, I designed all of this and put all of the materials in straight away myself" (I_Teaching_002). At the same time, the IT team plays the role of gatekeeper to systems and data: "the question comes around, can we give this person these permissions on database, and it's actually fairly normal for people from [IT] to turn around and say 'No, no you can't, it won't work here.' Well, did you know they might be tempted? But they're actually also students in university, and you're asking for access to student records. So we do, we say no" (I_Technical_001). It also sometimes imposes stricter restrictions that can later be revised: "And that in actual fact, the school benefits if we say no first and then further details allow us to relax the constraints far better… actually, almost making a show of saying no, because it tells everybody this matters. So, that it means there's a culture about that" (I_Technical_001).

Software developers would usually be involved in developing the VLE and adding additional functions as well as working on the School's website (I_Technical_012). The developers are heavily involved with the VLE and contribute to "everything basically; student-facing site, lots of tools for administrative staff, faculty, for managing data, operational stuff, things like metric system, which is strategic, information and support strategic decision-making" (I_Technical_012).

One of the important members of the team is the Technology Utilisation Consultant, whose role is to mediate between the technical staff, the academics, and other employees at the School: "And general views on technology in business school that there was a real role for somebody that understood the constraints under which faculty and teaching faculty in particular were working, but they could also understand the constraints under which the software developers are working. And so I was basically spotted as a good mediator between those two groups of people, who aren't necessarily very good at speaking to one another because those are two very specialised areas. And the role was created to be effectively a liaison between two very technical specialities" (I_Technical_001). The Technology Utilisation Consultant explained that there is "a constant negotiation and a set of interactions around the strategic use of technology" (I_Technical_001), pointing towards two fundamental directions: "Someone might decide how to … that they want to do something with the technology, and then it will be my job to translate that to things that software developers can do. But similarly, there'll be strategic decisions about technology that have an impact on other sorts of decision-making where we move" (I_Technical_001). In the words of the Technology Utilisation Consultant, technology development at the School is both bottom-up and top-down.

Records show an attempt to devise a strategy for the IT team in 2014. The strategy was pioneered by the Associate Dean for IT Solutions, who in one of the meetings (M_012) explained his ambition to produce "an overall strategy which would take into account both top-down and bottom-up approaches" to improve the quality of teaching using technology. A related attempt concerned creating a business plan for the unit, which covered the development of a digital campus: "the digital [School] should be considered as a territory and its people. Our digital environment is the space – a walled garden in which our students, faculty and alumni interact and express themselves. In many respects, when we move into the digital conception of the institution, what we are doing is making more territory" (M_011). This is aligned with the sentiment shared by the Technology Utilisation Consultant, who was hired around the time as the VLE was being developed for the School because "the School had decided to basically move online".

Thus, the overview presented here indicates that the School has well-founded and developed structures and strong management concerning the running of the School as well as its technology. The Technology Strategy Committee oversees IT development projects, but at the same time the IT team seems to have a fair decision-making capacity and freedom to work on some projects.

5. The VLE

The Virtual Learning Environment (VLE) is a proprietary system at the School. It was developed by the IT team more than 10 years ago (S_025) in collaboration with various stakeholders across the School. The system does not only serve to support teaching, but it also has a number of administrative components ("loads and loads of things are related to it right now" I_Technical_001) and is at the core of the processes at the School (I_Technical_001). The VLE grew into a vital part of the School: "At the business school, this is how you communicate. This is what membership of the business school means" (I_Technical_001). In what follows, I will provide a description of the logical architecture of the system before moving on to discuss the teaching-oriented tools, and then administrative components.

5.1. Development of the VLE

The VLE first emerged out of a need to digitise lecture notes, module registration forms and other programme administration documents (I_Technical_001): "And in the previous building, there was an office for the undergraduate programme administrators that the students could visit for queries. And during office hours when that office was open, there was a queue of students at that door that rarely ever dropped below 50. (…) They were just going to pick up paperwork, and it might be some lecture notes, a photocopy of lecture notes that it might be, your module registration forms or … you know. It was just programme administration. And [the VLE] is basically first specified with the job of getting rid of that queue of students" (I_Technical_001). As such, the system emerged from the undergraduate programmes office. The next step in the development of the VLE was the digitisation of the distance learning MBA, which used to be done on paper by mailing the documents over (I_Technical_001). Distance learning students were given access to module contents and could submit their assignments to receive feedback online, but their submissions would still be printed at the School for marking, and then scanned and returned back to students: "So in actual fact, so we gradually ended with a situation where the students were submitting in the first instance all that was submitted here, and then it was printed out and sent to the tutors because they refused to look at screens. So students' submissions went electronic first, and the rest of it was paper.

And what really happened was just actually the quality of people’s devices improved. And if you're a distance learning tutor, you finally, for example, got a nice laptop from the clunky old thing and you like using it. You then start saying, I think I’d rather look at the essay here than have a pile of paper. That happened gradually, and we didn't force it. And we got to the point where people are actually saying, I’d rather do this. And the majority was saying I want to do it electronically. And we let that evolve rather than force technology onto people. And then we certainly had that situation where everything was electronic. But what that did was that it gave us a very elegant mechanism for just managing assessments” (I_Technical_001).

Since then, the system has evolved significantly over the years, with important contributions from the e-Learning or Teaching and Learning Support team (I_Technical_012), still focusing on teaching and learning as its main role. The TSC oversaw a number of iterations of the VLE’s interface (e.g. project “2010-01-A.1 Redesign of [the VLE’s] interface (Phase 1:EE) 2010-01-A.2 Redesign of [the VLE’s] interface (Phase 2:General), M_003). Another significant upgrade came around in 2014: “[Information Systems Consultant] and [Technology Utilisation Consultant] presented a series of sketches and mock-ups and explained the key concepts behind [the VLE] version 9. This version would introduce a substantial change to the user interface, and many of the proposed changes were demonstrated. The committee welcomed the proposal and it was widely agreed that these changes would represent a significant positive change to the user experience” (M_013). The IT team has always been chiefly in charge of development, and often would serve as a main engine of change (M_007). The strategic role of the system is evident in some TSC meeting minutes: “while others such as the upgrade of [the VLE] infrastructure were ‘one way bets’… if they go well no-one will notice whereas if they don’t everyone will be annoyed. Happily it seems that no-one noticed; we’ll settle for that!” (M_007) or “Upgrade of [the VLE] to latest version of ColdFusion - Complete This upgrade in the underlying technology on which [the VLE] is built is complete and did, as promised, involve some ‘heart in throat’ moments.” (M_007).

With time, the VLE began to take on other functionalities and became a central system for all types of users at the School: students, academics, and administrative staff. At the time of the case study, several functionalities of the VLE were under development, including “beasting” (I_Teaching_002), that is, giving some members of staff the possibility to impersonate another user, for example to see the same error they see, or to publish teaching materials under their name (I_Technical_001). Some functionalities rolled out during the study included the peer feedback module, whereby students were asked to rate group members’ contributions on a behaviourally-anchored scale, and such assessment was then incorporated into final, individual grades (I_APS_013). The newest function being developed at the request of the senior management was the metrics system, which explicitly pulled statistical data from a variety of sources, including module feedback, to provide a dashboard for senior management (I_Technical_001, I_Technical_012).

5.2. Logical structure of the VLE

The VLE is built on three pillars of the data structure: students, faculty and academic module occasions, where both students and faculty are associated with module occasions (I_Technical_001). This means that "staff and students are both registered for academic modules. That's the core of it, for everything" (I_Technical_001). This is the biggest difference between popular, off-the-shelf systems and the VLE at the School: "So in my experience the data model behind most VLEs has always seemed to be that you have a teacher. And the teacher has students in a class. And that's the kind of basic model. In the business school and in any big commercial operation, you would never expect the person who stands up in front of the class to be doing all of the grunt work, the admin and the prep and the publishing. And so it's actually not the right model. Not that general abstract model. It isn't entirely correct. So for example teams like mine and teams like the teaching and learning support group who help people produce web content for teaching and learning and administrators are actually the people who run courses. And then faculty can just turn up and teach. And that's our model. And [the VLE] is built around that model" (I_Technical_001). In this sense, the VLE treats both students and academic staff as consumers who meet on the VLE, and administration staff are responsible for facilitating this encounter.

The VLE is a representation or "a single source of truth" (I_Technical_012) about student and faculty data: "If I was doing a student induction, I would say, if you think you're studying a module and you're attending at a class but it's not showing, you're not getting credit for it. And it's the same for faculty. Because if you think you're teaching on a module and it's not in that box, you're getting no teaching credit for it" (I_Technical_001).

The VLE draws from varied and disparate databases around the School. The Management Information System (MIS) holds data on courses available, cohorts, students within the cohorts, and their login histories, as well as submitted assignments. Modules are broken down into module occasions, registrations on module occasions, associated teaching content, assessment methods, and detail. Library details are also held on the VLE. On the staff end, an important component is the Academic Balance Model (ABM), which assigns academics teaching credits on module occasions they teach. Some data is pulled from the MIS and stored in the no-sequel MONGO database as content read logs, while actual content details are taken from a separate SOLR database, and interactions with the VLE are taken from web servers.

This part of the system has been developed to support the learning analytics function described in the next section.

5.3. Teaching functionalities on the VLE

"Most of the features of [the VLE] have been developed with faculty in [the School] in order to support real teaching patterns" (S_025); therefore, the VLE offers "a range of tools (…) that can be used to enhance learning for the students" (S_024), including: structured forums, video and photo assignment submissions, interactive questionnaires, collaborative online spaces, course-specific blogging platforms, and "analytics for online content enabling detailed progress and engagement tracking for teaching faculty" (S_025). Faculty are assigned to module occasions they teach on and can add teaching materials to them themselves or ask the Teaching and Learning Support team for assistance. Faculty are also notified of assignment submissions for marking. They also use the system for personal tutoring of their students, where they can see individual students' academic records and attendance records, "along with a graph that shows when you submit your work, how close to your deadline you are" (I_Technical_001). Examples of teaching tools include specific lesson activities, gated content which can be accessed only after completing certain activities, photo walls, and similar.

The regular uses of the VLE among teaching staff include adding teaching resources, sending out communications, publishing results, and accessing the Academic Balance Model, a system developed to allocate teaching, administrative and research hours according to a points-based system (e.g. INotes_007, INotes_008).

5.4. Administrative functionalities on the VLE

Administrative staff rely heavily on the VLE in their work. Those working in roles supporting teaching and learning add materials to the VLE, set up templates, folders, fora, and work together with academics on designing appropriate exercises (I_APS_013, I_APS_015). In other functions, administrative staff would use the system to access documentation, such as policies, procedures, handbooks (INotes_020), as well as to use tools designed specifically for them, for example Module Approvals, where they can oversee changes to existing and proposals for new modules, as well as the Online Exam Board system (INotes_020, INotes_014). Overall, administrative staff were appreciative of the number of improvements to their work that the VLE has brought, with occasional comments on potential future developments. Significantly, administrative staff tend to focus on a higher level than a particular module, but they look at whole degrees and programmes (I_Technical_001).

5.5. VLE use training

The system was developed to be intuitive and not to require any documentation and technical specification ("Strategically we don't do documentation for largely, two reasons. One is that in particular these days; you wouldn't expect to have a manual to use Facebook. You wouldn't expect to have a manual to use LinkedIn. (…) It's a principle. So if you really need to explain it then it's probably bad design. You change the design. But the other issue for us that [the VLE] was simple when we started" (I_Technical_001). New members of staff are introduced to the system by the Technology Utilisation Consultant, who demonstrates how the VLE works for a particular member of staff, as the system is "personalised" depending on the role played (I_Technical_001): "Front page tends to have a lot of information crammed into them because they're gateways to the rest of the information. So a front page is really for an experienced user. So my script in as much as I have one is to basically say like ignore all of this complexity. And I take a piece of paper and put it over the screen and hide most of the front page. And there is a menu at the top which is called quick links. And it actually is the list of activities that you personally are associated with. So it's a very small one. So basically, it's a little box at the top of the screen that has the names of those modules on it. So that is this website." New staff are encouraged to experiment with the system in their first weeks on the job and are offered help from the Technology Utilisation Consultant.

The VLE developed into a system at the core of the School's "digital campus": "We're at that special [point] where … if people say, oh I missed something in [the VLE]. They do say that. And we know that that's the preferred way that people have now of being notified, so that window is there. That space is defined" (I_Technical_001). The VLE became the de facto digital space for the School, much aligned with the vision set out in the TSC several years before.

6. The LA system

Analytics of online content is advertised to the School's staff as one of the ways in which the IT team supports teaching (S_025). In general, the LA database collects data about all actions on the VLE and displays some of it in a pre-aggregated format to students and mostly academic and administrative staff.

6.1. History of development

The development of the LA system can be traced back to early 2013 when the TSC received a project proposal from the then e-Learning group to develop capacity within the VLE for "[2013-01-C] Monitoring Lesson Understanding and Tracking Progress" (M_001). The project was first aimed at Distance Learning MBA students, as the School has a "duty of care" towards them "to ensure they are understanding module content", "to continually improve module content", and to "provide them with adequate support to complete the programme" (M_001). The project proposed to develop a simple view of students' progress through modules, including lessons viewed and assignments submitted, as well as to add a self-reporting question confirming understanding at the end of each lesson. The rationale for the project was to "focus the tutorial support resource, and ultimately improve student retention and progression. This in turn should lead to higher revenues" (M_001). The key pedagogical drivers for the implementation of the project were to "encourage students to engage more with the discussion and interaction and to make sure that they were getting the most from the teaching materials" (M_002). It was explained in the project proposal that "the project would leverage recent work in [the VLE] which records in fine detail engagement with the site including reading resources, registering for modules and many other activities." (M_002). The project was approved in January 2013. It was not clear from the documentation when exactly the "recent work" recording data about the use of resources was done in the VLE, and when questioned about it, one interviewee related that the data-gathering functionality was developed together with the e-Learning team in a more bottom-up approach ("It's not a tremendously formal process. We work very closely on all sorts of things so we have monthly meetings to discuss things and then additional meetings too, for particular projects", I_Technical_012). In 2014, the TSC received a proposal for "[2014-09-A] Student and Tutor Monitoring for Online Modules" (M_013) put forward by a representative of the Master's programmes who "presented a proposal to collect both explicit and implicit data from student and tutor interaction with [the VLE]. This data would be aggregated and shared with academics, tutors and administrators, along with students themselves, to act as an early warning system which would identify when students were not engaging with the learning materials" (M_013). The proposal was approved.

In early 2015, the new version of the VLE was demonstrated at the TSC, and the demonstration included "learning unit developments including analytics" (M_019). As the work progressed, the previous "[2013-01-C] Monitoring Lesson Understanding and Tracking Progress" project and "[2014-09-A] Student and Tutor Monitoring for Online Modules" were merged and resubmitted as "[2015-10-D] Student and Tutor Monitoring for Online Modules" (M_021) with an explanation that "this version includes the aspect of monitoring tutor interaction in order to maintain standards and the student experience" (M_021). This effectively extended the scope of analytics to cover staff activity. The same project incorporated an earlier "[2012-04-A] Enhanced Support for DL Tutors".

As recently as in 2016, the TSC held a discussion on “making [the VLE] data available for research projects”, as “recently there have been a number of requests from the academic community within the School for access to [VLE] usage data in order to support research. The School would like to support this activity whilst having oversight of who is working with our data. The school is also cognisant of the implied workload in providing this data for research activities and would like to create a policy which is sustainable whilst delivering the maximum impact to the School” (M_022). This demonstrates increasing maturity and awareness of the value of the LA data within the School.

6.2. Back-end of the LA system

In general, the LA system collects all usage data drawn from various databases. Data is stored in a flat log of actions, and analytics is mostly drawn from pre-aggregated collections of actions from an NoSQL MongoDB database and displayed on the VLE through a REST API. The analytics is displayed in the LA system under a button on the screen titled “Moderation”.

The flat log storing all VLE actions consists of the following fields: user ID, timestamp, specification (actor, IP, type of action <login|view|comment|create-<type>|goal-<id>|videosession|accesslibrary> and others), item ID. Based on this data, pre-aggregated collections are created, for example by action, last access, last user access, count, and similar. These collections were decided upon by the developer of the LA system in collaboration with the then e-Learning team (I_Technical_012). Pre-aggregated collections can, for example, list a history of actions for a given VLE user, by attaching to the user ID a particular action and timestamp in the following manner:

```
User ID:
    Action:
        View:
            Time:
                Item ID: Number of interactions
                Item ID: Number of interactions
```

In the words of the Information Systems Consultant who developed the system:

> “So, the gist of it is that it’s … we have the concept of actions, so an action being viewing something, commenting on something and so on, viewing videos. Whenever one of those activities happens, we generate a chunk of data which represents that interaction, and that goes into at least two places. So, one, it goes into a flat log which is a matter of record. It means we can go back in future if we want to do new things with it and restructure, and it also goes into some pre-aggregated collections of data. So, the gist of it is because of the log data and the tens of thousands of modules to do this, to just ask all the data questions is quite a complicated and expensive thing

essentially, so what we do is we ask the question in advance and record the data, we [store it] in different ways. What I mean is that you'll have a count, you'll have a bit of data that says how many people have viewed this since the count of 800, but we’ll also have a log that says these are all the instances that happened, and we also have the distinct list of all the people who have proving that’s happened. For the learning unit style content, i.e. lessons within a sequence of lessons and so on, we record that data for an individual page for the immediate lesson, i.e. the chunk of content and then for all site content. (…) It varies depending on what you're doing. So, for example, viewing a video, it’ll have information about the segments of the video you watched and how many times you rewound it and all sorts of things. Yeah, and then it also has this stuff which is the context of which it was viewed, i.e. what lesson it was part of. If you look at … This item, this is aggregated information about that from the perspective of a particular item. So, you can say this is the last time it was viewed and the total number of times it was viewed”.

(I_Technical_012)

The database that stores the pre-aggregated data enables the creation of person-item states displaying the relationship between individuals and content: “the relationships between persons, whoever that is, and this bit of content is the actions, so: last time they viewed it and the number of times they viewed it, and then the history” (I_Technical_012).

6.3. Front-end of the LA system

Pre-aggregated LA data is displayed in general to all academic staff on the module occasions they teach, as well as to administrative staff with appropriate permissions. Clicking on the “Moderation” tab, staff get access to a set of usage statistics concerning the piece of content they are viewing in the VLE. The statistics available vary from the simple number of views of a page, resource or video, to a breakdown of times when the resources were accessed and by how many users, to more sophisticated displays of user progress through the course material.

In Figure 11 below, an academic can see the number of views or non-views of a message sent to users. Users, either staff or students, are listed individually by name with their last login time. An academic can view users’ profiles and contact them through this window.

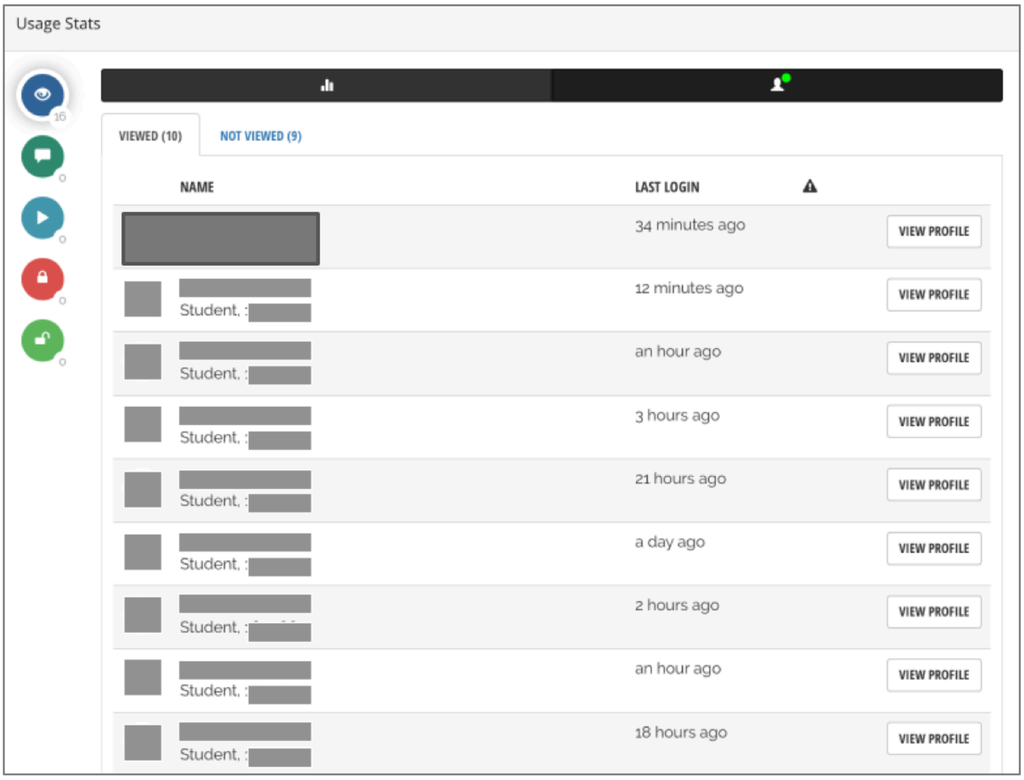

Figure 11 LA system: usage statistics for messages, S_016

Similarly, an academic can change the view to display the aggregated number of views during a specified period of time, from a day to a year, as displayed in Figure 12.

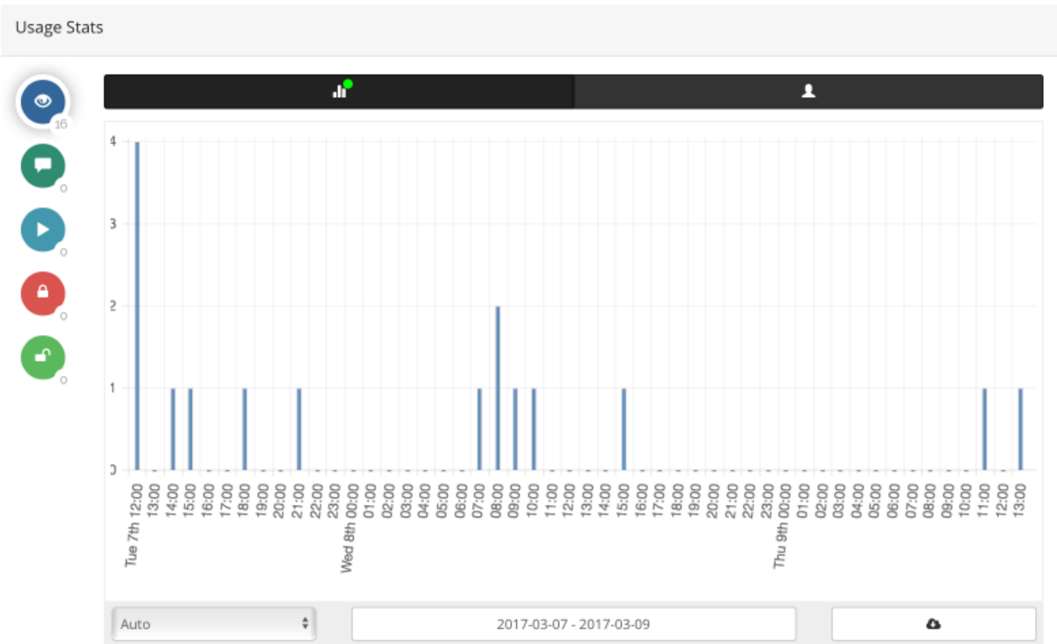

Figure 12 LA system: aggregated usage statistics for messages, S_017

As for resources made available on the VLE, academics can use the "Moderation" tab to access a range of LA data on their module occasions. At the most basic level, academics can view progress through the material of each individual user, be it student or member of staff, as shown in Figure 13.

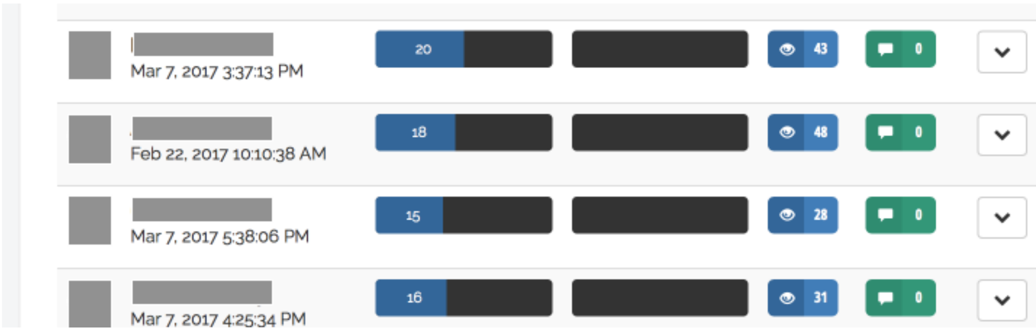

Figure 13 LA system: progress statistics, S_019

In this view, an academic can see how users are progressing through viewing the materials online and how many of them self-reported completion. Academics can also access the breakdown tab which aggregates users into quartiles of activity, as shown in Figure 14.

