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Big Data in Education: Using educational data mining and learning analytics to improve policy in the field of education

Master Thesis

Technology Governance

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I hereby declare that I am the sole author of this master's thesis and it has not been presented to any other university for examination. All works, major viewpoints and data of the other authors used in this thesis have been referenced.

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The master's thesis meets the established requirements

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Abstract

The thesis gives an exploratory overview of the state of the art of learning analytics and educational data mining in higher education. It highlights the emergence of learning analytics (LA), its drivers, processes and the opportunities it offers for improving policy making in the field of education. While education sector lags behind other sectors in generating valuable insights from big data, to enhance the learning experience, numerous institutions in Australia, UK and US are making significant progress in the field. The field of learning analytics and its associated fields holds much promise in its potential to address the issues and challenges facing higher education institutions. However, in order to adopt learning analytics in the educational domain, universities are in need of policies and frameworks to aid their transition to new educational models that will address these complexities and challenges. This thesis undertakes a comparative case study analysis to address the opportunities learning analytics offer for policy making and to compare the work being done on preparing to make use of educational data to improve policy in Australia, UK, US. Its primary finding is that all three countries echo a strategic national plan to address issues facing their higher education institutions such as reducing drop outs and enhancing learning experience through personalization and real-time feedback. The thesis concludes with a comparison of the selected countries, where according to document analysis US and Australia are ahead of UK in implementing LA on an institutional level whereas UK is progressing more on a national level by equipping institutions with necessary mindset for embracing LA.

Keywords: learning analytics, educational data mining, policy making, education, Australia, UK, US

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1. Introduction

The increasing need for the attainment of transversal skills (Technopolis,2015) and increasingly diverse learning environments, which go beyond traditional education, places higher education institutions to seek more scalable approaches that will allow them to: 1) enhance learners' and institutions' performance, 2) improve pedagogical planning, 3) reduce institutional expenditures, 4) identify students disposition to learning 5) reduce school drop outs, and 6) increase opportunities for personalized learning (Larusson & White, 2014). Numerous commentators have suggested that new educational models are required to provide the quality, scale and flexibility necessary for the needs of modern society (Siemens, 2005). Historically, it has been a tendency to evaluate students' educational progress by ranking them according to their academic performance (Spector et. al., 2014). This way of evaluation, known as summative assessment, can be described as the traditional way of assessing the achievement of students (e.g. through standardized tests), which is utilized mostly for accountability. On the other hand, learner-centered measurement, relies on a more formative assessment, which is supported with in-time feedback to recognize the learning process and plan the next steps of instructional adjustments. This type of assessment has shown to optimize and personalize learning experience (Shute, 2014). The role of assessment, especially formative assessment, as part of teaching becomes evident when considering the increasing numbers of school-leavers (Steiner et al., 2014). According to the OECD report 84% of teenagers within OECD countries complete upper secondary education. On the other hand the European Union completion rates of upper secondary education indicate 87.3% (OECD, 2013). In this rapidly changing world, the priorities of educational institutions and policy makers are to minimize the number of school drop outs, increase the number of students to have completed tertiary education, develop their learning skills, and increase the opportunities for personalized learning (European Union, 2014).According to researchers, a teenager's decision to leave school is because of problems with school engagement, attendance and behavioral problems. Both summative and formative assessment constitute effective data to identify students at risk and provide effective intervention (Lee Goss & Andren, 2014). Moreover, the increasing need for personalized learning environments proofs that one-size-fits-all didactical practices will not meet students' requests. (Johnson et al., 2013).

The emerging sciences of learning analytics (LA) and educational data mining (EDM), discussed in more detail later in this paper, are considered to potentially improve educational assessment and feedback in educational process, reduce dropout rates, and personalize the learning experience (ibid). LA offers the possibility to monitor the learning process and implement real-time assessments and feedback systems in order to improve learning (Solar, 2011). The field of learning analytics and its associated approaches and methods to data analysis holds much promise in its potential to address the issues and challenges facing higher education institutions. However, in order to adopt learning analytics in the educational domain, universities are in need of policies and frameworks to aid their transition to new educational models that will address these complexities and challenges. Likewise, quality assurance bodies and government ministries also require policies that will facilitate promotion of (inter-)national and regional priorities, benchmarking of practices implemented in institutions, and coordination of the cross-institutional collaboration and exchange of data, best practices, and experiences.

Even though LA has gained much interest by researchers, limited attention has been paid to the policy instruments and structures needed to adopt analytics in the educational sector (Solar, 2014). Due to the lack of empirical work, there is limited number of papers published regarding learning analytics implementation at scale. Thus, the aim of the current thesis, is to address the use of educational data mining and learning analytics for policy making in the field of education, with a particular comparison of the national policies for adopting analytics/educational data mining (LA/EDM) of the fore runner countries in the fields: Australia, USA and UK. Moreover, this thesis aims to compile recommendations of how LA/EDM research needs to progress; i.e. what needs to be done so that big data in the field of education can be used for policy making. Due to the novelty of the field, policy comparison of the adoption of LA/EDM tools in education policies of leading countries have not yet been carried out. This means that the thesis has the potential to contribute to the analysis of using big data in education. Thus, the current thesis will fill a gap in the emerging literature and will help researchers identify common policies and problems in the field of LA/EDM. This helps to outline also new avenues for research in the field. The study will also contribute to the sector-wide reflection which is needed to make progress towards a more complete picture of the role of analytics in education. The research strategy of the current thesis is to develop a comparative analysis of different countries at the forefront of using LA/EDM to improve their educational policies. The research design used to carry out this thesis is qualitative in nature and uses a comparative case-study approach providing an understanding between the context and the processes, the structures and the actions used in adopting LA/EDM in the aforementioned three countries.

The thesis reviews the work being done on preparing to make use of educational data to improve policy in US, UK, Australia. In doing so, the current thesis has two important research questions: namely, (1) what are the opportunities LA/EDM offers for policy making in the field of education and (2) what are the approaches of different countries in the sample towards using LA/EDM to improve policy in the field of education. The thesis also asks if there are differences between the approaches taken (if yes, then the thesis tries to highlight what the former is dependent on). With regard to research methods, to generate a good understanding of the cases, the current thesis will utilize both qualitative and quantitative data. From qualitative sources of data, documentation and archival records will be used as primary sources of evidence for addressing ethical considerations, use of educational data for prediction and intervention and the progress and expectations in educational data mining. From the quantitative side, statistical data will also be used.

In order to present the comparative analysis, the current thesis is divided into three chapters. The first part of the thesis presents a brief and synthetic overview of previous research on how big data is used, analyzed and how it is changing different policy fields and how it is particularly influencing the field of education. The second part constitutes the comparative analysis of the thesis. Here the comparison of the countries will be based on collecting data from documents published by internationally known research groups working on LA, or the national higher education agencies of the selected countries.

The thesis ends with the conclusion, which summarizes the main findings and proposes policy recommendations for the field.

2. Literature Review

This section of the thesis will present a systematic literature review on the main challenges and insights of learning analytics. It seeks to define, big data, learning analytics and its related areas. The followed methodology of the literature review will be based on the structure proposed by Okoli & Schabram (2010). Thus, to compile the literature review, a four-step process was followed: a) literature search – data collection, b) evaluation of the findings – selection of the documents limited to keywords, c) analyzing the findings, and d) writing the review (ibid).

During the first phase, the collection of previous studies regarding Big Data and LA/EDM was carried out. International databases and academic papers such as Scopus, ERIC, Science Direct, EBL Library and ACM Digital Library were scanned to conduct the data collection. Articles published by major organizations dealing with LA/EDM such as, LAK conference, EDUCAUSE, JISC and Solar, were searched. The key terminology used for the search included '*learning analytics*', '*educational data mining*', '*learning analytics case studies*', '*big data in education*', '*policy making in data driven approaches*'. The research looked at contributions from the last 10 years, mostly from the last 5 years when the emergence of LA/EDM has had a larger impact.
In this thesis approximately 60 documents were reviewed and placed into context. 15 of the reviewed papers were solely for policymaking in LA, while the rest has treated the opportunities LA offer for policymaking as a separate part at the end of each article.

Learning analytics relies on the existence of Big Data, thus the emergence of the former, will be discussed first before moving onto LA.

2.1 Big Data in Education: LA, Concepts, Dimensions and Related Fields

2.1.1 Big Data

The nature of data is changing and many organizations are in trouble, due to the complexity of managing and analyzing new data formats. Basu (2013) shows that the vast majority of today's business organizations use structured data like numbers and strings, but this has nothing to do with the complexity of data itself. The unstructured data newly generated by organizations come in very different formats such as books, files, video, audio, meta-data, images or any data not easy to be understood by machines. Moreover, IBM indicates that, 80% of data generated by organizations are actually unstructured data and most of these data manage to reach corporate warehouse. "Data Warehouse", as a term has the meaning of a large storage of data or centralized database. It shows a perfect vision of central data storage as a basis to inform decision making by means of data. The collection and storing of large amounts of different data formats has become easier due to the recent developments in database technologies. Moreover, with the help of analytical tools that are available, the complex data collected can be turned into a pattern that has meaning and value, and this phenomenon is perceived to be Big Data (Manyika et al, 2011). The Big Data concept describes data that is enormous and circulating rapidly; in this way it surpasses the limits of processing it by a traditional database system (ibid).