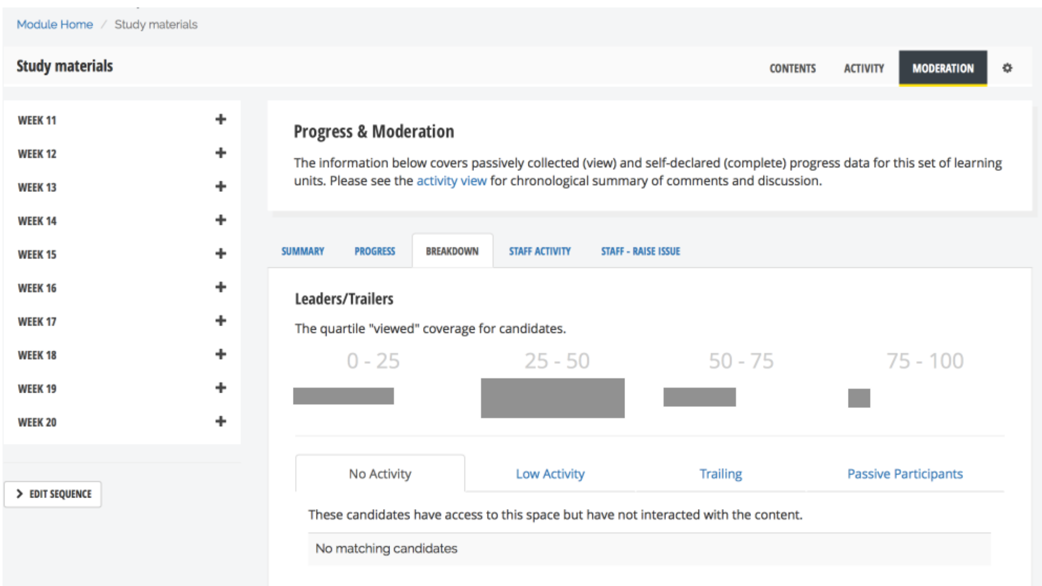

Figure 14 LA system: breakdown of activity into quartiles, S_018

The greyed-out areas on the screenshot contain small, circular photos of students falling into each quartile. Finally, academics can also see the number of views of their resources organised per week of teaching, as shown in Figure 15.

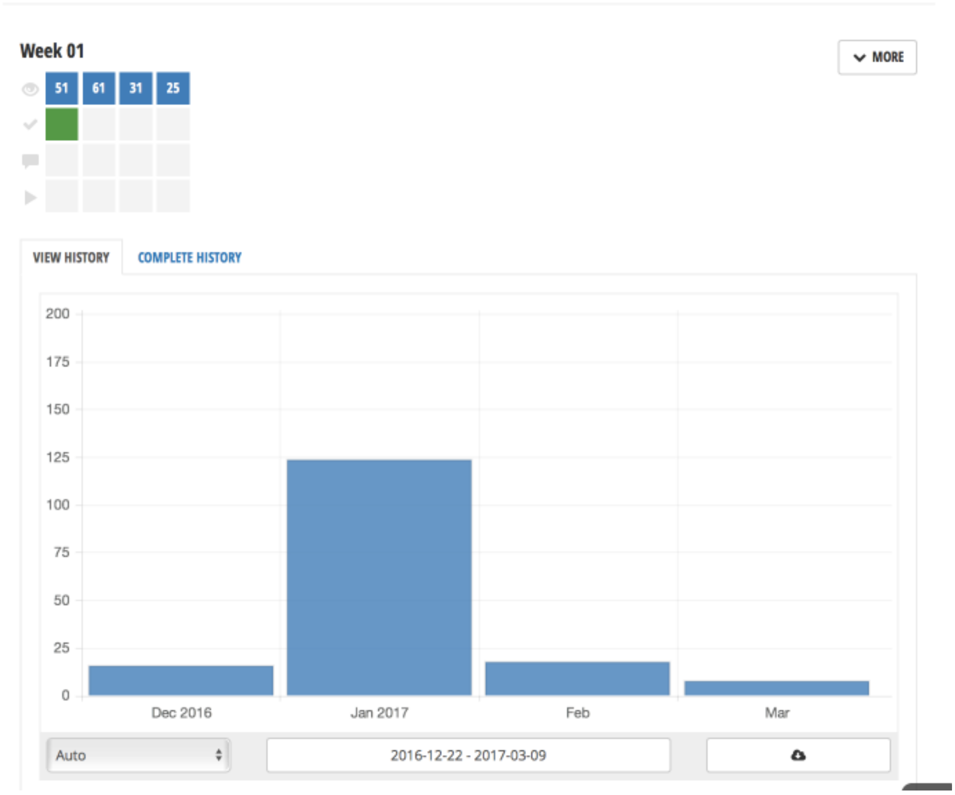

Figure 15 LA system: weekly views, S_020

6.4. Adoption of the LA system at the School

The adoption of the LA system at the School is limited mostly to the Distance Learning team and a group of analytics enthusiasts. This is one of the reasons why the IT team admits "it's not that we're doing any particularly complex analysis. What we're trying to do is expose to people that the data exists at all. And in order for them to actually work out what they want to do with it" (I_Technical_001). In order to raise awareness of the LA system, the Technology Utilisation Consultant organised a number of workshops, one of them attended by myself: "I mean to be honest in the last year we've done a few seminars. And I've done some seminars, not particularly well attended. I think you came to one of them" I_Technical_001). During the seminar, he admitted that there was no "strategic approach to analytics" at the School (S_023B).

The LA system was demonstrated at a Tutor Away Day in 2014, where "this group was particularly interested in the Engagement Analytics facilities which were first deployed in the finance SPOC and for which we have a project planned for further development [2014-09-A] Student and Tutor Monitoring for Online Modules. It was felt that this technology would be well used in Distance Learning and was enthusiastically welcomed by the tutors." (M_014).

The Technology Utilisation Consultant also decided to sensitise new members of staff to the data available: “I have recently started mentioning that really there’s so much information. I mean when a new member of staff turns up, they're presented with a tremendously large amount of stuff. And I don't think the analytics really starts to make sense until you're using it yourself. And once you've done something that's represented in the analytics, that's the time to have a look at it. Because it's only when you've done something, you know, that you've marked a few pieces of work and you posted some resources, it's only then when it starts that it’s worth looking to see whether anyone [inaudible 00:31:01]. You can’t, in the abstract; I don't think it makes sense to introduce too much from the word go. But I do point out absolutely that of course everything that happens here generates data and almost all of that will come back to you at some point” (I_Technical_001).

The Technology Utilisation Consultant acknowledged that there is a problem with encouraging staff to make use of the data: “But you can see how many people have turned up when you do that sort of thing. It’s a tricky problem for us at the moment. And the reason for that is that it doesn’t matter how many workshops I do about analytics, only the usual suspects will turn up. That's the way that it works. People who are really interested and we got good relationships with them and if you do it, they'll come. Most people are too busy and most people don't notice. And it's quite difficult to communicate with a very large … like 400 people.” (I_Technical_001).

When asked about his colleagues’ reactions to the introduction of the LA system, the Technology Utilisation Consultant admitted that some of them were cautious, but overall the functionality was very well received: “Well, you know, people have made the occasional joking remark in committee meetings saying, ‘This all a bit 1984 isn't it?’ It’s a university, people are going to make those remarks. And I made that, I’d made them myself, you know. But no, in actual fact, the context of all of that has always been that that’s come up because people wanted to use the data, because they wanted to think they generated the data, so it hasn’t ever come up as a… it’s never come up as a negative thing in its own rights, that was raised as a subject in its own word” (I_Technical_001).

The sentiment towards the LA system among the LA enthusiasts at the school can be best summed up by the words of one academic interviewee:

> “Online, before the beauty of analytics, we were doing that online in a very cold way. We were losing the ability to see where different people were. We were basically getting people involved in rote learning or moving at the same step, and it’s a pass or fail. The measurement was very crude. Now, we’ve got all of this intricacy. You can get more of a

> sense of, ‘Okay, well this person has looked at videos. They've hovered a lot in that area. They've then done the self-assessment quiz. They've managed to get half of it right. They’ve then contributed to this.’ Their response… this is actually really good. And you're getting a pattern of that person’s learning over the number of tasks that they've done. It's not the same as looking them in the eye and feeling what they are feeling as they are learning and seeing their sense of achievement. But you can kind of, as a human being, you kind of imagine that. If you've been a teacher face to face a long time, you kind of imagine that sense of … you associate it to what you're seeing on a page. And then when you do meet the person either online or face to face, you do have a sense of who they are in terms of what they have achieved. But there was a period when the analytics were not as they are today, when online learning I think was a very impersonal activity.”
>
> (I_Teaching_002 Follow-up)

7. Conclusions: towards an analytical campus

This detailed case study narrative served as the basis for the analysis that follows. Apart from presenting the overall, global context in which the University competes and outlining the relationship between the University and the School studied, I focused on drawing attention to various elements of the School relevant for the analysis of the case study: the role of the Technology and Strategy Committee, the work done by the IT team, the involvement of the Learning and Teaching Support, among others. I then fleshed out the inner workings of the Virtual Learning Environment developed, deployed and maintained at the School by the IT team, and summarised how the VLE is used by various stakeholders. Finally, I presented the history of the LA system and outlined the front-end and back-end of the system.

What emerges out of this thick description is a School who made digital transformation its key strategy and a priority to ensure growth and revenue. The metaphor of a “digital campus” is a very fitting lens through which the case study site can be seen. Essentially, the School, through the work of the IT team guided by the Technology and Strategy Committee, developed a digital equivalent of its physical functioning: students, academics, and other members of staff became users, the School and its premises became the VLE, and the actions of teaching and learning, core to the functioning of the School, became interactions on the VLE. This is even likely to gradually replace the physical School, as in the words of one interviewee: “In my opinion, I think our on-campus students are going to be on-campus Distance Learning students, and they’re going to work through [the online] material” (I_APS_005). The progressive mediation of teaching and learning with technology is propagated and advocated for as a tool to introduce efficiencies, increase revenue and heighten student engagement. Somewhat on the sidelines, as a by-product of the interactions on the VLE, the LA system was developed to introduce further efficiencies. However, the digital campus is extended even further through the mapping of teaching and learning at the core of the School’s activities into data points subjected to various analytical processes. By capturing and representing these core activities through data, the School creates an analytical campus in which all actions and interactions are recorded and analysed.

In the following section, I propose a reading of my findings from the case study through the analytical framework presented earlier, in the context of the above narrative.

Chapter 9: Analysis

1. Introduction

In this section, I examine the analytical detail to lay bare the workings of the LA system as a technology of measurement, together with the mechanisms and effects caused by the extensive data production taking place. Set against the thorough description in the previous section, I begin my analysis by analysing Learning Analytics (LA) as a Big Data Analytics (BDA) system, with a focus on the characteristics of big data. I then delve into the characteristics of the LA system as a technology of measurement by focusing on the measurement processes involved. Next, I outline the mechanisms of production of LA data that rest upon these processes. I finish this section by outlining how the LA system gives rise to reactivity, with an overview of the mechanisms and effects of reactivity, as well as emerging effects in the context of BDA.

2. Learning analytics as big data analytics

In Chapter 2, I synthesised the current literature on the characteristics of big data that form the necessary foundation for BDA. In this section, I intend to analyse the LA system investigated through the lens of these characteristics to argue that LA data is indeed big data. My second aim in this section is to critically appraise and problematise the claims about the characteristics of big data, on the basis of data collected.

To begin with, it is worth noting that a number of interviewees themselves acknowledged that the LA system is in fact a type of big data for education. As expressed by one interviewee, "when you go from not knowing anything to now, actually, guys, the weak link is your imagination, then that's fascinating. But it's big data, isn't it? It's like all areas of big data, and people are only starting to realise, 'gee, guys, wow, do you know how much we know'" (I_APS_005). Other interviewees drew parallels between the LA system and constant data generation in other big data-based services like Google and Facebook (e.g. I_APS_005, I_APS_013). This from the outset confirms that the LA system is at least perceived by staff as a nexus of big data. Other interviewees, if they did not mention explicitly that they understood the LA data as big data, pointed out that this type of data collection marks a departure from previous forms of collecting data in higher education. Below, I aim to break down and analyse this departure.

2.1. Volume

The LA system provides access at the School to “more data” (I_Teaching_002 Follow-up). It was clear from the interviews conducted that the predominant feeling was one of abundance of data. Some interviewees emphasised that these amounts of data are unprecedented and give insights into previously unknown areas of teaching and learning (I_Technical_001, I_Teaching_002). It was pointed out that having data drawn from different sources created a vast pool of data in the LA system that just by its sheer quantity could lead to new insights (I_APS_005).

However, volume was not universally received as a good thing. A number of interviewees pointed out a certain doubt or worry that while the School has more data than ever, this does not feed into decisions, as there are difficulties with processing and interpreting this data in a useful manner (I_Acacemic_009). It has even been suggested that smaller quantities of data available in the past were put to better use than large volumes of LA data now. Part of the problem was a lack of resources available to process the data (I_APS_029), as different members of staff struggled to find time to analyse and interpret data from the LA system. A related issue concerned the perceived lack of skills related to reading and interpreting data (I_Acacemic_009): in order to make use of the LA data at a larger scale, more members of staff would need to be trained to use it, as expressed by another interviewee: “nobody’s ever going to read it or look at it or understand it because I think [the IT team] do love data and they know that they can produce all sorts of data, and sometimes you get a lot more data than you really need” (I_APS_013). It has also been noted that large amounts of data may lead to drawing incorrect conclusions: “I also worry that because of the amounts of data that [are] available, we may draw conclusions and see patterns where there are none. It's just patterns and chaos which naturally occur. So there's trouble as well as beauty in it” (I_Teaching_002 Follow-up). Thus, to sum up, while volume is an attribute of LA and big data, lack of proper resources and skills in place to analyse and interpret it may have opposite effects of making even less use of data than before.

2.2. Velocity

The LA system enables real-time logging of all actions in the system. No delay between actions on the VLE or associated systems was mentioned in the interviews. While the VLE activity can indeed be stored in the database without delay and displayed in the LA system, it was not possible within the scope of this project to obtain more information on the types of database connections between other databases, e.g. MIS or SITS, and the LA system, thus a delay in supplying data cannot be ruled out. Further, data is generated in various systems at different frequencies, for example the VLE tracking data may well be real-time, but other MIS or SITS or feedback data has a much more periodical nature. The LA system's dashboard allows for displaying the numbers of views in the nearest hour.

Without a doubt, the LA data is produced at a speed corresponding to the velocity and frequency of user actions in the VLE. This of course means that some interviewees appreciated having feedback on the success or popularity of their messages, resources, and feedback much quicker than after the term ends: "So this morning, we were saying 'oh, so and so's tracking stats don't look very good. He's not logging in regularly and he's not … he's writing one post every six posts rather than one post every four posts'. So somebody needs to get on that. It's only Week 4 of the course. We already picked up that a tutor is not doing specifically what we asked. So it means we can adjust that during the course. We don't have to wait until the end and then get poor student feedback about that tutor" (I_Teaching_002 Follow-up).

However, other interviewees signalled that the speed at which data makes its way into the system can lead to premature conclusions and decisions based on quick reactions rather than a careful analysis. The speed of data was sometimes linked to the speed of decision-making, and not solely in a good sense (e.g. I_APS_015). The consequences of this for big data can be quite severe, as quick decisions are not always the best decisions, and some phenomena need time to develop before they can be fully appraised. Furthermore, high velocity of data also requires intensive resources to facilitate its processing, which as with volume can be problematic.

2.3. Variety

The LA system incorporates different sources of data, therefore it satisfies the criterion of variety. It draws mostly structured, but also some unstructured data in the form of images and comments from a broad range of systems. This variety is often perceived as a positive feature of big data in the wider literature, giving access to data points of different types. As expressed by one interviewee: "it's just now we have more ways of measuring available, people are thinking that this data is somehow more significant than it used to be" (I_Teaching_002 Follow-up).

However, looking under the bonnet of the LA system, it could be argued that in the context of higher education, the purported variety of data is in fact drastically limited. While without big data, academics or teaching staff would rely on their own observation, intuition, and a range of interactions with the students and their behaviours, with the LA system the spectrum of data available becomes narrowed down to a prescribed number of actions on the VLE. The variety of big data does not cover social actions taking place outside the VLE and in the classroom, or even during out-of-classroom interactions. As such, the VLE collects only online actions and puts more emphasis on those, removing focus from other types of data (that cannot be easily represented as data and quantified). Thus, despite many claims concerning the variety of data available, big data may in fact narrow down the scope of data collection and be even more dangerous in doing so, as it makes strong claims concerning its variety.

Within the LA system, the users of the feature may end up relying disproportionately more on a narrow breadth of data collected from the VLE and associated systems, discounting other potential sources of data concerning teaching and learning. As one interviewee emphasised: "But I'm just worried about people like that coming in who maybe don't have a lot of classroom teaching experience having a certain perception that the data is going to tell them what the student's progress is. And I just don't feel that it will, it's their interaction with the students and the data that will tell them what the progress is. You can't take that human relationship out of that. There's still got to be socially constructed understanding of what's going on in the learning experience" (I_Teaching_002 Follow-up).

2.4. Granularity

Granularity is often cited as a sought-after, defining quality of big data. Both researchers and practitioners state that big data is far more granular than other previous available sources of data, and thus gives more or different insights. For example, in the LA system investigated, one interviewee expressed that: "Whereas now, because we're getting people to engage with materials online and do their testing online, we're also saying 'how long did somebody take to come up with that answer?' Not just 'did they come up with the right answer?' So we can go more granular with the information. And it's not just a black and white thing anymore" (I_Teaching_002 Follow-up). The LA system analysed gives a granular overview of user actions on the VLE, for example down to counting clicks per every hour, as shown above.

Further, every single action on the VLE is stored in an operation log, detailing the user ID, type of action (<login|view|comment|create-<type>|goal-<id>|videosession|accesslibrary|… others>), time of action, IP address, and what item was actioned upon.

Such high-resolution and fine-grained data was overall considered useful among the interviewees. For example, as an explanation of how this granularity feeds into decisions: "So that's how many video plays, 239 video plays. So you can kind of choose a day of the week or month or year to see, have they done it immediately the day it was released? Or, you know, if nobody's looking at it until the Monday, why are we putting it out on the Friday, you know?" (I_Teaching_002). The same interviewee explained that "when it's granularity, you can get more breadth and width. You can compare much larger data sets than we could have in the past because it's computable. (…) At a fine level, I can look very closely at the learning activities and behaviours of an individual person and give them a much better service" (I_Teaching_002 Follow-up). A longer quote from the same interviewee explains the perspective on the benefits of granularity:

> "Online, before the beauty of analytics, we were doing that online in a very cold way. We were losing the ability to see where different people were. We were basically getting people involved in rote learning or moving at the same step and it's a pass or fail. The measurement was very crude. Now, we've got all of this intricacy. You can get more of a sense of, "Okay, well this person has looked at videos. They've hovered a lot in that area. They've then done the self-assessment quiz. They've managed to get half of it right. They've then contributed to this. Their response… this is actually really good. And you're getting a pattern of that person's learning over the number of tasks that they've done. It's not the same as looking them in the eye and feeling what they are feeling as they are learning and seeing their sense of achievement. But you can kind of, as a human being, you kind of imagine that. If you've been a teacher face to face a long time, you kind of imagine that sense of you associate it to what you're seeing on a page. And then when you do meet the person either online or face to face, you do have a sense of who they are in terms of what they have achieved. But there was a period when the analytics were not as they are today when online learning I think was a very impersonal activity."
>
> (I_Teaching_002 Follow up)

This very promising vision of the role of analytics and the granularity of its insight into teaching and learning is not universal, though. In stark contrast, another interviewee emphasised that the LA data "at the moment, they're not granular enough to be of any assistance" (I_APS_004) in their particular role. The same interviewee continued to flesh out the issue: "I went to [Technology Utilisation Consultant] and said, can you, you know, how many people... And the report I get back is something like, you know, 20% of the student group have read 40% of it, which is interesting but it doesn't tell me which bits of the student group are reading it. And if they're reading it, well why are they reading it? Well what are we doing different in that particular course that we're not doing elsewhere that's causing them to read it?" (I_APS_004).

There are certain risks associated with the current level of granularity in the system, as I encountered in one interview presented below.

> "I_Academic: Because obviously when you create these videos, you think like, well, would the students really watch those or not? And when we got the statistics, we saw that we had 300 students there. And the viewing statistics, they were anything between 1,600 times to 2,700 times for video. So, every single student, on average, they watch all the videos like four, five, six times. We're really glad about that.

> Interviewer: Do you know if that data was granular enough to tell you each student watched it five times in its entirety, or was it five attempts to watch it that may cover different times?
> I_Academic: Right. Okay. It wasn't granular enough because it was what you said, it was attempts. So, it was basically one view, what they call a view meant that the student loaded the web page. So, we didn't even know whether they clicked the video. So, we just assumed that."
>
> (I_Academic_007)

In this example, it is evident that granularity of the LA data causes difficulties with interpreting it correctly, and it may lead to misunderstandings, as it did in this case where the interviewee initially assumed that a particular resource was very popular, while in fact the system was capturing web page views, which may not correspond to views of the whole resource per student. This is symptomatic of a wider problem with the LA system related to its granularity: without proper descriptions and definitions, data points may be difficult to interpret, or even plain misleading, as poignantly explained below.

> "I_Acacemic_2: But you see, it was either the way the data was presented or what it actually meant when you tried to interpret it, it was like….
> I_Acacemic_1: In some cases, there were no data definitions, so there was a name but it didn't define what it was. In some cases, the name suggested it was a proportion or account or, as it turned out, it was a percentage in…. We also found that there was tendency to present the data at a very high level of granularity. So, they would tell us what every individual student was doing, but we couldn't actually find out what the cohort was doing."
>
> (I_Acacemic_009)

The LA system provides data that is very granular indeed, but this causes difficulties with interpreting it correctly and deriving useful insights from it. Thus, granularity of big data may in fact obstruct the usability of data rather than enhance it in the system studied.

2.5. Exhaustivity

Exhaustivity of big data is often referenced as one of its defining characteristics, as it is claimed that big data can collect data on entire populations rather than samples, or collect all data rather than just some variables. On the face of it, the LA system is exhaustive in this sense: it logs user actions of every user ever logging in to the VLE, and it logs all the pre-defined actions. As one interviewee expressed it, "the data's there, everything is there" (I_APS_005), and another, overwhelmed by the sheer exhaustivity of the LA system exclaimed "let's have a look now and see if it's still listing the world and his flipping wife" (I_Acacemic_009). The same interviewee pointed out, dismayed, that the LA system displayed historical data about a deceased colleague (I_Acacemic_009).

Some interviewees pointed out that this exhaustivity could be misleading or even false. Some teaching staff expressed their doubts that teaching and learning behaviours can even be captured in the VLE, as they made limited use of the system (I_Teaching_025). This is an important point to make: big data may indeed be exhaustive with respect to collecting data in a particular system, but this does not mean that it captures a specific phenomenon in an exhaustive manner. Assuming otherwise can have serious consequences, in this case mistaking the LA data for data about teaching and learning in general. This sentiment has been captured well by one of the interviewees:

> "I think there's this tendency for people to see data as a…a cure-all for everything. So if people become too fixated on the data, they forget about the humans behind the data. So, you know, I guess the worry is that a person teaching is presented with this information. You can see what your students are doing and you rely on that data to make decisions about the students without actually talking to the students. You know. It doesn't tell the full picture at all. If you talk to somebody perhaps, they're bored because they're finding it too easy, or perhaps they're having difficulties and they need support with something. So I guess it's just making sure that you don't forget that you've got humans there generating the data, and it doesn't kind of become this thing that is a cure-all. And also, you know, data's not perfect. So again it's a bit like with the whole big data, you know, push. People saying we've got loads of data now so we can tell everything. No, it's just as biased as a small data set, you know. So I guess it's that risk, you know, that people misuse it, but mainly that you forget that, you know, that human contact with the student is really important to teaching I think."
>
> (I_Teaching_011)

This particular interviewee expressed very well the issue of big data, and the LA data as well, capturing only parts of the picture, therefore going against the claim of its exhaustivity.

2.6. Veracity

Veracity, that is, the accuracy of big data, has also been heralded as one of the most important characteristics, marking a stark contrast in comparison to other types of data collection. It is claimed that because big data is collected in an exhaustive manner and with no a priori theory, it is more accurate. As one of the interviewees, a technical member of staff, claimed: "it's very black and white" (I_Technical_012), and "this is just the fact" (I_Technical_012). The LA system investigated is no different here, in the sense that its developers intended it to be an accurate and truthful record of user activity online (I_Technical_001, I_Technical_012).

However, in the case study there were significant problems with veracity of the LA data because it was prone to misinterpretation. That is, it accurately captures and displays the number of clicks, but it can be interpreted and acted upon as if it constituted a different data point altogether: “I've kind of got used to what the data does and doesn't show us because I've had that many conversations with the people responsible for this. But actually I've made certain assumptions in the past, I’ve said ‘oh I can get this’. And then I've gone back to [a colleague] and said ‘so I can get this, right?’ ‘No…no it doesn’t show us that’. And I don't think there's a clear…I don't think there's a transparency in what that data is. So just, you know, very simply when you look at the access statistics it is really…somebody has clicked on it, but I would imagine many people around here probably think ‘oh that student has looked at that lecture now’, but it doesn't tell you that. So I guess that it's not very transparent” (I_Teaching_011). Continuing in a similar vein, the same interviewee spoke directly to the issues of veracity of such data: “I would somehow like to know if people are actually using the resources rather than just clicking on them” (I_Teaching_011).

Another set of issues has been pointed out in relation to how the LA system actually captures views. Users for example may receive an email digest that contains a particular resource or a message and read it in their email client, thus being familiar with its contents, but they would show as not viewed in the LA system: “we can make an assumption that I might need to cover that for that particular group because it looks like they haven’t really looked at it. Although, you know, it’s possible that they could see the advert there and they went and looked at it in another way, or that a few of them were looking at it together” (I_Teaching_018), thus again challenging the veracity of the data. A technical member of staff admitted in one of her reports, when explaining surprising findings from the LA system, that “Another reason could be that they are accessing the resources via another route, perhaps by sharing a computer with another student or downloading/printing the material, so these analytics may not always be totally accurate” (S_021). She also further added: “When it comes to stats, it is very easy to misinterpret the data and what exactly it shows. For example, a high average mark on a module may indicate successful module delivery; however, without digging into the data further, you can’t tell if everyone got a high mark or if most people got low marks but the average was brought up by a couple of outliers. There have been a couple of occasions where it was clear to me that the programme team had misinterpreted the stats, and I had to explain to them exactly what the numbers represented” (S_022).

Similar worries around the veracity of data were expressed by a member of senior management, who in the group interview admitted that “the only concern of mine is around the information given about student behaviour that comes to faculty is that it’s so crude, still. So there’s lots of data, but most of it is of very, very poor quality. It doesn’t matter how much poor quality you have, it’s still poor quality” (GI_001). Thus, the claims of veracity of big data should come with a number of qualifiers, as is evident in the LA system studied.

2.7. Use-agnosticity

As presented in Chapter 2, one of the defining characteristics of big data is its use-agnosticity, sometimes captured in its "sorted-on-the-way-out" nature. This means that big data that is collected can then be re-used and re-purposed for other types of analyses, or perhaps even different uses altogether.

The LA data is, by all means, a by-product of online activity on the VLE: it is "the data that comes off education, [it] is not its purpose and it's not its driver" (I_Teaching_002). The staff interviewed were also aware that this data can be used for other purposes: "So it's really good that we've started to collect the data and we've got this quite rich set of data already. (…) It's just that quite a bit of information (…) could be used for other purposes as well." (I_Technical_010). The "sorted-on-the-way-out" nature of big data is perhaps best explained by one of the technical members of staff: "So, [the] idea of it is that it's taking all that data, pre-aggregating it at different levels of granularity such that you can make comparisons horizontally and vertically in an interesting way, sort of choose just … so it can be reports for any module since the aggregate of it across all the years and all occasions, the specific occasions within the year and that sort thing. But you can also search for individual teaching faculty. You can search for courses and programmes and teaching groups. So it's aggregated in all those dimensions" (I_Technical_012). This provides an explanation as to how the data can be displayed and re-cast to suit particular needs as and when needed.

Use-agnosticity and this openness to sorting data on the way out as and when needed was met with resistance from a particular duo of interviewees who are professional data modellers: "And so, we actually, because, of course, we're actually all data analysts or modellers, we actually found it at that time, we found it very difficult to understand, most of it extremely opaque. From our professional perspective, we considered it unusable" (I_Acacemic_009), because "this [LA system] was designed without consulting us, so we didn't understand what questions it was trying to answer" (I_Acacemic_009). Trying to diagnose what caused such use-agnosticity, one of the interviewees stated: "I think what happened was that either it was built with other staff, or worse, it was built with people second-guessing what staff might want, which is what I suspect" (I_Acacemic_009). These particular interviewees were adamant that for data to be useful, "questions should come first" (I_Acacemic_009), and that "it may well be that the people designing that system were posing questions, but they weren't intuitive to ask who might be using it" (I_Acacemic_009). As the system was developed without inputs from the team of data modellers, they expressed their surprise at this:

"I_Academic_1: Nobody's ever asked me how I might want to use it or….
I_Academic_2: No, what questions are important (Overlapping conversation) The other thing that's very frustrating is, given that we have a lot of expertise in data visualisation from an analytical perspective and we are data analysts, to not ask us just seems mad.
I_Academic_1: Yeah, just seems mad. (Coughing)
I_Academic_2: But then I suppose we did come to an existing system, didn't we? (Coughing) But even then, when it became clear at that meeting that none of us knew what was going on, you think somebody (Overlapping Conversation).
I_Academic_1: I mean, there were five highly experienced analysts in that room. People with dec-…between them, probably approaching….
I_Academic_2: I wouldn't be able to guess. Everybody's got….
I_Academic_1: Everybody…well I've done 20 years, so I would say probably a century, a century of analytical experience. Probably that's an underestimate, because if you think about [a colleague] and [a colleague], more than a century of analytical expertise and we didn't understand it."

(I_Acacemic_009)

The scale of the problem is further emphasised by the interviewees: "And it's just silly…for us, it's silly things like, there are certain conventions about diagramming, but there are also some things that are actually technically incorrect, and some of those diagrams are actually technically incorrect. And we, as analysts, look at that and go, 'Ah! It's wrong!' For example, if your x-axis is continuous data and you're doing a histogram, your bars should touch because you're looking at the dispersion across the range. And you have a look at the bars and they're discrete. And you're just going 'I'm sorry, that's just sloppy, because it's wrong'" (I_Acacemic_009). The scale of discontentment with the apparent disregard for the modellers experience was evident as they were walking through the LA system step by step.

"I_Academic_1: And it's just, if our students did that, we'd mark them down.
I_Academic_2: But also, they haven't labelled the y-axis, so that I think (Overlapping Conversation).
I_Academic_1: Yeah, there's no scale.
I_Academic_2: I think it's number of clicks.
I_Academic_1: Yeah.
I_Academic_2: But I'm not sure.
I_Academic_1: Yeah, no scale.
I_Academic_2: No units.
I_Academic_1: No units.
I_Academic_2: If we would, we'd mark the students…
I_Academic_1: We would, we would be so rude about that. They wouldn't do very well, would they?
I_Academic_2: No.
I_Academic_1: That's a pass, probably-ish. Well, it's got no title, no axes labels. Oh, just heaven forfend, it's just wrong. And there are definitely … we definitely saw histograms there, where they got separate bars on a continuous horizontal axis.
(…)
I_Academic_2: And average what?

I_Academic_1: Oh, it's average mark, you find out by looking down there, so. But even so, it's still wrong. Ah! There's one, right.
I_Academic_2: This is your histogram.
I_Academic_1: That's the histogram. Wrong. Just so wrong. If I sent that to the external examiner, the external examiner would be very rude."

(I_Acacemic_009)

To sum up, it transpired from the interviews that despite the fact that the School has a team of experienced data modellers, they were not involved in the creation of the LA system, or even consulted on its development. Instead, the main developer responsible for the system is a programmer majoring in artificial intelligence, who described his level of skill in statistics as follows: "it's, I'm a bit rusty on some things but I did artificial intelligence at university, fairly statistics course so …" (I_Technical_012). Thus, the LA system was in large parts developed by a programmer with a degree in artificial intelligence with limited inputs from other members of staff skilled in data modelling or statistics, and with scant contributions from other members of staff, including the system's primary users. Another technical member of staff (a web developer) who was partially responsible for bringing in the users' perspective to the LA system described her involvement in these words: "I think mainly based on my experience in the role as technology integrator, I know what the programme teams wanted. I know what they want, what kind of data they want to see, and also we had conversations with members of staff which were outside my expertise to see what kind of metrics they would want to see" (I_Technical_023).

But the LA system does not seem to only exclude the data modellers' experience. It was accepted by an interviewee that "it allows me, because I've got skills with the data as a trained statistician, it allows me to actually make use of that data" (I_Teaching_011). This interviewee pointed to the fact that certain skills are required to properly make use of and interpret this data, otherwise "there's always a danger when giving people access to data who are not trained at working with data – that they will see something, and they will therefore jump to the conclusion that this has a causal link with something else" (I_Teaching_011).

Juxtaposed with earlier claims of various teaching and academic staff misinterpreting the data, it is not unfounded to claim that making the LA system use-agnostic and open to "sorting-on-the-way-out" lifts it out of well-established data and statistical expertise required to interpret the data correctly. Instead, members of staff with no or little training on how to work with data are presented with an LA system where they can modify the data without the prerequisite skills.

Thus, use-agnosticity and sorting-on-the-way-out in the LA system investigated meant that the input from the programming team was overwhelmingly emphasised, at the expense of inputs from data modellers and statisticians, as well as pedagogically-skilled teaching and academic staff. The resulting LA system then seems deprived of important expertise, although available at the School, in statistics and pedagogy. This means that the LA system itself may not have benefitted from this expertise in its development, but also its use may be hampered by the lack of appropriate skills.

2.8. Conclusions

At the start of this section, I set out to analyse whether the LA system can indeed be seen as containing big data. Through a detailed description, I have proven that the LA data I encountered in this study were indeed characterised by the main features of big data, as discussed in Chapter 2, namely volume, velocity, variety, exhaustivity, granularity, veracity, and use-agnosticity. It can then be concluded that the LA system deployed at the School deals with big data, and can thus be seen and treated as a subset of BDA.

Secondly, I aimed to provide a detailed critique of such characteristics of big data, and through bringing in evidence from interviews and documents collected, I explained, on the basis of the study conducted, how each of these purported qualities of big data are far more problematic and complex than the majority of the literature would like to assume. Each characteristic, in practical applications, comes with significant qualifications, limitations, and outright negations of claims often made about big data. This, in itself, brings in important factors to consider about the nature and standing of big data and its analytics.

3. Learning Analytics as a technology of measurement

In the case study, the LA system in the VLE has rapidly emerged as a new way of uncovering, representing, and quantifying social actions related to teaching and learning, sometimes referred to as "measuring success" (I_APS_013), "a measure of accomplishments" (I_Technical_001), or "measuring value" (I_Academic_007). This suggests that recasting LA as a technology of measurement and analysing the associated processes can prove to be a fruitful perspective on how LA systems attempt to measure teaching and learning. At the same time, I uncover the characteristics of the LA system as a digital artefact and highlight the observed benefits and shortcomings of its nature.

3.1. Measurement processes in Learning Analytics

Like most technologies of measurement, as described in Chapter 2, Learning Analytics relies primarily on the process of *representation*, i.e. transforming objects, states or processes into information about them. Such information is essentially selective, abstractive, and reductive of what it represents, as outlined in detail earlier. It is clear from the technical documentation and detailed description that the LA system investigated relies on representing teaching and learning as "views", "log-ins", "comments" (S_002), and all six different types of "actions" prescribed in the system (I_Technical_012). In other words, to learn and to teach becomes to log in to the system, to view a resource, and possibly to comment on it. Needless to say, this is a selective and arbitrary representation of what constitutes a highly complex and socially-embedded phenomenon of teaching and learning. Teaching and learning become objectified, and specific properties are assigned to them. As one interviewee expressed clearly: "just because someone's looked at a page doesn't mean that they learnt" (I_Teaching_016). These processes become decomposed and broken down into user actions which, from the perspective of the developer who created the LA system (I_Technical_012), somewhat represent what happens in the process of educating. Thus, to paraphrase Kallinikos (1995), in the LA system the interior texture of teaching and learning is dissolved into six isolated actions, which become the only visible symbols of educating. As such, they also become measurable, from the particular viewpoint or mind-set of a software developer. Without representation, teaching and learning would not be able to yield themselves to processes of measurement, and would not trigger the host of other procedures which are built upon this representative information.

Some interviewees, notably mostly technical staff, seemed less sensitised to the transformative nature of representation in LA. According to one interviewee, data "makes a historical fact" (I_Technical_001), exemplifying the approach within which some users equate data with activities and actions. Most, however, display a somewhat weaker form of this strong conviction that data is a fact about learning. However, they use mediating, in between descriptors, suggesting that this data represent progress (I_APS_013), success (I_APS_013, I_APS_021, I_Teaching_027), engagement (I_APS_017, I_APS_019), etc.

One interviewee in particular captured this idea very well: "So you can show it to the students, and they get the sense of 'Wow, I want to be up with those guys.' You don't even have to say anything because the sort of herd mentality means that through that visualisation of the data, it's such a simple idea, the students can see that 'Oh, I haven't been doing enough, but my face is in that picture. Can I see myself?'" (I_Teaching_002). Being "up with those guys" means being in the top quartile of activity in the system, and the quotation is so insightful not only because it confirms what the interviewee thinks about this data, but also because it is symptomatic of how data in the LA system is equated with success, progress, or failure and shortcomings in the process of education.

When asked directly whether they thought the LA data represented learning, most interviewees reflected cautiously and qualified their statements, even if what they responded previously was symptomatic of a more simplified view of what the LA data represented: “So it would be very easy for us to use the data to make sweeping judgements, thinking that the data is representing the learning when actually it's just part of it” (I_Teaching_002). “It gives us insights and it gives us, like, spotlights to investigate further. But I wouldn’t like to think it actually represents the learning” (I_Teaching_002). Others would say “yes, you can’t know whether they understood it. You can only know… you can’t even know whether they viewed it, you can only know that they clicked on it” (I_Teaching_018).

Such a revised approach and understanding of what data represents upon reflection is not surprising, especially among the teaching and academic staff, given the context. As summed up by one of the senior managers “we’re all basically social scientists (…) so we’re not just going to buy into these stats somehow revealing the truth about the nature [of] learning” (GI_001). This creates an interesting dynamic between technical and administrative staff, who tend to have a more straightforward interpretation of the LA data, and the teaching and academic staff they support, who develop more nuanced views on what the data mean. For some users, and certainly the developers of the system, the LA data represent learning, or at the very least success or progress, while others take a more cautious approach.

Representation is a necessary pre-condition for *commensuration* and *quantification*, i.e. translating qualities into quantities. In the LA system investigated, learning something well or sufficiently may then become 43 or 28 views (S_019). Making progress in education may become translated into being in the top quartile of 75 to 100% viewed material (S_018), and being a good teacher may mean making comments on the forum every fifth entry (I_Teaching_018). The inherently qualitative character of teaching and learning becomes commensurated into numbers of clicks, views, and comments, and being a good student or member of staff becomes quantified as higher numbers of recorded user actions. In line with Espeland and Stevens’s comments on commensuration (1998), qualitative differences between how students learn and how teachers teach become differences of magnitude expressed in numbers. Commensuration is treated in more detail in the discussion of the mechanisms of reactivity.

As a result of quantification, *numbers* become omnipresent in the LA system. As outlined in Chapter 2, numbers by their nature force some sort of valuing or valuation (Adkins and Lury, 2012), and higher scores and numbers are often conflated with better quality or higher achievement. Juxtaposed with the complex and not fully understood process of learning, numbers of views or comments are deceitfully factual, neutral, and certain. This meant that at the School, some employees would be seen as more dutiful because there was a higher number of comments displayed in the LA system next to their name (I_Teaching_002). However, a particular duo of interviewees expressed their frustration with such use of numbers in the context of education, especially when not clearly explained in the context of the LA system itself:

> "I_Academic_2: And I don't understand what these numbers are, either. What does nought to 14 mean?
> I_Academic_1: They're not defined. Yeah, they're not defined. Yeah.
> I_Academic_2: And what's 14 to 28? And what's 6%?
> I_Academic_1: Yeah. Can you see? From an analytical perspective, we just went (Whooshing Sound).
> I_Academic_2: I don't know what 6% means because (Overlapping conversation).
> I_Academic_1: No. Six per cent of what anyway?"
>
> (I_Acacemic_009)

While this frustration can be in part explained by the background of the interviewees, who are both data modellers, as I delve into detail below, it serves as a very good example of the arbitrariness of numbers and numerical values in the LA system.

Numbers yield themselves to calculation, they can be added, subtracted, divided, multiplied, and so on. Such calculative practices create new entities and relationships, but are also associated with additional work. Although at this level this additional work may seem insignificant, it exemplifies the scores of mathematical manipulations that underpin more complex statistics involved in LA. In the quote below, students become represented as pictures, and these pictures are then counted. The mere fact that there are 16 pictures creates new potential relationships with other numbers: 16 out of how many, for example. It also shows how the interviewees become involved in the additional calculative work.

> "I_Academic_1: No. Six per cent of what anyway? And counting pictures to find the answer is just ridiculous. We don't even know the total. So even if we count the pictures, we've got, I don't know, say there were 16 pictures, 16 out of how many? And 16 out of how many, okay? Sixteen out of those that are here, but how many? Is it a proportion of all students? All the (Overlapping conversation)….
> Interviewer: It's at a (Overlapping Conversation) 16 pictures.

I_Academic_1: Exactly. Exactly. All the things we would want to know are not answered by this, unless we're happy to sit there and literally count."

(I_Acacemic_009)

Calculative practices presuppose and reinforce standardisation and normalisation. In the context of LA, standardisation is often an a priori condition for the collection of data. At the School, a common template was introduced for most modules in an effort to introduce a shared standard across different modules, but an interesting insight was offered by a member of the IT team: "So the rationale for this was that we've got piles of data in different bits of sources, which is structured for its operational purpose. That makes it difficult to create in an ad hoc way or report on it and so on. So this is an effort to kind of extract to normalise that in some of the data source for the purpose of this kind of thing" (I_Technical_012). Thus, on the one hand modules are standardised according to a template to introduce homogeneity, and on the other hand the template is pushed out in an effort to offer more data. Indeed, modules that do not follow the shared template do not have access to the vast majority of the LA data.

Standardisation in the sense of uncovering or creating standards can also be seen in the ambition of the newest addition to the undergraduate office team, the Student Experience and Engagement Manager, who in an interview expressed a hope to work with the IT team to develop several profiles of students based on their LA data in order to "know what does a typical user look like" (I_APS_029). Standardisation in this sense can also lead to the creation of certain thresholds of user inactivity triggering staff interventions, or even automated interventions via email, thus realising Brunsson and Jacobsson's (2000) vision of embedding authority in systems and not in (education) professionals. If certain standards and norms of activity are created, users can then be *classified* and *categorised*, as for example seen in the quartile distribution (S_018). Students who have viewed between 0 and 25% of content become classified as "trailing" or "passive participants", and those with 75 to 100% of content viewed become leaders and are often seen by teaching staff as leading in the class (I_Teaching_002).

Indices, *indicators*, and *rankings* can then be created on the basis of such classifications. At the very basic level, the LA system displays to students where they are placed within the cohort: "I mean, for example, when you go and pick up your mark, what you'll see is where your mark sits in relation to the marks of all the other students. So the information is presented to you not as, it's not a piece of paper with a mark on the bottom as it used to be. It's a mark next to a graph which shows where your data sits in relation to everybody else's data. (…) That mark exists in the context of everyone's data. So what the students have been shown isn't just their own. (…) Because that wider context is what makes them motivated. So you'll know if you're first one in class. You'll know if you're on the top. You'll know if you're in the bottom of the group. You're not getting a single mark" (I_Technical_001). This is symptomatic of how quickly and easily numerical data can become a competitive ranking in the system.

The LA data undergo complex *statistical manipulation* before they are displayed to users. Some of it is simple mean, median and standard deviations:

> "I_Academic_2: We keep, yeah, we keep min, max, mean, and standard deviation.
> I_Academic_1: Standard deviation. (Overlapping conversation) And it'd probably be nice to see the median and the mode as well, because they've all got different purposes. Or why not make it interactive so you can choose your measure? Choose your measure of central tendency. Do you want, you know, range, interquartile range, and median, or do you want mean and standard deviation?"
>
> (I_Acacemic_009)

But the underlying statistics are often more complex than this. For example, one part of the systems offers trend lines, and as explained by the developer:

> "Oh, these are just regression[s]. So if you look at all these points of data and you want to draw a trend, like, so that would be a basic trend that I can do on a polynomial regression to get it."
>
> (I_Technical_012)

Regressions and other procedures become coded into how the LA system works.

3.2. Learning Analytics as a digital technology of measurement

Thus far, I have tried to show how LA, and BDA in general, is a continuation of measurement processes long present in the history of technologies of measurement. By deploying representation, quantification, and other processes through statistical processing and computation, LA is a yet another tool used to perform measurement. In this sense, following the data in the case study, I agree with other scholars who see the BDA phenomenon as a new incarnation of established calculative practices. However, here is where I depart from this thinking. While LA, and BDA in a broader sense, is a technology of measurement, its digital nature has significant implications for the nature of measurement itself.

As discussed in Chapter 2, section 4 on the nature of measurement devices, throughout history the highest standard for technologies of measurement was their stability, replicability of measurement, and reliability, among other features. This meant that technologies of measurement were meant to be unchangeable and non-malleable, and great effort was made to keep them so. For example, the original standard one-metre bar was kept secure in Paris as a reference. What are the characteristics of the LA system at the School, when investigated as a technology of measurement?

3.2.1. Distributedness

First, the LA system as a technology of measurement bears characteristics of distributedness. Data displayed to the users do not come from a single source; quite the opposite, it is derived from a number of different systems, as discussed earlier.

The LA system incorporates data from the main Management Information System, for example information about cohorts, courses, students, and their assessments, as well as login history. Module-specific data is linked to the Academic Balance Model, which reflects the number of teaching hours each member of staff is obliged to perform under their contract. Staff are further identified by their details and the tools available to them. This data is complemented by library information. A separate SOLR database holds cached content of VLE pages, as well as permissions to access this content and its locations. A non-sequel MONGO database holds logs of page reads, including the identities of the users, the content accessed, action taken, and timestamps, and a similar set of data about website interactions taken from web servers. Such a tight integration of various databases is seen as possible due to the in-house nature of the VLE and LA systems: “I think developing it in-house means that it talks quite well to the other systems that we use. So, it integrates with our student management system, which is the MIS. And that has also integrated with SITS, which is the student management system that they use at the main site. I really like that side of it” (I_APS_015).

The LA data displayed is effectively an assembly of different databases, functions, and items, all working on different systems, infrastructures, and databases. This also means that the LA system does not have clear-cut borders and allows for adding (and removing) other sources of data. As the developer stated, “we've got piles of data in different bits of sources which is structured for its operational purpose” (I_Technical_012).

This distributed nature of the LA system entails constant work to maintain connections between databases. These connections are different protocols of data transfer which not only transport but also transform data, from one format to another. Database connections are in general easily established by the software development team, who themselves proposed connecting and integrating different databases. The distributed nature also entails fluid boundaries of the system. As one interviewee explained, “because of the way we currently use it, this data doesn't include all information about the content. (…) In order to interpret any of this, you will require to get this from somewhere” (S_002).

Among the undeniable benefits of BDA resulting from its distributedness, the interviewees mentioned the fact that the LA system allows for a much wider range of sources of data, as opposed to previous forms of performance measurement. As a result, it is seen as giving a better overview of activity: “The fact that the data’s there, everything is there, guys. Imagine, what would you like to know there, you know? And you think, well, okay, what would I really like to know about a student or a tutor? When they’re studying, how they’re studying, do they skim read? Do they skip forward quickly first? Do they come back and then review it? How do they learn? And then how can I use that information? Can we develop our resources in a better way there? (…) [D]oes the student prefer text pages than videos? That all kinds of things I think there is about, wow” (I_APS_005). What’s more: “It's just now we have more ways of measuring available, people are thinking that this data is somehow more significant than it used to be” (I_Teaching_002) and that “you can compare much larger data sets than we could have in the past because it's computable” (I_Teaching_002).

However, it became clear in the interviews that there were some shortcomings resulting from the distributedness of the LA system. First, the distributed and ever-changing nature of the LA system meant that the interviewees were never sure what data is and what data is not being fed into the system. This led to confusion and uncertainty, raising questions about transparency: “I've kind of got used to what the data does and doesn't show us because I've had that many conversations with the people responsible for this. But actually I've made certain assumptions in the past, I’ve said, ‘oh I can get this’. And then I've gone back to [member of technical staff] and said ‘so I can get this, right?’ ‘No…no, it doesn’t show us that’. And I don't think there's a clear…I don't think there's a transparency in what that data is” (I_Teaching_011). Second, the seemingly all-encompassing character of data collection was seen as posing a risk of hiding absences: “The metrics system can only show you the data that we gathered, and there might be absences in that data. Sometimes for very good reasons, sometimes for less good reasons. But it's too late to do anything about that now. So I'd be cautious about the incomplete nature of that” (I_APS_021). Finally, the distributed nature and many connections between databases entailed constant work by the technical staff to ensure that all required databases are indeed feeding data properly.

3.2.2. Editability

Editability is also a prominent characteristic of the LA system, allowing for reorganisation, addition, deletion, or updating, and it features as an in-built characteristic of the system. This means that the LA system can be continuously modified by rearranging elements, deleting, adding new elements, or modifying functions. Editability is built into the system. At the very foundational level, the LA data themselves are open to being edited, as "[the] idea of it is that it's taking all that data, pre-aggregating it at different levels of granularity such that you can make comparisons horizontally and vertically in an interesting way, sort of choose just … so it can be reports for any module since the aggregate of it across all the years and all occasions, the specific occasions within the year and that sort thing. But you can also search for individual teaching faculty. You can search for courses and programmes and teaching groups. So it's aggregated in all those dimensions basically, so it means you can do things like, say, look at this module and then compare it with [a different] member of faculty. (…) And then for each of these, you can drill down and see more information. All manner of statistics" (I_Technical_012).

If one of the stakeholders requests an additional statistic, e.g. a trend line, it can be added with minimum effort. The LA system offers a simple dashboard in which information displayed can be reorganised according to the selected criteria of the user, e.g. time or date. Changes to the LA system in terms of its interface or dashboard are also introduced on a regular basis and efficiently. In fact, the software development team invites requests to develop different views and dashboards to reorganise the data being displayed to users.

One of the undeniable benefits of the editability of the LA system was the ease with which the display could be modified to suit the needs of different stakeholders. The IT team was often praised in the interviews for their openness to produce views or statistics that are needed. As one interviewee pointed out: "Like those things that I showed you before, those dashboards, before we didn't have those. Now, we're going to [the software development team] and we say, 'Guys, can you produce us this? And we'd like to monitor this,' and they do it there." (I_APS_005). In another example, a member of the technical team explained how another colleague was helped: "[A colleague] asked me a couple of times over the last couple of years for extra information. I think in one instance I probably added something to the user interface to let [the colleague] get to it, and another time I've done some queries to find that data." (I_Technical_012). The LA system seems to have been built with editability as a feature, as "the idea is eventually that, based on feedback from people, it may be designed a bit more with specific questions in mind" (I_Technical_010).

The IT team was also often praised for implementing changes quickly, for example “where I worked before, any changes we wanted to systems had to be applied for, and then maybe six to twelve months later they might be in the next phase and…and all of that. And so that can be quite frustrating. But here, you know, it can be really, really responsive, and it's a massive…it's a massive thing” (I_Technical_010).

Conversely, editability was often seen as a source of potential drawbacks. The pace of change, and perhaps even the fact that the system was being edited, was sometimes surprising to interviewees: “Actually, you know what’s interesting, they’ve added something new in here since I looked at it last time, this was not in here before, they’ve added the marker” (I_Teaching_025). This feeling of constant change sometimes raised suspicions of weak governance around the LA system, in the sense that edits and modifications were being requested from and implemented by the software development team with little procedural rigour, and were often not communicated out to the wider group of users. As a result, interviewees hinted at a lack of universal acceptance of the system due to its ever-changing nature and lack of transparent communication, as well as the steady updatability of data.