The most prominent definition about Big Data is the one presented by Viktor Mayer-Schönberger and Kenneth Cukier in their book: *A revolution that will transform how we live, work and think*. They defined big data as: "The ability of society to harness information in novel ways to produce useful insights or goods and services of significant value" and "…things one can do at a large scale that cannot be done at a smaller one, to extract new insights or create new forms value" (Mayer-Schönberger & Cukier, 2013:2). The concept of Big Data also encompasses new techniques and technologies to track, store, and analyze data sets that are big and large and possess different structures. As new concepts evolve, critique becomes common thing. Critics object by saying that the concept of Big Data is not just about data size but complexity as well. Yang (2013) argues the meaning of Big Data has not much to do with the concept of data itself, but is more associated with the fact that technologies have developed that are able to process big volume of various data at higher speeds. Thus, Big Data is less about size of data sets, but about the capacity to search aggregate and analyze large datasets (Boyd and Crawford, 2012).

Big data has found its place in education due to the acceleration of blended [1]and online learning which has brought the emergence of learning management systems (LMS) such as Moodle and Blackboard (Table 1). Its techniques will be quickly implemented in education setting to inform decision making (Johnson et al., 2013).

Online learning in the current thesis does not only refer to courses or trainings conducted totally online like distance education or MOOCS, but also to any unit of study supported or delivered with online components to enhance learning experience (Sclater, 2016).

In addition to the increase of blended and online learning and the adoption of learning management systems (Moodle, Blackboard) (ibid), big data becomes a central factor in higher education setting (Clow, 2013; Ferguson, 2012; Johnson, Adams Becker & Hall, 2015). The deployment of big data in education indicates that educational data can now, be gathered and analyzed in real time and automatically, without the need of expert centers to calculate (Williamson, 2016).

LA and EDM can be described as educational application of big data (Johnson et. al., 2014a) and consist in the research and implementation of methods on how to extract meaningful information from this big data.

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[1] Blended learning is any formal or informal education that combines online technologies with face to face learning requiring the physical presence of both teacher and student. (Wikipedia)

2.1.2 Learning Analytics and Educational Data Mining

The rapid increase of information, originating from LMS, instrumental educational software, internet usage in education, and the creation of state databases of student information (Romero & Ventura, 2013) have allowed the collection of unprecedented amount of data about learning, teaching and institutional processes. The massive use of technology in the education systems, comes with a large capacity of tracing the students (Pardo & Siemens, 2014). When students interact with their learning environments, such as libraries, LMSes or labs and utilize web tools into these settings, as SNAPP or Meerkat-ED(other LA resources are listed in Figure 1), tools that analyze students' interactions within discussion forums, they leave traces of educational data (Friesen, 2013; Reyes, 2015).

Figure 1. Examples of LA Resources

Moodle https://moodle.org/	Open-source learning platform
Blackboard Analytics http://www.blackboard.com/Platforms/Analytics/Overview.aspx	Packaged self-service analytics applications
GISMO http://gismo.sourceforge.net/	Interactive tracking system built for Moodle that displays data through a graphical interface
SNAPP http://www.snappvis.org/	Web tool that provides social network analysis
Meerkat-ED http://webdocs.cs.ualberta.ca/~rabbanyk/MeerkatED/	Web tool that analyzes participants and their interactions in discussion forums
SunGard Assessment and Curriculum Management http://sungardk12.com/assessment-curriculum-management/	Learning performance solution for assessment management and analysis and curriculum management
Desire2Learn http://www.desire2learn.com/	Integrated learning platform that addresses challenges with engagement, retention, and learning outcomes
Pittsburgh Science of Learning Center DataShop http://www.learnlab.org/technologies/datashop/	Data repository and analysis service that provides access to intelligent tutoring systems datasets
Mulce http://mulce.univ-bpclermont.fr:8080/PlateForme-Mulce/	Research project that shares datasets of learners' online interactions
LinkedEducation.org http://linkededucation.org/	Open platform that promotes sharing of educational data and resources

Source: Reyes 2015:76

This has challenged educational institutions to deal with increasingly large amounts of data (Ferguson, 2012). Making use of this vast amount of data to optimize learners experience and the environment it takes place, is of central importance. Educational domain has been unable to efficiently use the available data to intervene in reducing or avoiding drop outs or providing a more personalized learning. Until now, gathering educational data from students and enhancing their instruction has not yet have a big impact (Long& Siemens, 2011). Researchers and analysts from the educational community has started to explore the potential of the data traces left behind, to understand the way students learn (Mostow & Beck, 2006).

LA and EDM aim at making sense of this generated learning-related data. They are not concerned with reporting the activities marginally or with theoretical insights. Instead, they provide 'actionable intelligence' in order to understand and develop learning process. The goals and processes of data analyzing in LA and EDM are quite the same. (Ferguson, 2012). Both research areas are defined similarly:

The most acknowledged definition about LA is the one proposed by LAK11 (Learning Analytics Knowledge Conference) as "the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs". Elias (2011:4) views LA as "an emerging field in which sophisticated analytic tools are used to improve learning and education". Siemens (2010: 3) describes LA as "the use of intelligent data, learner-produced data, and analysis models to discover information and social connections, and to predict and advise on learning".

Similarly, the International Educational Data Mining Society (IEDMS: 2) describes EDM as a:

"Discipline, concerned with developing methods for exploring the unique types of data that come from educational settings, and using those methods to better understand students, and the settings which they learn in".

Apart from these, many other definitions exist, due to the infancy of the field. Although with slightly different perspectives, both EDM and LA concentrate on educational context, analyze data originating from learning environments, and report this data with the aim of optimizing and understanding the learning practices.

The origins of EDM are rooted back to the late 1990ies; LA emerged especially in the last 10 years ((Ferguson, 2012; Romero & Ventura, 2010). While EDM has a focus on automated methods such as the use of data mining techniques to analyze educational data (data-driven analytics) (Ferguson, 2012), LA has a more pedagogical focus, it aims using human-led methods to make sense of educational data and extract useful information to support teachers and learners(learner-focused analytics) (Siemens&Baker,2012). As Clow (2013:687) pinpoints it: “Learning analytics is first and foremost concerned with learning”. Both fields of research are so closely related that is inevitable not to overlap. LA and EDM have the same goal: improving education quality, through data-intensive methodologies. In some review articles they are both described interchangeably. (Baker & Inventado, 2014; Romero & Ventura, 2010). In the remainder of this document, the term LA will be used for referring to the extensive research domain and processes of both LA and EDM.

2.1.3 Historical contributions to LA

LA has built on existing fields of research. These mostly include: business intelligence (BI), recommender systems, action research, personalized adaptive learning and academic analytics.

Data centric approaches are part of the Business Intelligence (BI)(also known as ‘business analytics’) methodologies framework that has helped businesses and organizations to generate insights from structured data, collected and analyzed by relational database management systems, to improve business decision making (Chen, 2012). As a derivative of BI, LA aims to use analytics’ methods to help inform institutional decision making on learning and learning practices. Data processing techniques and standardized data formats are available. This, as well as the increasing tendency of education institutions for creating a culture that values data-based decision making, have empowered the progress in analytics tools that support structuring, collecting and analyzing data (Baker & Siemens, in press). The idea is, in the end, to use educational data for recommendations (of course material, activities, people) and to suggest instruction in a similar way as it is done with books, music, entertainment etc. in e-commerce (Johnson et al., 2014b). Furthermore, recommender systems (Adomavicius & Tuzhilin, 2005), adaptive learning and intelligent tutoring systems are strongly linked with learning analytics (Brusilovsky & Peylo, 2003). Recommender systems in education aims using the experiences of a community of students to support individual students by recommending a learning path. In this way, a real-time assessment and feedback systems are intended to be applied, to support the learning objectives (Draschler et al., 2009).

Potential insights can be gained by combining learning analytics and adaptive learning systems too. Adaptive learning, in line with the objectives of LA "responds to a student's interactions in real-time by automatically providing the student with individual support" (EdSurge, 2016).

Further research areas in the educational domain that are related to LA are academic analytics and action research. Academic analytics and LA initially evolved conjointly; in 2010 analytics in education started to separate to solely create learning analytics and academic analytics (Ferguson, 2012), but similar objectives between them naturally remain. Buckingham Shum (2011) pinpoints academic analytics as being closely linked with the field of business analytics and intelligence in corporate settings, while LA is more concentrated on data that is strictly related to the learning process on the micro-level of learner interactions. Academic analytics focuses more on the analysis of institutional data to support the operational and financial decision making (Goldstein and Katz, 2005). This level of analytics, is more general compared to LA, since the focus is more on the analysis of the units of the academy (i.e. predicting enrollment, increasing number of graduates) than the learning process itself (Long & Siemens, 2011). While LA is more concerned with the improvement, reflection and intervention of the learning process on a local level of teaching, academic analytics is situated more on the political and economic challenge of the educational outcomes at national or international domain (Ferguson, 2012).

Learning analytics can be considered as a reflective instruction practice, known as "action research" that guides instructors to investigate, assess, self-reflect and regulate their didactical methods to enhance the teaching-learning practice (Dyckhoff et al., 2012). Action research aims at assuring quality in education and optimizing the teaching process; starting points are usually research questions coming from instructional process (Chatti et al., 2012). In future learning scenarios, LA will embed action research strategies because it ease awareness, reflection and investigation of teaching practices (Dyckhoff, 2014).

2.1.4 Developments of LA

Brown (2011) pinpointed LA as the third wave of big developments in instructional technology domain. First wave initiated in 1991 with the advent of LMSs which was teacher-centered, concentrated on “Web 1.0”. It consisted of non-interactive webpages; therefore it is also called as “read only Web” (O’Reilly, 2005). The second wave of instructional technology was more learner-centered and consisted of interactive web based systems where “Web 2.0” (social networking, or massive open online courses (MOOCS)) technologies emerged ; enabling students themselves to generate data, that is the reason why it is called read/write web (ibid). Recently, education analysts have started to research how to actively make use of Web 2.0 tools. Consequently, LA initiates the third wave, enabling “information on what works and what does not with respect to teaching and learning” (Brown, 2011). First wave of Instructional technologies would transmit learning materials as simply viewing the text or image, whereas systems of the Second Wave of instructional technologies broadly employs enriched learning materials such as enriched PDFs, videos, or even recorded lectures which are widely known as MOOCs. To evaluate the students, basically check if the content was transmitted successfully, based on the traditional teaching (First and Second Wave), students would be evaluated through multiple choice questions (MCQs) or short answers. Considerable research has shown that MCQs assess the declarative knowledge of students and not explanatory knowledge of “how” and “why” that is required for solving harder tasks and problems. I believe the third wave of instructional technologies where analytics has been incorporated, has already started. This Wave has students build and construct their knowledge actively, rather than just transmitting the content. This is in line with the idea of students using LA, as they learn by doing.

Ferguson (2012), pinpoints three factors that drive the development of LA. Due to the vast amount of information that can be collected based on the activities of users within or around LMSs and because their actual built-in analytics do not offer much potential interpretation of the student activity data, educators have started to think how technically possible can they "make use of this data to improve learning outcomes" (Buckingham Shum & Ferguson 2012). So, according to Ferguson, the first factor of LA development is a technical challenge. Second driver is an educational challenge. The wide adoption of formal online learning, beside its advantages, has come together with a lot of challenges. When learning online, students and teachers lack visual cues. Teachers may not understand if students are fully engaged, bored or face difficulties with the activities in online environments. Therefore, they have started to think of possibilities LA offers to improve e-learning. The last factor of LA development is the political/economic challenge. Since, many countries are showing an increasing demand to measure, demonstrate and enhance education performance nationally and internationally, analytics has become a potential solution. The abovementioned drivers presented by Ferguson, create three different groups of stakeholders: instructors/learners, educational institutions and governments (Ferguson, 2012). Even though LA is in its initial steps of massive deployment, actual LA implementations indicate potential improvements in the teaching-learning practices (Simsek, 2012).

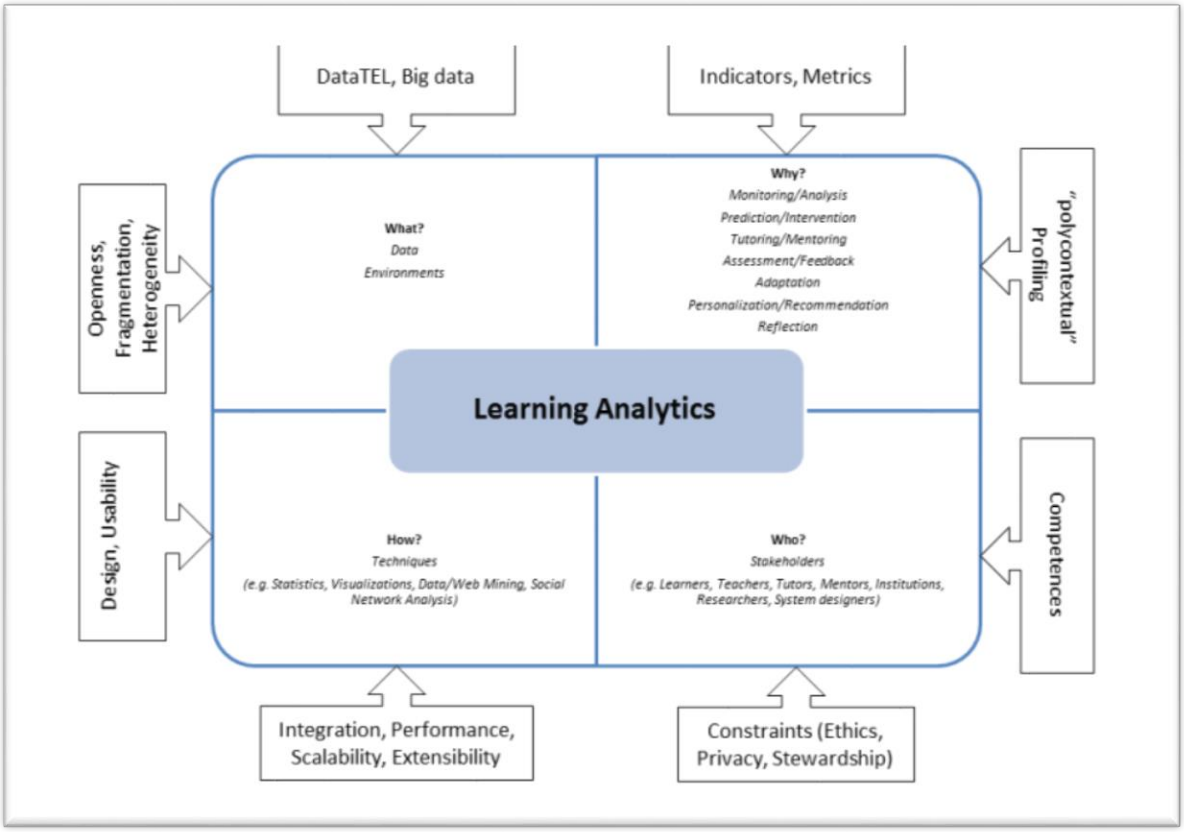
To sum it up, LA offers precious advantages to students, instructors and is used extensively in the institutional domain to provide feedback about student's behavior, support formative assessment and enhance institutional performance regarding school-leavers or at risk students (Technopolis, 2015)

2.1.5 The process of LA

Plenty of researchers have developed various reference models of LA to support educators with critical insights with the aim of presenting the dimensions or steps of LA implementation. On behalf of Educause, Bichsel (2012) articulates that LA can be considered as having a common process of implementation. According to her, a five-staged cycle takes place: a) Choose a strategic question, b) gather data to answer that question, c) analyze the data in a way that predictions can be generated, d) present the data in an actionable and understandable format, e) feedback into the process to address strategic questions or search new ones. Similarly, Campbell and Oblinger (2007) propose a model based on 5 dimensions: capture, report, predict, act and refine. Another paper that sets out different dimensions of LA is the one presented by by Chatti et al (2012).As depicted on figure 2, they try to describe the dimensions of LA by answering 4 questions:

a) What? – What type of data do educational systems collect?
b) Who? – Who are the stakeholders affected by the analysis?
c) Why? – Why does the system collect and analyze this data?
d) How? – How is this data analyzed, what are the techniques?