3.2.3.Interactivity

The LA system investigated is also interactive. Different from editability, interactivity means “offering alternative pathways along which human agents can activate functions embedded in the object, or explore the arrangement of underlying information items” (Kallinikos, Aaltonen and Marton, 2013, p. 358). The key here is the possibility to explore information (or in this case, data) in different ways and through different actions and choices. The LA system investigated offered a variety of ways to access data, either directly at a database level, through external files, or through dashboards.

At the most technical level, data in the LA system can be accessed directly in the database. It is split into a summary and a full history collection. The summary collection contains cumulative totals and the most recent records, while the history collection contains a set of users and total numbers of actions by time. The database can be browsed directly by users with access rights and the required knowledge.

During the case study, one interviewee went directly into the database and looked at specific actions of particular (anonymised and test) users of the system exactly the way they were logged into the database, and at the other end of the spectrum, some interviewees used the LA dashboard in the VLE. Some interviewees requested or downloaded themselves Excel files with the LA data, and others prepared reports and summaries based on these data for more senior managers. Each of these potential points of access offers a different level of insight, granularity, and use of the LA data.

Interactivity means that stakeholders can access data in formats most relevant to them, and thus it fosters productivity, enabling the production of reports, diagrams, and even research outputs. Metrics data are made available in the ways most suited to stakeholder needs. On the other hand, the fact that the LA system data can be accessed in different formats with differing levels of granularity and content entails "a contingent nature" (Kallinikos, Aaltonen and Marton, 2013, p. 359) of these data, which co-depend on who is accessing them and how. The LA system and its data becomes dependent on selective choices of users as to which elements to use and how to interpret them, entailing the potential subjectivity of the data.

3.2.4. *Openness and reprogrammability*

Finally, the LA system has also proven to be open and reprogrammable, i.e. accessible and modifiable by another digital object, different from the one governing its own behaviour (Kallinikos, Aaltonen and Marton, 2013, p. 359). Different from editability, reprogrammability means that there is interference in the logical structure "that governs the object and the mechanisms of information production and processing" (Kallinikos, Aaltonen and Marton, 2013, p. 360). To exemplify, reprogrammability was expressed by an interviewee who was explaining how he might have been able to obtain access to the specific data he wanted: "So, I guess they just need to write the programme to record this data and then make it available for us or someone who wants to use it." (I_Academic_007). The character of the LA system was summed up well by another interviewee, who said "it's built but it's not quite fully done" (I_APS_006). This represents the constantly evolving and changing nature of this part of the system, which goes beyond just features and the way data are displayed, but rather concerns the underlying logic of the LA system.

The LA system is constantly and systematically reprogrammed, but such changes are implemented by the software development team with little or no communication, and the team effectively takes on the role of gatekeepers not only in relation to the data, but also in relation to what kinds of changes to the system can be implemented. At the same time, the underlying LA system databases have to be accessed and modified by specialised database management software, which allows for changing the relationships between different database schemas.

On the one hand, openness and reprogrammability are a source of constant evolution of the LA system and thus increase the likelihood of its relevance among stakeholders and in relation to the development of the organisation. The reprogrammable nature of the LA system facilitates quick reactions to changes needed in monitoring as a result of changes within the organisation. On the other hand, reprogrammability carries the risk of data incompatibility if the underlying logical structure of the database is changed, for example by including additional data sources from a certain year onwards. This renders data far less useful and potentially confusing: "(…) [I]f you change key functional points, like when they have to read this, like, move it forward for some reason by a week, and that could, when you look at it in a very abstract data, you kind of sense it's difficult to, I mean, that's where it becomes more of a challenge to make sense of that on behalf of other people" (I_Technical_012). Despite its open nature, the LA system can only be reprogrammed by the software development team, which led to gatekeeping behaviours visible in the interviews, for example when a member of the technical team explained their role in deciding what to "show" to members of staff and what not to.

3.3. Conclusions

Thus, I have analysed and discussed how distributedness, editability, interactivity, and openness and control, characteristics of digital artefacts such as BDA, are visible in the LA system I studied. The characteristics of the LA system as a digital object, together with the benefits and drawbacks in terms of measuring teaching and learning activities, are summarised in the table below.

Table 11 Benefits and drawbacks of measuring performance with BDA

Feature	Description	Benefits	Drawbacks
Distributedness	Digital objects "are transient assemblies of functions, information items, or components spread over information infrastructures and the Internet" (Kallinikos, Aaltonen and Marton, 2013, p. 360)	- Wider range of data available - More detailed overview of activity	- Reliability of various data sources - Issues around transparency - Constant work required to maintain connections
Editability	Pliability and possibility to modify or update, either through rearranging the elements the object is composed of, deleting or adding elements, or modifying some of their functions	- More analytical flexibility - Ease of change of metrics - Adaptability to the needs of stakeholders	- Weaker governance - Lack of universal acceptance - Perception of constant change of metrics
Interactivity	Digital artefacts means they offer "alternative pathways along which human agents can activate functions embedded in the object, or explore the arrangement of underlying information items" (Kallinikos,	- Productivity around metrics - Format adjusted to needs	- Data co-depend on users - Subjectivity of measurement

	Aaltonen and Marton, 2013, p. 358)		
Openness and reprogrammability	Digital artefacts can be accessed and modified by other digital objects or programs leading to changes in the governing logical structure and the mechanisms of information production and processing	- Constant evolution of metrics - Quick response to organisational changes	- Incompatibility of data across time - Gatekeeping behaviours

4. Producing Learning Analytics Data

In this section, I focus on investigating how LA data is produced in the system, drawing from the analytical framework outlined in Chapter 6. In doing so, I depict the complex datawork involved in making these data available and I problematise the representation of teaching and learning as data. I also contribute to the ideas around the encoding of the everyday (Alaimo and Kallinikos, 2016) by applying the theoretical framework to a new context and confirming its validity.

4.1. Encoding

As explained in Chapter 6, encoding means formalising users and their activity as objects along pre-established actions (Alaimo and Kallinikos, 2016). Users, both students and members of staff, become reduced to and represented as simple "actor: <personId>," (S_002) in the database. Users become actor-objects, i.e. objects that perform action-objects on item-objects. Actors are stripped of everything but their "personId", which is a single, immutable number that allows them to be identified across time and actions. As objects, users lose all qualities and become represented by an arbitrary identification code (which is different from their School ID or student ID number for privacy reasons, but a separate database schema holds identifiable information that enables a "personId" to be matched with an actual individual). "Actor: <personId>" corresponds to the user who is logged into the VLE at that time. Needless to say, if login details are given to another user (which is against the School's policy) the actions of this user will be logged as the same <personId>, and if more than one users access a particular resource at the same time from the same account, for example by watching a lecture recording together during revision, they will also be logged as one, single <personId> (S_002).

The database holds a "PersonState" record which shows the most recent "state" of the actor. This includes their last action, the corresponding timestamp, the count of actions, as well as last login details. The database also holds a "PersonState_history" record, which provides a summary of all actions ever performed by this particular <personId> with their numbers and time stamps (S_002). The constant and perpetual logging of action-objects under the actor-object is essential to enable linking of item-objects with particular actor-objects for further aggregation.

Such encoding of users as actor-objects enables the creation of relationships between actor-objects and other types of objects. For example, the database holds a "PersonItemState" record, linking the user ID with the object ID, the action that links them, time it was taken and the number of times it was performed (S_002). This record creates another object, an actor-item-object, which binds the actor-object with an item-object to encode their interaction. Such new actor-item-objects, i.e. single encounters of items by actors, themselves become computable objects and are open to further processing and use. In other words, a single use by a user of a resource in the VLE is not just an action, it becomes an object open to aggregation and correlation.

There is a limited number of actions that an actor-object can perform on an item-object. In an interview, the developer responsible for the creation of the system mentioned there are "six or something like that" (I_Technical_012) actions available. These include page views, comments, viewing videos, log-ins, creating, and accessing an external resource: action: "<login|view|comment|create-<type>|goal-<id>|videosession|accesslibrary|… others>," (S_002).

Thus, returning to what was discussed under representation earlier, those who make use of the system often use it as if the LA data was representing teaching and learning, while in fact they represent six basic actions. Therefore, "login" is the encoded engagement with teaching and learning; "view" is the encoded reading of a resource (and possibly even engaging with it intellectually and understanding it, as a number of interviewees admitted they interpreted this metric); "comment" is the encoded participation, and "create", for example uploading a photo or a file, is the encoded equivalent of participating in the teaching and learning. Everything that users do on the VLE can only ever be recorded as these actions.

Items, on the other hand, become encoded as "ItemState" and similar "ItemState_history" item-objects, listing their individual item IDs, the actions carried out on the items, the actor-objects that performed the actions (complete with timestamps) and the overall number of actions performed (S_002).

The LA system database only holds ID numbers of items, but does not contain any other details about what the actual items are. In order to obtain this information, the database has to be correlated with another database containing the actual content.

Recording VLE activity along these prescribed actions is not, as such, a problem. However, the fact that the data points concerning these actions become then interpreted as representative of teaching and learning processes is a source of concern. Teaching and learning are complex social actions, which even outside of the VLE context can hardly ever be translated into specific measurable and countable actions (see one interviewee: "But the point is, it just counts clicks. So, if you want to look busy, you just click on a page. It doesn't mean you've read it. And this is the other thing we were talking about if you remember on the day, counting the clicks, click on a page, don't read it, don't do the exercises. Or if you really want to look busy, click on every exercise, click any answer, get the feedback, don't read the feedback. Then it looks like you've read the page and done the questions. You've done nothing. So, it's actually not telling us anything apart from they've clicked on the page. Just because they've clicked on it doesn't mean they've done anything" (I_Acacemic_009)). And yet the interviewees in general see the LA data as representing real-world actions: "So if I post a message and I want to know if people have read it, then I'll tend to look, and you get basically a list of those who've read it and a list of those who haven't. So I tend to use that more than anything just to see - are people actually listening to what I'm telling them?" (I_Teaching_011).

The wealth of pedagogical literature indicates that there is little consensus among education theorists as to what activities or outcomes are representative of learning, and thus it is difficult to agree that a mere six actions recorded in the LA system in the VLE at the School capture this process. Similar thoughts have been expressed in the interviews: "Yeah, I think, you know, measuring learning is one of the most difficult things you can do. It's almost like when you try to measure value created by a service. Because essentially, that's what it is. We're providing a service to the students, and the value that they get is their learning. But I haven't really seen that many good approaches on how you measure value or a consulting service or an investment bank or whatever. It's a similar kind of problem. It's really, really difficult to measure the learning. It's much (…) easier to measure what students do, what kind of activities they engage with, their performance, and so forth. But to really measure the learning gain. There are some, you know…I think the methods and technologies are improving. And there's going to be better possibilities for measuring learning more accurately. But most certainly, it will still be a very, very difficult thing" (I_Academic_007). Additionally, data collected in the system this way is used to assess teaching performance, as highlighted by a number of interviewees.

Even if, as some interviewees pointed out, the LA data stand for engagement, progress, or success, it is then again problematic to agree that this is the case. Educational engagement and learning gain are yet again complex constructs which are notoriously difficult to pin down and measure. As pointed out by one interviewee, “If you talk about [the VLE] data, so the data on the activities that students do online, I think that helps us to understand the process that they engage with during the module. Whether that produces learning or not, with all of this data, we don’t know” (I_Academic_007). This highlights the fact that in this interviewee’s mature view, the LA system captures the process of how students work with the VLE material, rather than learning. However, for many interviewees, clicks and views often become conflated with engagement: “I think with the broader view, just the quartiles, it's just giving you that feel for how engaged the cohort is. So roughly speaking - are people generally clicking on the materials? I mean it's a little bit lacking because it doesn't tell you whether they've actually done anything with the materials, it just tells you have they actually clicked on it” (I_Teaching_011). This pertinently shows how, despite seemingly being aware that clicks are just clicks on materials, the interviewee still interprets them as engagement.

If, following the stream of constructivism within education, students construct their own knowledge based on the resources available to them, including the contents of lectures, readings, exercises, and assessments, assessing progress or success may be entirely impossible without access to the thoughts and ideas within individual students. Learning is highly conditional on individual circumstances and preferences, and the LA system does not make it possible to record such idiosyncrasies, even if they are known to staff. For example, in the interviews it transpired that a number of students take the courses from areas in the world with poor Wi-Fi connectivity, therefore they often download course material up front, and then progress through it offline. In the LA system, this is recorded as one login several weeks ago and can be interpreted as low engagement with the course, prompting interventions from staff (I_Teaching_002). Such detail escapes the rigid records of the LA system.

Similarly, teaching can be argued as significantly more than adding resources or replying to students’ comments on the VLE, and yet, for example, the number of comments on the forum may be used to assess tutors’ performance and make decisions on contract extensions.

Both teaching and learning are also embedded in wider societal structures and are subject to external influences, and conversely, they serve much wider purposes than just providing discipline-related education to individuals. Thus, the LA system not only commensurates vast individual experiences and preferences for teaching and learning into six encoded actions, but at the same time it flattens the societal role played by teaching, learning, and widely conceived education into viewing, commenting, and similar transactional-level actions.

4.2. Aggregation

Encoding social activity in the LA system as actions in the VLE enables further aggregation, that is, adding individual data points and looking for new patterns and information – a form of generalising data about users and their activities. While some LA system users look at the LA data at the individual level, most use requires aggregation of the individual data. As exhibited by one interviewee, "I guess…the individual student data…when you look on a screen and you basically see every student listed and, you know, you kind of have a box. The more green I think it is, the more they've clicked on. That I don't find very useful actually. I think that's obviously telling us individually who's looking at things and occasionally the odd student stands out, but I don't tend to really use that because it's too much to go through. I think with the broader view, just the quartiles, it's just giving you that feel for how engaged the cohort is. So roughly speaking are people generally clicking on the materials?" (I_Teaching_011). Indeed, in the first description of the conceived LA project it was stated that the [2014-09-A] Student and Tutor Monitoring for Online Modules would "collect both explicit and implicit data from student and tutor interaction with [the VLE]. This data would be aggregated and shared with academics, tutors and administrators, along with students themselves, to act as an early warning system which would identify when students were not engaging with the learning materials" (M_013), with the idea of aggregation embedded very early on in the development. The usefulness of aggregation was also emphasised by the senior managers: "I think we're starting to scratch the surface of what we do with that information, and the problem is it's useful to have information in certain ways, it's useful to aggregate and disaggregate so we can start going through it and start looking for patterns within that. But that's something we've just started to do more than anything else and we've … it's been a lot of work in the system in terms of integrating the Management Information Systems into that" (GI_001). This also brings up the aspect of correlation shown below.

In fact, most of the LA data is already pre-aggregated in the database as "we've got piles of data in different bits of sources, which is structured for its operational purpose. That makes it difficult to create in an ad hoc way or report on it and so on. So this is an effort to kind of extract to normalise that in some of the data source for the purpose of this kind of thing." (I_Technical_012). Aggregation at the database level is required to enable successful use of the system: "So, [the] idea of it is that it's taking all that data, pre-aggregating it at different levels of granularity such that you can make comparisons horizontally and vertically in an interesting way, sort of choose just … so it can be reports for any module since the aggregate of it across all the years and all occasions, the specific occasions within the year and that sort thing." (I_Technical_012). The reason why data is aggregated by default is that "if we went just with this data here, you'd have to say 'go to here, find every element that matched that bit of content in the whole aggregation', which is potentially very expensive" (I_Technical_012). Instead LA data is pre-aggregated to fit most needs and requests, and if new perspectives are required, "what we could do is, we would say, typically, 'go back to here,' and then we would run a process overnight, for example, which answered that new question and put it all in this format so that it fitted in the overall ecosystem" (I_Technical_012).

In the actual database, item-object ID would be associated with all timestamps and actor-objects that have viewed it. Similar aggregation is maintained for actor-objects. Further, aggregated data is often the default view available within the LA system. For example, users would usually see aggregate blocks of the numbers of views, as shown earlier.

Aggregation, while a potent way to describe general trends and patterns, in the case of the LA system investigated, there is a risk of enshrining some perspectives in data while obscuring others. The overall rules of aggregating data are pre-set by the developer responsible for the system, and the users of the LA system have very little input into how the aggregation is carried out, if they are aware of it at all. Aggregation puts emphasis on numbers and, relying on the characteristics and role of numbers, engenders comparison and thinking in sizes and magnitudes. An item-object with more views easily becomes a better, more successful item in the eyes of the LA system users, often simply because higher numbers are conflated with higher quality, as explained in Chapter 2. Aggregation powers comparison, but it hides away the distinctive features of what is being compared in the LA data: a message announcing the place of the exam may receive a higher aggregate number of views, while a well-attended, in-person lecture may have fewer aggregate views. Yet, in the LA system one item-object will yield high view results, while the other one – low, thus leading to comparisons that disregard the individual features of items (remember that in the LA system, all items are just represented by their individual ID numbers, and the system does not hold any other details about the items).

Aggregation also reduces the importance of who does the viewing: staff or students, and which students. The system removes individuals and instead presents aggregates: "X percent of students still haven't read their student handbook three…three months in or something. I might…I might use it in a general, high-level context…but not…rarely on an individual basis" (I_APS_008). Going back to the notions of constructivism in education, this approach seems to be in contrast with seeing learning as an individual process carried out by students, and instead it treats students as a mass.

4.3. Correlation

Correlation enables the comparison, contrasting and further processing of aggregate data. The LA system relies on correlation to present the data in an interpretable way:

> "Because of the way we currently use it, this data doesn't include all information about the content:
> * Just stats keyed on person and item IDs
> * Content-descriptive data is elsewhere, e.g. titles, structure, where content appears within the system
> * Enrolment data / who has access
> In order to interpret any of this, you will need to get this from somewhere."
>
> (S_002)

This means that in order to enable interpretation of the LA data, the LA system has to draw from a number of other databases.

The MONGO no-sequel database which holds "Content Read Logs" (person, content, activity, timestamp) and Web Site Interactions (person, action, timestamp) draws data about content from the SOLR database, as well as a range of details from the MIS system. Such setup allows for correlating data as needed, and in fact it is technically possible to correlate library physical access data with interactions in the VLE and display this in the LA system (I_Technical_001). At the time of the study, work was being carried out to migrate the MIS system onto the VLE to increase its ease of use and enable further "integration" of data, which can be understood as the possibility to cross-check and correlate it (e.g. M_023).

Correlation and the propensity to correlate is an essential step to enable use-agnosticity of the LA data. If it is possible to correlate different databases in differing configurations at any point in time, this opens up unspecified numbers of possibilities of how the data collected can be used.

However, it also carries the risk of apophenia, that is "seeing patterns where none actually exist, simply because enormous quantities of data can offer connections that radiate in all directions" (boyd and Crawford, 2012, p. 668). Correlation can also lead to conflating correlation with causation, and misinterpreting causes and effects. An important feature of correlation is its power to create entirely new data points and datasets by bringing together data from disparate sources. Different data of varying quality can easily become one, a new dataset which is then used for other purposes and by other applications. Correlation makes it difficult to trace where specific data originates, and thus, datasets become more and more obscure. It is harder to track and uncover potential faults, but it also requires higher levels of database expertise to understand and use such complex datasets. Correlation in the LA system studied removes the complex set of interconnections between different databases that are invisible to those who use the data, and thus it gives the impression of a somewhat mirror-like representation of what happens in the VLE. Disparate databases, connections and protocols are abstracted, hidden away, and a set of correlated datasets are presented in a neat interface to unsuspecting users.

4.4. Conclusions

In this section, I uncovered the processes of encoding, aggregation, and correlation involved in the production of data in the LA system. I explained how teaching and learning processes become encoded in the database as six basic actions of viewing, clicking, and so on, and how they become further aggregated to display total numbers. Finally, I have shown how the LA system relies on constant correlation of disparate databases. While drawing out the functioning of these processes, I highlighted their problematic nature involved in representing teaching and learning in data.

5. Conclusions

This chapter provides the analysis of the key building blocks essential to set the foundation for the reactivity of LA discussed in the next chapter. It is important to understand the ambivalent ontology of BDA, as well as the various measurement processes it relies upon, to make an argument regarding its reactivity, as I have done in this chapter.

Chapter 10: Reactivity of Learning Analytics

1. Introduction

In this chapter, I analyse the ways in which the Learning Analytics (LA) system shapes work at the School, and how such shaping transforms the organisation itself. First, I describe the intended uses of the LA system, that is, drawing on the data, I show how the LA system is used in line with the LA literature. I then outline the reactive effects of the LA system, i.e. effects that were not intended when the system was designed, developed, and implemented. These are: gaming the system, redistribution of resources, redefining of work and practices, and change of values, and they stem from the theory of reactivity. Finally, I provide an analysis of the mechanisms of commensuration, self-fulfilling prophecy, reverse engineering, and narrative present around the LA system. I end this section with a proposed set of three emergent effects that I identified in the LA system studied that are not covered by the theory of reactivity: acceleration, standardisation, and discipline.

2. Intentional shaping of teaching and learning practices

As presented in Chapter 3, I surveyed LA literature to tease out the most common, intended uses of LA systems studied by researchers. I employed my findings to verify whether similar patterns of use emerge in the LA system studied. Outlined in the table below, the dataset provided a confirmation of the most frequent uses of the LA system among different groups of staff. Additionally, the figure below summarises how particular uses of the LA system, identified in Chapter 3, were present at the School. There are three uses stipulated in the literature that were not present in the data, and this can be mostly attributed to the level of maturity of the LA system in place.

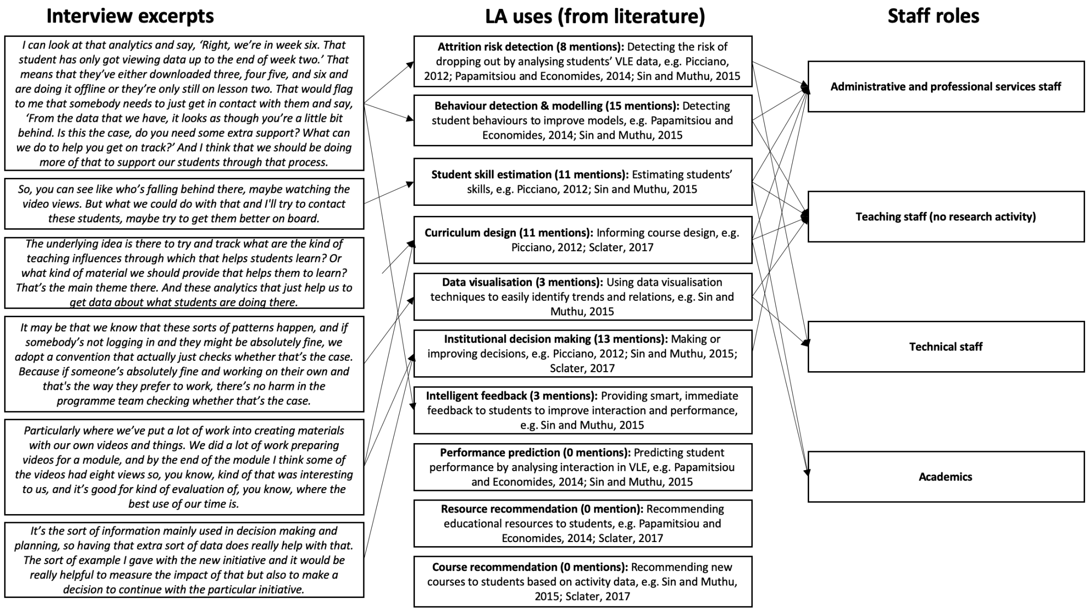

Figure 16 Summary of the uses of the LA system identified in the data

2.1. Administration and professional services staff

A total of 13 administration and professional services staff interviewed covered a variety of roles in operations and programme management at both undergraduate and postgraduate levels, as well as teaching and learning support roles and administrative roles within the registrar's function.

The most prevalent use of LA among them was related to the design and tailoring of materials, such as course handbooks or pre-enrolment spaces. Staff would look at LA to "actually see that people are reading" (I_APS_006) the handbooks or "to know how wide the audience has been for something if you need to make amendments to it" (I_Technical_010). An important use was related to detecting risk of attrition, as "with the volume of students we have it's very easy for people to go missing" (I_APS_006), so LA is used to "reach out to them earlier to see if there's anything that can help them" (I_APS_015). Administrative staff working in more technical roles, liaising with the development team, also emphasised behaviour modelling enabled by LA to present "a baseline of activity that we would expect to see from a student, so that you could then identify students who aren't hitting that" (I_APS_021). They also expressed their belief that "that will change the nature of things (…), proactively alerting us to those students who might need our help, those tutors who might need our help, really powerful" (I_APS_005). There was a particular interest around "tracking behaviour across the module in the way that the students interact with the material, the way they view it, the timings of it" (I_APS_015). Administration and professional services staff used the LA system significantly less for performance prediction, student skill estimation, or the understanding of the learning process.

2.2. Teaching staff

The nine teaching staff interviewed included those whose academic responsibilities were solely in teaching and administration of teaching modules, but who at the time of interviewing had no research duties. Teaching staff were primarily using LA for curriculum and course design, because "if you're generating different kinds of resources and it's quite time consuming, it's quite resource-intensive, then you want to know that it is having some effect" (I_Teaching_003), and data "give (…) an idea of how things are evolving and how successful they are, how well received they are" (I_Teaching_027). Data can then be used to make changes to a curriculum by revising particularly intensively viewed resources or introducing changes for the following cohort. Teaching staff are also interested in uncovering and detecting behaviours, as they "can look very closely at the learning activities and behaviours of an individual person and give them a much better service" (I_Teaching_002 Follow-up). They emphasise that "before the beauty of analytics (…) we were losing the ability to see where different people were" (I_Teaching_002 Follow-up), pointing to the usefulness of LA as a student skill estimation tool as well.