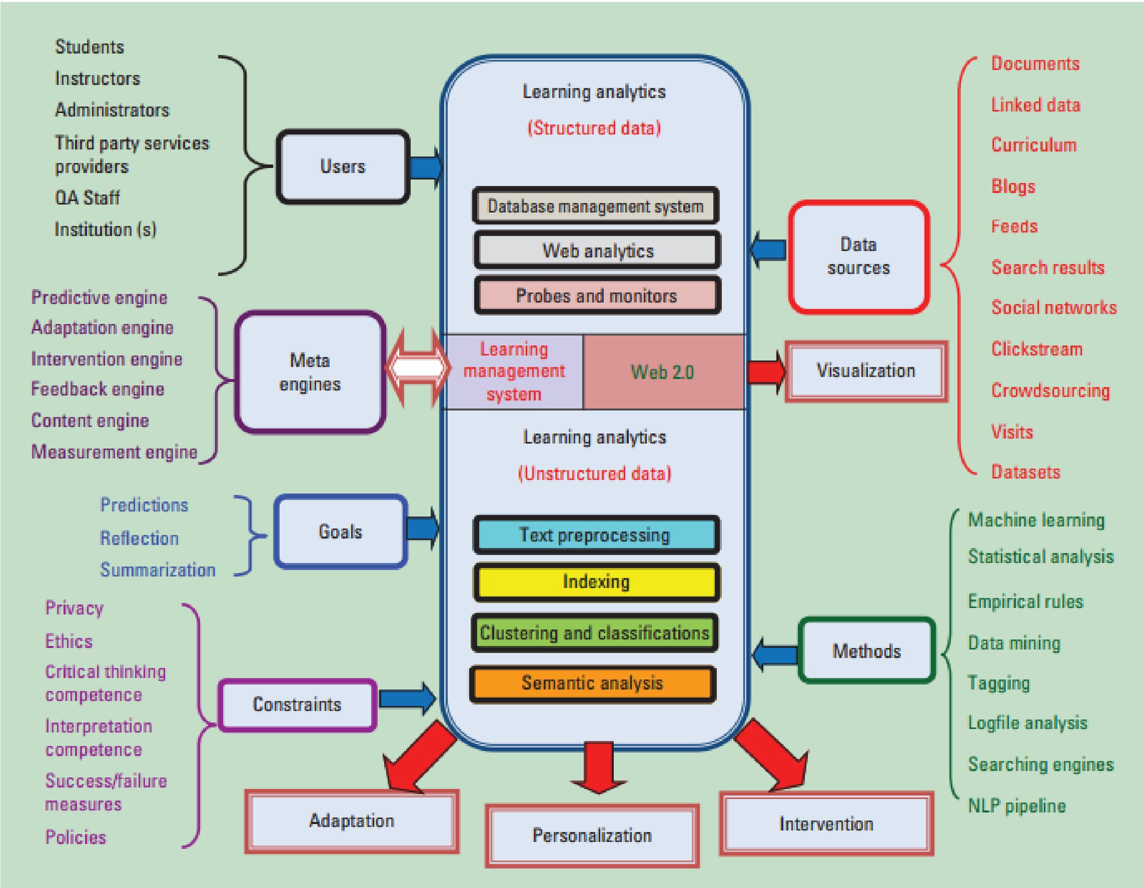
Figure 2. Learning Analytics Reference Model



Source: Chatti et. al (2012)

Another model of LA process namely, a Comprehensive Learning Analytics Architecture, is illustrated by Fiaidhi (2014) as shown in figure 3. The most important feature of this model is the management of unstructured data. According to the author incorporating the LA tool that deals with unstructured data with the previous research that have been done so far in the domain, will catalyze the process for redesigning educational institutions.

Figure 3. A comprehensive learning analytics architecture



Source: J.Fiaidhi (2014)

Additional work related to LA process is the paper presented by Verbert et al (2013), a synopsis of research into dashboards, offering helpful insights into the field, with concrete examples (Other illustrations include Clow, 2013 and Norris & Baer, 2012).

Due to the complexity of the models presented above, it can be difficult for most of the readers to clearly understand LA and the way it works. On the following paragraph I will explicitly describe, step by step, the way LA process is conducted.

The first step in LA is the collection of data. Nowadays, students can access learning resources from centralized educational systems (LMS, Moodle, Blackboard) and distributed learning environments (social media, MOOCs), enabling them to leave a plethora of digital traces behind (Pardo & Siemens, 2014). Therefore, behavioral data taken from learning environments (course access, project submission, logs) and functional data (student information systems, end-term reports) are accumulated, analyzed , processed and reported by LA data processing algorithms (Sharples et al,. 2015). Collected data can be structured which is then can be directly accessed with data mining techniques i.e., server logs or unstructured data, which are not readable by data mining techniques i.e., forum postings (Baars & Kemper, 2008). When information is collected from LMSs, the system itself easily provides structured data about students and their interactions with the course material (Pardo and Kloos, 2011; Simsek, 2012), otherwise some sort of structure is given before the analysis (EDUCAUSE, 2011). At the end of the collection of the educational data, analytical techniques are applied to analyze and interpret the datasets about learners. Well-established analytic techniques(the most common ones are classification & prediction Chatti et al., 2012) should be employed to extract meaningful data, when analyzed (Pardo and Kloos, 2011). After the analysis has been conducted, both LMSs and other tutoring systems with large amount of datasets, share an important component of LA named as visualization, a method where the analyzed outcomes are displayed into charts or graphs, to be understood by the audience of LA stakeholders (Brown, 2011). GISMO (Table1) is an example of visualization (Reyes, 2015), an intelligent tracking system integrated within Moodle displaying data about learners' experience, and supporting instructors to guide their decision-making (Romero & Ventura, 2013). The most cited example about LA implementation is "The Signals" project at Purdue University, where the institution developed an "early warning system" detecting at risk students (Sclater et. al, 2016). In this project data collection is based on students' interaction with LMS, their prior academic performance and student characteristics. Then, this data is mined by data mining algorithms to identify at risk students, which are then alerted by a "traffic light" in which red, yellow and green indicate the drop out possibility (Pardo and Kloos, 2011).

This is then transformed and processed to produce a 'traffic light' indicator identifying struggling and at risk students. Faculty member and teachers can then intervene to prevent their drop out (Sclater et. al., 2016). Based on the visual representations, instructors can chose to send an email to the student showing his/her academic level or even face to face meeting (Arnold, 2010).

2.1.6 Big Data in Education: Opportunities and Limitations of LA

The advancement of LA technologies can inform the next step of innovation in education systems (Siemens, 2011) and transform institutional decision-making (Boyd & Crawford, 2012). Emerging from a variety of other research disciplines, (i.e., cognitive science, data mining, business analytics, psychology), learning analytics can be applied to face-to-face education environments, and computer-based environments such as LMSs, computer supported collaborative learning, and intelligent tutoring systems (Romero & Ventura, 2013; Wang, 2016). LA not only analyzes the data collected from student demographics or examinations' results , but it also examines data generated from time spent online, number of pages read, discussion forums, and even visual and facial reactions (Bousbia & Belamri, 2014).

Until now, education researchers have been unable to sample massive amounts of data to conduct their research, due to the limitation of collecting and analyzing tools. Furthermore, they used methods such as perception based data collected through questionnaires or interviews which are time consuming and have limited interpretation possibility (Daniel, n.d). However, the progressive LA techniques provide researchers with vast amount of dataset at a low cost, removing the obstacles of sampling randomly, enabling generalizability and validity (Mayer-Schönberger & Cukier, 2013). LA offers educators the possibility of observing students' progress through automated systems to figure out how they are performing when interacting with the learning system, instructor or other students. This information can then be used to identify students who are struggling to complete their course, providing feedback, to support their learning skills.

As information about how students learn becomes more accessible, opportunities for achieving best learning outcomes are possible (Buckingham Shum & Ferguson, 2012), offering stakeholders(government, institutions, instructors, learners) new insights to interact with this flow of information (Greller & Drachsler, 2012). Government standing at the top, engage policy makers and educational agencies to make use of analyzed data like characteristics of student motivation to make policies for the whole school system and evaluate education on a national and international level (Reyes, 2015). Moreover, using Big Data in education enable education policy makers to plan post-education employment, by balancing the number of student graduates with the employment market needs (Jantawan & Tsai, 2013).

Following the top-down hierarchy in traditional education, part of this flow of information are institutions, teachers and learners. For institutions, LA enables methods to solve issues such as: reducing dropout rates, monitoring graduation rates, assess and enhancing courses (Greller & Drachsler, 2012)

Institution entities analyze data from both student and teacher perspective, in order to establish new promising polices to achieve the objectives of the learning process. During the teaching - learning process, institutional analysts, analyze traces of data generated by instructors as well (Xu & Recker, 2012), therefore, they can identify areas of improvement by instructor to optimize instructor-learner interactions with the learning environment. Contrary to the traditional methods, by using LA, a student's learning progress can be measured at the time of occurrence, at any level of stakeholders to support early interventions (Reyes, 2015). On the teacher level, the analyzed data about students' learning experience can help them indicate knowledge gaps, by developing the adequate educational curriculum to meets the students' needs or altering their didactical strategies. LA can predict students' performance and their behavioral patterns by means of sophisticated predictive analytics techniques and suggest a personalized learning experience which can be adapted when students' need it (Siemens, 2012; Verbert et al., 2012; Reyes, 2015). Data coming out from an LA application, provides stakeholders an extensive overview into the performance of the institutions, instructors, students and other stakeholders related to educational domain.