Teaching staff have also forayed into using LA to understand the learning process better but surprisingly many of them expressed doubts over the presumed link between LA data and learning, as "it [LA] gives us insights and it gives us spotlights to investigate further, but I wouldn't like to think it actually represents learning" (I_Teaching_002 Follow-up). It has been suggested that "people who don't have a lot of classroom teaching experience [have] a certain perception that the data is going to tell them what the students' progress is, and I just don't feel that it will (…), there's still got to be socially constructed understanding of what's going on in the learning experience" (I_Teaching_002 Follow-up). Teaching staff were less interested in using this tool to detect attrition risk.

2.3. Technical staff

The five members of technical staff interviewed included three members of the IT team and two members with technical expertise embedded in programme management teams. Their most common uses of LA were related to making data visible to students and tutors, as per feedback and requests. While they did not make use of LA for themselves, they often worked with other members of staff to uncover or analyse patterns and provide feedback. The technical staff saw themselves often as advocates and promoters of the LA system, as they were “trying to expose to people that the data exists at all” (I_Technical_001), and they were convinced that there was a need for transparency around the data collected. They were of the belief that students could particularly benefit from seeing their results in the context of the whole cohort, “because their wider context is what makes them motivated” (I_Technical_001).

2.4. Academic staff

This group, which included five academics, covered all those whose main responsibilities at the School were related to research, and only a small proportion of their time was devoted to teaching. In their encounters with the LA system, academics were mostly concerned with its use to understand the learning process, yet again, interestingly, they have called the relationship between LA data and learning into question. Some expressed the view that “we’re doing it for measurement’s sake rather than for actual learning” (I_Academic_022), and reflected that “whether that [different types of activities] produces learning or not, with all this data, we don’t know” (I_Academic_007). There seemed to be a consensus that LA data “don’t tell us much about learning per se because we don’t know what they do with the material” (I_Academic_028). This stands in quite stark opposition to views widely held by the administrative and professional services staff, who tend to equate numbers in the LA system to actual actions. Academics were less likely to use LA data for curriculum or course design, as was expressed by one of the interviewees: “I think because we’re quite confident in our material, because we’ve run our material for over 20 years, we don’t tend to get many comments (…) that make us want to change the material, so we’re not using it [LA data] in that way” (I_Acacemic_009). Academics also seemed to be less concerned with attrition risk detection.

2.5. Conclusions

As evident above, the LA system is widely used at the School by different groups of staff. Perhaps unsurprisingly, different groups of users use the system for different purposes. However, this fact has not been yet explored in the literature; therefore, one of the interesting findings from this project is the grouping of particular uses of the LA system by different types of users, as presented in the table earlier.

3. Effects of reactivity

Aside from the intended (even designed) uses of the LA system, a range of reactive effects, as proposed within the theory of reactivity, was uncovered. Such effects can be attributed to the reactive nature of the LA system, and the existence of the LA system is a pre-requisite for such effects to emerge. Returning to the TMSA framework, the effects of reactivity allow for elaboration upon the unintended effects of human agency leading to structural transformations. The effects of reactivity can thus lead to the reproduction or transformation of the existing structuring conditions. The analysis of the effects of reactivity presented below can be used to demonstrate how changes related to BDA at the work-practice level can lead to transformations at the organisational level.

3.1. Redefining work and practices

One of the most prevalent unintended effects of the introduction of LA was the fact that LA data led to changes in work and working practices, as already signalled by critical researchers of education, whose arguments I have summarised in the background literature. Indeed, also in the case studied, for example, teaching staff found that "it [LA] detracts from the job of educating" (I_Teaching_011) and introduces a host of different data-related activities which ultimately take away time they would otherwise spend teaching or interacting with students. Importantly, a number of interviewees have experienced what they called "the move towards e-learning" (I_Teaching_011), that is, an impression or encouragement they received that e-learning elements should be introduced even in face-to-face teaching, with some residential modules introducing two or three weeks of online classes with an explicit connection to "the move towards using the data that you get from e-learning" (I_Teaching_011). While it could be argued that the move towards e-learning can have other causes, such as savings, resourcing, and the immense profitability of distance learning programmes, the conviction with which some interviewees expressed their view that they were being almost forced to introduce distance learning components in their face-to-face modules seems to confirm the attribution of these changes to the LA system: "Maybe the data can strengthen them more to having more like more online programmes. Or also to have the campus based programmes to move closer to the distance learning approaches, I guess" (I_Academic_007). It has been pointed out that "The university seems to have become a lot more open to online learning as a way of engaging students, not as a way of just disseminating information. And I feel that part of that is to do with the ability to monitor the analytics and understand the students better" (I_Teaching_002 Follow-up). One interviewee in particular, puzzled as to why she was asked to introduce a few weeks of distance learning into her residential course, arrived at the conclusion that it was due to the trackability and traceability of online actions as opposed to classroom activity.

Although curriculum and course redesign has been identified as one of the desired uses of LA, several of the interviewees pointed out that this can lead to some less positive effects, such as "teaching then [becoming] completely oriented around 'well, I need to make sure that the materials are really exciting because they're going to rate me on that'" (I_Academic_022). Some of the interviewees expressed a concern that as a result of the LA data, they may have to restructure their materials and practices towards what causes students to "engage more", i.e. to what generates more views, comments, and clicks, rather than towards what is intellectually more challenging and stimulating: "I think the risk is always, if you know something is going to be measured in a particular way, that you will change your curriculum to be in that way" (I_APS_020). It could be argued that the changes around module structures and course design result from a push towards delivering a standardised, uniform experience to students. However, several of the interviewees pointed out directly that they believed such changes facilitated LA data collection, as evident from this interview: "For example, instead of doing a lecture, you do a film so that the contact time is interacting rather than passive. It really matters where the people watch the video. So all the people doing that [have] been using analytics desperately, you know, to see whether it's worth the investment in doing that. And to tell apart things like, you know, something I'm very glad to see is that people have completely given up on the idea that it's worth having an hour-long video, putting it in front of the students. No, never (chuckles). So, and it's interesting, there are people who don't use analytics, and they are much more likely to say I did a two-hour lecture" (I_Technical_001). Examples like this one provide evidence of the impact of LA data on wider teaching practices.

On one occasion, it was suggested that data from the system could have been used to fight off an impending closure of a course, as "if we were fighting for survival, we might use this data to construct ammunition as to how wonderful and active our students are", which would be a very different way to defend a successful module, and would result in different practices. Other examples of redefining work and practices include relying on the LA system to provide evidence for plagiarism claims (I_APS_019) and to correctly calculate fees for withdrawing students, which could only have been done on a term basis before (I_APS_014).

As pointed out, redefinition of work or practices could have other potential explanations in general, but the traces of changing practices identified above are likely to be linked to the LA system. First, the interviewees themselves felt this was the case, and second – it is not a baseless assumption that if practices change towards becoming more standardised and countable, it is because there is a system to count them. As evident in this interview:

> "Interviewer: So sort of zooming out, I'm looking at the school as a whole, since the moment you introduce these sort of analytics elements to the system, have you noticed any sort of any changes, anything that is done differently now because of the fact that this analytics system exists?

I_Technical: Yes, structure. People are starting to say it's absolutely no good having the traditional thresholds we've got. The points that you notice, whether or not anyone's paying attention, spread so far apart, we need to have activities so things can't drift.
Interviewer: So, the actual structure of teaching?
I_Technical: Teaching, yes, absolutely."

(I_Technical_001)

Thus, the LA system changes existing practices by standardising them within and across different members of staff: "There are definitely institutional changes with the way we structure online teaching. So there's been a huge push to develop a standard template for everybody who teaches. So a template for [the VLE] for uploading your materials. I guess in having that standard template it automatically standardises the data you collect in the background because everybody's materials are structured the same. I don't think it's a great idea actually. I think it's kind of a regression to the mean sort of strategy that is basically trying to drag up those people who don't do anything, but you know, talking to people, and the way I feel...it's…it's pulling you down because then you feel like 'I can't take… ,' you know…" (I_Teaching_011). This approach also pushes for previously face-to-face or non-digital practices to involve the VLE.

3.2. Resource redistribution

Perhaps the most striking way in which resources are re-allocated at the School as a result of LA data is related to the use of tutors. On some courses, LA data is used to decide whose contracts should be extended or terminated if tutors do not correspond to enough views or comments in the system: "if I look at the online tracking of staff engagement and people are repeatedly not doing what they're supposed to be doing, they'll be on the blacklist and they won't have the contract renewed; it's a really cut and dried thing" (I_Teaching_002). Similarly, the same interviewee explained that following the Away Day when the LA system was presented to the team, "since that training, I've had module leaders come up to me and say, 'I've realised that two of the people in my team have not been doing what they're supposed to be doing. Would you support me in not renewing the contract?' And I've been able to say, 'Yes, absolutely'" (I_Teaching_002). Likewise, some members of staff I interviewed use the LA data "as an impetus to get people to agree to fund more online tutor posts", and "I can get a bigger team through using those stats to prove that there's a lot of need for more people to interact with the students that are posting those posts" (I_Teaching_002). Thus, data from the LA system is directly responsible for reallocating financial and staff resources where more activity data is present, to the point that "the data helps legitimise that and it builds in more resources, gets more scholarships, changes our recruitment focus. So, a huge impact that adds in to a story that's already there, but it gives it a bit more strength" (I_Teaching_002).

Relatedly, it has been pointed out that "nobody would ever have invested if those changes [in student engagement] weren't measurable, and it's a fact that changes have become measurable, and this is why more power and more investment has gone into non-faculty, which, in any university, investing in non-faculty has always actually been something that has to be profoundly justified, but our measurements environments makes that uncontroversial, and that's quite unusual in those respects" (I_Technical_001). To quantify that, as an example, the teaching and learning support team has grown from a team of four to 17 members of staff at the time of the study, and "we've got a dean of pedagogy now, so there's a whole kind of structure in there now to support teaching, because I think that the data is saying that this is what we need" (I_APS_015). At the time as the study, the School also created a new post related to student satisfaction and engagement, which included monitoring LA data as part of the job specification (I_APS_029). An example of how such redistribution of resources happens is neatly presented in the quote below, where an interviewee explained why the School invested in developing pre-arrival modules.

> "I presented to this huge group of about 30 people. They've been saying for ages 'we need something online to engage the students in what work is and how to study at university before they arrive'. But they never got around to designing something. And they kept saying 'we need pre-arrival programmes, but we don't have the facilities in the summer to put on the pre-arrival programmes in person that would be necessary, because we used everything conference-based over the summer. So we can't do what other universities do'. So when I designed my pre-arrival module for my students and I presented it to them, there was this immediate thing of, 'Oh, this is actually interactive and really engaging'. And you can see which of the students are logging in and not logging in. You can see which are progressing through certain things. You can see which ones are having trouble with things. We can learn about our students. We can see which students understand instructions and not. So there was lots of information available in the by-product data that I hadn't thought of that people at [committee] thought would be very useful for them to know before certain students arrive. So you can kind of spot things like dyslexia and disability in people's postings. You can spot languages issue if people are struggling. So there's lots of things that I hadn't designed in. And they moved away from seeing it as an information-giving service to actually a way of looking at what students are producing, and that by-product, and drawing some conclusions about the cohorts before they actually get onto campus."
>
> (I_Teaching_002)

Interestingly, a few interviewees pointed to the fact that the IT team solicits projects and ideas for the development of the VLE to ensure its continuing relevance at the School, and the growth of the team, which could be presented as yet another symptom of reallocating resources. As pointed out above, one of the main developers of the LA system is a graduate in Artificial Intelligence, and others on the team also have strictly technical or programming backgrounds. Apart from resource redistribution, this point can be linked with changing work practices, as the LA system and its design was primarily created by developers with backgrounds in IT and Artificial Intelligence dictating the different elements of design and use of the system.

It has also been pointed out that there is an increasing pressure to collect and obtain data for senior management, as "they have kind of an ability to prioritise this" (I_Technical_012). Together with other reputational rankings, there is a significant amount of work involved in collating all the required and necessary statistics, and the School has a rankings task force in place, which comprises members of careers, alumni, and corporate relations, and hope was expressed that some of the LA data could be used to provide further evidence of student engagement.

3.3. Change of values

In general, it has been observed that many of the interviewees have pointed towards the increasing value and importance attached to student feedback: "student feedback data predominate and made it more powerful than possibly it should be" (I_APS_013). Interviewees pointed to the fact that "it has made us collect other sorts of feedback almost obsessively" (I_APS_013), and that LA data has gained more prominence and importance, especially in light of suggestions from the wider sector that it could be incorporated in the TEF scores. Shortly before the study, a new system allowing students to give feedback on the feedback they received was introduced as part of "more emphasis on teaching and teaching evaluations" (I_Academic_022). It has been suggested that this is related to changes in what students expect, as "what they want now is just to do with power, power of data" (I_APS_014). Another interviewee pointed out that "people are feeling more and more that they're being judged by these young person's statistics" (I_APS_024). Further, the emphasis on employing teaching fellows was linked to what LA data point towards as "we employ teaching fellows because they have that focus on teaching rather than being research-focused" (I_APS_015), which is a significant shift for a research-led university.

It has been pointed out that there has been a move away from “treating them [students] like an adult learner” (I_Teaching_025) towards “hand holding to the extreme” (I_Teaching_025). Some interviewees suggested that they have experienced a significant move away from allowing students to look for things, develop research skills, and critically analyse large amounts of material towards making material available on the VLE in bite-sized chunks, which they suggested was the result of LA data suggesting that students are less likely to click on longer videos or reading materials. A summary of the worry around this change in value is evident from the interview below.

> “It’s more a philosophical issue, because I often think about what is the purpose of a university, and I’m afraid, and now I’m not really talking about [the School]. I’m talking in general, that if we are too much driven by all these numbers, all this data that we have, that we might lose sight of that in favour of trying to act upon those numbers, to produce a change. For instance to be better rated in NSS, we might make decisions that might not be in line with the purpose of a university. We’re not Amazon, you see, so how many smilies, you know, like come on, really? I don’t think that’s the … I wouldn’t say that we are here to make students happy, of course we want them to be happy, that’s not the point, but we are not in the happiness business; we are in the business of teaching, of developing their skills, developing their minds, and possibly we can kind of lose sight of this if we are too much… too caught up with this number and that number, and just changing this stat and pushing at this metric; I’m afraid of that, but I don’t have the answer. I wish I had, but it kind of worries me.”
>
> (I_Teaching_027)

Relatedly, a number of interviewees pointed out an increasing value of student interaction and a push towards building interactive components into their courses. This has been linked to the fact that interaction on the VLE generates data, and therefore provides a form of a measurement which can be made useful for other purposes, as opposed to students interacting offline where their activities cannot be measured by the School. One interviewee emphasised that he creates engagement and interaction in classes rather than “by looking at some data on the screen” which turns him into “someone who stands back and observes and evaluates from a distance”. He emphasised that that as a lecturer he is “part of the module. The module and I are two aspects of the same thing” (I_Teaching_026). Therefore, the push towards student interaction, especially online, may be seen as a shift away from the importance of the role of a lecturer.

Tracing these changing values back to the LA system is not straightforward. When presented with this hypothesis, the senior management suggested that it is indeed the other way round: they instigated a change of values towards higher quality teaching, for example, and the LA system merely measures the outcomes of this change in corporate culture (GI_001). This perhaps could be the case, but it is important to note that the LA system emerged bottom-up, rather than top-down. It was proposed by a mid-manager who thought it was pertinent to measure student and staff activity on distance learning courses. Once senior management were made aware of the existence of the LA system, various member of staff began to realise the data were used to measure their performance and thus focused on improving their results in what was measurable and countable. In other words, I would like to posit that while the increased value ascribed to teaching might have come from the senior management, the existence of the LA system increased the rate at which the change of values penetrated the organisation. While it was more difficult to define or measure good quality teaching even if it was aspired to, the LA data provided a number of measurable proxies to quantify teaching quality, which meant that the aspirational value could be verified much faster.

3.4. Gaming the analytics

The fact that LA could be gamed was mentioned in several interviews, including the validation with senior management: "It's interesting because obviously within the thing you've got some of the gaming aspects. Now, it may be that some of the students will click on just to click through: if we know they're only clicking on to go through something, is it because they have to go through something? That's not good for us. So we need to be able to go back and say 'do we need to amend something accordingly'" (GI_001).

The interviewees were concerned and sometimes sure that students would "just click on everything, (…) play the system. If students think 'I need to look as if I'm busy and engaging', then they'll play the system" (I_Acacemic_009). As one interviewee suggested, "people who actually previously didn't bother to do that will use a little of their valuable time which could be actually spent getting an education, they'll actually use that time to play the game. You will get gaming. People will game. People will work out how much clicking do I have to do to register this level on this measure. It's extremely negative" (I_Acacemic_009). These insights come from a researcher in performance measurement who explicitly pointed out the fact that measurement "produces aberrant behaviour which in my area we call maverick behaviour, so when you measure something, people modify their behaviour to satisfy the measure. So, if the measure is misspecified, you'd get aberrant or maverick behaviour. So, if clicking is viewed as a sign of progress, people will click" (I_Acacemic_009). While the link to data and LA is made explicit, gaming remains a worry in the way LA is used at the School: "it's not really indicating that they've probably completed that page, it's indicating that 'oh, I'd better do this otherwise the programme team will get on to me'" (I_Technical_010). Similar thoughts were expressed by several interviewees who expressed their limited trust towards LA: "I might make an assumption that Tom Miles, to use an example again, or A.N.Other student, isn't coming to lectures and seminars but is engaging in some other way. But it might be literally that he's just clicking on it and not engaging with it and just scrolling very quickly through" (I_Teaching_018). There was also the concern that students may think "they have to do it to be seen to have completed everything" (I_Technical_012).

A related effect was observed in relation to the role of LA data regarding reputation and impression management, especially in modules where there is a mark allocated for student participation. A link between LA data and reputation has been established by a few of the interviewees: "on some courses, that emphasis on reputation is in fact built into the way the courses work, so your online presence and all of your activity forms are taken in a quite powerful way" (I_Technical_001). Indeed, one of the interviewees agreed that "there's a student, for example, she's always the first, so you can go and look two minutes after you've posted something and she's always looked at everything first. Now, from an impression management point of view that's quite clever; I do have a positive impression of her as a result of that even though she's relatively quiet in class, just because she seems super on it and interested" (I_Teaching_018).

However, it is not only students who might engage in conscious gaming of the system, but in fact the interviewees pointed out repeatedly that members of staff, as a matter of fact, engage in reputation management, as "it's pretty critical for (…) external online tutors to be representing themselves well at the moment because it's a matter of 'are we going to renew our contract or not?'" (I_Teaching_002), and they also pointed out that the system relies on "quantifying the tutor engagement" (I_Teaching_002). This aspect is further explained: "This tutor has posted X amount of comments online, this tutor has posted that amount of comments online, you know. Oh, this person has posted 55 comments, this person has posted two. Bad person, you know. I make that assumption, I made that assumption, you know. I can understand why senior management might make assumptions about us, but they're not always the whole are they? That one person who made two ended up on stress leave, you know, so there were things going on as to why they only posted twice" (I_Teaching_025). It has been suggested that one of the desired developments in the LA system would be an average number of words per comment by an online tutor, as some members of staff noticed that tutors were raising their number of comments by replying in very short, conversational posts, rather than content-based responses.

4. Mechanisms of reactivity

The proponents of the theory of reactivity stipulate that the reactive effects result from a number of mechanisms at play. In this section, I outline how the mechanisms can be identified in the LA system studied. In line with TMSA as the theoretical framework, it can be argued that the LA system, as a technological object, is implicated in human agency, thus the reactive effects visible at the organisational level can be traced back to the mechanisms of reactivity emerging from the interaction between the technological object and its human users.

4.1. Commensuration

Commensuration, explained in detail in Chapter 2, the transformation of different qualities into a common metric, is at the very foundation of the LA system studied. Its main principle assumes that the complex and highly variable process of learning can indeed be encoded in, or commensurated to, a set of simple actions such as a "view" or "comment", which are then treated as data. Various interviewees implicitly assume that there is a direct connection between data in the system and learning. For example, using the LA data to decide who will get a participation certificate relies on the assumption that clicking on the VLE equals participating, or doing the job ("I can just view under the staff activity who's doing what they should be doing or not" (I_Teaching_002)). In this instance, the qualitatively very different, individual processes of learning become commensurated to highly limited data points, along established paths (Alaimo and Kallinikos, 2017). Perhaps the most striking example of this at play is the use of LA data by staff to correctly assess the student withdrawal date: even if a student entered a later last attendance date when withdrawing, LA data was used to check when was the last time the student actually used resources, and a lower fee was calculated as a result. Again, this involves commensurating learning and being a student to data in the system. A more detailed explanation of the issues involved in commensuration can be found earlier in this work under encoding and representation.

It can also be inferred that the use of LA can lead to focusing attention on achieving as many clicks, views, or comments as possible, shifting attention away from the quality of these contributions. Some members of staff admitted that since the directions from the School were to increase student interaction, they have built in mechanisms forcing students to interact online as much as possible, which sometimes may mean that interaction quality will drop, but LA will show higher numbers of clicks and views ("we get the data and then we get diverted into just pursuing the data instead of focusing on the goal" (I_APS_004)). Relatedly, since some staff now just look at the summary of the number of comments made by other staff as part of their job, a concern was expressed that this may mean that the average quality of comments will drop for the sake of their number. As pointed out above, some interviewees have also admitted that they would build their impression of students based on their LA data, commensurating the meaning of a good student to a student with a high number of clicks and views in the LA system.

Interestingly, a number of interviewees implicitly rejected what I present here as the commensurative nature of the LA data, stating for example that the data "tells us how many pages the students have viewed; viewed does not mean read or engaged with, it doesn't give us any idea of how much they've learned" (I_Acacemic_009). Such views were in the minority, however. Such differences in the understanding and interpretation of analytics data further differentiate the complex scenario of the LA system.

In the context of the study conducted, commensuration brings together issues discussed under encoding and representation, as both of these processes are highly contingent on qualities being commensurated into quantities. Much of the discussion under these areas above is relevant and pertinent to the present analysis of commensuration in the LA system.

Commensuration can be identified as a reactivity mechanism leading to the redistribution of resources to obtain more data, equated with more interaction and engagement, as well as a change in values from depth and analysis to numbers and speed. Finally, commensuration can also be identified as the causal mechanism that leads to standardisation.

4.2. Self-fulfilling prophecy

Although self-fulfilling prophecy as a mechanism of reactivity was not as clearly identifiable as, for example, commensuration, I have come across some concerns among the interviewees responsible for the development and implementation of the system that reactions to measures may confirm the expectations embedded in measures.

For example, one of the struggles an interviewee faced was related to revealing LA data to students on a larger scale: "The genuinely interesting problem we are facing at the moment is that we can't tell any student at any point in their degree 'okay, you've read at the moment 30% of the materials. Do you know at the moment, you're behind on the reading and most of the people on your module have actually read 60% by now?' But the question about that is whether that's healthy feedback. Is that … what does that do, for example, to someone who is struggling?" (I_Technical_001). Another issue: "I don't know how students feel when it's like, you were 99th out of 100. I don't know if that could be negative and whether we've got the support then to back it up if the student who has a bad reaction to data, because data's not neutral" (I_Technical_001), which hints at the potential self-fulfilling prophecy mechanism at the back.

Further, it has been suggested that teaching staff may be prone to thinking that "a student hasn't opened six of ten lecture materials", so they jump to the conclusion: "lazy student, I'm not going to help them, [but] that might be the student who needs the most help" (I_Teaching_025). Again, this is potentially symptomatic of self-fulfilling prophecies.

Similarly, the view of one of the interviewees that "some of the staff, who know who they are, see it as Big Brother watching what they're doing. I'm assuming they're the people who have something to hide, and they won't be staying with us" (I_Teaching_002), provides an example of what might also be interpreted as a potential self-fulfilling prophecy. In this situation, a member of staff's rejection or dissatisfaction with data may cause them to be perceived negatively, and this perception may lead to their departure, rather than them behaving in a way that would cause their dismissal.

The mechanism of self-fulfilling prophecies can lead to changes in what is valued, as well as to the redefining of practices, as discussed above.

4.3. Reverse engineering

Reverse engineering, i.e. working backward through the construction of a completed measure to understand how it works, often with the aim of trying to influence the measure, has been present throughout the study and can be identified in a number of instances.

The concern about reverse engineering related to LA was expressed well by one of the interviewees: "'I want to do well, I want to get a first. I'd put more work into these or I'll set…' you know, they'll set themselves up in a way, [while] one of the virtues of the degree is that it is a sort of very rounded measure of accomplishments, but the moment we start giving really quite high-resolution data…" (I_Technical_001). This exemplifies the fact that students may lose focus from their degree and its value, and start studying to the data. A similar idea was expressed by another interviewee, who stated "the more we add data analytics (…) the more we're instrumentalising their understanding of learning, you know, it's a box to tick, it isn’t a concept or an idea to engage with, to understand. It’s a ‘what do I need to do to get my 2:1 at the end of it?’ and ‘this is going to help me’” (I_Teaching_025).

However, it is also interesting to note how staff themselves plan to increase the LA data on their modules by reverse engineering student activity and motivating students to get onto the platform: “‘we’ll be giving certificates out to people who achieved completion of at least 75%’, and suddenly (…) all the numbers were like ‘vroom’” (I_Teaching_002). Similarly, staff would reach out to students showing as having low activity on the system to get their activity higher, or even display LA statistics in lecture rooms to encourage students to view and comment more frequently. These interventions are symptomatic of thinking how the LA data can show more interaction and engagement in order to take appropriate steps aimed at increasing the “numbers” in the LA system, which is a clear example of reverse engineering. In other words, some teaching staff themselves would implicitly try to trigger reverse engineering in students by showing them the data of high-achieving students.

Similarly, staff pointed out that “if you want to look busy, you just click on a page” (I_Acacemic_009), which may suggest a clear link between gaming the system as one of the effects and the mechanism of reverse engineering, i.e. identifying that if activity data in the system is used to judge performance, then clicking around seems to be a plausible action to be seen as better performing: “if clicking is viewed as a sign of progress, people will click” (I_Acacemic_009).