As mentioned previously, LA implementation in the educational domain is a nascent field, therefore it is confronted with numerous challenges. A considerable number of institutions are in the explorative and experimentation phases. Many researchers have considered education institutions as complex adaptive systems, (Thille et. al., 2014) which can be supported by strategic policy frameworks (Macfadyen et.al, 2014). In their paper, *"Embracing Big Data in complex educational systems"* Macfayden et.al, (2014) have identified two socio-technical factors that challenge LA deployment and need to be addressed by institutional policy and strategic planning: the challenge of changing stakeholders understanding of student evaluation and the challenge of establishing the proper technological infrastructure on an institution basis. Furthermore, Educause (2016), pinpointed significant challenges that institutional policy makers are facing such as: concerns on data quality, lack of interoperable systems, lack of institutional leadership, and missing institutional culture for data centric decision making.

Since information, and to a degree knowledge, has become an easily accessible commodity, faculty members, learners or other stakeholders are required to move from being knowledgeable to being self-directed learners, with the affinities and awareness of knowing the way they personally learn, in order to potentially address institutional challenges (Siemens & Dawson, 2015). To be ready to work in this contemporary dynamic context, learners need to possess skills such as self-directedness, resilience, information seeking and evaluation, creativity and other types of skills often referred to as the 21st century skills. Therefore, many institutions are in the process of redefining their institutional learning and teaching strategies through which they will provide support for flexible learning, study independence and student-centred and/or personalised learning. To achieve this goal, teaching needs also to be based on novel pedagogies that can scale to address the needs of the growing number of students and life-long learners who will likely have relations with the institutions through their entire careers rather than for a set period of time. At the same time, policy makers need to be able to monitor the quality of their investment and the ways how some of these priorities are implemented and addressed by the higher education institution.

2.1.7 Opportunities LA offer for policy making

Top-down and expert-driven approaches to policy development, do not reflect sufficiently the complexity of modern pluralistic societies and as such decrease the chances of success of new policies (Head & Alford, 2013). More importantly, as summarized by Macfadyen et al. (2014: 23) "modern policy problems are not technical puzzles that can be solved through the application of scientific knowledge, but instead exist in continuous states of flux within dynamic systems and have communicative, political and institutional elements. Solutions to such ill–defined and multi–factorial challenges … will always be provisional, and must be negotiated between multiple stakeholders in situations of ambiguity, uncertainty and values disagreement (Rittel & Webber, 1973)." This approach also recognizes that policy processes are rarely linear and logical and that a one-size-fits-all approach to development is not possible due to numerous contextual factors. Contemporary research suggests the use of adaptive approaches to policy development, which allows institutions to be more agile and responsive to the continuously changing social, economic, and technological factors (Uhl-Bien et al., 2007) surrounding the higher education sector.

Policy making in education is being driven by new ways of digital 'policy instruments' that enable educational 'policy to be made material and operational' (Lascoumes and le Gales, 2007: 4). Learning analytics brings a new kind of policy instrumentation in educational policymaking developing methods of prediction and pre-emption. Such 'big data' approaches are different from the large-scale data-sets utilized in actual methods of policy making (such as international assessment). The central aim of this, is that LA for policymaking is situated to short-circuit existing educational data practices, providing data and feedback to flow synchronously and recursively within the pedagogic apparatus of the course itself. Thus, while large-scale statistical data systems acting 'at a distance' (Miller & Rose, 2008) still affects policy making of national education systems at the moment, new big data analytics supports them by enabling automated feedback aimed to guide 'up close' through continuous interaction with the individual learner in real time. Policymaking in education is turning out to be increasingly informed through such digital policy instruments and the data infrastructure in which they are put (Williamson, 2016).

3. Empirical Research

This chapter explores the research design and data collection method of the thesis. It will justify the research approach and chosen research strategy. Since the thesis seeks to explore the opportunities LA offer to enhance policy making in the field of education by comparing top three leading countries in this domain, qualitative research design was conducted. According to Zigmund et.al. (2013:64), "Research design is a master plan specifying the methods and procedures for collection and analyzing the needed information". Thus, the design is used as a general guide on how to process the research, but it is open to change during the process of study. In order to present an in-depth analysis of the policymaking in LA of the selected countries, two broad research questions were addressed in this study. They are: (1) what are the opportunities LA/EDM offers for policy making in the field of education and (2) what are the approaches of different countries in the sample towards using LA/EDM to improve policy in the field of education. To answer the questions of the study, a qualitative exploratory case study was conducted. Qualitative research is a flexible research method which combines multiple field of research, regardless of the topic or research paradigm (Willis, 2007). It is primarily concerned about "…insight, discovery and interpretation rather than hypothesis testing" (Merriam, 1998: 10). This is in line with the intention of the current study.

To better understand the policymaking of LA in UK, US and Australia, the research methods of qualitative inquiry and techniques of the exploratory case study are combined. Yin (2oo3) highlights case study, as a comprehensive research strategy, including the logic of the research design, data collection techniques and substantial methods for data analysis. Gall et al. (2007) notes that almost any topic in the qualitative research domain can be explored by case studies. Moreover, case studies have been defined as "a basic form of qualitative research" (ibid: 447). The results of case study research, would be limited to explore a phenomena rather than, generalizing to a larger scale (Stake, 1995). Furthermore, as Yin (2003) has suggested, case studies concern theoretical generalizations or generalizations of similar cases. As the current thesis will conduct a multiple case study, two stages of data analysis will be followed: the within case analysis and the cross-case analysis. Thus, at first the selected cases will be analyzed as a single comprehensive case, then cross-case analysis begins (Yin, 2008; Merriam,2009). Using two or more case studies is advantageous over single case study, because it provides more compelling evidence and robustness to the overall study (Herriott & Firestone, 1983; Yin, 2003). Moreover, it increases the possibility to replicate the outcomes (Yin, 2003).

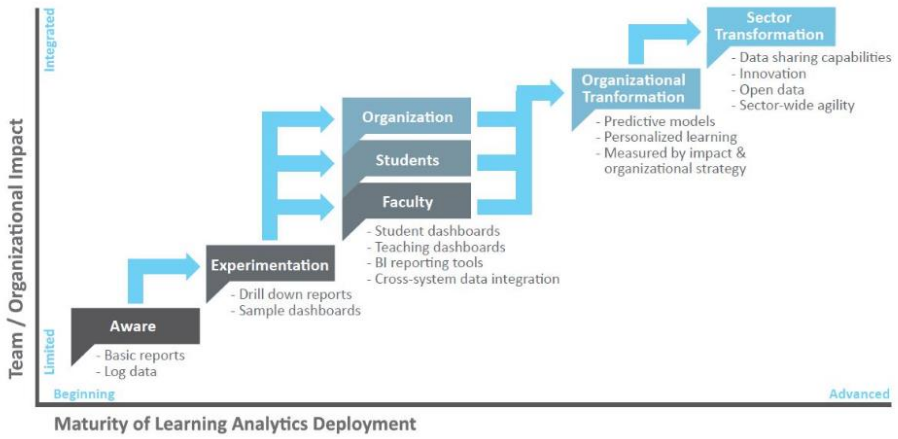
Case study uses strategies such as surveys, interviews, and the analysis of archival documents. This study will be based solely on the document analysis of the legal documents or reports published by the higher education institutions responsible for learning analytics, as well as reports published by SOLAR, LACE, LASI etc. As a data collection method, document analysis is applicable to qualitative case studies, generating rich descriptions of a phenomena, event, organization or program (Stake, 1995; Yin, 1994; Bowen, 2009). Many researchers in social sciences use case study strategy such as: experiments, surveys and the analysis of archival documentation (Yin, 2003). However, each of these research strategies should be addressed upon (a) "the types of research questions posed", (b) "the degree of control the investigator has over the behavioral events", and (c)" the degree of focus on contemporary as opposed to historical events"(ibid:5).

In terms of the first condition posed by Yin (2003), research questions are categorized as: "explanatory", "descriptive" and "exploratory". Research questions focusing on *what* questions are exploratory, *who* and *where* questions are likely to favor descriptive case studies whereas *how* and *why* questions are most suited for explanatory case study, history or experiments. The two main research questions addressed in the actual study are "what" questions, i.e., "what are the opportunities LA/EDM offers for policy making in the field of education" and "what are the approaches of different countries in the sample towards using LA/EDM to improve policy in the field of education?" Based on Yin (2003), an exploratory case study is chosen as the research strategy here. Additionally, the exploratory case study is suggested when very little prior research has been done on a phenomenon (Mayer& Greenwood, 1980). In the current thesis, very little research has been conducted on the development of institutional policies for systemic adoption of LA. This is well documented in a recent SOLAR report (Siemens et al., 2014) in which several cases studies, collected from some of the cutting-edge institutions in analytics adoption, are featured.

3.1 Learning analytics and higher education policy

Learning analytics provides opportunities to develop more scalable early support models that can help address priorities concerning most of education policy makers, regarding educational drop outs. Under its priorities for smart growth, the OECD indicates that high numbers of young people are dropping out education/training without skills and qualifications needed to start a career. This level of attrition ultimately creates significant economic losses and does not match to the needs of labor market. High attrition levels prevent to increase the number of Europeans aged 25-34 with university degrees, and Europe (about 33%) is already lagging behind the USA (40%) and Japan (50%) by the number of university degree holders in this age category(OECD). The adopton of analytics enable universities to improve admission numbers, the student learning experience, reduce dropouts, curriculum design, and increasing the quality of instuction (ALASI, 2015). While learning analytics can offer many insights into developing intervention strategies to increase the student retention numbers, and thus the overall number of university graduates, the current level of adoption in higher education is very low. Although learning analytics has gained much attention and has been/is being adopted by many higher education institutions in Europe and the world, the maturity levels of institutions to be data informed are only in the early stages. According Learning Analytics Sophistication Model (Figure
4) (Siemens, Dawson, & Lynch, 2014), most institutions are in the first (aware of analytics and use some basic reports) and second (experimentation with data) stages of the widely-accepted analytics maturity model proposed by Baer and Norris (2013). The dearth of frameworks for policy development and availability of case studies is one of the major factors impeding the adoption of learning analytics in higher education institutions. The availability of such a policy framework would provide the necessary guidance for institutions to progress their analytics implementation and move towards the more advanced stages of the learning analytics maturity model. This stage includes the wide use of analytics by critical stakeholders (students, faculty, and administrators), performing institutional transformation towards personalized learning and measurement of the impact organizational strategies, and contributing to the transformation of the entire higher education sector.

Figure 4. Learning Analytics Sophistication Model



Source: Siemens et al. (2014)

3.2 Country profile

3.2.1 Australia

Australia is comprised of 6 states (New South Wales, Queensland, Western Australia, South Australia, Tasmania and Victoria) and two territories (the Northern Territory and the Australian Capital Territory), and three levels of law-making: federal/national, state/territorial and local (CIA, 2016). Compulsory education starts from the age of six to sixteen and the official language of teaching is English. In Australia, the general funding and coordination of education is a responsibility of federal authorities, whereas the budgeting for individual institutions is planned by state/territorial authorities. Similarly, the national education objectives are projected in joint consultation. In 1995, the Commonwealth, State and Territory introduced the Australian Qualifications Framework (AQF) (AQF, 2016). This agreed policy, aimed to support the national systems of qualifications (post-compulsory education) and to facilitate the mobility between higher education, vocational education and training and schools.

In response to the proposal of colloquially known Bradley's Review (2008), creating a national agency for maintaining the quality of all types of tertiary education, Australian Federal Government launched the brand new national mechanism, the Tertiary Education Quality and Standards Agency (TEQSA) (2011), which was primarily responsible for the external monitoring and cyclical evaluation of all higher education institutions (TEQSA, 2013). The Bradley Report offered a blueprint for policy setting to inform reforms in the higher education sector. It primarily consisted of: increase the number of undergraduate holders, push up equity access, decrease tuition fees and improve quality standards (Marginson, 2013).

Over the last 30 years, Australian higher education system has dramatically changed to respond the social and political demand (Beer, Jones & Clark, 2012; Bennett & Hempsall, 2010). It once had few numbers of government-funded institutions but now it is comprised of 38 public universities, three private universities and 150 providers of higher education. The public and private universities are autonomous self-accrediting institutions and both funded from government or non-government sources (Department of Education, 2015), meaning that public-private divide is no more sharply distinctive. One distinctive feature about tertiary education in Australia is its large amount of international students. Australia is a key destination hosting 7% of world international students, placing Australia the third most preferred country after the United States (almost 17% of foreign students worldwide) and the United Kingdom (13%) (OECD, 2011).
Deloitte Access Economics for Universities Australia, estimates the learning and teaching function of Australian Universities provides $140 billion per annum worth of direct benefits to Gross Domestic Product (GDP), which is approximately 8.5 per cent of GDP, compared to $10 billion per annum direct benefits provided by research in tertiary education. The public funding of higher education as a proportion of GDP has declined to two thirds of the OECD average. In 2017 it is expected to fall even more until 0.54 per cent of GDP (Marginson, 2016). Currently, Australian government appears to be unable to formulate a new vision that supports the dramatic increase of students and research areas. New reforms may change regulation and policymaking. For instance, the

foundation of the Tertiary Education Qualifications and Standards Authority (TEQSA) which is trying to define and manage scholastic standards in Australian tertiary education.

The introduction and the widespread of online learning has placed Australian higher education under challenges of making use of the data generated by this technology to enhance learning and teaching in a systematic way (Macfadyen & Dawson, 2010). An increasing range of opportunities offered by technology and data analytics, might be seen more as a challenge rather than an advantage (Verbert et al, 2013). At present, Universities in Australia are confronted with four emerging challenges: 1) The rapid growth of digital economy and emerging technologies such as LA, 2) Growing globalization possibilities such as Asian potential, 3) Reorganization of economy and industry, 4) The necessity to improve the productivity of higher education institutions as a primary national innovation effort (Universities Australia, 2013).

Despite providing a relatively well-resourced and mature tertiary education (Universities Australia, 2013), with a high number of international students (with a total of 1.37 million enrollments in 2014, where 25% is comprised of international students) (Department of Education, 2015), Australian higher education is lagging behind other alike countries in performance and investment. According to OECD, Australia is placed the 9^{th} out of 30 member countries, of 25-34 year-olds having finished university studies, down from 7th a decade ago. Moreover Australian tertiary education has been considered as the most expensive among the other heavyweight countries like US or UK. These indications positions Australia with great challenges need to be adressed. The country will need a well-thought strategy to meet the demands of an increasingly moving global economy. To improve education quality, universities have projected strategies relating to graduate attributes, widening participation, student retention and teaching quality (Nelson & Creagh, 2013). To advance the higher education sector, The Office for Learning and Teaching (OLT) in a joint effort with SoLAR are making use of Learning Analytics to move the education sector towards a coordinated learning data and analytics model (SOLAR, 2013). In Australia, a considerable number of universities are starting to adopt learning analytics to meet the demands of the digitized economy to optimize learning and teaching, which later contributes to a stronger economy with high living standards.

Recently, numerous initiatives deriving from Office of Learning and Teaching have focused on establishing institutional frameworks to progress research in Learning Analytics (Dawson & West, n.d), generating insights from data of social media interactions (Liu et. al. 2015) and understanding how data can be used by institutions to improve course design, student success, faculty development and predictive modelling (Diaz & Brown, 2012). Various higher education institutions have also designed bespoke systems for learning analytics (Siemens et. al., 2013). By way of example, the University of South Australia has established a well-equipped staff to analyze data generated from LMS and other online activities (T. Rogers, in press), while Western Sydney University uses a commercial business analytics application to prevent student drop out (Barwick, 2014). Analysis, identification, and referral systems are taking place at Edith Cowan University (Jackson & Read, 2012) and the University of New England (Leece & Hale, 2009).

To sum up, learning analytics in Australia besides being modest in scale, is practically slanted towards institutional implementation and narrowly engaged on using learning analytics tools to boost retention. But is aspirationally working on personalization which encompasses differentiation and individualization. Additionally, The Australian Government's Office for Learning and Teaching (OLT) published a report (Colvin et al., 2015), which offers guidelines for the basic tasks higher education institutions need to follow to support learning analytics implementations. As the field of learning analytics develops, the focus of theory and practice is increasingly moving from traditional post-hoc analysis to exploration of the opportunities that real-time data sets bring (Norris & Baer, 2013). In a near future, learning analytics promises trusted metacognitive resources for students through improved data collection techniques and improved design of instructional intervention.

3.2.2 United Kingdom

The UK has long had a highly developed economy. It is the fifth-most immensely colossal economy in the world and the establishing partner of the EU. The education sector of UK, has been an ecumenical bellwether in infrastructure development and in academic and administrative application of online technologies (Wright, 2003). The country is fortified by national initiatives such as the Higher Inculcation Academy, Joint Information Systems Committee (JISC) and the UK Edification and Research Networking Sodality (UKERNA). The Higher Inculcation Academy offers funding, resources, and support for different e-learning initiative. Jisc supports higher education on innovative utilization of information and communication technology by providing access to electronic resources, advice and access to a sophisticated communication network called the Joint Academic Network (JANET), connecting all universities, colleges and Research Council sites. The UK has a very sophisticated higher education system. In order to continue its leading position, the sector needs to adapt the challenges that data revolution has brought, particularly implementing learning analytics. The higher education commission of UK believes that learning analytics is a powerful way to: provide students feedback, increase retention, and assist institutions to achieve their strategic goals. Moreover HEIs should consider implementing LA systems to enhance teaching and learning as processes. (UK Commission, 2014)

Higher education institutions in UK are known for its world-class data collection system making UK the only country in the world to have a separate agency for higher education data and statistics. Open data (data.gov.uk) was first launched in UK in 2009, making non-personal UK government data available to the people. In 2011 BIS (Bussiness and innovation Systems) published the paper "Students at the heart of the system", where a set of policies were summarized, to enhance the quality and the amount of information. The paper also outlined the necessity to redesign the framework for HEIs. This led to the creation of the Higher Education Data and information Improvement Programme

(HEDIIP). Later on, in 2012 the government of UK published the Open Data White Paper where it describes its plan of increasing access of data and making smart use of it. At the same year, the Coalition Government recognized the power of big data analytics including it in the “eight great technologies” and since then they entitled a separate Minister for universities and Science. Higher Education specific policy has increased its focus in the potential of data analytics regarding the provision of a better and more frequent information about the education sector. This then resulted in the creation Key Information Set (KIS) including information about: 1) courses; 2) costs; 3) Employment; and 4) student unions.