Quite strikingly, reverse engineering can be identified as a mechanism associated with gaming, as well as standardisation among students and staff, and redefinition of practices.

4.4. Narratives

Narratives, described by Espeland and Sauder (2007), as repeatedly told stories providing causal explanations for changes, were perhaps the most clearly visible – potentially because they are the least abstract – mechanism of reactivity visible in the study. Out of a number of narratives that emerged through the interviews, the narrative of “student engagement” was the most prevalent one, repeated at all levels of seniority and in different contexts.

Student engagement as a goal was posited as the main explanation for why LA was implemented and why these data had to be used. Remarkably, the project itself was frequently referred to among senior stakeholders on the committee as Engagement Analytics. The narrative constructed around engagement and the need to measure it justified the use of LA across the school.

A frequently told story emphasised the need to increase student engagement, as this by itself fed into the School's reputation, standings, recruitment, and financial success. Therefore, it seems from the interviews that if a tool such as LA would help measure and increase engagement, it would be welcome. It has been emphasised on a few occasions that the School has "a duty of care around engagement" (I_APS_004), further emphasising the fact that engaging students became the de facto main goal of the School.

As such, engagement became a goal in itself, and the VLE became a mechanism of increasing engagement, while the LA system became the way to measure it: "[a colleague] directly works with the people running those modules and she helps them put the interactive bits and then measuring engagement" (I_Technical_001). As one interviewee pointed out, she is "always checking in to see that students are engaging with materials" (I_Teaching_002), and she sees the LA data as a valuable tool to ensure that students in fact engage, rather than learn. Another interviewee added that "it's very much about engagement level, how far is it going, what additional methods we might need to put in place" (I_Teaching_027). Again this emphasises the fact that the School seemed to have become more interested in generating and measuring engagement.

The emphasis has also shifted towards the idea of "continuous engagement", i.e. designing continuous activities for students to get "much, much smaller bits of data" than just their end-of-term outcomes (I_Technical_001). Keeping students engaged became the modus operandi and the goal of course redesign activities. For example, the structure of the distance learning MBA changed to introduce gated content, forcing students to work on certain activities to access further materials in the modules: "engagement is the big issue, really, of trying to help, particularly with this new structure of the course, it's going to be much less forgiving of not getting going with it and not engaging" (I_Technical_010).

Various interviewees have emphasised the vital role of LA in helping them track engagement: "there was not really any way to see anything about engagement really before" (I_Technical_010). Conversely, the LA system helps in "quantifying (…) tutor engagement" (I_Technical_010) to an extent that previously was not achievable: "I also look at staff activity because we are concerned about tutors who don't engage sufficiently. They're paid to engage with an online course" (I_APS_013), so the narrative points more towards tutors being paid to engage, rather than to teach or supervise.

The same narrative is perhaps what has driven the School to create a new post during the case study, which was explicitly related to engagement: Student Experience and Engagement Manager, with one of the role's focuses being the use of LA data to improve engagement.

The narrative of engagement and the role of LA data as the best tool to capture it can be identified as a mechanism behind changes in values, redistribution of resources, and redefining practices, as well as disciplinary measures taken and the speeding up experienced by various interviewees, as discussed in more detail below.

4.5. Conclusions

In this section, I reported on the identified broad spectrum of uses and effects of learning analytics at the research site, including some emergent effects not foreseen in the literature that I will briefly discuss below. I then uncovered a number of potential mechanisms suggested by the theory of reactivity that would account for the reactive effects. I suggested, based on the data, that the LA system as a technological object becomes the foundation, or source, of the reactive mechanisms which become embedded in agency.

5. Emergent effects of reactivity

During the study, a number of effects were uncovered that seem to result from the mechanisms of reactivity but go beyond the four groups of effects described by Espeland and Sauder (2007). Namely, I identified the disciplining nature of analytics, its standardising effects, and finally, acceleration. These effects extend the theory of reactivity and allow for the modification of its framework to fit the context of BDA, with important differences and considerations outlined.

5.1. Discipline through analytics

Although not included in Espeland and Sauder's theory, one of the clear and visible effects of the LA I discovered in the case study was the disciplinary nature of data and analytics, both towards the students and staff. As an example, the LA data is used at the School in plagiarism cases where students who claim they have not seen anti-plagiarism regulations are traced in the system, and it is then confirmed they did in fact view pages related to plagiarism. Another example is related to claims that students submitted their work after the assigned deadline because although they had been logged in before the deadline, there was a problem at the point of submission: "with the data we've got, we can go in and see that in actual fact the student didn't log in until 11.59 (…) so over time those complaints seem to have declined" (I_APS_021).

A number of academic or teaching staff openly use the LA system to encourage students to engage with module contents: "I will say explicitly 'oh, only half of you have done the quiz, you've got five minutes now to do it'. And they're like 'How did she know?' And then I'll show on the screen. 'My god, my god, she can see'" (I_Teaching_002). Other tutors made references to the LA data in their lectures to impress on students the need to read or view a particular resource, with data allowing the lecturer to "give them warning" (I_Teaching_018). An important consequence of the introduction of the LA data was the much more fine-grained and continuous nature of assessment: "paying attention to what's in between and thinking, you know, people's model is moving away from those discrete assessments events, being the way that the course is articulated, and thinking much more in terms of continuous engagements, and getting much, much smaller bits of data but for a continuous activity" (I_Technical_001). The important change is that discrete assessment events used before for discipline purposes become replaced by constant, real-time monitoring of actions.

Some members of staff were surprised about the fact that staff behaviour was traced in the system: "so now they're able… so is somebody else using this data analytics not to help shape my teaching or the student's learning, but [as] a managerial tool to evaluate our performance?" (I_Teaching_025). It has been suggested that due to the mere fact that staff activity is monitored, tutors became more compliant: "so they monitor staff activity because in the past, when it wasn't monitored, some tutors will literally not do anything" (I_APS_005). Another example from the interview highlighted how this data was used in a disciplinary manner: "I use it to – this is going to sound awful, I have to put this in a nice way – I use it to basically track tutor activity in the Distance Learning MBA. So, we would use it just to make sure that they are logging in regularly. We can use it to tell us where they've recently posted, that kind of thing" (I_APS_015). Some administration and professional services staff responsible for quality look at the mean, mode, and standard deviation of student grades, and if they notice anything different from previous years, they "would seek [an] explanation from the person who's marked". The availability of LA data also made it easier to monitor and contrast performance in comparison to previous tenures and teaching teams. Disciplinary effects were also widely identified among the members of staff interviewed: "But I think for my staff, for some of the staff, who know who they are, they see it as Big Brother watching what they're doing. And I'm assuming they're the people who have something to hide, and they won't be staying with us" (I_Teaching_002). It has been pointed out that "Some staff have raised in the past that they don't…they said 'You're monitoring me,' and they've had issues with that. (…) I'd say I guess some people might say there are ethical issues, because it's data and you're monitoring, you're tracking there. I don't think there is, but some people might" (I_APS_005). Some interviewees expressed a certain unease about the data being present: "I suppose I do sometimes worry that it's a bit like… it's overly monitoring, it's overly… it's intrusive in some way" (I_Teaching_018). The sentiment can be best summarised by the quotation below.

> "If we can make clear ties between how the measurement helps learning, I think people will buy in more, will engage with it more. They'll see it as more than being subjected to Big Brother. It's useful, it's meaningful, it contributes to this environment of intellectual engagement rather than ticking boxes. It definitely changes your behaviour when you feel like you're being tracked on things."
>
> (I_Academic_022)

The disciplinary nature of the LA data was in fact highlighted by one of the developers behind the system: "So those kind of, effectively, disciplinary structures (…) are really what's made sense, I think, for most members of faculty - that the data in [the VLE] is important. It is being used. It isn't necessarily student analytics. It wasn't student analytics or the learning experience. It's actually the disciplinary structure of the institution" (I_Technical_001). And the members of staff, at least some of them, are acutely aware that the LA system is used in this way: "So there is, my sense, a definite use of the online data to use as a performance evaluation of us as staff" (I_Teaching_025). This is crucial, as even if the LA system was not used with the intention to discipline staff, their perception of its role in this regard will shape their behaviours, as "It definitely changes your behaviour when you feel like you're being tracked on things" (I_Academic_022).

5.2. Standardising through data

Although this effect is also not present in the theory of reactivity guiding the study, I have nonetheless identified its presence. As already hinted in the discussion of redefining of work and practices, the interviewees have pointed towards certain standardising effects of the use of LA: "There are definitely institutional changes with the way we structure online teaching. So there's been a huge push to develop a standard template for everybody who teaches. So a template for [VLE] for uploading your materials. I guess in having that standard template it automatically standardises the data you collect in the background, because everybody's materials are structured the same. I don't think it's a great idea actually. I think it's kind of a regression to the mean sort of strategy that is basically trying to drag up those people who don't do anything, but you know, talking to people, and the way I feel...it's…it's pulling you down because then you feel like I can't take…you know" (I_Teaching_011). In fact, a number of interviewees expressed doubts concerning the introduction of the standardised template not only because it required them to re-work their materials or required them to introduce more activities of different types, but because this move was seen as an attempt to standardise or regulate, which goes against the grain of education itself.

The introduction of a common template to facilitate data generation was identified as a potential cause of turning education "very samey, so if one particular approach is shown to have positive scores, then you could end up in a situation where everybody is forced or encouraged to use that particular method" (I_APS_017), and LA could slow down innovation in teaching. It has been pointed out that "lecturers and professors don't like to be limited by templates" (I_Academic_028), and therefore the particular move towards standardisation was not universally welcome among the teaching and academic staff. Administrative staff, however, have overwhelmingly noted the positive sides of it, such as consistency and improvements in student experience. As one interviewee pointed out: "it's a bit like going to IKEA. You walk into an IKEA, you know exactly what you're going to get, and I think they want students to have that experience with their modules" (I_Teaching_011). A similar sentiment was expressed by another interviewee, who highlighted that: "Well, I guess it could become very samey, so if one particular approach is shown to have positive scores, then you could end up in a situation where everybody is being forced/encouraged to use that particular method, whereas I think in the past there's been an understanding that different methods work for different students, and work for different academics, and indeed different topics" (I_APS_017).

Some administration and professional services staff responsible for quality look at the mean, mode, and standard deviation of student grades, and if they notice anything different from previous years, they "seek explanation from the person who's marked", and the availability of LA data also made it easier to monitor and contrast performance in comparison to previous tenures and teaching teams. Such actions also drive further standardisation in marking.

5.3. Acceleration with analytics

Interestingly, another effect that a number of interviewees have hinted at is the speeding up of various aspects at the School. Decisions are made more quickly, development happens at a faster pace than in the past, changes can be made much more quickly than from one year to another. At a technical level, acceleration is made possible through integrating databases: "our students do module registration online, and as soon as they're registered on a module it's immediately available to them through [the VLE], because the whole thing is all driven from a single data source" (I_APS_021). This constitutes a significant acceleration in comparison to the usual university experience.

A salient feature of LA is that it provides nearly real-time feedback on how students progress through the VLE material, prompting some of our interviewees to introduce changes in their teaching materials within the same cohort, rather than for the next year:

> "Yes, so if we look at the patterns of video engagement and we see that lots of the students have been hovering over a particular point, because we can do that in lecture capture, you can look at the pattern of engagement. Then we can go to the next lecture or webinar and say: 'Looks like lots of people were pausing over the bit when I talked about this. Let's just go over that. Were there any questions about it?' And that can help you provide that personal service for those individuals. Or if you see that everybody's kind of floated along absolutely fine, and then one person is really [held up] on something, get in touch with that individual and see if they need any remedial assistance. So it does enable you to have that sort of formative learning experience with the students rather than waiting for that [inaudible 00:12:29] to end. Then it is too late to help them out."
>
> (I_Teaching_002 Follow-up)

Staff are able to identify struggling students much faster: "it's enabled us to have quick warning signs that people are struggling and enable people to get through the programme who wouldn't have previously" (I_Teaching_002 Follow-up). "It's very easy for people to go missing, and plus, I only need to really pick up on problems, you know, at the end of term or even [in] some cases when we get through exams and have not shared that through exams, and then dig back in and you find out they've not contacted the person, the tutor. We don't know about it or haven't done certain things, so I'm really, really keen to use the analytics and [take] a risk to actually to get to know students quicker just so we can head off the sorts of problems" (I_APS_006). As expressed by another interviewee:

> "Remember, and we'll get to this, that student then, we didn't have a clue what they were doing. They were sitting at home, writing assignments, we'd send out boxes of materials, and we'd see them once a year for what's called a September seminar on campus here. Other than that, the only time we knew there was a problem was when they didn't turn up for the September seminar, the residential break. And that's why I kind of get excited by this, and I've also been here long enough to say, 'Guys, you have no idea, when I started here we didn't have a clue whether our students were working, what they were struggling on.' So where we are now is just amazing."
>
> (I_APS_005)

This interviewee returned later to the same thread in the conversation and again emphasised the role of faster feedback:

> "Because we'll have gone from students who didn't have a clue what they were doing to now knowing everything about their learning. Not just their activity levels, but we can do tests at the end of lessons and we can find … we can check their understanding literally in real time rather than when the only time we found out was when the exams, the exam, they failed it, and thought, 'You didn't understand that, guys, did you.' So an academic can then intervene, and maybe in one of those webinars you say, 'Guys, I've actually noticed that you're struggling with lesson one on balancing a balance sheet, and it's this area. Let me just explain this again to you,' and intervene at the most appropriate time that, which from my background in that very traditional sit-at-home and just read and write to where we are now, it's just incredible, just incredible."
>
> (I_APS_005)

It also seems much easier to quickly identify underperforming staff and fix issues before the end of term:

> "And at the moment, we're in the first few weeks of, I think we're in Week 4 of the first two modules that we're running, and we've got some other modules that started a couple of days ago on the old programme, some electives. So (…) I have fortnightly meetings with the director of teaching and learning support, and his consultants. So this morning, we were saying 'oh so and so, his tracking stats don't look very good. He's not logging in regularly and he's not, he's writing one post every six posts rather than one post every four posts. So somebody needs to get on that.' It's only Week 4 of the course. We already picked up that a tutor is not doing specifically what we asked. So it means we can adjust that during the course. We don't have to wait until the end and then get poor student feedback about that tutor. We can help that tutor improve during the module."
>
> (I_Teaching_002 Follow-up)

Many interviewees agreed that this was not possible before, agreeing that "it gives people a chance to learn, to understand quickly that they're doing something wrong rather than get to the end and say: "Why didn't anyone tell me?" So from our perspective, sort of quicker interventions and staff training, basically, and giving people a chance to rectify their behaviour before it becomes problematic" (I_Teaching_002 Follow-up).

The pace at which the VLE enabled instruction to take place has also led to the idea of "continuous engagement", as discussed above, which would not have been possible without the LA data in the background.

While inconspicuous, the change in speed brings profound consequences for teaching and learning practices, and education in general. For instance, as pointed out in the educational literature reviewed in Chapter 3, education requires periods of reflection and time to internalise new material. Doing things quickly in education, in other words, does not equal doing things better, and in fact may lead to opposite effects. And yet acceleration through analytics has even further-reaching consequences for other types of social activities. I begin the discussion chapter with an elaboration of the consequences of acceleration.

6. Conclusions

In this chapter, I provided an overview of how the LA system is intentionally used at the School and delved into how the reactive mechanisms embedded in it lead to unintended effects at play at the organisational level. I have provided evidence for the existence of emergent effects, namely discipline, standardisation, and acceleration. Together with previous parts of the analysis, this chapter focused on displaying the highly transformative character of the LA system and on outlining the ways in which the LA system represents the world of teaching and learning in data by transforming it through encoding, aggregation, and correlation, and how the LA system further deploys this data to feed back into the world of education, as summarised in Figure 10.

Chapter 11: Discussion

1. Introduction

In this chapter, I summarise four main themes arising from the analysis and I discuss their consequences and implications for Information Systems (IS) and the field of management more broadly. First, by extrapolating the findings of the Learning Analytics (LA) case study to the wider context of Big Data Analytics (BDA), I discuss the implications of conducting measurement through data analytics systems. Second, I discuss how the study contributes to testing and the extension of the application of the theory of reactivity to the study of BDA. Finally, based on the findings of previous chapters, I develop the concept of the analytical cage as a new form of organising human activities that emerges as a result of placing actors within BDA settings that encode their actions. I show how the findings from previous chapters contribute to the formulation of this concept, I sketch out the elements of analytical cages, I show how they operate, and discuss their consequences for organisations.

2. The consequences of measuring the social with Big Data Analytics

The LA system studied is, by all accounts, an example of BDA at play. As outlined in the analysis chapter, it satisfies the popular criteria for big data, and it is recognised as big data by the users of the system themselves. The analysis, however, highlighted significant difficulties with accepting common assertions pertaining to the characteristics of big data. These often include volume, velocity, variety, granularity, exhaustivity, veracity, and use-agnosticity. While the LA data, as numerous excerpts confirm, can be described using these characteristics, a careful study of the system undermines the substance of many of these claims. I assess the shortcomings of these characteristics, and propose an alternative approach to qualifying data as big data.

In terms of volume, it can be argued that big data indeed brings more data to organisations. However, without investing or allocating appropriate resources, more data remains unused. Faced with a lack of proper skills and a trained workforce, existing members of staff may even limit their use of data in comparison to previous, smaller sources. It is also evident that the sheer amount of data alone is unlikely to benefit either the employees or the organisation at large – resources are needed to appropriately process, analyse and interpret big data, thus emphasising the fact that the its value, if any, lies in its analytics. At the same time, many within organisations believe that big data can exist and be used autonomously, since its automated analytics promises to provide ready-made insights. Such perceptions further undermine moves towards developing big data analytical capabilities among staff.

Velocity of big data is highly dependent on various database connections and integrations working properly with a guaranteed up-time. In complex, highly integrated systems where data is produced at different speeds and with varying intervals, velocity is always contingent on the source and frequency of data generation. This can lead to situations where some data points are generated and interpreted in real time while other sources of data have not yet been incorporated into the database. These differences remain hidden from users' view, and decisions can thus be made based on partially outdated data. This problem does not depend solely on the fitness-for-use or appropriateness of BDA systems, but rather on the periodic nature of some of the activities measured through data. In other words, the issue is inherent in activities undertaken.

Variety and exhaustivity in a big data organisational context are subject to some severe limitations, despite promises to collect more diverse data than previously. Significantly, variety and exhaustivity are limited only to activities, actions and behaviours that take place online in a traceable and measurable context. Anything that happens offline remains untracked and unrecorded, and this fact is hardly ever advertised to users, who may instead work under the assumption that data made available to them exhaustively cover a wider variety of sources. Since social big data can only encode activities that conform to pre-defined categories of online actions, it could be argued that the variety of data is even reduced in comparison to previous or other modes of data collection, as shown in the analysis chapter. If there exists a limited, prescribed number of types of actions that can be recorded in a system, some variety will be undeniably lost. The study conducted also casts doubt on whether social activities can be exhaustively captured by big data at all.

Big data promises unprecedented granularity of data. Complex behavioural patterns, highly involved social activities, and contingent actions become broken down into discrete data points, as exhibited in detail in the analysis chapter. However, due to the nature of the mechanisms behind generating such a high level of granularity, there is an inherent loss of information and context resulting from this process. Without such information or context, highly granular data may be open to misinterpretation. Moreover, social activities can often only be analysed, understood, and interpreted if treated holistically. An analytical approach relying on studying their highly granular components may well obscure rather than inform the understanding of their nature. A single data point, or even the aggregate level, may lead to misunderstanding and wrong conclusions being drawn about the overall user profile or activity.

One of the biggest challenges concerning the characteristics of big data is its supposed veracity. Contrary to many claims in this respect, big data proved to be far less accurate in the study. There can be many scenarios imagined, and a number of them were provided in the analysis chapter, where big data does not accurately reflect the number of discrete actions or the people who took them. Such discrepancies may have severe consequences on further analytics, interpretation, and use of big data, and yet they can only be properly recognised and appreciated based on topic- or industry-specific knowledge. Indeed, a recurrent question and doubt in the case study concerned the very meaning of big data collected within the organisation. Various members of staff understood the data points differently, and some admitted they realised that they assumed inaccurate definitions of what the data points corresponded to. Thus, what emerges is a complex landscape of different understandings and interpretations of the same big data within a single organisation. It is difficult to then make claims of the veracity of such data if it not only fails to conduct accurate measurement, but it also stands for the truth concerning different phenomena.

Use-agnosticity is often heralded as the key defining feature of big data. Instead of asking specific, pre-determined questions, it is now possible to collect all data available and ask questions later (captured by the ominous claim of “the end of theory”, Anderson, 2008). However, this means that using big data within organisations may be restricted only to those who have the right statistical and computational skills to formulate questions and query databases – not very different from previous forms of data. Other members of staff who do not have such skills may see their uses of big data limited and their perspectives excluded. Use-agnosticity then becomes limited to uses that fall in line with what is permitted within the scope of statistics and computing, and what is envisaged by a subset of users.

All of the above suggests that the characteristics of big data identified in the dominant literature actually fail to capture the defining and differentiating nature of this phenomenon. If it can be shown that volume, variety, velocity, exhaustivity, granularity, veracity, and use-agnosticity do not fully define, or in some cases even obscure the phenomenon, these characteristics are of limited help in defining big data.

I proposed analysing BDA systems as technologies of measurement that are essentially distributed, editable, interactive, and open and reprogrammable. The implications of the distributed nature of BDA for measurement are significant. First, a distributed technology of measurement is one that is never fully defined, closed-off, and completed, which is in stark opposition to previous, established attempts at designing data-generating tools, as discussed in Chapter 3. Second, the distributed nature of analytics means that BDA requires considerably more, if not constant, work to establish and maintain connections between disparate sources of data. Third, BDA can only fulfil its purpose reliably if all of these distributed sources actually function properly and provide the required data points. However, any faults in data transfer mean that losses may go undetected by users, undermining the validity and veracity of the measurement process. Thus, distributed technologies of measurement are less robust and more exposed to malfunctioning: a threat to one source of data equals a threat to the whole technology of measurement within an organisation.

Editability as a feature of BDA can be problematic insofar as it breaks down the stability and familiarity of, and trust in the tool which are necessary to ensure consensus over its use and applicability – necessary conditions for successful measurement. A technology of measurement which constantly changes on the surface is one that is more difficult to universally accept within an organisation. Reorganising, adding, and removing can undermine trust in the veracity of measurement. It also requires work from those who can implement such changes.

Interactivity of BDA means that there is no one universal output of the system. In fact, quite the opposite is true: different measurements are possible, measurement loses objectivity and gains “a contingent nature” (Kallinikos, Aaltonen and Marton, 2013, p. 359). Metrics become dependent on selective choices as to which elements to use and how to interpret them. Users of BDA, through interactivity, become involved with the measurement output, bringing in their worldviews, perspectives, knowledge, and decisions. As different users can interact with different elements of the system at differing levels, this creates a myriad of different possible measurements, which of course goes against the intention of creating a stable, universal measurement system leading to the generation of reliable data.

Conducting measurement through technologies that are inherently open and reprogrammable, such as BDA, poses some risks concerning the very nature of the measurement process. To begin with, constant reprogramming of BDA and its underlying database structures may mean that measurements cannot be compared across groups or in time. This poses a threat to the robustness of the measurement process, as, in other words, the criteria for measurement constantly change. Secondly, changes to BDA systems, even assuming best efforts, may not be communicated as widely as to be known by all users; therefore, some users may use it unaware of the changes and worse, compare data between cohorts or across time without knowing that criteria have changed. Lastly and relatedly, openness and reprogrammability of BDA mean that it ceases to be an independent tool for measurement, and instead it becomes interwoven with the people who have the authority and knowledge to introduce changes. Openness and reprogrammability of the LA system thus introduce a dependence on those who hold power to select and implement modifications.

Thus, I argue that the defining features of big data and its analytics lie not in the characteristics of the data output but rather in the distributed, editable, interactive, open, and reprogrammable nature of the systems that enable data production. Previous forms of measurement and data generation relied on systems and mechanisms of a far more defined and definite nature that aimed to ensure objectivity, precision, and accuracy, among others. Big data analytics systems defy these principles by their very makeup.

3. Testing and extending the theory of reactivity

As argued earlier, the theory of reactivity is a productive and fitting lens through which I proposed to study BDA. The present project aimed to test the application of this theory in the context of BDA as well as extend it in this new setting.

The theory of reactivity (Espeland and Sauder, 2007) was first developed to study the impact of rankings on US law schools, and it uncovered a range of mechanisms and effects at play when the organisations measured changed their practices and routines in response to the rankings. The educational context, measurement aspects, and signs of changing practices and organisational transformations are shared between the original context of the theory and the case study investigated. However, Espeland and Sauder's rankings were external to the organisations they ranked and were compiled by independent ranking institutions, while BDA systems are embedded internally within organisations, which leads to disciplinary mechanisms and power dynamics within organisations resulting from BDA. Second, rankings are compiled by the employees of ranking-making institutions, while in the context of BDA, code replaces the human work involved in creating rankings. Third, BDA provides commensurated data at a much faster pace than rankings, customarily published at set intervals during the year. Finally, rankings primarily serve outside audiences, while BDA systems are used by internal stakeholders in decision-making processes.

Despite these differences, the case study confirmed that the theory of reactivity holds in the context of BDA. The same mechanisms and effects as those described originally by Espeland and Sauder were present, namely commensuration, self-fulfilling prophecy, reverse engineering, and narrative in terms of mechanisms, as well as effects such as gaming the system, redistribution of resources, redefining of work and practices, and change of values. This is explored in depth in Chapter 10. Based on this analysis, it can be concluded that BDA systems become nexuses of reactive mechanisms and lead to reactive effects within organisations.

In the study, new reactive effects emerged, therefore extending the theory of reactivity. Discipline, standardisation, and acceleration are all effects of reactive behaviours of the members of staff, but they emerge as a result of the digital character of BDA systems, and are further discussed below. Although the disciplinary character of the system was not planned or intended by senior management, its presence was confirmed by a number of employees, including the developers of the system itself.