As mentioned earlier, UK higher education’s collection and making use of this data is the best in the world. The responsible central data collection body is HESA which holds information about student body, degree results and destination of alumni after graduation. According to a survey done by HEDIIP, 525 HE data collectors and 93 organizations collecting this data were identified. Undoubtly there is duplication of data since the data collectors to not collaborate with each other. HESA should rationalize the data collection process, collaboration with other institutions in the higher education setting.

The results of the survey conducted by HeLF (Heads of eLearning Forum) in June 2015, show that approximately half of the HEIs in UK have not yet adopted LA, about a third are in the first stages of implementation and a fifth have partially implemented, Where one institution has fully adopted LA and disseminated within institution.

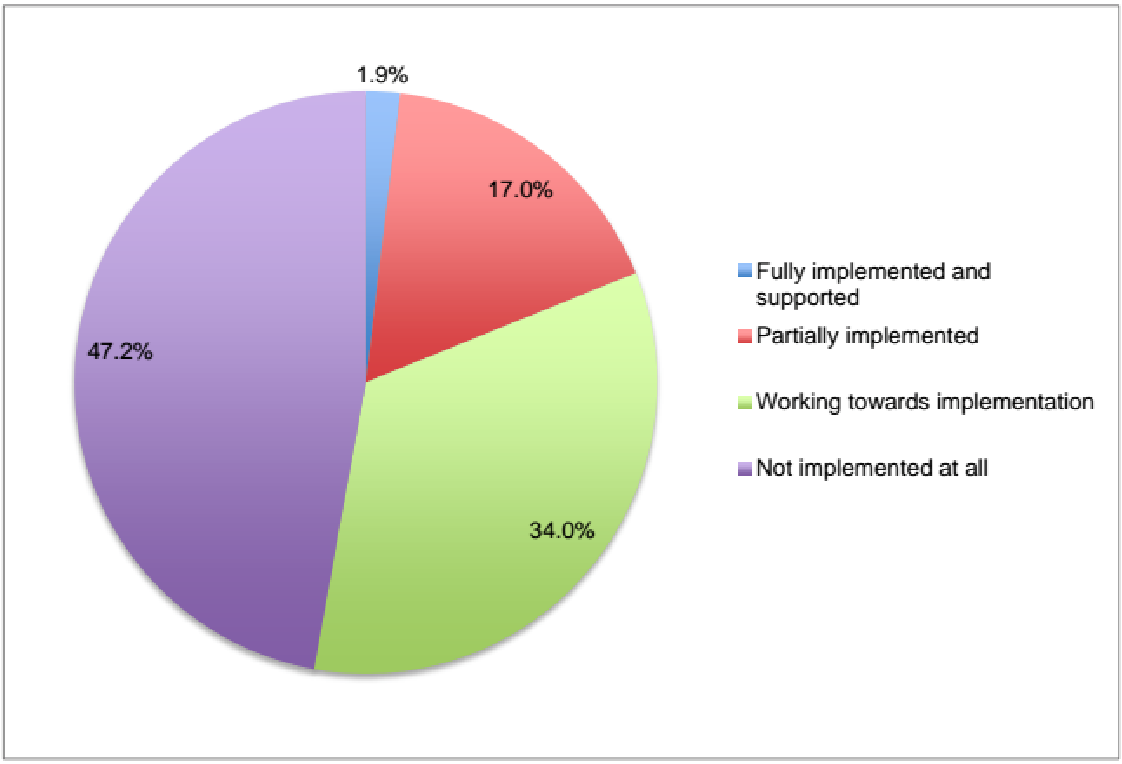


Figure 5 : The level of LA implementation in UK

Source: *Heads of E-Learning Forum, Learning Analytics in UK HE 2015* Survey Report

Institutions in the UK are implementing learning analytics for a variety of reasons and in a variety of platforms, methods and metrics. In 2014, Jisc undertook a research to find out the level of learning analytics deployment in UK (Sclater, 2014). According to the results of the study the early adopters of learning analytics were motivated for introducing learning analytics for reasons such as increasing retention, providing better feedback to the students and enhancing teaching and learning. Some universities had critical issues with retention and saw learning analytics as an approach to identify endangered students. Providing students themselves with better feedback on their academic achievement was also mentioned as being a vital important driver. Many institutions raised the necessity to give information on the attendance of international students to UK Visas and Immigration (Jisc, 2016). Capturing students' attendance throughout campus infrastructures provides effective proxy for student engagement and enables an institution to identify students, both foreign and local, who perform poorly. Another driver highlighted by some universities was the National Student Survey; capturing significant data about students learning behaviors or learning styles, enables a university to identify and address students learning difficulties by providing feedback. Manchester Metropolitan University saw a nine per cent increment in student satisfaction over two years to its efforts to reorganize its curriculum based on better analysis of student necessities. Some universities value LA as an approach to tailor teaching by building bridges of communication between students and academic staff. Some universities perceive LA as an approach that can help in improving instruction, particularly by frequently evaluating students work with marks, so that a better relationship can be built among university students and staff.

LA is perceived by some universities as a way of enhancing teaching, in particular by encouraging more timely marking of student work, and helping to build better relationships between students and staff. For many universities the focus was on putting the analytics tools in the hands of staff who work directly with learners, and providing them with actionable insights into student performance. At Nottingham Trent University it was found that tutors were helping students who asked for support not the student who really were at risk (ibid).

The primary goal of LA there was to support identify learners who were struggling, prior drop out. Many universities indicate different levels of academic achievement among diverse ethnic communities or genders and describe how they are using analytics to identify and increase academic support to individuals from underperforming groups. The University of Derby leveraged analytics to guarantee that its institutional decision making on supporting students from other ethnic backgrounds was informed by evidence. It published a handbook for the university staff to improve the academic achievement of minority students. On an institutional level, the University of Edinburgh and the Open University have implemented systematic LA. While other 50 institutions (universities and colleges) are piloting Jisc's beta learning LA service, which comes with a dashboard and student app, as well as materials to aid users. The latest research conducted by UK Heads of Elearning Forum (HeLF) where 53 institutions participated, observed that the primary reason of UK universities focusing on learning analytics is because of student retention and the improvement of learning. In addition, the research found that approximately half of the participating institutions have not yet deployed learning analytics, a third are particularly working on the technical infrastructure and only a fifth have somewhat implemented. The study also highlights that the most of the universities lack leadership and senior managements had not yet fully understood the benefits of LA, this varying across institutions (Newland et al., 2015).