The key difference between rankings, and indeed other forms of measurement, and BDA in terms of its disciplining nature lies in the perceived continuity and totality of assessment. Unlike in the context of rankings, where special ranking submissions can be carefully prepared and submitted at specified intervals, BDA is seen as constant monitoring of every action, task, and activity online. Rather than having the opportunity to do some work and reflect on its results to potentially improve or change the course of action, users whose work is turned into data and displayed in the BDA system experience assessment with every data point captured. This leads to the eradication of distinctions between activities and their assessment, and instead every activity enforces discipline.

Standardising through data is essentially a result of conducting measurement by means of computer code in BDA systems. With rankings, both those who compile ranking submissions within organisations and those who work for ranking publishers use their judgment, interpretation, and sometimes manipulation, to present data in one way or another. On the other hand, pre-programmed data types, schemas, categories and their counts, enshrined in code, remove these degrees of freedom.

BDA systems do not allow for flexibility in interpretation or presentation of particular practices, but instead either classify them into one of the six types of online actions, as seen in the case study, or render them invisible and thus worthless outside of the system. Such hard-coded standards are produced by IT professionals or programmers who design BDA systems from their perspectives and with their own assumptions. Activities, such as teaching and learning in the case study, become thus standardised according to rules set out by professionals with backgrounds in disciplines often different from those that allow for a deep, contextual understanding of what is standardised. Moreover, they become standardised according to categories and criteria formed by the rule of code that are thus difficult to negotiate, confront, or revise. As argued earlier, BDA systems with their precise yet narrow stylised activity types may fail to accurately capture most of the value of some work practices, resulting in their standardisation vis-à-vis standards that are not productive or positive.

Acceleration with data seems to result directly from the fact that BDA provides feedback in cycles much faster than other forms of data or measurement. In the context of the case study, it was frequently raised that before BDA, changes to the contents of modules could only be acted upon after an end-of-term survey, therefore affecting only the incoming cohort in the following year. With BDA, staff were able to implement changes within cohorts. Similarly, underperforming members of staff were identified in the first few weeks of their contracts, rather than on the basis of negative feedback from students in end-of-term surveys. Such quick reactions and changes were not possible before BDA was introduced, in contrast with the workings of rankings.

Decisions on an individual level are made faster with BDA, and thus it can be posited that organisational change also happens at a quicker pace. To return to the ideas of morphogenesis and morphostasis (Archer, 1982) that fed into the Transformational Model of Social Activity, if action (social elaboration) happens in shorter periods between T2 and T3, the T4 of structural elaboration, either in the form of reproduction or transformation, is brought forward as well. As a result, the transformed or reproduced structures feed into the subsequent cycles at a faster rate with BDA than with previous forms of measurement, including rankings. This seems to indicate that change at the structural and therefore organisational level accelerates as a result of faster feedback from BDA.

It is therefore clear that the theory of reactivity applies in the context of BDA, but it can also be further extended by three effects particular to this context: discipline, standardisation, and acceleration. These three new effects are attributable to the continuous nature of data production, standardising properties of computer code, and immediate feedback from BDA systems. Taken together, the mechanisms and effects, both established and new, explain how organisations change through the unintended consequences of measurement through BDA, as elaborated upon below.

4. Big data analytics and organisational change

The central preoccupation of this thesis is understanding how BDA shapes the organisations it is supposed to describe or measure. In order to operationalise this question, I proposed the use of the Transformational Model of Social Activity (TMSA) to provide a theoretical background for understanding change. Within the TMSA, social structures enable and constrain human agency, thus giving shape to its intentional outcomes, while the unintended consequences of agency may transform or reproduce these social structures. As explained in detail in Chapter 5, in the case study investigated social structures correspond to the organisational structuring capacity, while agency is equated with work practices surrounding the use of BDA, the technological object. While the intended uses of BDA are largely congruent with the uses envisaged in the literature, the theory of reactivity helps unpick the unintended, reactive consequences of human agency leading to the reproduction or transformation of the organisation.

The case study narrative provided a detailed description of the structuring capacities of the organisation that enable and constrain the agency of its staff. The competitive environment of higher education in the UK, with its many rankings, assessment frameworks, and surveys, requires the organisation to put emphasis on teaching and learning performance in order to attract revenue. Competition between business schools makes it necessary for the organisation to communicate the need to perform and measure impact for the purposes of rankings and accreditation. Within the wider university, the organisation studied is one of the main sources of revenue, and ensures its relative independence and separation in terms of decision-making through the continuing generation of surplus, intrinsically linked to the number of students (or customers).

Thus, despite being a research-focused institution, the organisation puts emphasis on teaching and learning activities as these are related to its revenue-generating capacity. Improving teaching practices was identified as a strategic priority by the Senior Management Group, who play a significant role in the organisation's structure. Decisions concerning technology and innovation within the organisation are largely made by the Technology Strategy Committee composed of representatives from various domains, including operations, administration, teaching, and IT. The Committee considers and prioritises IT projects for development. The IT team is then responsible for delivering the projects and serves a strategic role within the organisation. One of the main responsibilities of the IT team is to maintain and develop the Virtual Learning Environment (VLE) that supports the organisation's operations. The VLE is seen as an integral part of the organisation: "this is what membership of the business school means” (I_001). Thus, some of the structuring forces identified at the organisational level include responding to competition successfully, increasing the importance of teaching, performing well in rankings, surveys, and assessments, and deploying technology to meet the strategic goals.

Against this backdrop, various groups of staff develop and maintain their social positions. Routines, purposes, and duties based on rules and the structuring capacities of the organisation, including those named above, define the scope of positions of administration and professional services staff, teaching staff, technical staff, and academic staff. What they do within the organisation and how they work with the BDA system is enabled and shaped by the structuring conditions of the organisation. The BDA system within the organisation first emerged as a way to support teaching and learning practices in line with the structural conditioning, and over time it gained its social position through being embedded in human agency.

Using the BDA system, employees changed existing or developed new practices, including, for example, improved attrition risk detection, behaviour detection and modelling, student skill estimation, curriculum design, data visualisation, institutional decision-making, or intelligent feedback, all attributable to the structuring forces of the organisation identified above. These uses, congruent with existing literature, provide for intentional shaping of teaching and learning practices, and justify the implementation of the BDA system. In other words, within the scope provided by the organisational structure, staff relied on the BDA system in ways that were envisaged.

Different groups of staff tended to use the system for their specific purposes, e.g. academics were more likely to use BDA for curriculum design and student skill estimation, while technical staff for data visualisation and attrition risk detection. This point further emphasises the fact that social positions are likely to shape the use of technological objects within organisations. The technological object itself gained its technological identity, as assigned by these different groups of staff. However, what made the BDA system a particular technological object was the fact that it was ascribed a measurement-related technological identity as its development continued towards accurate tracking of staff and student activities. In the eyes of its users, the BDA system became a way of measuring teaching and learning practices, and this newly gained social position gave rise to unintended consequences.

As presented in detail in Chapter 10, the BDA system became increasingly focused on tracking and measuring online activity of staff and students through encoding, aggregating, and correlating data. The data generated on the basis of staff and student activity was presented back to the users, thus turning the BDA system into a nexus of reactivity. As argued and confirmed multiple times earlier in this thesis, reactivity leads to changing and adjusting behaviours by users when aware of their activity being monitored or measured. Reactivity emerged in this context because the BDA system enabled the mechanisms of commensuration, self-fulfilling prophecy, reverse engineering, and narratives to develop.

Thus, staff activity became commensurated (through encoding) to six basic activities that supposed capture teaching practices, including their quality and intensity. If staff activity, aggregated, showed what was interpreted as the signs of an underperforming employee, this employee was more likely to be treated as such, and the assumption was made that "they won't be staying" (I_Teaching_002), thus potentially leading to self-fulfilling prophecies. Encoding teaching and learning practices in a highly granular manner fostered reverse engineering, where more emphasis was being placed upon the number of clicks on a particular resource or views of a particular video than on the quality of teaching provided. As a result, staff were more likely to focus on producing content that attracted higher numbers in the BDA system rather than content that had higher instructional qualities.

The BDA system allowed for positive, nearly celebratory narratives around student engagement to emerge. In relation to measuring student activity, higher numbers of views and clicks were interpreted as positive signs of student engagement. These results were enthusiastically received and celebrated as the organisation's success in creating an engaging environment for students, the measurement of which was seen as non-existent or unreliable with the tools available previously. Thus, the BDA system became a fertile ground for these reactive mechanisms to arise and begin operating.

In turn, these mechanisms led to reactive effects, which in this case were the unintended consequences of human agency that led to changes at the organisational level within the structuring capacities. Among the effects stipulated by the theory of reactivity, all four, namely redefining work and practices, resource redistribution, change of values, and gaming the analytics, were identified. Three additional effects, extending the theory of reactivity to the BDA context, were uncovered.

Crucially, the reactive effects operate unintentionally, that is, users may not even be aware that what they value is changing, or that they re-allocate resources as a result of the analytics while acting intentionally towards other ends. For example, using the BDA data consciously to redesign curricula or courses (an intended use) gave rise to an environment where e-learning became the most valued mode of delivering teaching (unintended change of values). Alternatively, using the BDA data purposefully to make staffing decisions (an intended use) was identified as a possible reason for posting more comments of lesser value (unintended gaming of analytics).

Therefore, as both the theory of reactivity and the TMSA suggest, the unintended consequences of human agency impacted the organisation at its structural conditioning level: certain teams were grown at the expense of others (resource redistribution), teaching or non-faculty staff were hired in higher numbers (change of values), etc. Some of these changes resulted in the reproduction of the same structuring forces within the organisation that shaped the agency in the first place, while others transformed the structuring conditions. Within the TMSA, structural reproduction is understood as a result of human agency unconsciously and unintendedly stabilising the present social structure, while structural transformation is an elaboration on or change in the social structure. Both are useful, if not essential, when analysing change at the structural or, in this case, organisational level.

Thus, reactive mechanisms and effects led to the reinforcing of the organisation's structuring capacity in its current form by emphasising teaching as a revenue-driving service, and the push towards performing well in a competitive environment, for example by enabling quick identification of underperforming staff, and fostering reputation and impression management among staff. At the same time, some unintended reactive consequences of actions of the users of the system led to the transformation of the organisation's structuring capacity, for example by using technology to replace face-to-face teaching practices, moving away from treating students as adult learners, and introducing the capacity to make changes within the same cohort or contract. A detailed analysis of the reproducing or transforming effects is beyond the scope of this project, but is very much encouraged as further research building on the present findings. It is therefore evident that such an approach, by placing increased emphasis on human agency, highlights its impacts on organisational structures.

5. The analytical cage as a new form of organising

The three preceding sections elucidate the findings stemming from three theoretical building blocks of the thesis, namely the theory of reactivity, encoding of social activity, and the ambivalent ontology of BDA as a digital artefact. Section 4, specifically, summarises the impacts of introducing BDA in work practices at the organisational level as a way of explaining organisational change. This emphasis on agency brings to the forefront perhaps the most significant organisational change stemming from the introduction of BDA: the emergence of a new form of organising, which I term the analytical cage. The findings indicate that placing actors within BDA settings that encode and measure their actions – as well as the actions of other users – changes the way in which organising takes place, and results in the intended and unintended consequences pointed to earlier. The cage here is a metaphor for the way in which an organisation organises the work of its employees, and is congruent with how this imagery has long been used in sociology (DiMaggio and Powell, 1983; Boiral, 2003), a point I return to towards the end of this section. In what follows, I consider the elements of analytical cages, the way they operate, and their consequences for organisations.

However, before proceeding, it is important to place the concept of the analytical cage against the current scholarship investigating new forms of organising in the context of big data analytics, if only in brief. Several researchers agree that the advent of big data analytics in organisations – whether termed datafication, datification, algorithmic intelligence, or similar – entails changes in how work is organised, coordinated, managed, or governed (Faraj, Pachidi, and Sayegh, 2018). These transformations have profound consequences and are often discussed as algorithmic management or coordination (Rosenblat and Stark, 2015; Schildt, 2017; Faraj, Pachidi, and Sayegh, 2018), data capitalism (Myers West, 2019), surveillance capitalism (Zuboff, 2015), or algorithmic governance (Campbell-Verduyn, Goguen and Porter, 2017; Coletta and Kitchin, 2017; Danaher *et al.*, 2017). These approaches focus by and large on the structuring capacity of the transformations analysed, and often present human actors as agency-less subjects of new data-based powers. The approach I propose, which attempts to balance the relationship between structure and agency, problematises this discourse by showing how human actors are involved with, and influence, the powers that datafication subjects them to. The analytical cage is thus a new form of organising in a datafied world which grants more agency to human actors than other approaches allow.

5.1. Elements of the cage

The analytical cage requires three elements: the entity that constructs the cage, the materials, and the design that regulates the actions of whoever is placed inside the cage. In the analytical cage, the construction is undertaken by a human actor working together with the BDA system.

The BDA system enables the construction and shapes it, while encapsulating some structuring elements of the organisation, as discussed above. At the same time, it needs to work together with the human actor – who is essential to generate data about his or her work activities. The analytical cage is constructed not only from the data obtained from the activity of the user in the cage, but also other users of the system, some of them conscious of the existence of the cage, some not, some within the organisation (like the members of staff interviewed), and some on the customer side (students in the case of LA). Thus, the human actor constructs the cage from his or her own data, as well as the data of other users, and in this sense the cages, become enmeshed and co-dependent while still maintaining separation.

Second, the materials used to construct the cage are defined by the types of data that result from encoding a pre-set and limited scope of activities in the BDA system – for example, the six activity types that the studied LA system encoded. Since the data is highly granular, the materials are insignificant for the construction of the cage in small numbers. Thus, the users of the system are compelled to carry out more and more activity to produce more data, and similarly encourage other users to participate in the generation of data that can then be used for the construction of the cage. Despite the small size of individual data building blocks, all of them are ultimately aggregated as the construction of the cage proceeds. Therefore, every tiny action, insofar as it falls within the prescribed remit of encoding, and the resulting data point contribute towards the outcome. It is evident that the data-material does not create impermeable boundaries that surround the human actor, but rather casts around the actor a net with threads made of data, with open spaces smaller than any activity that the actor may perform – and which captures them within.

Third, the design – or shape – of the cage that delineates the permitted remit of actor actions constructed out of the data-material is never predefined and set, but rather undergoes constant change. In other words, the boundaries of the cage are always fluid. This is because of the inherent properties of the BDA system as a digital artefact – as an object with an ambivalent ontology, it is never stable itself, and thus it confers a similar lack of stability onto the agency of the user. Therefore, the design of the cage constructed by the human actor may change over time, or may never be fully conceived.

And yet the actor-as-constructor does not engage in a completely random enterprise of construction. Indeed, the actor's actions are regulated by a series of mechanisms – reactive mechanisms – and their effects influence the user activity and, consequently, the data-material produced out of it. These reactive mechanisms are made possible by the BDA system as it obtains its technological identity as a measurement system, and thus compels users to change and adapt their behaviours in response to being measured as well as influence the behaviours of other users whose data-material is deployed in the construction of the cage. It is the data, together with its analytics, that elicits reactive responses when displayed back to human actors.

In other words, construction of the cage is dependent on two elements: on one hand, the ambivalent ontology of the BDA system, and on the other, the reactivity of the human actor towards the analytics, which dictates the placement of all data-materials (thus evidencing the active role played by the human actors in the constant designing and shaping of the analytical cage through reactivity to the analytics as measurement).

5.2. Operation of the cage

The analytical cage does not prescribe and regulate activity and performance through a set of specific rules or procedures set out by the organisation up front, but rather it entails a fundamental shift towards self-regulation on the basis of constantly renegotiated and changing statistical entities in the form of data.

In the context of BDA, the organisation does not need to impose rules, guidelines or specific numbers that users have to conform to in their analytical cages. Rather, through the power of measurement and the associated counting, numbering, and statistical processes described earlier, human actors work out (note the work that is required in this process) the “right” amounts and values of data, and adapt their activities accordingly. Even without set guidelines or recommendations, the statistical and measurement forces embedded in analytics will lead to a gradual regression to the mean with few outliers. In other words, setting performance standards is delegated to analytics.

Of course, thus defined standards are in constant flux as more and more data is generated in real time out of a constantly changing BDA system, the consequences of which were discussed in the previous section. This also means that the analytical cage is constantly being made and remade. Therefore, constant data generation is needed to sustain the existence of the cage. Moreover, ceasing to engage in the perpetual, constant construction does not mean that the analytical cage disappears – quite the opposite: as the human actor cannot opt out of the permanent, real-time generation of data-material, the analytical cage, left without active construction, may grow more and more restraining.

Besides eschewing overt regulation, discipline and comparison of activities, the organisation puts instead the onus of control on the user – who is now responsible for ensuring his or her own obedience to rules, guidelines and standards, as well as promoting similar conforming behaviours among other users (be it members of staff or students in the case of LA). The user needs to engage in self-regulation and self-discipline, rather than relying on formal expectations and requirements established by the organisation. It is the users who become responsible for verifying whether their work practices and activities conform to the analytical requirements, and it is the same user who needs to carry out work to generate the data-material for such purpose.

Ultimately then, the human actors become, within the analytical cage: the sources of activities used to derive standards, the constructors of the cages, and the users whose activities are regulated, while being responsible for regulating their own behaviours. This increased responsibility for self-regulation and self-control, as well as control over other users whose data-material is used to construct individual cages, can be disguised as greater autonomy, but in fact it represents a shift of work and responsibility from the organisation to individual human actors.

5.3. Consequences of working in the analytical cage

As a result of constructing analytical cages, human actors obtain changed social positions and identities within organisations. The analytical cage becomes necessary for the human actor to establish and maintain their position and identity, as the cage begins to represent some sort of a standard of work and the level of performance of a given actor. In other words, being a good employee comes to mean being an employee with good data, which can only be obtained by constant engagement in the construction and maintenance of the analytical cage. In this sense, the analytical cage is used productively to ascertain social positions and identities, as well as to shape and even constrain them. So far in the discussion, the imagery of the cage was deployed mostly to discuss constraint and regulation. However, the analytical cage can also operate as a form of protection and preservation of the human actor. The user can deploy the cage as a shield from outside pressures and interference from other actors, the organisation, or structural forces. Data-material can be used as evidence and support for user arguments and cases, and the shape of the cage can be employed to delineate the space that a given user occupies within the organisation. However, because it is the user who holds the responsibility for the construction of the cage, self-regulation, and standard-setting, this greater perceived autonomy may lead to intensified conformance with the construction, maintenance, and reproduction of the analytical cage.

A cage, even if self-constructed and self-managed, is still a cage. It dictates specific ways of acting and behaving, which in itself can lead to resistance and attempts to fight the cage (Prasad and Prasad, 2000; Dobbin, Schrage, and Kalev, 2015). However, the analytical cage is significantly more difficult to detect, resist, and fight due to its fluid, ever-changing character. The boundaries are always shifting, and the exact shape of the cage is elusive, thus making it more difficult to mount specific, justified criticisms of certain standards.

The shift of responsibility for control from the organisation to the users of the system may create an illusion of autonomy among the users. They internalise the existence of the cage and at the same time feel more in control through the responsibility for its construction. Such a feeling of autonomy and control can in turn lead to increased compliance, as users either do not realise that they are placed within the cage, or they feel empowered by the increased responsibility, trust, and freedom seemingly awarded by the organisation.

The way the analytical cage operates may lead to the standardisation of behaviours and activities, as discussed earlier. This is not new or specific in relation to analytical cages. What is different, though, is the speed of this process. In other words, standardisation of employees and their behaviours in analytical cages is likely to progress at a faster pace, as their activities and performance are monitored in real time, and the results of analytics are displayed instantly. This is in stark contrast to other forms of managing and organising work practices, in which performance and outcomes are assessed periodically.

Thus, users internalise analytical cages with the illusion of added autonomy, as organisations transfer control and regulation responsibilities to the users. Users feel more in control of their data and their cages, so they are likely to be more compliant. However, individual users also become elements of decentralised mechanisms of organisational control, as they need to ensure that other users' data-material is beneficial to the construction of their own analytical cages. Thus, the organisation relegates some control towards the users, who in turn are likely to be more compliant themselves and encourage higher compliance among the users in general.

Finally, working in an analytical cage has profound consequences for learning and development. All measurement and analytical processes put a premium on stability and averages, and punish differences. To learn, to develop, or even to innovate essentially requires stepping out of the known, stable practice, i.e. stepping out of the analytical cage. However, the way the cage operates penalises such behaviours and thus discourages users from exploring new avenues.

5.4. The evolution of the cage

Of course, the imagery of the cage is not new. Quite the opposite, it has been a popular trope among social scientists since the publication of Weber's influential essay in the 1930s (Greenwood and Lawrence, 2005). Weber defined his iron cage as an expanding bureaucratic structure that, in response to the desire for predictability and control, traps and subjects human behaviour to rules and procedures, and reduces them to cogs in a machine (Maley, 2004). This metaphor has been extended and elaborated upon in organisational studies to represent inflexible control of values and behaviour of employees by organisations (Greenwood and

Lawrence, 2005). The iron cage operates through the means of rules and procedures set out by organisations which are considered fixed and inflexible, and which employees have to, often blindly and unquestionably, follow. The iron cage is created and controlled by "the hands of the master", those who run and control organisations (Maley, 2004). Thus, the metaphor of the iron cage is undoubtedly a starting point for the analytical cage, but the way the latter operates entails a new form of organising: formal organisational rules and procedures are replaced by analytics derived from data-material. Instead of being inflexible, the shape of the cage is constantly changing, and the organisation as such is not in charge of setting up and controlling the cage – it is the user, together with the analytics system, who is charged with this task.

The analytical cage is also different from Panopticon sometimes deployed to study analytics-based organising (Faraj, Pachidi, and Sayegh, 2018). In the analytical cage, there is no illusion of a guard who may or may not be watching that leads to certain desirable behaviours. Rather, the user is placed in charge of regulating, controlling, and managing their own behaviour, as well as the behaviour of other users, and it is the potency of statistical and analytical processes that compels the user, through reactivity, to conform. In other words, the user is the guard and thus is more likely to conform to the rules. As every individual user becomes tasked with self-regulation and self-control, though the data-material may come from other users, individual actors may engage in exerting control over the behaviour, and thus data, of other users, and at the very least encourage them to partake in data generation.

The proposed concept of the analytical cage is also different from the emergent literature on algorithmic management, which puts more emphasis on the role of algorithms in directing and regulating behaviours, at the expense of the role of data in these processes (Rosenblat and Stark, 2015; Schildt, 2017). Algorithmic management explains organising by putting regulative power in computation and sets of computer procedures. The analytical cage, however, emphasises the role of the user as an essential element of the new form of organising, as the user is the source of data required to generate analytics. In the analytical cage, the user is not deprived of agency, but rather their agency becomes intimately interwoven with the analytical processes of BDA.

6. Conclusions

In this chapter, I synthesised the findings to provide an overview of the consequences of conducting measurement through BDA, I summarised the application of the theory of reactivity in the study of BDA, and I summarised how the changes at the level of working with BDA lead to the reproduction or transformation of organisational structures. These findings respond directly to the lack of cross-level research in IS investigating the changes in organisational structures and models that accompany the work-practice level of introducing BDA (Günther *et al.*, 2017). Thus, to realise value, organisations need to account for the unintended effects to foster the transformation or reproduction of their organisational structures and models accordingly.

The findings also allowed me to propose the concept of the analytical cage as a new form of organising, closely related to the issue of organisational change. Thus, BDA changes organisations in which it is embedded not only through the reproduction or transformation of organisational structures, but also, and perhaps more importantly, by allowing for a new form of organising which underpins these changes. The analytical cage organises human activities by placing actors within BDA settings whose mechanics are characterised by the encoding and measurement of the actor's actions in real time, and by constantly changing systems. Within the analytical cage, data-material and analytics generated and acted upon by the users replace organisation-defined rules and procedures, effectively delegating regulation, discipline, and control to individual users and creating a decentralised mechanism of organisational control whereby users exert control over each other to ensure regular production of good data. This changes the nature of work practices, which become interwoven and dependent on data about users, standardises individual actors at a faster pace, and limits learning and development. Organisations implementing BDA need to take into account the analytical cage, including its elements, operation, and consequences, and appreciate that the very nature of such systems will likely lead to both intended and unintended consequences at the organisational level.

Chapter 12: Conclusions

1. Introduction

In this chapter, I summarise the findings that arose from the study and return to the main research question to provide a compact response. I explain the implications resulting from the findings, and I outline the main contributions of the study in the field of Information Systems (IS). Further, I relate these findings to the body of literature on Learning Analytics (LA) to draw out practical implications which also extend more broadly into the use of Big Data Analytics (BDA) systems. I also highlight the limitations of this study and outline areas of potential future research that this research enables.

2. Summary of findings

This research project was conceived as a qualitative investigation into an organisation that implemented a BDA system in order to understand whether and what kind of intended and unintended organisational changes can be observed as a result. Drawing from a rich tradition of case study research in IS, qualitative data in the form of interviews, observation notes, and documents were obtained, coded, and analysed with analytical support from the notions of data production and the theory of reactivity. At a higher theoretical level, the Transformational Model of Social Activity (TMSA) was deployed to understand how changes in human agency at the work-practice level, resulting from the implementation of a technological object – namely a BDA system, can lead to the transformation or reproduction of organisational structures, which was the main objective of the project. This research also strove to analyse the production and characteristics of BDA data in order to reconcile opposing views on its nature. Further, the study enabled a contribution towards extending the theory of reactivity in BDA. Importantly, the findings provided building blocks for the concept of the analytical cage.

The analysis and synthesis undertaken in this dissertation provide a comprehensive answer to the main question of *how big data analytics changes organisations that implement it*. To reiterate, the introduction of BDA systems as technological objects impacts work-level practices of staff who begin working with BDA. Such systems give new or improved capacities to staff who engage in intended uses associated with BDA. Because BDA systems encode, aggregate, and correlate data about staff and customer activities, with the results of such measurement being made visible to staff, over time they become treated as technologies of measurement. With this new technological identity ascribed to them by staff, BDA systems become nexuses of reactive mechanisms (commensuration, self-fulfilling prophecies, reverse engineering, and narratives), and when enmeshed with human agency they lead to unintended reactive effects (redefining work and practices, resource redistribution, change of values, gaming, discipline, standardisation, and acceleration). Such unintended reactive effects at the work-practice level lead to organisational change, by way of either reproducing or transforming the structural capacities of organisations, which in turn enable or constrain future human agency. These findings relate directly to the lack of cross-level research in IS pertaining to the work-practice and organisational level of BDA.

The emphasis on agency allowed for the proposal of the concept of the analytical cage as a new form of organising emerging unintentionally from the introduction of BDA. The analytical cage is a new form of organising whereby data and analytics are generated and acted upon by the users and require their agency in production and operation. Analytical cages are shaped by the processes of data encoding, but also by reactivity that human actors exhibit as their actions are constantly measured in real time in ever-changing analytics systems.

Finally, in meeting its other objectives, the study offered the opportunity to test and extend the theory of reactivity into BDA. As a result of a number of important distinctions which differentiate the initial context in which the theory was established and the present setting of BDA, the theory can be extended to include three new reactive effects: discipline, standardising, and acceleration.

3. Contributions and implications

The main area of contribution of the study is the field of IS and its growing literature on BDA. Importantly, the study offered a cross-level investigation of how changing work practices lead to both intended and unintended transformations of organisations (Günther *et al.*, 2017). The analysis and discussion herein contribute to the numerous voices in the critical BDA strand of IS literature which call for more research into understanding the effects of BDA and its impacts on transforming behaviours (Lycett, 2013; Newell and Marabelli, 2015; Markus, 2017). Significantly, it provides a better understanding of the role of BDA and its consequences for organisations, as well as fleshes out how the intended and unintended transformations can limit or lead to more value derived from BDA.

A significant set of implications of this study concern organisations implementing BDA. The findings indicate that in order to realise value from BDA systems, organisations need to account for reactivity, including its mechanisms and effects, and be aware that the nature of such systems can lead to both intended and unintended consequences at the organisational level. To realise value from BDA, organisations need to manage or embrace the unintended effects in order to foster the transformation or reproduction of their organisational structures and models accordingly.

The concept of the analytical cage is a direct contribution to the developing stream of research focusing on understanding the consequences of datafication and problematises this discourse by emphasising human agency involved in phenomena sometimes termed data capitalism, algorithmic management and coordination, or algorithmic governance.

This research project belongs to a small but growing pool of empirical studies that analyse various purported labels of big data in practice. It argues that the often-cited novel characteristics of big data, such as volume, velocity, variety, granularity, veracity, and use-agnosticity can not only be challenged through an empirical study of BDA, but it can also be shown that these properties can limit the usefulness of BDA within organisations. An alternative reading of BDA as a digital technology of measurement was proposed to understand how the distributed, editable, interactive, open, and reprogrammable (Kallinikos, Aaltonen, and Marton, 2013) nature of BDA can offer a productive lens through which to view the phenomenon, but also how it emphasises the problems surrounding the use of BDA for measurement.

The project also confirmed that investigating the production of data through encoding, aggregation, and correlation (Alaimo and Kallinikos, 2017) is a useful lens that provides a thorough understanding of how online activity becomes translated into data.

Finally, in meeting its other objectives, the study offered the opportunity to test and extend the theory of reactivity (Espeland and Sauder, 2007; Sauder and Espeland, 2009) into BDA. As a result of a number of important distinctions which differentiate the initial context in which the theory was established and the present setting of BDA, the theory can be extended to include three new reactive effects: discipline, standardising, and acceleration. This work fits in the recent applications and extensions of the theory of reactivity in the field of management (Pollock and D'Adderio, 2012; Pollock *et al.*, 2018).

However, the study also contributes to the growing body of literature on LA, and specifically unpacks how the introduction of LA impacts higher education institutions. While some researchers pointed towards the wider transformations in education resulting from the use of big data, and by extension LA (Thompson and Cook, 2014, 2017; Sellar, 2015b, 2015a), thus far comprehensive case studies investigating the changing nature of teaching have been sparse. In this respect, this research depicts the ongoing transformation of teaching and administrative practices within a higher education institution which can be traced back to the increasing use of LA. This comprehensive analysis of the organisational transformations within the context of LA complements a body of research hitherto focused on analytical tools, statistical models, and students, while neglecting the institution.

Finally, the study builds a foundation for a novel treatment of BDA in the context of measurement, and performance measurement and management more specifically (Melnyk *et al.*, 2014; Micheli and Mari, 2014; Kornberger, Pflueger, and Mouritsen, 2017). By highlighting the implications of measuring staff activities and behaviours for performance assessment purposes, this research contributes to the rich body of literature on the role of digital technologies in organisational measurement.

4. Limitations and further research

The present study was undertaken to provide a thorough understanding of how organisations change as a result of the implementation of BDA. It focuses on tracing the mechanisms and effects of the changing work practices that then influence the structures of organisations. Due to the scope of the dissertation, the study did not extend into analysing the transformative and reproductive nature of such effects in detail. There is an evident need to study such changes in greater depth in order to understand what steps organisations can take to ensure that the implementation of BDA brings the desired changes in a managed way. For instance, on the basis of findings described herein, further, more longitudinal studies could look into longer-term organisational changes and the results of using BDA data for decision-making at strategic levels.

This research contributes to the study of value of BDA by pointing towards organisational transformations resulting from the implementation of such systems. More research is needed in this direction to uncover what the required qualities of organisations are, and what shape changes ought to take in order to foster successful realisation of the value of big data. For instance, attention should be paid to understanding how reactivity can be used to steer intended and unintended effects within organisations, e.g. by studying what kinds of work practices and what characteristics of systems can guide employees towards the desired behaviours. This poses interesting questions in relation to performance measurement and management, and the usefulness of BDA in this area.

Importantly, this study serves as a foundation for further research concerning analytical cages, i.e. new forms of organising that depend on the agency of human actors in order to exert their regulatory and disciplinary powers within the contexts of progressive datafication of work and organisations. Such an endeavour could proceed, for example, by studying the construction and exact workings of analytical cages, and their consequences.

More, smaller studies focusing on the individual mechanisms and effects of reactivity are also desirable to understand how BDA can be directed towards eliciting the envisaged change in individuals and organisations. One interesting observation, while outside of the scope of this study, concerned the different perspectives of interviewees concerning the value of data, depending on the type of the interviewees' work and their seniority within the organisation. Thus, a better understanding of the perceptions of the value of BDA within organisations emerges as an interesting avenue for future research.

Further, while this study focused on an organisation deploying a BDA system in part to monitor and manage the performance of its staff, additional studies are needed to confirm whether the theory of reactivity, as well as findings from this project, hold up in customer-facing BDA systems. The case study analysed in this project concerned a higher education institution, albeit one with a strong business orientation and rigorous management structures in place. Even so, a similar study of a more typically market-oriented private company could further refine the findings.

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Appendix 1 – Pilot study report

The initial analytical work has led to the construction of an analytical framework that could operationalize the theory of reactivity and frame the study. Based on reading, background knowledge and discussions with practitioners, the following levels of potential reactivity to data have been identified:

- Level 1: Data collection, just the fact that data is collected causes reactive effects.
- Level 2: Data visibility, making data visible in the system causes reactive effects.
- Level 3: Data analytics, further analytics of data collected causes reactive effects.

It was further hypothesised that such reactive effects feed into actions while they are still performed, therefore leading to morphogenetic or morphostatic effects on the structure (Archer, 1995). The pilot study server thus as a way of testing the viability of this analytical framework and confirming these initial hypotheses.

A 90-minutes long semi-structured interview was conducted with the module leader, following a loosely defined topic guide. This part of the pilot study yielded information about how the module leader used LA and its data, as well as pointed towards changes (at various levels as per the analytical framework) in their own teaching practice, as well as wider institution. The interview confirmed the viability of the study as the system is used by the employees of the School and the interviewee pointed out some changes pointing towards potential reactivity. The interviewee also allowed me to browse through the LA system, take screenshots and observe how he would normally use the system for different purposes. A 45-minute focus group was also conducted in March during the last seminar for students participating in the module. Overall, 7 students participated, along 1 lecturer. During the focus group, we discussed data collection as an example of a feedback system used at School, to frame the focus group within the scope of the module. We reviewed several examples of how data about student actions within LA is made visible to module leaders. A discussion focused around four core issues followed, and also confirmed potential reactivity in place.

The last part of the pilot study involved the analysis of data reported on student's actions in LA. I imagined it as a comparison of number of views, clicks and other actions before the focus group was held and after it was held. I was expecting to discover spikes of numbers of views induced by the discussion about LA data. However, no such differences were observed and there was no increase in overall activity after the date of the focus group compared to previous days. There was nothing different from the normal, expected pattern. At that point, I did not find these results conclusive for two main reasons. First, the sample was too small, it only consisted of focus group participants, therefore any substantial differences in activity cannot be ruled out on this basis. Second, the focus group was held on a Thursday in the last week of term when students may have other commitments or plans and they may not have had the time to log into LA. Due to this particular timing issue, it cannot be ruled out that the system would have registered different numbers of views and clicks if the focus group was held in a different week.

The above findings seemed to provide evidence required to confirm whether the theoretical framework of reactivity is useful in this context, as well as whether the suggested analytical framework to operationalize it was workable.

First, the evidence from data sources above indicated that there was some sort of reactivity taking place, that is "individuals alter their behaviour in reaction to being evaluated, observed, or measured" (Espeland and Sauder, 2007, p. 6). Even this preliminary data collection suggested that there were mechanisms of self-fulfilling prophecies as well as commensuration at play in LA. As evident from the focus group conducted with students, the participants were aware that if they have ever been shown their predicted classification, they may well start behaving like a 2.2 or a First student, which can be interpreted as an example of a self-fulfilling prophecy. The mechanism of commensuration was also clearly at play, creating numbers of clicks and scores which are supposed to correspond to the learning process, as evident from all sources of data.

In terms of potential effects of reactivity, it has already been identified that LA may lead to the reallocation of resources, for example by students who would be willing to focus their time and energy on modules in which the system says they are performing worse than in other modules. Reactivity in LA also leads to redefining of work and practices, for example by changing how teaching content is structured in the VLE, as evident from the interview. Both in the interview and the focus group, participants pointed out that gaming the system may be one of the obvious effects. The focus group has also confirmed that some students may experience a change of values and become more attached to what the data says about them rather than what they really learn. Even with this limited scope of data collection it was thus clear that the theoretical framework of reactivity was a useful lens for the purposes of this study.

Second, the pilot study has also confirmed that reactivity in LA feeds into the very action that is being performed. In other words, data in these systems feeds into a single, on-going activity of a teaching module. This has been confirmed in the interview with the lecturer stating that this data could be useful to help him tailor the course contents throughout the duration of the course, rather than only modify it for the future cohort based on more typical student feedback. But also in the focus group students agreed that access to this sort of data would help them modify their efforts and behaviours within one module, rather than just receiving a final grade when it is too late to decide to put more effort into a particular module. This also seemed to be confirmed in the way the VLE and LA structured databases and data classes by constructing “Module Occasions” for which data was collected.

Third, data from this pilot study confirmed that the proposed analytical framework is a reasonable and well-founded approach to studying the VLE as a typical LA. There is evidence pointing to the existence of and differences between reactivity at different levels within LA.

On Level 1, just the fact that data is being collected had an impact. The analysis of VLE confirmed that in order for this data to be collected, the platform had to be structured in a specific way for different data classes to be possible, and teaching content had to be structured in a specific way to enable data collection practices. Students in the focus group suggested that just the awareness of the data collection process was likely to at the very least make them subconsciously alerted to it, and at most change their behaviours.

On Level 2, making data visible had a clear impact, or led to reactive effects. Data from the interview confirmed that lecturers were likely to modify teaching content based on viewing data shown to them. Moreover, they were likely to “prod” students who fell into lower quartiles of engagement. Students participating in the focus group confirmed that they were concerned teachers may form or confirm stereotypes based on viewing data.

On Level 3, data analytics was likely to lead to changes in behaviours, although this point was the least supported in data from the pilot study and required further data collection. It has been suggested in the interview that the peer assessment tool, here treated as an example of data analytics, was likely to make students game the system or engage in strategic behaviours aimed at maximising the score, yet this was a hypothesis of the interviewee rather than a fact he experienced. Students in the focus group also hypothesised that if they were shown predictive analytics of their scores, they would most likely reallocate resources, or at the very least feel motivated or demotivated by these predictions. Since predictive analytics is not a part of LA as of now, these points were hypothetical, nevertheless indicative of potential future results in the main study.

Appendix 2 – Example interview guide

Date:
Time guide: 60 minutes

Interviewee No.:
Name:
Role:
Module taught:

Introduction

Introduce the interviewer, restate the goal of the project and purpose of interviewing. Reassure of anonymity and confidentiality, been through ethics approval. Ask for their consent to record the interview and say that they may be transcribed at a later stage.

Section 1: Background questions

Years of experience in teaching

Current teaching responsibilities

Fitting teaching around other responsibilities

Section 2: Use of [VLE] for teaching

Experience and training in using [VLE]
Potential questions to ask: How long have you been using [VLE]? What do you think of this platform? Have you received any training? Is there any support for it? Documentation? Would you say you know it fairly well, or would you like some further instructions?

Comparison with other VLEs
Potential questions to ask: Have you ever used other learning environments, such as Moodle or Blackboard? Is this your preferred platform? What are the good and bad sides of it?

Current use of [VLE] for teaching
Potential questions to ask: How do you use [VLE] for the teaching of your module? Before, during and after the teaching module? Can you talk me through this space and different components? How did you create it? Why is it structured like it is? Did you receive any help or support when setting it up? Who else has access to it - administration? Support staff? How do they use it (and can I contact them)?

Section 3: Use of data collected in [VLE]

Awareness of data collection
Potential questions to ask: Are you aware of [VLE]'s data collection capacities? What do you currently know about it? Have you received any training or information in relation to this? What do you know?

Current use of data collected
Potential questions to ask: Can you talk me through how you use this data in your module?

Usefulness of data for teaching
Potential questions to ask: Do you think this is a useful component? Do you think you benefit from LA in your teaching? What can you do with this data that you weren't able to

do before? Is there anything that you do in your teaching now that you wouldn't be able to do without this data?

Problems or issues with data use
Potential questions to ask: Can you think of any downsides? Potential problems or doubts that you have? Anything you're unsure about?

Communication with students about data use
Potential questions to ask: Do you know if your students make any use whatsoever of this data? Have you talked to them about this function?

Section 4: Analytics

Further use of data
Potential questions to ask: Do you use it as a basis for any further analytics, e.g. frequency, reading or viewing statistics? Looking for any patterns? Who developed these tools? How do the results feed into your teaching practice? Have you introduced any changes into the module or teaching based on the data?

Peer assessment tool
Potential questions to ask: One of the elements that are in use in your module is the peer assessment tool. How long have you been using it? Are you confident you know how it works? Have you received any training or guidance on its use? Do you have any concerns around it?

Effects of peer assessment tool
Potential questions to ask: Do you use this tool for yourself? Have you used the resulting outputs in any way? Have you noticed anything in particular about how students use this tool?

Next session:
Section 5: Closure

Assessment of effectiveness of this data-driven approach
Potential questions to ask: What do you think in general about this data-driven approach to teaching? Do you benefit from it? Does it help you do your job better or quicker? Do you think students benefit from it?

Changes resulting from data approaches
Potential questions to ask: Would you say that the way you teach changed because of this data-driven approach? Apart from your own work, do you see any other changes at the institution resulting from the wider spread of this approach?

Concerns and issues
Potential questions to ask: Do you have any concerns around how student data is used? Anything that we haven't covered yet?

Wishlist
Potential questions: How, in the ideal case scenario, would you see this initiative developing? What would you like to be able to do, either in your module or the whole school as an institution?

Appendix 3 – Coding scheme

Name	Description	Files	References
Big Data Characteristics		26	77
By-productness	Others point to the fact that one of the characteristics of big data is the fact that it is a by-product of everyday life practices (Cohen, 2013; Bhimani and Willcocks, 2014; Couldry and Powell, 2014)	5	6
Exhaustivity	Schönberger and Cukier claimed that an important characteristic of big data is its exhaustivity, that is the possibility to capture the entire system rather than relying on samples (2013)	2	2
Extensionality	The ease of adding or changing fields	0	0
Granularity	The decomposition of behavioural patterns into such granular traces involves a loss of meaning, however this loss is then compensated by increasing opportunities to aggregate data and subject it to analysis (Kallinikos, Aaltonen and Marton, 2013)	10	13
Lifted out of expertise	As argued, “data generation is lifted out of the prevailing expert-dominated cultures by which the information needs of practice fields have been defined” (Kallinikos and Constantiou, 2015, p. 71), and instead large populations of users or technically-minded database administrators carry out the process	12	25
Lossiness	It often does not include any information about the social context in which it was produced (Griswold and Wright, 2004), sometimes referred to as its “lossiness” (Busch, 2014)	3	3
Real-timeliness	Big data can be real-time, near real-time, batch, structured, semi-structured or unstructured (Murthy, Bharadwaj and Subrahmanyam, 2014). It can be both quantitative or qualitative, indexical, attribute or meta-data (Kitchin 2014)	1	1
Relationality	(Boyd and Crawford, 2012), so the possibility to cross-reference different datasets through common fields	1	1
Scaleability	Scaleability (Marz and Warren, 2012) have also been identified as important features of this phenomenon	0	0
Sorted on the way out	“Sorting in the way out”, where data “is captured and stored without such a plan and on the assumption that it may be variously used a posteriori” (Constantiou and Kallinikos, 2015), as proposed by Weinberger (2007)	3	4
Use agnosticity	One of the salient features of big data is that it relies on data that was not initially intended to be used for certain purposes (Puschmann and Burgess, 2014), thus creating “data shadows” (Graham, 2014), layers of information about objects, “data fumes” (Thatcher, 2014), or “data footprints” (Lewis, 2015)	3	4
Variability	Big data is a type of data whose meaning can be constantly shifting in relation to the context where	2	2

Name	Description	Files	References
	it was generated, so it is important to talk about its variability		
Variety	Various sources of data (Laney, 2001)	1	1
Velocity	Increased point of interaction speed and the pace data is generated in interactions (Laney, 2001)	0	0
Veracity	Big data can be messy, noisy, uncertain and contain errors, therefore veracity is also mentioned as one of the features (Marr, 2014)	10	13
Volume	These processes have a non-trivial impact on the practices of measurement when conducted via computational means. Measurement practices carried out with help from computation become functionally enclosed, objectified and automated	2	2
Big Data Production Processes		15	34
Aggregation	Aggregation relies on adding together individual encoded data points and looking for patterns revealing new information. It is an attempt to generalise data about people and their social activity (Alaimo and Kallinikos, 2016). Aggregation relies on the prior encoding in the sense that without encoding users and their activities as predefined data points, it would be far more difficult, if not possible, to aggregate the diverse world of people and behaviours	11	13
Correlation	Finally, correlation is the process by which aggregated users and their actions can be compared, contrasted and otherwise processed to look for patterns. This relies on further datawork (Alaimo and Kallinikos, 2016)	4	4
Encoding	Encoding is the process of formalising users and their activity as objects along pre-established actions (Alaimo and Kallinikos, 2016). Users and their social activities become disaggregated into countable clicks, likes, views, which allows to identify, count and compare with ease. In other words, encoding entails the objectification of people and their social activity and corresponds to the mapping of reality through data (Kallinikos and Tempini, 2011)	10	17
LA Applications		31	90
Attrition risk detection	Detecting the risk of dropping out by analysing students' VLE data	8	9
Behaviour detection & modelling	Detecting student behaviours to improve models	15	21
Course recommendation	Recommending new courses to students based on data about their activities	0	0
Curriculum design	Informing course design	11	14
Data visualisation	Using data visualisation techniques to easily identify trends and relations	3	5
Institutional decision making	Improving decisions	13	24
Intelligent feedback	Providing intelligent and immediate feedback to students to improve their interaction and performance	1	1
Performance prediction	Predicting student performance by analysing	0	0

Name	Description	Files	References
	interaction in VLE		
Resource recommendation	Recommending educational resources to students, sometimes known as adaptive learning	2	2
Student skill estimation	Estimating students' skills	11	14
Measurement and technology		12	22
Distributedness	"Seldom contained within a single source or institution" (Kallinikos, Aaltonen and Marton, 2013, p. 360)	5	6
Editability	It is possible to modify and update them continuously and systematically	6	8
Interactivity	Offering the possibility to explore information through the responsive and loosely bundled nature of the digital artefact	3	3
Openness & reprogrammability	They can be accessed and modified by another digital artefact or users	4	5
Measurement processes		32	73
1. Representation	Seen from this perspective, measurement as information provides a selective, deductive, abstractive, subjective, reductive representation of objects it measures	25	51
10. Computation	Computation "entails the relentless analytic reduction of the composite character and complexion of the world" (Kallinikos, 2009, p. 183). These processes have a non-trivial impact on the practices of measurement when conducted via computational means. Measurement practices carried out with help from computation become functionally enclosed, objectified and automated	0	0
2. Commensuration & quantification	Measurement entails not only representation, but also translation of qualities, of how things are, into quantities. Sociological literature names this process commensuration, that is "the transformation of different qualities into a common metric" (Espeland and Stevens, 1998, p. 314) and states that it "encompasses all human efforts to express value quantitatively" (Stevens and Espeland, 2004, p. 375)	4	5
3. Numbers	In this sense, again, numbers as outcomes of measurement are productive (Beer, 2016). But also, drawing from Badiou's philosophical take, numbers force some form of a unity, singularity on objects or people who do not fit into such a form. Thus, representing something as a number is a transformation, a mutation of its intrinsic character to fit into a fixed format (2008)	2	2
4. Calculation	Therefore, calculation can be seen as a set of operations, previously impossible, carried out on (measurement) numbers which are derivative in relationship to beings, and yet serve as instruments that shape and influence the interpretation of these beings	0	0
5. Standardisation	Standardisation is an essential component of measurement precisely because of its dual character: it sets aspirational standards, and yet it gives rise to sameness; it helps to identify similarities, but at the same time it creates	5	7

Name	Description	Files	References
	distinctions and differences. It is also an ongoing process which can never be complete		
6. Classification, categorisation & aggregation	Classification as "a spatial, temporal, or spatio-temporal segmentation of the world" and identify classification systems as "sets of boxes" (Bowker and Star, 1999, p. 10); "once categories are in place, people's behaviour increasingly conforms to them" (Espeland and Stevens, 1998, p. 331). This meant that new classes led to the formation of new objects, such as "the population characterised by a mean and a standardized dispersion" (Hacking, 2006, p. 142)	3	3
7. Indices and indicators	Indices and indicators shed a slightly different light on the issue of measurement. They act by putting together measures of different aspects, or sometimes of completely different things. As a result, they produce measurement outcomes that are increasingly less transparent and straightforward to interpret	1	1
8. Rankings	Rankings are a particular type of indicator that also creates relationships of order, of higher up or lower in a ranking. This is different from indices because it creates competition between ranked bodies: for one to score higher, another one has to score lower, unlike in indices where it is possible for more than body to obtain a particular score. A ranking as a form of measurement creates interdependencies between ranked bodies unlike any other practice	2	4
9. Statistics	"Statistics" is often understood as "the collection, classification, analysis, and interpretation of numerical facts or data" (Kish, 1987, p. 598) and thus is not only a continuation of these previous practices of measurement, but also adds complexity to the processing of measurement data by relying on probability calculations and predictions	0	0
Narrative		92	263
1. Global business school context	The educational context of business schools in the UK, TEF, rankings	12	25
2. University context	Relationship between the School and wider university	9	11
3. School	How it works, organisational diagram	28	56
IT Team		6	12
4. VLE	How VLE works and came to be	53	110
5. Analytics Component		35	61
Reactivity		40	188
Effects		25	68
Change of values	Change of values pertains to the effect that measurement gives additional validity and weight to what is being measured, because "what cannot be measured cannot be verified" (Aaltonen and Tempini, 2014, p. 106)	12	19
Gaming the system	Those who are being measured may resort to gaming the system, that is "manipulating rules and	7	14

Name	Description	Files	References
	numbers in ways that are unconnected to the motivation behind them" (Espeland and Sauder, 2007, p. 29)		
Redefining work & practices	Redefining of work and practices describes how work is being changed as a result of reactivity (Espeland and Sauder, 2016), for example by focusing the curriculum on bar passage or preventing academic staff from going on sabbatical in autumn as this may impact staff-to-student ratios (Stake, 2006), or changing the way admissions are processed (Espeland and Sauder, 2016). Other authors pointed towards reorganisation of structures and increased attention paid to how work carried out by individuals affects rankings (Hazelkorn, 2007)	12	24
Redistribution of resources	Redistribution of resources as an effect leads to withdrawing or limiting resources in one area of an institution and re-directing them to another one (Espeland and Sauder, 2016)	6	11
Emergent effects		21	55
Acceleration		8	15
Discipline		14	30
Standardisation		7	10
Mechanisms		32	65
Commensuration	Transformation of different qualities into a common metric (Espeland and Stevens, 1998), translating complex processes into single figures (Miller, 2001), often relying on simplification and normalisation (Sauder and Espeland, 2009)	8	11
Narrative	A story featuring characters, events, scenes and plots involving a conflict or problem (Espeland and Sauder, 2016), can be celebratory or defensive, often including causal explanations for changes	27	40
Reverse engineering	Working backward through the construction of a completed measure to understand how it works (Espeland and Sauder, 2016)	5	7
Self-fulfilling prophecy	Reactions to measures which confirm the expectations embedded in measures (Espeland and Sauder, 2007) which in turn encourage behaviour that conforms to them (Espeland and Sauder, 2016)	7	7