3.2.3 United States

The federal government is the main provider of education in United States, whereas the control and funding comes from the three levels: federal, state, and local. Decision for standardized tests are taken by the governors of the state together with their responsible state department of education. Nowadays, American higher education is facing huge challenges as a matter of severe economic recession, decrease in public funding, enrollment surges and a significant high dropout rate (Picciano, 2014), where in 2011 nationwide more than 1 million students dropped out before graduation (Wolf et. al, 2014). To effectively address these challenges, federal government and nonprofit organizations have highlighted the potential of Big Data and analytics as part of the solutions driving change in higher education (Rubel & Jones, 2016). The 2010 National Education Technology Plan (U.S. Department of Education, 2010), emphasized that higher education practice must adopt digitally enhanced learning environments for having a broader access to diverse learning materials and connections to the broader learning community, which goes beyond the classroom and national borders. In the US, numerous initiatives have identified the potential of learning analytics as a critical research field to enhance education. By way of example, as part of their Next Generation Learning Challenge initiative, the Hewlett and Gates foundations granted almost $24 million to higher education projects where $3 million of that amount were given to learning analytics projects (Next Generation Learning Challenge, 2013). The Department of Education's MyData Initiative, empowered by Obama's administration aims to equip students with downloadable copies of their academic data, to foster students establish a third party analytic service to mine those machine readable data to generate more insights (Office of Science & Technology Policy, 2012). The federal government has collaborated with companies like Pearson and Microsoft to facilitate interoperability standards between MyData portal and their technology enhanced educational software to ease accessibility of students. Another initiative of federal government to reveal how particular institutions and student demographics are related to outcomes, is the conversation about establishing a federal unit record system (FURS) (Nelson, 2013). FURS would provide the U.S. Department of Education with a diverse dataset of demographics, grades, need based aid eligibility, moreover track students' academic performance throughout their entire academic careers and record their earnings after graduation. Merging these data sets from the primary, secondary, and postsecondary levels may push the decision making opportunity informed by learning analytics and inform curriculum design. It could also be integrated in the MyData project (Rubel & Jones, 2016). Due to the lack of policy plan and unclear privacy issues, the initiative has not yet proceed into real life (Flanagan, 2016). A recent U.S. Department of Education brief emphasized learning analytics as the "human tailoring of responses, such as through adapting instruction content, intervening with at-risk students, and providing feedback" (Bienkowski et al. 2012: 13). Accordingly, this practice "does not emphasize reducing learning into components but instead seeks to understand entire systems and to support human decision making" (ibid). Higher education institutions in US are primarily using learning analytics to improve institutional efficiency and effectiveness (Siemens, 2013) and improvement in student performance retention, and graduation rates (Rubel & Jones, 2016). The U.S. Department of Education's National Education Technology Plan, as one part of its strategy for 21st-century learning enhanced by technology, intends to develop techniques to use data from virtual learning systems to improve teaching and learning experience. US higher educational institutions continue to leverage 4 primary LMSs: Blackboard Learn, Instructure Canvas, Moodle, and D2L Brightspace (Edutechnica, 2016). Jisc (2016), outlined that large scale adoption of LA are in the USA. To continue with, adoption of learning analytics being higher in USA rather than in UK, appears to be happening within individual institutions rather than at a sector level. Some universities and colleges have united LMS and SIS-type datasets across institutions. Aiming to establish predictive models about student retention and student achievement, APUS, Colorado Community College System, RSC, the University of Hawaii System, the University of Illinois–Springfield, and the University of Phoenix created the Predictive Analytics Reporting (PAR) framework (Ice et al. 2012; Rubel & Jones, 2016). In total the amount of data sets were more than 3 million course records and 640,000 student records, which were deidentified due to the protection of students' privacy. Universities in USA use learning to intervene when students are struggling in performance. For instance, some scholars believe that learning analytics should deploy nudging techniques (i.e., scripted and manual intervention strategies) to support students' behaviors (Carmean and Mizzi 2010). The application designed by Arnold (2010) and Purdue University's Course Signals system, uses a red, yellow, and green light system to nudge students to access learning materials to perform better in their class. Teachers meanwhile can make use of the system by sending "e-mails and reminders, text messages," or direct messages generated by the system (Mattingly, Rice, and Berge 2012: 243). The University of Texas, ASU, and Harvard University have started their work on setting up their own adaptive analytics technology, which suggests learning material for individual students based on their learning attitudes, past academic acheivement, and system-identified learning styles (Parry 2011; Parry 2012). The software developed at Harvard University, the "Learning Catalytics" even analyzes contrasts in learner responses to in-class questions to match students up in real time in a course for class discussion (Parry 2011). Universities are additionaly working on automated eAdvising systems to help (and track) students when picking courses for their majors. Austin Peay State University has developed a recommendation system, which suggest courses based on a student's chosen major, requirements for graduation, and academic performance regarding that of her classmates (Denley, 2012). The intervention system of ASU's eAdvising software works by sending e-mails to students and their advisors, showing messages on students' advising dashboards that they are "off track" from their system-generated progress plan, and impeding students from registering for courses if they fail to take action (ASU 2011; Parry 2012). Another significant use of learning analytics is combining learning data with that coming from non-education data sources. Pioneering research in learning analytics is mining student data while they are on the social web. "Every Tweet, every Facebook status update, every social interaction," argue Long and Siemens (2011, 32), is a possibility for universities and researchers to comprehend learning behaviors. Similarly, Samford University is analyzing social and behavioral data patterns from students in its "Class of 2017" Facebook group, in order to find out "who's likely to enroll" and "who's on the fence" (Hoover, 2012: 2). While this has more to do with admissions than students learning, it gives a small picture of how students who actually enroll are constantly traced in Facebook and how those information could illuminate administration and offerings related specifically to their learning.

3.3. Comparison of LA adoption among Australia, UK and US

US, Australia and UK are facing a critical challenges in the higher education setting. There is an international belief that "the reach, quality and performance of a nation's higher education system will be key determinants of its economic and social progress.
If we are to maintain our high standard of living, underpinned by a robust democracy and a civil and just society, we need an outstanding, internationally competitive higher education system" (Bradley et.al., 2008).

The Higher Education Commission of UK stated that the US and Australia have advanced more compared to UK regarding the adoption of learning analytics on an institutional prospective. While there exists a brilliant work within individual institutions, less attention is being paid on how the sector is performing in this realm thoroughly, especially in the US. Direct comparison is considered to be difficult due to the lack of empirical research in these areas.

Implementation of data strategies has been a difficult issue both for the US and Australia, including cultural obstacles, ability issues and resources deficiency, which the UK can learn from. By way of example in Australia, the Government lately took on a project to clarify the reason why learning analytics has been, as it says, "limited in scope and scale" even though institutions carry a positive opinion on the potential impact of it. Fifty percent of the interviewed institutions regarding the research, had already an implemented learning analytics program, and no university had a program operating over the whole institution. The case in which learning analytics has been applied there occur two diverse streamlines between institutions: one focusing on retention, the other one on pedagogy, curriculum, and learning. The reports suggestion was that these streamlines are not assumed to reach a point where we see universities enlarging their operation field of their data strategies so they are capable of including both goals. The drivers responsible for implementation of learning analytics are both shaping the way programs currently operate and how they will be operating in the future. The UK might see alike difference in the functions of LA which is a case UK should look to prevent. Plenty of research is being done in the US regarding the potential of LA and predictive learning analytics, however currently there is a lack of evidence of the effects on learning outcomes. The Campus Computing Project conducts a yearly survey of CIOs in universities across the US, results of 2015 (surveying 417 participants) reveal that: 94% of participants agree that "digital curricular resources make learning more efficient and effective for students"; and 96% that "adaptive learning technology has great potential to improve learning outcomes for students." Verifying the impact has been a clear challenge for institutions in the US. The University of Georgia lately announced to the United States Senate Committee on Health, Education, Labor and Pensions and explained how data analysis has contributed into increasing their graduation percentage by %22, with a huge increase recorded among minority students. They proposed a bunch of options with which policymakers could help them and others enhance these successes. Again, this effect might generate great benefit to the UK, but with the REF and future TEF it might be more prepared for questions on impact. In next five years both the US and Australia will be able to see the benefits of increasing learning analytics, especially the move to whole system models, personalization and predictive analysis. The US market emphasizes that curiosity among students regarding ethics of data usage could rise significantly in the next 5 or 10 years. On the other hand Australian market thinks that data will head to a drive in recruitment, which in turn may affect some ethical issues around using data in student recruitment. Another issue that the UK will need to monitor is certainly the recent increase of the student's number cap and diversification of the HE market. All three countries echo a strategic national plan to improve student retention.

The deployment of LA strategies to reduce student drop outs, has a direct impact on investment and this is in line with various government initiatives internationally (Dawson & Siemens, 2014). By way of example, the Australian Bradley Report (Bradley, Noonan, Nugent, & Scales, 2008) highlights the urgency for increasing student retention; UK's JISC initiative called for data informed policy making; and the US "Building a Grad Nation" (Balfanz et. al., 2010) emphasized a strategy for addressing the nation's growing level of attrition. Even though the few examples above are just a fraction of where local and international research in the field is being focused, it is clear that there is both a richness and multiplicity to the field.

4. Conclusion

The acceleration of big data in education, means that large amounts of students' data can now be gathered and mined, providing data tracking, learner profiling, real time feedback and customization of learning experience. The generation of such educational data indicates the emergence of a new form of policy making informed by learning analytics. Learning analytics, also known as educational data mining, tracks students' data from the interactions they have with learning materials within campus and outside, such as social media interactions, to monitor and then assess their disposition to learning, in order to then algorithmically provide feedback, enhance and personalize their learning experience. As students' academic performance is tracked, it is then compared with norms algorithmically agreed from an international database and then used for customizing their future instruction, providing policy makers with actionable insights needed to find solutions to identified problems of higher education such as student retention, attainment of transversal skills and real time feedback.

The aim of the current thesis was to investigate and analyze the opportunities LA, as an application of Big Data in education, offer for policy making. For this purpose a literature review was conducted to provide a deep overview of the field itself, while empirical research was based on a comparative analysis of the fore runner countries in the field of LA/EDM. Based on this framework, the analysis of three countries was first conducted solely to provide a clear view of the role of LA in the higher education context, then a comparison of the national policies for adopting learning analytics/educational data mining was compiled. In its results, the research finds out that the field of LA is still in its infancy and due to the lack of empirical work, limited number of papers are published. Higher education institutions of countries under study are primarily in the stage two (experimentation) according to maturity level of LA. As a result of document analysis, U.S and Australia have advanced more compared to UK regarding the adoption of learning analytics on an institutional level, while on a national level UK has seen more progress. This thesis is limited only to the document analysis of the published reports on LA and EDM, A more complete research would be realized by conducting surveys and interviews with various stakeholders of higher education institutions.

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